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How Important Are Composition Effects for Aggregate Wage Growth?*

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Abstract: Previous studies have ascribed the modest procyclicality of average hourly earnings growth to composition bias. These studies argue that by placing more weight on low-skill workers during expansions than during recessions, average hourly earnings growth generates a downward bias in estimated cyclicality. This paper uses data from the Survey of Income and Program Participation to document that this downward bias is, instead, the consequence of an aggregation effect that involves a relative-earnings weighting of individual wage growths. We also find that the aggregation effect largely accounts for the lower level of average hourly earnings growth as compared to other aggregate wage growth measures.

Keywords: Wage growth; Aggregation effects; Composition effects; Wage-inflation Phillips curve

JEL codes: J31, J33

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I. Introduction

Since the seminal research by Bils (1985) and Solon, Barsky, and Parker (1994), it has been widely accepted that the cyclicality of aggregate wage growth measures is meaningfully influenced by changes in the composition of workers arising from entry and exit over the business cycle. For example, Solon, Barsky, and Parker (1994) argue that the modest procyclicality of average hourly earnings (AHE) growth reflects a countercyclical composition bias generated by placing a relatively higher weight on low-skill/low-wage workers during expansions than during recessions. To investigate this bias, Solon, Barsky, and Parker (1994) use the Panel Study of Income Dynamics (PSID) to estimate the average cyclicality of individual wage growths—which avoids composition effects—and find that the estimated cyclicality is much higher than that of AHE growth. They subsequently perform a calibration exercise and report that the composition effect is an important source for the difference in the two cyclicality estimates. They conclude that the composition effect biases AHE growth in a countercyclical direction from average wage growth (AWG) and that this bias is economically significant.

This paper reexamines the effect of changes in the composition of workers on the behavior of an aggregate wage growth series. We show that growth in an average wage, such as AHE, can be decomposed into two components. The first component is an aggregation term describing how individual wage growths are weighted in computing the growth of the average wage. Because individual wage growths only involve workers who are employed at the beginning and end of a period, the aggregation term captures constant-composition wage growth.[1] In the case of AHE, the aggregation term involves a relative-earnings weighting of individual wage growths. The second component is a composition term reflecting how changes in the workforce—through entry and exit, as well as changes in hours among workers who remain employed—interact with wage level differences across workers to impact the growth of the average wage. The decomposition plays a central role in evaluating the sources for the different behavior of AHE growth and AWG.

[1] While the aggregation term only involves workers employed at the beginning and end of a period, the composition of these workers will change over time. Given shifting age demographics and wage growth profiles of the workforce, this will affect the relative weights on individual wage growths, causing the aggregation term of aggregate wage growth to vary over time. However, this composition effect reflects long-run trends and does not correspond to the conventional view that considers changes in the composition of the employed over the business cycle.

We use monthly micro data from the Survey of Income and Program Participation (SIPP) from 1983 to 2022 to construct an AWG and an AHE growth series.[2] Following the analyses of Bils (1985) and Solon, Barsky, and Parker (1994), we compare the cyclicality of our SIPP AWG and SIPP AHE growth series and find that the cyclicality of SIPP AHE growth is meaningfully lower. Using our decomposition of SIPP AHE growth, we then produce separate estimates of the cyclicality of the aggregation and composition terms where, by construction, the two estimates sum to the estimated cyclicality of overall SIPP AHE growth. To the best of our knowledge, our study provides the first direct estimation of the cyclicality of the aggregation and composition terms for a micro-based AHE growth measure.

In contrast to Solon, Barsky, and Parker (1994), we find that the aggregation term, rather than the composition term, largely explains the lower cyclicality of AHE growth compared to AWG. That is, the previous emphasis on workers entering or exiting employment as the source for lower cyclicality is misplaced and should instead be directed toward workers who maintain employment at the beginning and end of a period. Specifically, our estimates indicate that the aggregation term accounts for 95 percent of the 23.5 basis point difference in cyclicality between AWG and AHE growth. Although the level difference between these measures has received less attention in the literature, we also document that AWG exceeds AHE growth by an average of 5.2 percentage points. Moreover, we find that the aggregation term accounts for 81 percent of this level difference.

