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Heterogeneity and the Effects of Aggregation on Wage Growth

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Abstract

This paper focuses on the implications of alternative methods of aggregating individual wage data for the behavior of economy-wide wage growth. The analysis is motivated by evidence of significant heterogeneity in individual wage growth and its cyclicality. Because of this heterogeneity, the choice of aggregation will affect the properties of economy-wide wage growth measures. To assess the importance of this consideration, we provide a decomposition of wage growth into aggregation effects and composition effects and use the decomposition to compare growth in an average wage—specifically average hourly earnings—to a measure of average wage growth from the Survey of Income and Program Participation. We find that aggregation effects largely account for average hourly earnings growth being persistently lower and less cyclical than average wage growth over the period 1990-2015, with these effects reflecting a disproportionate weighting of high-earning workers. The analysis also indicates that composition effects now play a more limited role in the cyclicality of wage growth compared to results reported in previous studies for earlier time periods.

JEL codes: J31, J33

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The behavior of aggregate wage growth is a topic of longstanding importance to researchers and policymakers in terms of both its determinants and its implications for other variables of interest. For example, the movement in wages is central to questions such as whether workers are experiencing gains in real purchasing power, the nature of the linkage of wages to labor market conditions, and the extent to which price inflation influences nominal wage growth and, in turn, nominal wage growth influences price inflation.

This paper explores the important, but often overlooked, issue of how data are aggregated across individuals to construct different economy-wide wage measures and the resulting implications for the behavior of these measures. As motivation for the analysis, we document considerable heterogeneity across workers in individual wage growth and its cyclicality. Because of this heterogeneity, the choice of aggregation will affect the properties of a wage measure. Consequently, it is important to take this consideration into account and to understand how it bears upon any resulting analyses and the reliability of any conclusions.

To illustrate this point, we examine growth in an average wage—specifically average hourly earnings (AHE)—and a measure of average wage growth (AWG) constructed from the Survey of Income and Program Participation (SIPP). We note that a key conceptual difference between these two wage measures is how each aggregates wage growth across individuals. AHE combines individual wages in levels using relative hour weights, thereby producing a measure of overall wage growth that, under some simplifying assumptions, is an earnings-weighted average of individual workers' wage growths. In contrast, AWG produces a measure of overall wage growth that is an equally weighted average of individual workers' wage growths. Given the heterogeneity in wage growth and its cyclicality that we document in the data, these different aggregation methods have several important implications.

A consequence of an earnings-weighted average of individual wage growth is that it places relatively less weight on younger, lower-earning workers and relatively more weight on older, higher-earning workers. Younger workers tend to experience faster wage growth. In addition, cyclical job-changing is more prominent among younger workers. Consequently, these considerations suggest that AHE growth will consistently be lower and less cyclical than AWG.

To quantify these implications, we compare AHE growth to AWG and evaluate the impact of the different aggregation methods on the behavior of the wage measures and their co-movement

with other variables of interest. A key aspect of the analysis is the decomposition of movements in AHE growth into an aggregation effect—the associated weighting of individual wage growth—and a composition effect—the differences in wage levels between individuals leaving employment and entering employment over a period and, for individuals working each period, the change in relative hours between high- and low-wage workers. The results show that over the period 1990-2015 AWG is systematically higher than AHE growth (measured in nominal terms)—on average by 3.6 percentage points—and that aggregation effects account for roughly 75 percent of this difference. This finding suggests that real wage growth over the past 25 years has consistently and notably exceeded that indicated by AHE growth.

We then specify an aggregate wage-inflation Phillips curve model and find that AWG is more cyclical than AHE growth by 21 basis points, with the aggregation effect accounting for roughly 79 percent of the higher cyclicality. Our evidence that the composition effect imparts a small countercyclical effect on wage growth contrasts with the significant countercyclical effect reported in Solon, Barsky, and Parker (1994) for data covering the 1970s and 1980s. As we demonstrate, this difference in the relative importance of composition effects may reflect Solon, Barsky, and Parker's use of the change in the unemployment rate as a cyclical indicator and evidence pointing to a change in this variable's statistical properties starting in the mid-1980s.

Taken together, our results suggest that aggregation is an important consideration when selecting an economy-wide measure of wage growth. While the literature, and most notably the studies of Bils (1985) and Solon, Barsky, and Parker (1994), has investigated how different aggregation methods may have different consequences for the cyclical behavior of wage growth, our analysis demonstrates that this consideration also extends to the level of wage growth.

The outline of the paper is as follows. The next section documents significant heterogeneity in individual wage growth and its cyclicality in micro data. We then define and discuss aggregation and composition effects arising from different methods used to calculate an economy-wide average wage and its growth rate. In the third section, we demonstrate that aggregation effects largely account for the persistent difference between measured AWG and AHE growth. We then estimate an aggregate wage-inflation Phillips curve model to contrast the cyclical sensitivity of AWG and AHE growth and show that, again, aggregation effects largely account for the difference. We then turn to a comparison to earlier studies and examine how differences in micro wage specifications

and sample periods may affect the estimated contributions of aggregation and composition effects to the cyclicality of wage growth. The final section offers concluding remarks.

Measuring Wage Growth

Aggregate wage measures can be constructed from group- or individual-level data. Measures using group-level data are based on group payroll and hours information for a pay period. Measures using individual-level data involve a mixture of reported wages for those paid by the hour and inferred wages for salaried workers based on earnings and hours over a pay period (or time period).

Data Sources

Average hourly earnings is a well-known and widely used average wage measure. The Bureau of Labor Statistics (BLS) publishes AHE monthly using data from the monthly Establishment Survey, a large, stratified random sample survey of roughly 140,000 businesses and 440,000 establishments.[1] The survey covers private, non-farm, non-supervisory workers. Each reporting establishment provides employment, payroll expenses, and total hours for the pay period covering the 12th day of the month. Payroll expenses reflect payments before deductions and include overtime, paid holidays, vacation, and sick leave. Bonuses and commissions are excluded unless they are paid monthly. The BLS uses the establishment-level data to calculate AHE as aggregate payroll expenses divided by aggregate hours. The Establishment Survey does not collect the underlying micro data, thus precluding analysis of the AHE series at the individual level.

For individual wage growth we use data from the Survey of Income and Program Participation (SIPP). The SIPP consists of a series of nationally representative short panels of individuals who are tracked across job changes as well as residence changes.[2] From 1984 to 2014, panels lasted between two and four years, with new panels often overlapping with previous panels. Following Gertler, Huckfeldt, and Trigari (2020), we begin our estimation sample in 1990 when the employer identifier becomes more reliable. All household members 15 years and older are interviewed. The SIPP collects data on sources of income, social program participation, and demographics. Until the end of 2012, the SIPP used a 4-month recall period in its interviews.

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[1] See Bureau of Labor Statistics (2018).

[2] An alternative source of micro data is the monthly Current Population Survey (CPS). The CPS data allow matching individuals over a 12-month period so long as the individual does not change residences. Consequently, a CPS measure of AWG will not include individual wage growth associated with moves. See Neumark and Kawaguchi (2004) for a discussion of the selection bias from not being able to follow movers.

Starting in 2013, the SIPP asks workers to recall information for the prior calendar year. The most recently published SIPP data are based on the 2014 panel and cover the period 2013 to 2016.

We restrict the SIPP sample to private, non-farm, non-supervisory workers who are not self-employed to align the data with the Establishment Survey data used to construct AHE. For individuals paid by the hour, we use their reported hourly wage and hours. For salaried workers, we impute their wage from their monthly earnings (including bonuses and commissions) and hours. We exclude any wages or earnings that were imputed or top-coded and any wage (reported or imputed) that falls below the prevailing federal minimum wage. We compute 4-quarter growth rates in individual wages by initially calculating 12-month changes and then averaging over the relevant months associated with a quarter. We symmetrically trim the top/bottom 1 percent of individual wage growth as well as growth in hours to remove outliers.

Heterogeneity of Individual Wage Growth: Level and Cyclicality

How much heterogeneity exists in the level and cyclicality of individual wage growth? What characteristics of workers generate this possible heterogeneity? To explore these questions, we turn to a micro wage growth regression that allows the level and cyclicality of wage growth to vary by individual. Using our SIPP data, we estimate the following panel cross-sectional individual wage growth specification:

$$\left(\frac{w_{t+4}^i}{w_t^i}-1\right)=\gamma\left(U_t-U_t^*\right)+\beta X_t^i+\delta\left(U_t-U_t^*\right)X_t^i+\varepsilon_{t+4}^i \tag{1}$$

where w_t^i is the wage observed for worker i in period t, U_t is the aggregate unemployment rate and U_t^* is the Congressional Budget Office (CBO) estimate of the natural rate of unemployment, X_t^i contains individual characteristics at time t, $\left(U_t-U_t^*\right)X_t^i$ are interactions between the unemployment gap and individual characteristics, and ε_{t+4}^i is an individual error. The dependent variable is the actual wage growth for an individual as opposed to the approximation given by the difference in log wages.

The results from estimating equation (1) using the SIPP data are provided in Table 1. The left-out group is single white males with a high school education. In specification (1) we control for the unemployment gap and individual characteristics. A one percentage point decline in the

unemployment gap is associated with a 69-basis-point increase in nominal wage growth. The estimates indicate that wage growth is lower for women and married individuals. Wage growth for college graduates is over 100 basis points higher than for high school graduates. Finally, wage growth is diminishing over workers' careers as they accumulate work experience. What specification (1) does not identify, however, is the degree to which the cyclicality of wage growth varies across workers. We explore this issue next.

In specification (2), we include interactions between the CBO unemployment gap and several individual characteristics. This more general specification allows both the level and the cyclical sensitivity of individual wage growth to vary. The results indicate that wage growth cyclicality is higher for Hispanics, women, and college graduates.[3] Married workers have wage growth that exhibits less cyclicality. As workers gain more work experience, wage growth becomes less responsive to the unemployment gap. For the left-out group (single white males with a high school education), the cyclicality of their wage growth is estimated to be -0.92 at the outset of their careers. After 15 years, this cyclicality is estimated to decline to -0.67, and after 30 years, it declines even further to -0.54. This pattern illustrates the degree to which wage growth cyclicality on average declines over a worker's career.

Figure 1 shows a kernel density estimate of the distribution of the predicted individual wage growth pooled over time based on specification (2). The distribution of predicted wage growth is right skewed. The 10-90 percentile spread is from 5.3 percent to 12.3 percent, while the 25-75 percentile spread is from 5.9 percent to 8.8 percent. Similarly, we can use the estimated coefficients on the interaction effects to generate the distribution of wage growth cyclicality across individuals. Figure 2 shows a kernel density estimate of the distribution of individual wage growth cyclical sensitivities. The distribution of individual wage growth cyclical sensitivities is left skewed. The 10-90 percentile spread is from -0.92 to -0.53, while the 25-75 percentile spread is from -0.79 to -0.58.

Figures 1 and 2 illustrate notable dispersion in both individual wage growth and its cyclical sensitivities. An implication of this heterogeneity is that the specific aggregation method associated with an economy-wide wage measure will impact the resulting level and cyclicality of that measure's

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[3] Solon, Barsky, and Parker (1994) find lower wage growth cyclicality for women using the Panel Study of Income Dynamics (PSID). This result was obtained by estimating separate wage growth regressions for men and women.

wage growth. To formalize this, we next present a decomposition of the growth of an average wage that highlights the specific contributions from two sources: an aggregation effect and a composition effect.

Aggregation Methods and the Growth and Cyclicality of an Average Wage

This section explores aggregation within the context of constructing an average wage. We examine how different choices for weighting individual wage data to construct an average wage produce different aggregation and composition effects for the growth in that average wage.

Aggregation and Average Wage Measures

We start with individual data on wages and hours worked and construct a measure of the "average" wage to summarize this information. We can describe any average wage measure as a weighted sum of the individual wage data. Let w_t^i denote the wage for individual i at time t and let s_t^i denote the weight assigned to that wage, where $0 < s_t^i < 1$, and the weights sum to unity across all individuals in the target group at time t. A general representation of an average wage is:

$$\bar{w}_t = \sum_{i=1}^{n_t} s_t^i w_t^i , \tag{2}$$

where n_t is the number of individuals in the target group reporting a wage at time t. The choice of weights, s_t^i, defines the aggregation method used to construct the specific average wage measure.

Now assume that we have individual data on wages and hours for two dates, time t and time $t+h$, and we would like to measure growth in the average wage over this period. The general expression for growth in the average wage, which depends on the selected aggregation method, is:

$$\left(\frac{\bar{w}_{t+h}}{\bar{w}_t} - 1 \right) = \sum_{i \in S} \left(\frac{s_{t+h}^i}{s_t^i} \right) \left(\frac{s_t^i w_t^i}{\bar{w}_t} \right) \left(\frac{w_{t+h}^i}{w_t^i} - 1 \right) + \left(\frac{\bar{w}_{t+h}^*}{\bar{w}_t} - 1 \right) , \tag{3}$$

where $\bar{w}_{t+h}^*$ is the "adjusted" average wage at time $t+h$ and is defined as:

$$\bar{w}_{t+h}^* = \sum_{j \in J} s_{t+h}^j w_{t+h}^j + \sum_{i \in S} s_{t+h}^i w_t^i , \tag{4}$$

and where J denotes the set of individuals who do not work at time t but enter work by time $t+h$ ("joiners") and S denotes the set of individuals who work in both time periods ("stayers").[4] As shown, $\bar{w}_{t+h}^{*}$ is calculated using the wages and weights at time $t+h$ for joiners and the wages at time t and the weights at time $t+h$ for stayers.[5]

The growth in the average wage in (3) consists of two terms: an aggregation and a composition effect. The first term—the aggregation effect—is the contribution to wage growth from aggregating individual wage growth. In the case of the average wage, growth in individual wages is combined using a weighting scheme that depends on the individual's share-weighted wage relative to the average wage, as well as the change in the individual's weight over the period. The second term—the composition effect—reflects impacts on the average wage from changes in the composition of the workforce (at both the extensive and intensive margins) between time t and time $t+h$. The contribution of changes in the extensive margin to wage growth reflects differences in the average wage for joiners as compared to leavers.[6] The contribution of changes in the intensive margin to wage growth reflects shifts in the relative hours worked between high- and low-wage jobs for individuals employed in both periods.[7]

We now apply the decomposition in (3) using two different choices of aggregation methods to construct the average wage. The first choice uses equal weighting by setting $s_t^i (=\,{}_1 s_t^i) = 1/n_t$. This aggregation method produces an average wage that is the mean of the individual wage data. We denote this average wage as ${}_1\bar{w}_t$, which can be written as:

$$
{}_1\bar{w}_t = \sum_{i=1}^{n_t} {}_1 s_t^i w_t^i = \sum_{i=1}^{n_t} \frac{1}{n_t} w_t^i \tag{5}
$$

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[4] See Appendix 1 for details.

[5] We will refer to individuals who work in period t but leave work prior to period $t+h$ as "leavers."

[6] To clarify terminology, we use "aggregation method" to refer to the weighting scheme selected to combine wage data in levels or growth rates. We use "aggregation effect" and "composition effect," respectively, in the context of decomposing wage growth into a component attributable to the individual wage growth of stayers and a component attributable to movements in the wage levels of joiners and leavers and shifts in hours among stayers.

[7] See Keane, Moffitt, and Runkle (1988) and Daly and Hobijn (2017) for a discussion of composition effects arising from unobservables.

The second choice constructs an average wage using weights equal to each worker's hours as a fraction of total hours. Letting h_t^i denote the hours worked by individual i at time t, H_t total hours at time t, and $s_t^i (= {}_2 s_t^i) = h_t^i / H_t$, we can write the second average wage measure as:

$$ {}_2\overline{w}_t = \sum_{i=1}^{n_t} {}_2 s_t^i w_t^i = \sum_{i=1}^{n_t} \frac{h_t^i}{H_t} w_t^i \tag{6} $$

As shown by (6), an equivalent way to construct ${}_2\overline{w}_t$ is to sum the earnings $(e_t^i = h_t^i w_t^i)$ across workers to compute total earnings (E_t) and then divide by total hours across workers. Expressed in this form, the second average wage measure, ${}_2\overline{w}_t = E_t / H_t$, defines AHE.

We now examine the growth rate of each of these two average wage measures. Using the definition of ${}_1 s_t^i$ in (5) and substituting into (3), the h-period growth rate in ${}_1\overline{w}_t$ is given by:

$$ \left(\frac{{}_1\overline{w}_{t+h}}{{}_1\overline{w}_t} - 1 \right) = \left(\frac{n_t}{n_{t+h}} \right) \left(\frac{W_t^S}{W_t} \right) \sum_{i \in S} \left(s_t^i \right)^w \dot{w}_{t,t+h}^i + \left(\frac{{}_1\overline{w}_{t+h}^*}{{}_1\overline{w}_t} - 1 \right) \tag{7} $$

where W_t^S denotes total wages of stayers at time t, W_t total wages of all workers at time t, $\dot{w}_{t,t+h}^i$ the wage growth for individual i during the period, $\left(s_t^i \right)^w$ worker i's wage as a share of total wages earned by stayers at time t $\left(\left(s_t^i \right)^w = w_t^i / W_t^S \right)$, and ${}_1\overline{w}_{t+h}^*$ the adjusted (equal-weighted) average wage at time $t+h$ defined accordingly from (4).

Next consider the growth in ${}_2\overline{w}_t$, or AHE. Using the definition of ${}_2 s_t^i$ in (6) and substituting into (3), the h-period growth rate in ${}_2\overline{w}_t$ is given by:

$$ \left(\frac{{}_2\overline{w}_{t+h}}{{}_2\overline{w}_t} - 1 \right) = \left(\frac{H_t}{H_{t+h}} \right) \left(\frac{E_t^S}{E_t} \right) \sum_{i \in S} \left(\frac{h_{t+h}^i}{h_t^i} \right) \left(s_t^i \right)^e \dot{w}_{t,t+h}^i + \left(\frac{{}_2\overline{w}_{t+h}^*}{{}_2\overline{w}_t} - 1 \right), \tag{8} $$

where E_t^S denotes total earnings of stayers at time t, E_t total earnings of all workers at time t, H_t and H_{t+h}, respectively, total hours at time t and time $t+h$, $\left(s_t^i \right)^e$ worker i's earnings as a share of total earnings of stayers at time t $\left(\left(s_t^i \right)^e = e_t^i / E_t^S \right)$, and ${}_2\overline{w}_{t+h}^*$ the adjusted (hours-weighted) average wage at time $t+h$ defined accordingly from (4).