What accounts for our evidence principally attributing the different behavior of the two aggregate wage growth measures to the aggregation effect? We demonstrate that the differences between AHE growth and AWG in their level and cyclicality are both largely a consequence of AHE growth involving a relative-earnings weighted average of individual wage growths, as opposed to the equal-weighted average used in AWG. Our analysis strongly corroborates findings from previous studies that wage growth is higher for younger, lower-earning workers (Mincer (1974) and Becker (1975)), as well as more cyclical for young workers (Topel and Ward, 1992) and workers who have low earnings (Bils (1985) and Blank (1990)). However, the relative-earnings weights used to construct AHE growth place relatively less weight on younger, lower-earning workers and relatively more weight on older, higher-earning workers. This weighting difference between the AHE growth

[2] As we discuss further in Section 3, we use the SIPP data because they more closely match the "pay period" focus of the Establishment Survey used to construct the official AHE series published by the Bureau of Labor Statistics. In contrast to other surveys, the SIPP data follow individuals who move residences.

and AWG series is captured by the aggregation term, explaining its dominant role in lowering the level and cyclicality of AHE growth compared to AWG. A critical implication of our analysis is that AHE growth and AWG can exhibit meaningful differences in levels and cyclicalities even absent changes in the composition of the workforce.

We also investigate why our conclusions differ from those of earlier studies investigating composition effects, with a principal focus on the results of Solon, Barsky, and Parker (1994). In contrast to our approach, which features precise expressions for the aggregation and composition terms as well as direct estimation of their cyclicalities, Solon, Barsky, and Parker (1994) decompose the cyclicality of their PSID AHE growth measure using a calibration exercise that relies on only two groups: men and women. As we discuss shortly, they include an analog to our aggregation term and quantify its cyclicality as a weighted average of the cyclicality of AWG for men and women. The cyclicality of the composition term is then backed out as a "residual" explaining any difference in cyclicality between AHE growth and their aggregation term.

Solon, Barsky, and Parker's approach (1994) is problematic for two reasons. First, their decomposition cannot be used to isolate the contributions of aggregation and composition. Specifically, their decomposition yields a term that is a weighted average of the cyclicalities of group-specific AHE growths and a second term capturing between-group composition effects induced by relative changes in hours between groups over the business cycle.[3] However, these group-specific AHE growth cyclicalities reflect both within-group aggregation and composition effects. The inability of their decomposition to separately identify aggregation and composition effects precludes an evaluation of their roles in the cyclical behavior of AHE growth.

Second, the calibration exercise in Solon, Barsky, and Parker (1994) replaces the group-specific AHE growth cyclicalities in their decomposition with group-specific AWG cyclicalities. While this leads to an inconsistency between the formulation of their decomposition and its empirical implementation, the group-specific AWG cyclicalities are free of composition effects and offer a parallel to our aggregation term. Nevertheless, the calibration exercise will not provide a reliable estimate of composition bias because their aggregation term applies equal weighting to individual wage growths (within each group), rather than the relative-earnings weighting derived in our analysis. That is, the group-specific AWG cyclicalities do not account for the interaction

[3] See the first term on the right-hand side of equation (5) on page 8 in Solon, Barsky, and Parker (1994).

between a worker's earnings share and wage growth, causing the procyclicality of their aggregation term to be overstated and, by inference, the countercyclicality of their composition term to be overstated as well. As further support for this point, we apply the Solon, Barsky, and Parker (1994) methodology to the SIPP data and find a marked increase in the implied contribution of the composition term to the difference in cyclicality between AWG and AHE growth.

Our analysis provides insights into other issues that have relevance to previous investigations assessing the roles of aggregation and composition in aggregate wage growth. One issue concerns the choice of the cyclical indicator. Bils (1985) and Solon, Barsky, and Parker (1994) use the change in the unemployment rate as their cyclical indicator. However, within our Phillips curve modeling framework, the change in the unemployment rate is used to capture a "speed-limit" effect that, by itself, does not convey information about the degree of slack or tightness in the labor market. Instead, we follow the Phillips curve literature and use the unemployment gap—the difference between the unemployment rate and the natural rate of unemployment—to estimate the cyclicality of wage growth. The unemployment gap aligns more closely with the cyclical component of the unemployment rate. Our results indicate that the unemployment gap is a more robust cyclical indicator compared to the change in the unemployment rate.

A related issue is that the sample periods for Bils (1985) and Solon, Barsky, and Parker (1994) are earlier than ours, and mostly occur prior to the Great Moderation, when the unemployment rate was more volatile and displayed larger changes. Our analysis reveals that using the change in the unemployment gap as the cyclical indicator dramatically increases the relative contribution of the composition term for the reduced cyclicality of AHE growth relative to AWG.[4] An implication is that applying our decomposition of AHE growth to data that covered the sample periods of Bils (1985) or Solon, Barsky, and Parker (1994), along with using the change in the unemployment rate as the cyclical indicator, would likely accentuate the estimated role of composition effects in aggregate wage growth.