It is important to note that the same underlying data on individual wages and hours as well as the participation pattern of workers are used to calculate (7) and (8). Given the heterogeneity discussed earlier, the corresponding growth rates and therefore the associated aggregation and composition effects will differ due to the aggregation methods used to construct the average wages in (5) and (6). In the case of the composition effects, recall from (2) and (4) that the calculation of the average wage at time t $(\bar{w}_t)$ and its adjusted value at time $t+h$ $(\bar{w}^*_{t+h})$ are directly linked to the choice of aggregation method.

Comparing Growth in an Average Wage to Average Wage Growth

It is instructive to consider the special case where no individuals join or exit work and individual hours are constant over the period from time t to $t+h$. Under these strong assumptions, there are no composition effects and the h-period growth rates in $_1\bar{w}_t$ and $_2\bar{w}_t$ simplify, respectively, to:

$$\left(\frac{_1\bar{w}_{t+h}}{_1\bar{w}_t} - 1 \right) = \sum_{i \in S} \left(s_t^i \right)^w \dot{w}_{t,t+h}^i \qquad (7')$$

and

$$\left(\frac{_2\bar{w}_{t+h}}{_2\bar{w}_t} - 1 \right) = \sum_{i \in S} \left(s_t^i \right)^e \dot{w}_{t,t+h}^i \quad , \qquad (8')$$

where $\dot{w}_{t,t+h}^i$ again denotes the wage growth for individual i from time t to $t+h$.

Note that the specific form of the aggregation method applied to the wage data in levels does not carry over to the aggregation effects in growth rates. For example, the construction of $_1\bar{w}_t$ uses equal weighting, but the aggregation effect in (7') involves an unequal weighting of wage growth by an individual's wage share. Similarly, the construction of $_2\bar{w}_t$ uses weighting by an individual's share of hours, but the aggregation effect in (8') involves a weighting of wage growth by an individual's earnings share.

This exercise highlights the contrasting aggregation effects underlying growth in the two average wage measures and also facilitates our introduction of AWG as an alternative measure of overall wage growth. Specifically, AWG is derived from an aggregation method that equally weights individual wage growth and is given by:

$$\overline{\dot{w}}_t = \sum_{i \in S} \left(\frac{1}{n_t} \right) \dot{w}^i_{t,t+h} \tag{9}$$

The AWG measure uses equal shares across workers to calculate the mean of individual wage growth and by construction does not involve a direct composition effect.[8] Moreover, we have not been able to identify an aggregation method for an average wage that generates a growth rate that equally weights individual wage growth, further illustrating that growth in an average wage and AWG are distinct measures.

The next section explores the implications of the different weighting schemes of individual wage growth for the behavior of overall wage growth measures where we restrict attention to the AHE specification for an average wage. This choice is partly motivated by the popularity of AHE as a wage series and its longstanding use in research and policy analysis, whereas $_1\overline{w}$ is less frequently used as a summary measure of wages. In addition, the correlation between an individual's wage share and earnings share is 0.97, suggesting a close correspondence between (7') and (8').

Aggregation and the Level and Cyclicality of Wage Growth

Considerable attention is paid to wage growth and its implications for the ability of individuals to improve their standard of living. Here it is useful to compare (7') and (8') and to examine how weighting by a worker's earnings as compared to using equal weights likely affects measured wage growth. As documented by Mincer (1974) and Becker (1975), life-cycle wage profiles are generally concave in workers' ages (or years of work experience). Early in their careers, workers tend to have relatively low wages and earnings, but high wage growth. By mid-career, workers tend to have relatively high wages and earnings, but low wage growth. Finally, by late career, workers tend to have flat to negative wage growth. This pattern for wage growth over the life-cycle is demonstrated in Table 1. That is, the life-cycle pattern of wages creates a negative correlation between a worker's wage (or earnings) and wage growth.[9] All else the same, this negative correlation will lower AHE growth below that of AWG.

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[8] The heterogeneity in individual wage growth shown earlier can introduce an indirect composition effect when comparing AWG over time. Entry and exit from working that changes the composition of this heterogeneity of the workforce can result in changes in measured average wage growth over time.

[9] Lippi and Perri (2021) use PSID data from 1967-2016 and find that the correlation between a worker's earnings growth and the earnings share ranged from -0.8 to -0.6 from the late 1960s to the late 1980s. Since then, the correlation has slowly declined to around -0.5 currently.

We use the decomposition of AHE growth in (8) to examine the contributions of aggregation and composition effects to the difference between AWG and AHE growth. Defining notation, let $\%\Delta AHE = \%\Delta AHE^A + \%\Delta AHE^C$, where "A" denotes the aggregation effect and "C" the composition effect. The difference between AWG and AHE growth can then be expressed as:

$$AWG - \%\Delta AHE = \left(AWG - \%\Delta AHE^A \right) - \%\Delta AHE^C \qquad (10)$$

The first term on the right-hand side of (10) is the contribution of the aggregation effect to the difference in AWG and AHE growth, while the second term is the contribution of the composition effect.

Another area of considerable interest is the cyclical behavior of wage growth and the factors that can account for differences in this behavior across various wage measures. From our earlier analysis, we can also explore the relative importance of aggregation and composition effects for the difference in cyclicality of AWG and AHE growth. To make this determination, we first consider how the cyclicality of AHE growth depends on the cyclicality of the aggregation and composition effects in (8). For AWG, we will only need to consider the cyclicality of the aggregation effect as our previous discussion of (9) highlighted the absence of a direct composition effect in this measure.

As discussed in the next section, we use an aggregate wage-inflation Phillips curve to analyze the cyclical behavior of wage growth. The specification relates wage growth to long-run inflation expectations, trend productivity growth, and a cyclical indicator measured by an unemployment gap. Let $\hat{\beta}_U^{AHE}$ denote the estimated cyclicality of AHE growth defined as the coefficient on the unemployment gap in the aggregate wage-inflation Phillips curve regression. The overall estimated cyclicality of AHE growth can be expressed as the sum of the estimated cyclicality of the aggregation effect and the estimated cyclicality of the composition effect from (8):

$$\hat{\beta}_U^{AHE} = \hat{\beta}_U^{AHE\_A} + \hat{\beta}_U^{AHE\_C} \qquad (11)$$

where $\hat{\beta}_U^{AHE\_A}$ and $\hat{\beta}_U^{AHE\_C}$ are defined and derived in a manner analogous to that for $\hat{\beta}_U^{AHE}$. The summation property of the cyclicality estimates in (11) allows us to identify the relative importance of aggregation and composition effects to the overall cyclicality of AHE growth.

Let $\hat{\beta}_U^{AWG}$ denote the estimated cyclicality of AWG that follows from the same methodology applied to AHE growth. The difference in cyclicality between AHE growth and AWG, using (11), is given by:

$$\hat{\beta}_U^{AHE} - \hat{\beta}_U^{AWG} = \left(\hat{\beta}_U^{AHE\_A} - \hat{\beta}_U^{AWG} \right) + \hat{\beta}_U^{AHE\_C} \tag{12}$$

Recall that AWG and the aggregation effect of AHE growth use the same data on individual wage growth. Consequently, the first term on the right-hand side of (12), $(\hat{\beta}_U^{AHE\_A} - \hat{\beta}_U^{AWG})$, captures the difference in cyclicality of the two wage growth measures from the different aggregation methods. The balance of the overall difference is attributable to $\hat{\beta}_U^{AHE\_C}$, which measures the cyclicality of the composition effect.

What is the likely difference between $\hat{\beta}_U^{AWG}$ and $\hat{\beta}_U^{AHE\_A}$? There is evidence that wage growth is more cyclical for young workers (Topel and Ward, 1992; and Table 1) and workers who have low earnings [Bils (1985), Blank (1990)]. These two findings are closely related to job-changing, which is more prominent among younger workers and is generally associated with large wage changes.[10] Because AHE growth disproportionately reflects the cyclicality of wages for older, higher-earning workers, the aggregation effect of AHE growth is predicted to be less cyclical than AWG.

An Assessment of Aggregation Effects

Level of Wage Growth

We begin by contrasting AHE growth from the BLS with the SIPP AWG. Figure 3 plots nominal four-quarter AHE growth and AWG from 1990 to 2015. The gaps in the SIPP AWG series are due to periods when there were no waves underway. The 2014 panel has fewer participants and therefore generates a noisier estimate of AWG. We indicate NBER-dated recession periods in grey. A key feature from Figure 3 is that the SIPP AWG is consistently higher than the growth in the BLS

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[10] As noted by Jacobson, LaLonde, and Sullivan (1993), job-changers tend to receive relatively large wage increases during an expansion and relatively large wage decreases during a recession. The former finding is referred to as the cyclical upgrading hypothesis and is a primary source of wage growth early in a worker's career.

AHE, with the average difference around 3.6 percentage points (6.43 percent vs. 2.84 percent).[11] An implication is that individuals have experienced much higher wage growth over this period when measured by AWG as compared to AHE growth.

As previously discussed, using relative earnings to construct an economy-wide measure of wage growth down-weights the wage growth of individuals early in their careers. Job-changing is also concentrated during these early years. Figure 4 shows our SIPP AWG series separated by individuals who stay with their same employer and individuals who change jobs. Outside of recessions, the average wage growth of job-changers is consistently higher than that for non-job-changers; the difference is 4.07 percentage points (9.82 percent vs. 5.75 percent) over our sample period. The strong wage growth for job-changers is consistent with the cyclical upgrading hypothesis examined in Okun (1973), Vroman (1977), McLaughlin and Bils (2001), Devereux (2002), and Hagedorn and Manovskii (2013). This finding suggests that earnings weighting is likely to have a meaningful impact on the level of measured wage growth.

The expression for AHE growth in (8) shows that earnings weighting of individual wage growth is an important element of the aggregation effect. Figure 5 illustrates how earnings weighting, by itself, affects the level of average wage growth. The earnings weighted AWG is consistently lower than the equally weighted AWG (4.52 percent vs. 6.43 percent), suggesting that the aggregation effect may account for a large part of the difference between AWG and AHE growth over time.

To assess the contribution of the aggregation effect to the difference between AWG and AHE growth, we first calculate a SIPP AHE series and then compute its growth. The comparison of the SIPP AHE growth and the BLS AHE growth is shown in Figure 6. The SIPP AHE growth tracks the BLS AHE growth (correlation of 0.65) but displays more volatility starting in 2013 due to the reduction in SIPP panel size. Over our sample period, the SIPP AHE growth is 2.76 percent compared to 2.84 percent for BLS AHE growth.

We now use the SIPP AHE growth series to undertake the decomposition in (8). Figure 7 shows the decomposition of SIPP AHE growth into its corresponding aggregation and composition effects. Over the sample period, the aggregation effect averages 3.69 percent, while the composition

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[11] If we calculated individual wage growth using the difference in log(wage) approximation, the resulting AWG over our sample period would be 4.27 percent compared to 6.43 percent, understating AWG by one-third.

effect averages −0.93 percent, with the latter indicating that on average composition effects act to lower AHE growth. Filling in the values for equation (10) yields:

$$AWG - \%\Delta AHE = (AWG - \%\Delta AHE^A) - \%\Delta AHE^C$$

$$6.43 - 2.76 = (6.43 - 3.69) + 0.93$$

$$3.67 = 2.74 + 0.93$$

The aggregation effect accounts for 75 percent of the difference between SIPP AWG and SIPP AHE growth.

Cyclicality of Aggregate Wage Growth

We next examine the cyclical sensitivity of AWG and AHE growth by estimating aggregate wage-inflation Phillips curve specifications for both SIPP AWG and SIPP AHE growth. As previously discussed, the regression model includes measures of expected inflation, trend productivity growth, and an unemployment gap as explanatory variables. As before, we construct SIPP AWG on a four-quarter change basis by averaging individual 12-month wage growth over the relevant months associated with a quarter.

Our specification relates aggregate wage growth from quarter *t* to *t+4* to explanatory variables merged in at quarter *t* and is given by:

$$\dot{W}_{t,t+4} = \alpha_0 + \alpha_1 \pi_t^e + \left(Productivity\ Growth \right)_t^{TREND} + \alpha_2 \left(U_t - U_t^* \right) + \varepsilon_{t+4} \qquad (13)$$

where we use the 10-year CPI inflation expectations from the US Survey of Professional Forecasters and proxy trend productivity growth by applying a Hodrick-Prescott filter to quarterly (annualized) productivity growth rates from the business sector.[12] We measure labor market conditions using an unemployment gap based on the CBO's estimate of the natural rate of unemployment $\left(U_t^* \right)$. Given the unequal sizes of the different SIPP waves, we use weighted least squares to estimate (13), where the weights are the number of individual wages used to construct a wage growth relative to the total number of individual wages for the estimation sample.

We first revisit the question of the cyclicality of AWG compared to BLS AHE growth for our sample period. The estimation results are presented in Table 2. The first specification uses the

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[12] We follow the approach described in Yellen (2017) to construct the measure of trend productivity growth.

SIPP AWG. As shown, a one percentage point decline in the unemployment gap is associated with a 71-basis-point increase in average wage growth.[13] In specification (2), we use the BLS AHE growth as the dependent variable and restrict the sample to match our SIPP sample. The results now indicate that a one percentage point decline in the unemployment gap is associated with a 33-basis-point increase in AHE growth. Note that the estimated cyclicality of BLS AHE growth is less than half that of SIPP AWG. This is consistent with the earlier findings of Solon, Barsky, and Parker (1994) using different micro data and an earlier sample period that the cyclicality of AWG significantly exceeds the cyclicality of AHE growth.

Decomposing the Cyclicality of AHE Growth

We now turn to Table 3, which reports the decomposition of the cyclicality of our SIPP AHE growth into the contributions from the aggregation and composition effects. Comparing column (3) to column (2) in Table 3, we first note that the estimated cyclicality of our SIPP AHE growth exceeds that of the BLS AHE growth by 17 basis points.

Recall from (11) that the coefficient on the CBO unemployment gap for AHE growth is the sum of the coefficients on the CBO unemployment gap for the aggregation and composition effects. The results in columns (4) and (5) in Table 3 show that the estimated cyclicality of −0.502 for SIPP AHE growth is comprised of an aggregation effect of −0.546 and a composition effect of 0.044. Substituting these values into (11) yields:

$$\beta_U^{AHE} - \beta_U^{AWG} = \left(\beta_U^{AHE\_A} - \beta_U^{AWG}\right) + \beta_U^{AHE\_C}$$

$$-0.502 + 0.713 = (-0.546 + 0.713) + 0.044$$

$$0.211 = 0.167 + 0.044$$

The aggregation effect accounts for 17 of the 21-basis-point difference in cyclicality, or 79 percent. While the sign of the composition effect is positive and indicates countercyclical behavior, the magnitude is economically and statistically insignificant.

We previously demonstrated that job-changing, which is concentrated early in careers when individuals have relatively low earnings, plays a meaningful role in explaining the difference in the

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[13] This is lower than the estimated cyclicality by Solon, Barsky, and Parker (1994) using data from the 1970s and 1980s. Sumner and Silver (1989) find that the estimated cyclical behavior of wages depends on the time period covered by the data.

level of AWG and AHE growth. We now turn to the importance of job-changing as a contributor to the role of aggregation effects in the cyclicality of wage growth. We explore this issue in Table 4, where our SIPP AWG measure is separated by individuals who remain with their same employer and those who change employers. For individuals who do not change jobs, a one percentage point decline in the CBO gap is associated with a 65-basis-point increase in wage growth. In contrast, the estimated cyclicality for job-changers is 85 basis points, which is 31 percent larger.

Taken together, our results indicate that the choice of aggregation exerts a significant influence on measured wage growth and that the corresponding aggregation effects play an important role in observed differences in the cyclical behavior of series. It is therefore natural to ask how our findings relate to those of other studies.

The most comparable analysis to our investigation is by Solon, Barsky, and Parker (1994), who use data covering the period 1968 to 1988 from the Panel Study of Income Dynamics (PSID), which, like the SIPP data, is a nationally representative sample of individuals of all ages. Using a decomposition that is detailed in Appendix 2, they report that composition effects account for roughly half of the lower cyclicality of AHE growth as compared to PSID AWG. This contrasts with our finding of only a modest contribution of composition effects to the lower cyclicality of AHE growth. The next section discusses composition effects in AHE growth and explores possible explanations for our evidence pointing to a smaller role.

Reconciling the Relative Contribution of Composition Effects to AHE Cyclicality

This section extends the analysis to focus on two issues that have implications for the estimated cyclicality of wage growth and the relative importance of composition effects. The first is related to the choices of the cyclical measure to gauge labor market conditions and the sample period used in the estimation. The second concerns the consequences of using a logarithmic approximation instead of the actual percentage change to measure AWG. As we discuss below, both issues may shed light on why the prior literature generally finds evidence that composition effects are important for understanding the cyclical behavior of AHE growth, while our results suggest only a modest role for composition effects.[14]

Earlier studies, such as Bils (1985) and Solon, Barsky, and Parker (1994), used the change in the unemployment rate as the cyclical measure for their analyses. However, aggregate wage-inflation

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[14] See Abraham and Haltiwanger (1995) for a survey of the cyclicality of wage growth.

Phillips curve specifications often use an unemployment gap as the cyclical measure, while the change in the unemployment rate (if this variable is included at all) is used to capture a "speed limit" effect.[15] Comparing the unemployment gap to its change, we find the former is a preferred and robust cyclical measure and that sharp movements in the latter, which are much more prevalent in the data prior to the mid-1980s, are associated with composition effects.

Table 5 offers insights into the use of the CBO unemployment gap versus the change in the unemployment rate (or the change in the CBO unemployment gap in our case) as the cyclical measure for our various wage growth measures.[16] Specification (1) repeats our earlier findings for ease of comparison. Specification (2) replaces the CBO unemployment gap with the 4-quarter change in the CBO unemployment gap as the cyclical variable. For AWG, using the CBO gap or the change in the CBO gap individually produces similar estimated cyclicality coefficients.

Turning to SIPP AHE growth in specification (2), we find that the change in the CBO gap generates a cyclicality estimate roughly half the size of that obtained using the CBO gap. As we continue down the column, we observe that this lower cyclicality of AHE wage growth is driven by the composition effect: the cyclicality of the aggregation effect declines by roughly 9 percent, while the cyclicality of the composition effect increases by a factor of 4. The estimated cyclicality of the composition effect of 0.23 reduces the overall cyclicality of AHE growth by 50 percent. Consequently, the relative contribution of the composition effect to the reduced cyclicality of AHE growth compared to AWG increases from 21 percent using the CBO unemployment gap to 49 percent using the change in the CBO unemployment gap.

Specification (3) of Table 5 reports the results from expanding our wage-inflation Phillips curve specifications to include both the CBO unemployment gap and the change in the CBO unemployment gap. As shown, the CBO unemployment gap displays comparable behavior across specification (1) and specification (3) for AWG. Turning to the change in the gap, the conventional view of a speed limit effect is that it should reinforce the unemployment gap effect; that is, it should display a negative sign. When we examine the change in the CBO unemployment gap across specification (2) and specification (3) for AWG, we observe a marked difference in the responses.

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[15] "Speed limit" effects are motivated by the possibility that the response of wage growth (or some other variable of interest) also depends on whether the unemployment rate is changing rapidly or gradually. See Fuhrer (1995), Turner (1995), Debelle and Vickery (1998), and Malikane (2014).

[16] Because the CBO natural rate of unemployment evolves only slowly over time, the change in the unemployment rate is essentially the same as the change in the CBO unemployment gap.

Specifically, the change in the gap reveals a loss in both economic and statistical significance and consequently does not offer any evidence of a speed limit effect impacting SIPP AWG.

Turning to specification (3) for AHE growth, we again observe the CBO unemployment gap displaying similar behavior to that in specification (1). However, the change in the CBO unemployment gap now has a positive and statistically significant effect: opposite in sign to the traditional view of a speed limit effect. As we continue down the column and look at the two components of AHE growth, we see that the positive coefficient on the change in the CBO unemployment gap reflects a strong positive composition effect in AHE growth. This finding indicates that rapid changes in the unemployment rate are associated with sharp differences in wages between job entrants and leavers that give rise to the positive composition effects on AHE growth.

The estimation results in specification (3) of Table 5 raise concerns about the specification of the micro wage growth regressions used in earlier cited studies. Specifically, our evidence does not support the practice of using the change in the unemployment gap (or the change in the unemployment rate) by itself as a cyclical measure. As shown, the properties of the change in the gap, such as the sign and statistical significance, are not robust to the inclusion of the unemployment gap as an additional cyclical measure.

A second consideration related to the previous discussion is that the volatility of the unemployment rate associated with speed limit effects for AHE growth was more pronounced in the sample period considered by Solon, Barsky, and Parker (1994). The "Great Moderation" beginning in the mid-1980s led to a reduction in the volatility of unemployment [see McConnell and Perez-Quiros (2000)]. This can be seen in Figure 8, which plots the 4-quarter change in the CBO unemployment gap from 1950 to the present. The two exceptions are the financial crisis and the COVID-19 pandemic, which both resulted in large spikes in the unemployment rate and likely account for the statistical significance of the change in the CBO unemployment gap in the AHE growth and composition effect regressions in specification (3).[17]

Another issue that bears upon the evaluation of composition effects is that the prior literature on the cyclicality of AWG initially adopts an individual log wage specification. Individual wage growth is then estimated taking the four-quarter difference in log wages. This approximation

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[17] The unprecedented fast rise and later fall in the unemployment rate associated with the COVID-19 pandemic generated outsized composition effects on AHE growth [see Howard, Rich and Tracy (2021, 2022)].

to the percentage change in a worker's wage is poor for large positive and negative wage growth. Consequently, this approach would differentially impact job-changers, who, we have shown, have higher wage growth cyclicality. Using this approximation for SIPP AWG reduces its estimated cyclicality from −0.713 to −0.588, a decline of 17 percent. As a result, the same composition effect for AHE growth now explains a relative larger proportion (51 percent vs. 21 percent) of the difference in the cyclicality between AWG and AHE growth.

Taken together, the results from Table 5 and Figure 8 point to two possible reasons why estimates of the relative contribution of composition effects estimated over the 1970s and 1980s are larger than what we report using more recent data. First, the micro wage growth regressions in these studies use the change in the unemployment rate as the cyclical variable, which, we have shown, increases the relative contribution of composition effects. In addition, the volatility in the unemployment rate was higher in these earlier decades, a factor that would also contribute to the relative importance of composition effects. Second, the micro wage growth regressions use an approximation to individual wage growth that lowers the estimated cyclicality of AWG. This also acts to raise the relative contribution of composition effects in explaining the difference in cyclicality between AWG and AHE growth.

Conclusion

The appropriate choice of an economy-wide wage measure depends both on the question of interest and on understanding the implications of how the data for that wage measure are aggregated across individuals. This paper focuses on the latter issue by investigating the interaction of alternative weighting schemes with the heterogeneity in individual wage data. To gain insights into the importance of this consideration, we compare growth in an average wage—average hourly earnings—to a measure of average wage growth constructed from SIPP data. We highlight differences in aggregation methods for each wage growth series and discuss how these differences bear upon the decomposition of wage growth into aggregation and composition effects.

The results indicate that the method of aggregation matters and can generate notable differences in the level and cyclicality between the two wage growth series. Specifically, we demonstrate that AHE growth compared to AWG places a higher weighting on older, higher-earning workers, who typically display lower and less cyclically sensitive wage growth. Consequently, AHE growth compared to AWG growth is lower on average by 3.6 percentage points and less

cyclical by 40 basis points over our 25-year sample period. Moreover, consistent with the documented heterogeneity in individual wage growth and cyclicality, we find that that aggregation effects—the weighting of individual wage growth rates—largely account for these differences.

The stronger role identified in some research for composition effects prior to the 1990s may reflect the use of the change in the unemployment rate and not an unemployment gap as the cyclical variable. We document that speed limit effects generate procyclical composition effects when the unemployment rate (or unemployment gap) is rapidly changing. Prior to the COVID-19 pandemic, large swings in the unemployment rate were more prevalent in the period before the Great Moderation. Further, the relative role of composition effects would be lower if AWG were measured using the actual growth in individual wages rather than an approximation. A topic for future research is to apply our methodology to the earlier PSID data to assess the implications of these two issues.

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Table 1. Individual Wage Growth and Cyclicality

	(1)	(2)
CBO unemployment gap	–0.690***	–0. 917***
	(0.017)	(0.062)
Female	–0.427***	–0.389***
	(0.056)	(0.068)
Married	–0.185***	–0.257***
	(0.061)	(0.074)
Black	–0.051	–0.098
	(0.097)	(0.117)
Hispanic	–0.114	0.037
	(0.096)	(0.118)
Other	0.166	0.225
	(0.135)	(0.175)
No high school	–0.135	–0.119
	(0.096)	(0.112)
Some college	0.235***	0.304***
	(0.069)	(0.083)
College graduate or more	1.059***	1.154***
	(0.078)	(0.096)
Work experience	–0.599***	–0.617***
	(0.028)	(0.028)
Work experience^2	0.222***	0.220***
(coefficient*10)	(0.021)	(0.021)
Work experience^3	–0.396***	–0.398***
(coefficient*1,000)	(0.057)	(0.057)
Work experience^4	0.264***	0.268***
(coefficient*100,000)	(0.051)	(0.051)

Table 1. Individual Wage Growth and Cyclicality – continued

	(1)	(2)
CBO unemployment gap interactions		
Female		–0.036**
		(0.033)
Married		0.058*
		(0.035)
Black		0.039
		(0.055)
Hispanic		–0.127*
		(0.053)
Other		–0.041
		(0.072)
No high school		–0.018
		(0.058)
Some college		–0.070*
		(0.040)
College graduate or more		–0.086*
		(0.046)
Work experience		0.020***
		(0.005)
Work experience^2 (coefficient*1,000)		– 0.258***
		(0.088)

Notes: Number of observations: 3,670,624. All specifications control for SPF 10-year inflation expectations and a measure of trend productivity. Standard errors are reported in parentheses and are clustered at the individual level.

*** significant at the 1% level,
  ** significant at the 5% level,
    * significant at the 10% level

Table 2. Comparison of Cyclicality of Average Wage Growth and Growth of AHE

Variable	SIPP Average Wage Growth (1)	BLS AHE Growth (2)
CBO unemployment gap	–0.713***	–0.330***
	(0.043)	(0.067)
RMSE	0.839	0.444
R-square	0.631	0.573

Notes: Specification (1) is estimated by WLS; specification (2) is estimated by OLS. Both specifications control for SPF 10-year inflation expectations and a measure of trend productivity growth. Standard errors are given in parentheses and are calculated using Newey-West with a bandwidth=4. Sample period is 1989Q4 to 2015Q4.
*** significant at the 1% level

Table 3. Decomposition of Cyclicality of AHE Growth

Variable	SIPP Average Wage Growth (1)	BLS AHE Growth (2)	SIPP AHE Growth Overall (3)	Aggregation (4)	Composition (5)
CBO unemployment gap	–0.713***	–0.330***	–0.502***	–0.546***	0.044
	(0.043)	(0.067)	(0.057)	(0.058)	(0.048)
RMSE	0.839	0.444	0.679	0.512	0.596
R-square	0.631	0.573	0.583	0.776	0.077

Notes: Specifications (1) and (3)-(5) are estimated by WLS; specification (2) is estimated by OLS. All specifications control for SPF 10-year inflation expectations and a measure of trend productivity growth. Standard errors are given in parentheses and are calculated using Newey-West with a bandwidth=4. Sample period is 1989Q4 to 2015Q4.
*** significant at the 1% level

Table 4. Average Wage Growth – Job-Stayers vs. Job-Changers

Variable	SIPP Average Wage Growth	Job-Stayer	Job-Changer
	(1)	(2)	(3)
CBO unemployment gap	–0.713***	–0.646***	–0.850***
	(0.043)	(0.040)	(0.111)
RMSE	0.839	0.622	1.275
R-square	0.631	0.846	0.574

Notes: Specifications (1)-(3) are estimated by WLS. All three specifications control for SPF 10-year inflation expectations and a measure of trend productivity. Standard errors are given in parentheses and are calculated using Newey-West with a bandwidth=4.
Sample period is 1989Q4 to 2015Q4.
*** significant at the 1% level

Table 5. Alternative Wage-Inflation Phillips Curve Estimates

| *SIPP AWG*	(1)	(2)	(3)
CBO gap	−0.713***		−0.643***
	(0.043)		(0.071)
ΔCBO gap		−0.686***	−0.182
		(0.103)	(0.135)
SIPP AHE			
CBO gap	−0.502***		−0.595***
	(0.057)		(0.078)
ΔCBO gap		−0.228*	0.238**
		(0.115)	(0.092)
SIPP AHE Aggregation			
CBO gap	−0.546***		−0.508***
	(0.058)		(0.072)
ΔCBO gap		−0.495***	−0.097
		(0.086)	(0.098)
SIPP AHE Composition			
CBO gap	0.044		−0.088
	(0.048)		(0.072)
ΔCBO gap		0.226**	0.335***
		(0.084)	(0.100)
Contribution of composition effect to reduction in wage growth cyclicality	21%	49%	

Notes: AWG is estimated using OLS, while AHE growth is estimated using WLS. All specifications control for SPF 10-year inflation expectations and a measure of trend productivity growth. Standard errors are given in parentheses and are calculated using Newey-West with a bandwidth=4. Sample period is 1989Q4 to 2015Q4.
*** significant at the 1% level
 ** significant at the 5% level
 * significant at the 10% level

Figure 1. Distribution of Individual Wage Growth
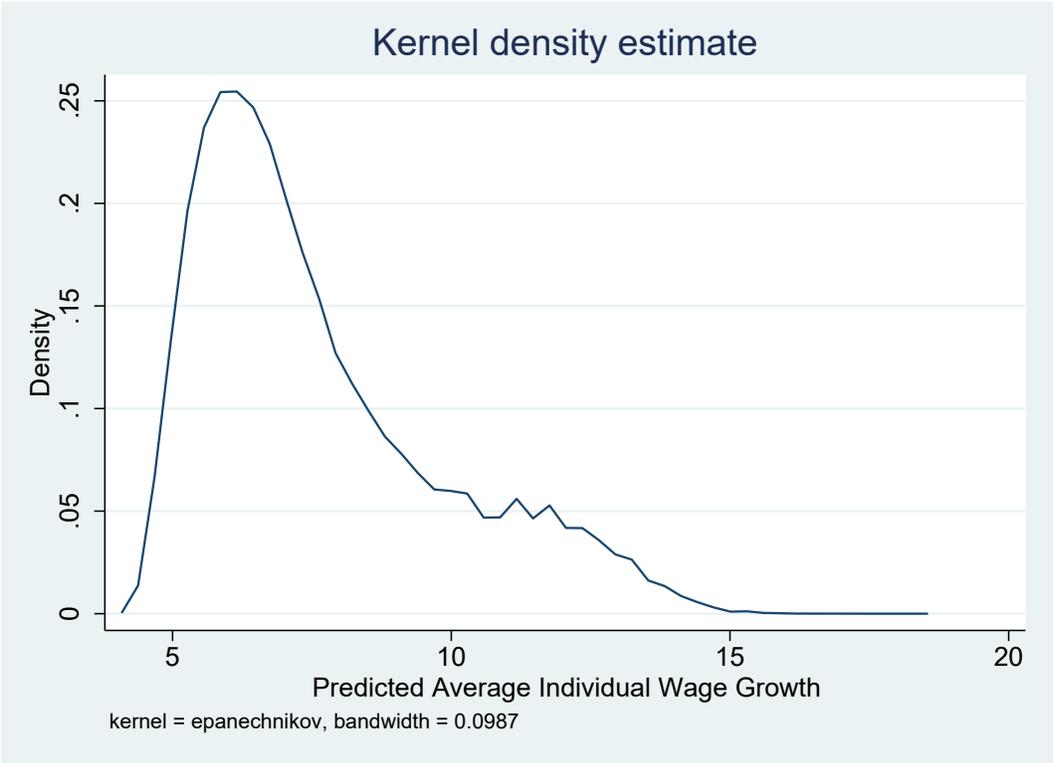
Figure 2. Distribution of Individual Wage Growth Cyclical Sensitivities
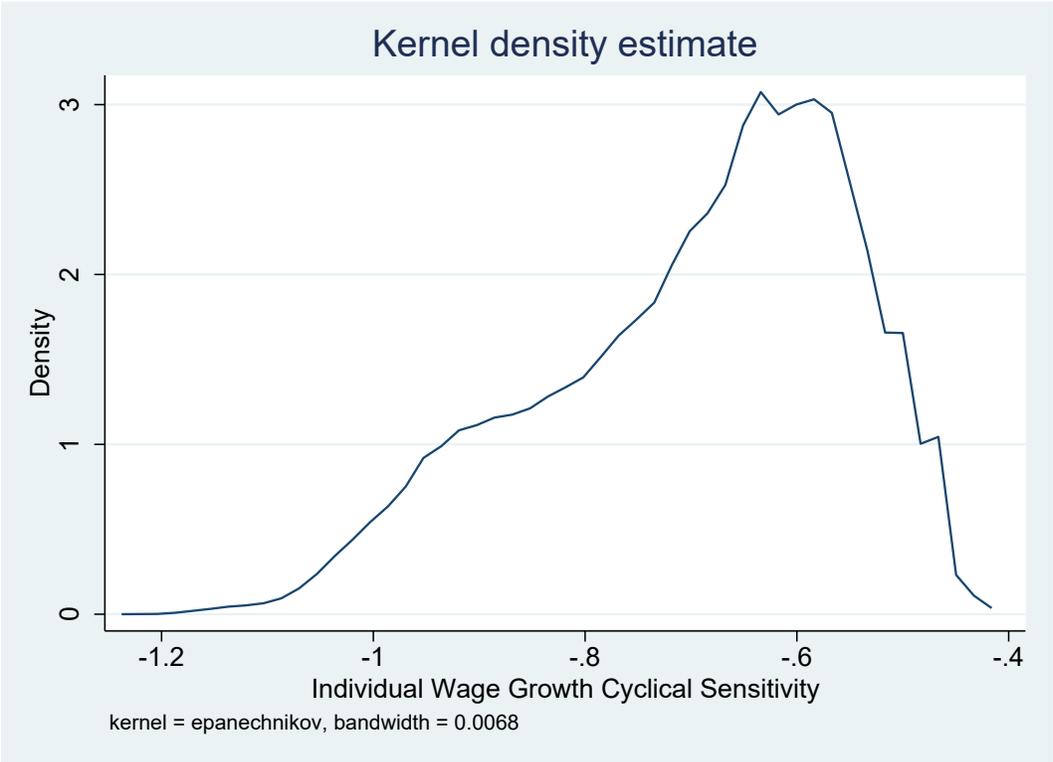
**Figure 3.** Comparison of BLS AHE Growth and SIPP Average Wage Growth

NOTES: Grey bars indicate recessions. Growth measured in actual percent change from quarter t to quarter t + 4.
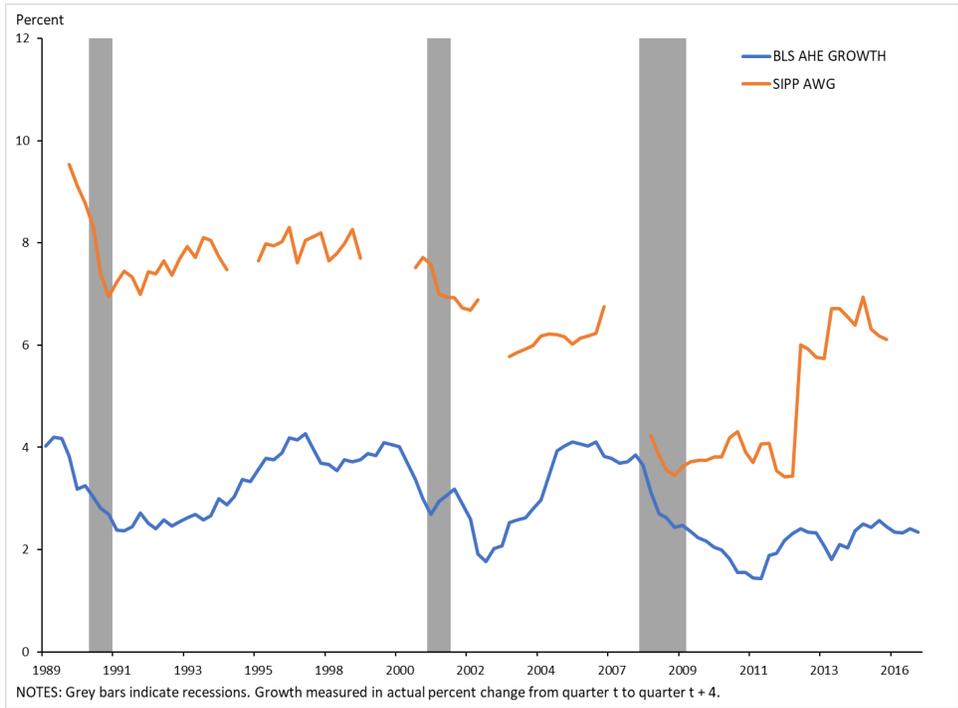
Figure 4. Average Wage Growth – Job-Changers vs. Job-Stayers

NOTES: Grey bars indicate recessions. Growth measured in actual percent change from quarter t to quarter t + 4.
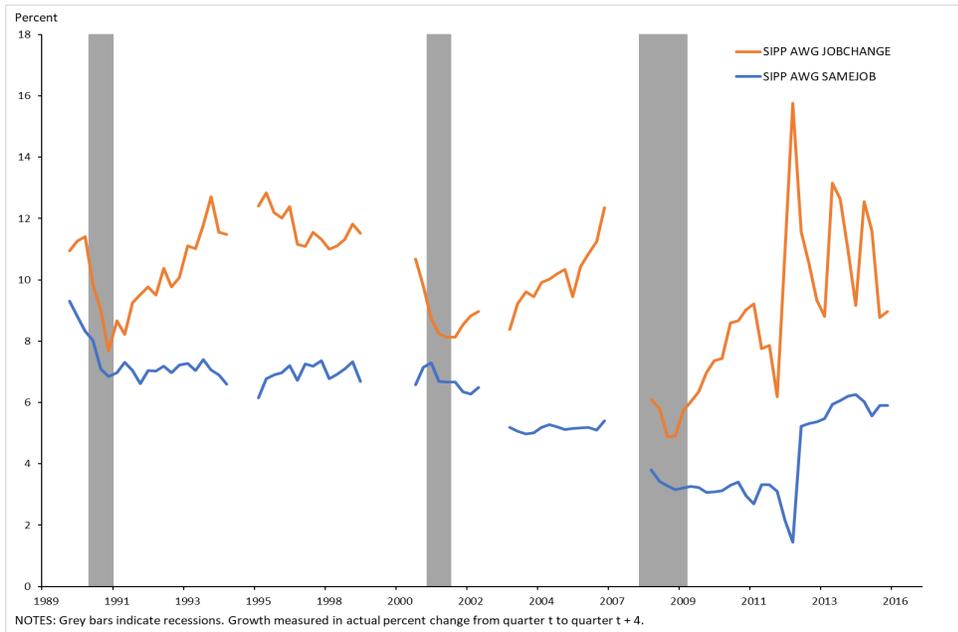
Figure 5. Effect of Earnings Weighting on Average Wage Growth

NOTES: Grey bars indicate recessions. Growth measured in actual percent change from quarter t to quarter t + 4.
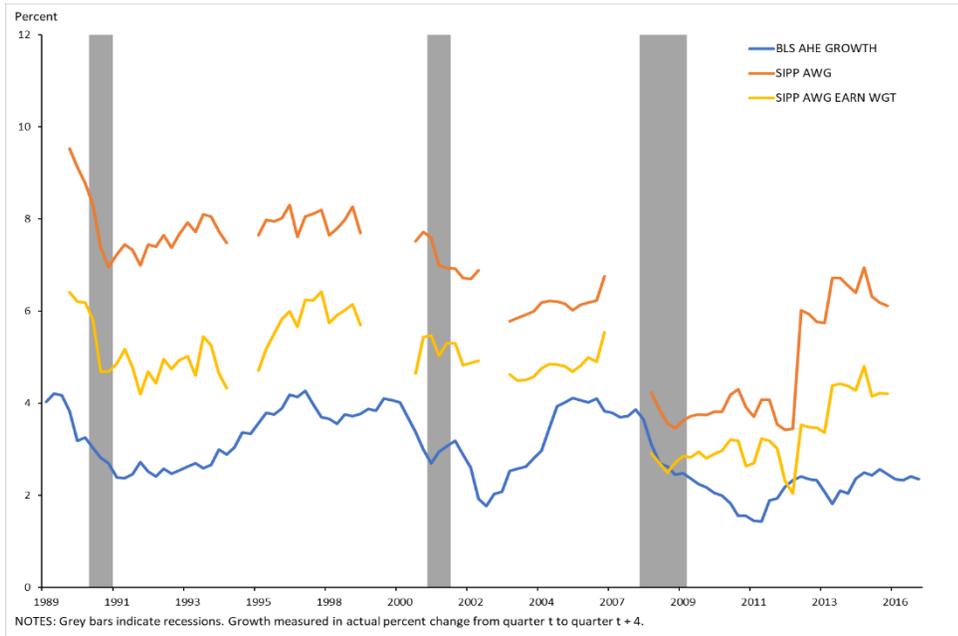
Figure 6. Comparison of BLS AHE and SIPP AHE Growth

NOTES: Grey bars indicate recessions. Growth measured in actual percent change from quarter t to quarter t + 4.

30
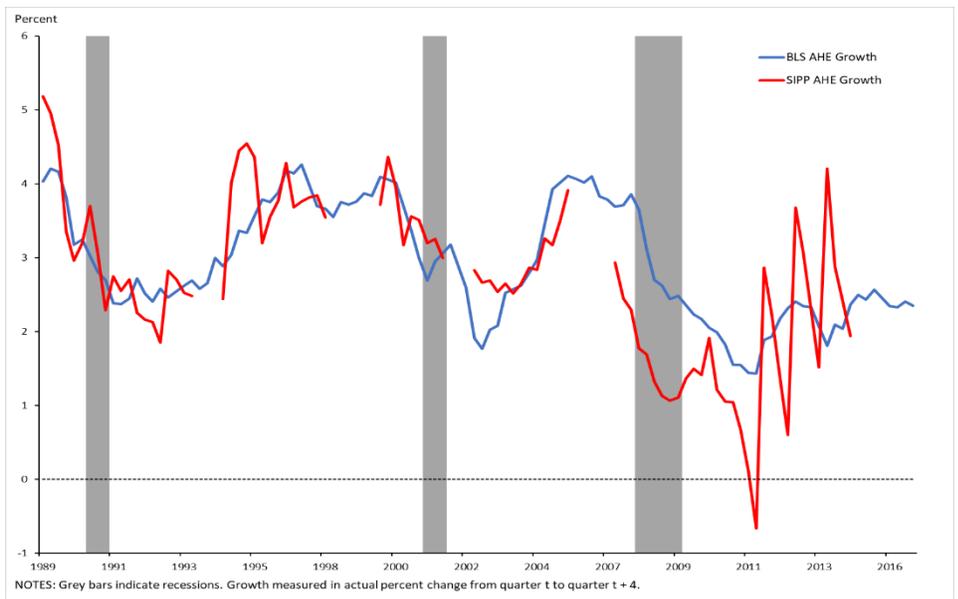
Figure 7. Decomposition of SIPP AHE Growth

NOTES: Grey bars indicate recessions. Growth measured in actual percent change from quarter t to quarter t + 4.
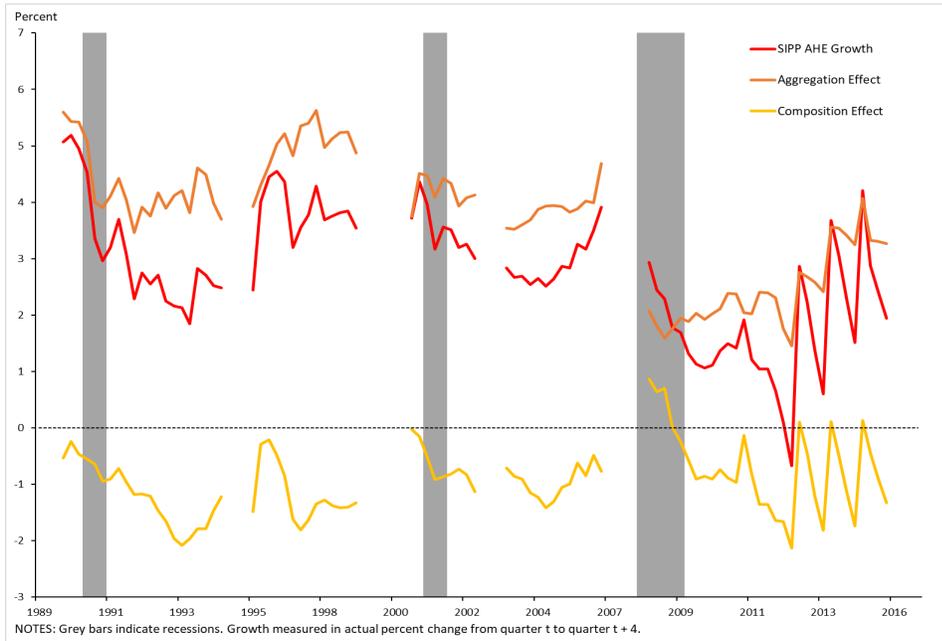
Figure 8: Four-Quarter Change in the CBO Unemployment Gap

NOTE: Grey bars denote NBER recession dates.
SOURCE: Congressional Budget Office.
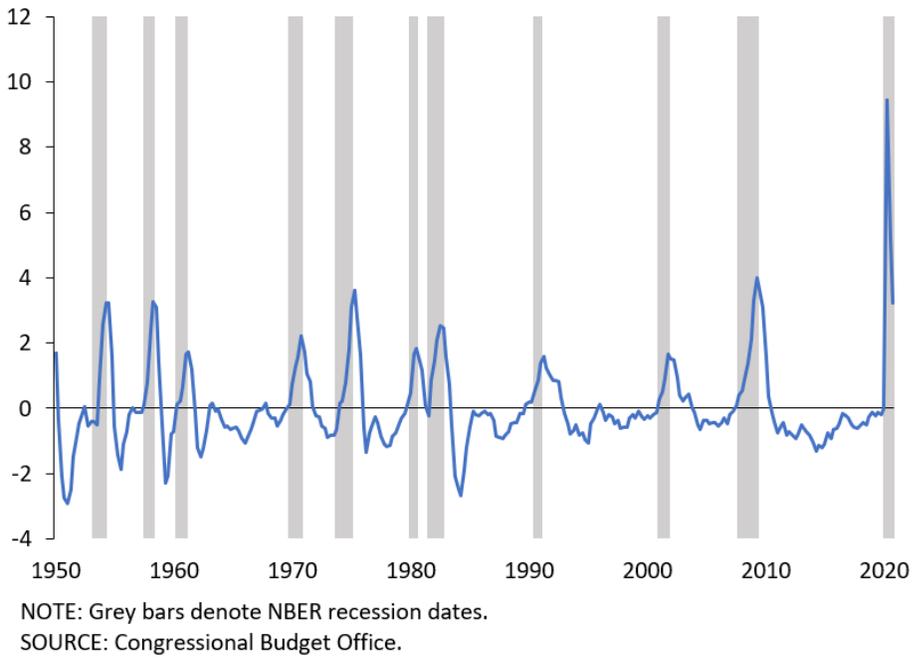
Appendix 1:

Let w_{it} denote the wage paid to individual i in period t and s_{it} the weight associated with that wage where $0 < s_{it} < 1$ and $\sum_i s_{it} = 1$. Let $\dot{w}_{it} = \dfrac{w_{it+12}}{w_{it}} - 1$ be the 12-month wage growth for individual i. Define an average wage $\overline{w}_t = \sum_i s_{it} w_{it}$ and similarly for $\overline{w}_{t+12}$. Let S denote the set of individuals who work in both periods ("stayers"), let L denote the individuals who work in period t and leave work prior to period $t+12$, and let E denote the set of individuals who are not working in period t but enter work by period $t+12$.

The 12-month growth in the average wage is given by

$$\frac{\overline{w}_{t+12}}{\overline{w}_t} - 1 = \frac{\sum_{i \in S} s_{it+12} w_{it+12} + \sum_{i \in E} s_{it+12} w_{it+12} - \sum_{i \in S} s_{it} w_{it} - \sum_{i \in L} s_{it} w_{it}}{\overline{w}_t}$$

$$= \frac{\sum_{i \in S} s_{it+12} w_{it+12} - \sum_{i \in S} s_{it+12} w_{it} + \sum_{i \in S} s_{it+12} w_{it} + \sum_{i \in E} s_{it+12} w_{it+12} - \sum_{i \in S} s_{it} w_{it} - \sum_{i \in L} s_{it} w_{it}}{\overline{w}_t}$$

$$\frac{\overline{w}_{t+12}}{\overline{w}_t} - 1 = \frac{\sum_{i \in S} s_{it+12}\left(w_{it+12} - w_{it}\right) + \left(\sum_{i \in S} s_{it+12} w_{it} + \sum_{i \in E} s_{it+12} w_{it+12}\right) - \left(\sum_{i \in S} s_{it} w_{it} + \sum_{i \in L} s_{it} w_{it}\right)}{\overline{w}_t}$$

Define $\overline{w}_{t+12}^* = \sum_{i \in S} s_{it+12} w_{it} + \sum_{i \in E} s_{it+12} w_{it+12}$, which is the average wage in period $t+12$ for individuals who work in both periods when we hold their wage fixed at the period t value. Substituting

$$\frac{\overline{w}_{t+12}}{\overline{w}_t} - 1 = \frac{\sum_{i \in S} s_{it+12} w_{it}\left(\dfrac{w_{it+12}}{w_{it}} - 1\right)}{\overline{w}_t} + \left(\frac{\overline{w}_{t+12}^*}{\overline{w}_t} - 1\right)$$

$$\frac{\overline{w}_{t+12}}{\overline{w}_t} - 1 = \sum_{i \in S} \left(\frac{s_{it+12}}{s_{it}}\right)\left(\frac{s_{it} w_{it}}{\overline{w}_t}\right)\dot{w}_{it} + \left(\frac{\overline{w}_{t+12}^*}{\overline{w}_t} - 1\right)$$

Appendix 2:

Solon, Barsky, and Parker (1994) start with the following specification for individual log wages:

$$\ln\left(w_t^i\right) = \mu_i + X_t^i \beta + \alpha U_t + \varepsilon_t^i$$

where X_t^i is a set of fixed and time-varying individual characteristics, U_t is the national unemployment rate at time t, and μ_i is an unobserved individual effect.

Using the panel structure of the PSID data, the four-quarter difference of (12) yields:

$$\ln\left(w_t^i\right) - \ln\left(w_{t-4}^i\right) = \Delta X_t^i \beta + \alpha \Delta U_t + \Delta \varepsilon_t^i \ ,$$

where the unobserved individual effect differences out, $\Delta U_t = U_t - U_{t-4}$ and $\Delta \varepsilon_t^i = \varepsilon_t^i - \varepsilon_{t-4}^i$. The difference in log wages approximates an individual's wage growth and the change in the unemployment rate serves as the cyclical indicator. The cyclicality of AWG in (13) is given by α.

Solon, Barsky, and Parker (1994) do not report an estimate of α for their pooled PSID data. Rather, they report an estimate of cyclicality for male average wage growth of $\alpha_M = -1.40$ and for female average wage growth of $\alpha_F = -0.53$. The results indicate a high degree of wage growth cyclicality for men.

The authors then estimate the cyclicality of BLS AHE growth over their sample period and obtain a value of -0.60. Because the BLS AHE series is constructed from data at the establishment level and not at the individual level, there is no direct approach available to evaluate the role of aggregation and composition effects. Instead, Solon, Barsky, and Parker (1994) use their micro data to construct a PSID AHE measure. They estimate the cyclicality of PSID AHE growth to be -0.57, which closely matches the corresponding estimate of the cyclicality of BLS AHE growth.

For their investigation into the relative contribution of composition effects to the cyclicality of PSID AHE growth, Solon, Barsky, and Parker (1994) start with a decomposition of their PSID AHE measure into J different groups of individuals. For individuals in group j at time t, let $_2\overline{w}_t^j$ denote their AHE, $\left(S_t^j\right)^h$ their share of hours, and $\left(S_t^j\right)^e$ their share of earnings. Using our notation, they express overall AHE as an hours-weighted average of the J group's specific AHEs:

$$_2\overline{w}_t = \sum_{j=1}^{J}\left(S_t^j\right)^h {}_2\overline{w}_t^j$$

The overall cyclicality of AHE and its components are given by:

$$\frac{d\ln({}_2\overline{w}_t)}{dU_t} = \sum_{j=1}^{J}\left(S_t^j\right)^e\left(\frac{d\ln({}_2\overline{w}_{jt})}{dU_t}\right) + \sum_{j=1}^{J}\left(\frac{{}_2\overline{w}_{jt}}{{}_2\overline{w}_t}\right)\left(\frac{d\left(S_t^j\right)^h}{dU_t}\right)$$

The first term is an earnings-weighted average of the cyclicality of the group-specific AHE growth. The second term captures the between-group composition effects induced by relative changes in hours between groups over the cycle.

To simplify, Solon, Barsky, and Parker (1992) consider two groups—men and women (J=2)—and within each group a set of workers with cyclically sensitive hours ("unskilled") and a set of workers with cyclically insensitive hours ("skilled"). They assume that wage cyclicality can differ across men and women, but within each group, wage cyclicality is the same across skilled and unskilled individuals. Let δ_1 denote the difference in AHE between men and women and δ_2 the difference in AHE between skilled and unskilled workers (assumed the same for men and women). Under these assumptions, the decomposition can be written as:

$$\beta_U^{AHE} = \left\{\left[1-\left(S^F\right)^e\right]\alpha_M + \left[\left(S^F\right)^e\right]\alpha_F\right\} + \delta_1\left(S^F\right)^h\left[1-\left(S^F\right)^h\right]\left[\frac{d\ln H^F}{dU} - \frac{d\ln H^M}{dU}\right] +$$

$$\delta_2\left[\left[1-\left(S^F\right)^e\right]\frac{dH^M}{dU} + \left(S^F\right)^e\frac{dH^F}{dU}\right]$$

The first term corresponds to our notion of an aggregation effect. The second term captures the between-group (men vs. women) composition effect, while the third term captures the within-group (skilled vs. unskilled) composition effect. Solon, Barsky, and Parker (1992) report a value of 0.27 for $\left(S^F\right)^e$ from the PSID data, which, when combined with their earlier estimates for α_M and α_F, yields an estimate of -1.16 for the aggregation effect. Given the estimate of -0.60 for β_U^{AHE}, they back out an estimate of 0.56 for the combination of the two composition effects. Note that the composition effect of AHE growth cyclicality is opposite in sign and roughly half the absolute size of the aggregation effect. This indicates that composition effects exert a strong countercyclical impact on AHE growth over the 1968-1988 sample period and mask the cyclicality of wage growth.

An advantage of our decomposition of AHE growth is that we do not need to specify the number of "groups" in the labor force and to assume that the AWG cyclicality is the same for individuals in a group. Our composition effect also captures both the within- and between-group effects without making additional assumptions on the cyclicality of hours across sets of individuals within a group.