The final issue is that previous researchers approximate individual wage growth using a difference in log wages. This approximation will be poor for large (in absolute value) wage changes that are relatively more common for job-changers—who also have higher wage growth cyclicality.

[4] Given the slow-moving property of the CBO's estimate of the natural rate of unemployment, the change in the CBO's unemployment gap is essentially the same as the change in the unemployment rate.

We find that using a logarithmic wage change approximation for individual wage growth reduces the estimated cyclicality of AWG by 32 percent. This finding, however, also has implications for the contribution of the composition term to the difference in cyclicalities of AHE growth and AWG. Because the approximation is not used to construct AHE growth or the composition term of AHE growth, the lower estimated cyclicality of AWG narrows the gap in cyclicality between AHE growth and AWG. With the cyclicality of the composition term unchanged, this results in the composition term being assigned a larger explanatory role for the cyclicality gap between AHE growth and AWG.

The outline of the paper is as follows. In the next section we define and discuss aggregation and composition terms arising in the calculation of an economy-wide average wage and its growth rate. Section III provides a discussion of the SIPP data. In Section IV, we demonstrate that aggregation largely accounts for the large and persistent level difference between measured AWG and AHE growth. We also use the estimates from an expectations-augmented wage-inflation Phillips curve model to contrast the cyclicality of AWG and AHE growth and show that, again, aggregation largely accounts for this difference. Section V undertakes a comparison to earlier studies and examines how differences in methodology as well as in the choice of cyclical indicators and sample periods may affect the estimated contributions of aggregation and composition to the cyclicality of wage growth measures. Section VI concludes.

II. Aggregation Methods and the Growth and Cyclicality of an Average Wage

To investigate how aggregation and composition affect the level and cyclicality of AHE growth, we start by providing a decomposition of AHE growth into these two terms. The aggregation term captures how individual wage growths are weighted in AHE growth. The composition term captures how wage level differences are weighted by changes in who is working and changes in hours for individuals who are working at the beginning and end of the period used to measure wage growth.

A key finding is that the aggregation term of AHE growth involves a relative-earnings weighted average of individual wage growths. This results in the early career wage growth of individuals being underweighted relative to their late career wage growth. We demonstrate that this weighting accounts for much of the lower growth and reduced cyclicality of AHE growth relative to AWG. A second finding is that the composition term involves both an extensive and an intensive margin. The literature has focused mainly on the extensive margin, which is the difference in wages between individuals exiting work and entering work over the period used to calculate AHE growth. There is also an intensive margin for individuals who remain working that captures the relative difference in wages for individuals whose hours shares are increasing versus decreasing.

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 working individuals in the target group at time *t*. A general representation of the average wage is:

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

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.[5]

Now assume that we have individual data on wages and hours for two dates, time *t* and time *t*+*h*, and we want to measure the growth in the average wage over this period. As shown in Appendix 1, the general expression for the growth in the average wage, which depends on the selected aggregation method, is given by:

$$\left(\frac{\overline{w}_{t+h}}{\overline{w}_t}-1\right)=\sum_{i\in S}\left(\frac{s_{t+h}^i}{s_t^i}\right)\left(\frac{s_t^i w_t^i}{\overline{w}_t}\right)\left(\frac{w_{t+h}^i}{w_t^i}-1\right)+\left(\frac{\overline{w}_{t+h}^*}{\overline{w}_t}-1\right), \tag{2}$$

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

$$\overline{w}_{t+h}^* = \sum_{i\in J} s_{t+h}^i w_{t+h}^i + \sum_{i\in S} s_{t+h}^i w_t^i, \tag{3}$$

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"). As

[5] It is common to think of the "average wage" as an equally weighted average of individual wages. We use the term average wage in the more general sense of any weighted average of individual wages.

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.[6]

The growth in the average wage in (2) consists of two components: an aggregation term and a composition term. The first component—the aggregation term—reflects the contribution to the growth in an average wage from aggregating individual wage growths.[7] In the case of the average wage, individual wage growths are combined using weights that depend 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 component—the composition term—reflects the contribution to the growth in an average wage from changes in the composition of the workforce (at both the extensive and the intensive margins) between time *t* and time *t+h*. The contribution of changes at the extensive margin to wage growth reflects differences in the average wage for joiners as compared to leavers.[8] The contribution of changes at the intensive margin to wage growth reflects shifts in the relative hours shares between high- and low-wage jobs for individuals employed at time *t* and time *t+h*.[9]

We now apply the decomposition in (2) using AHE as the average wage measure. This consists of selecting weights equal to each worker's hours as a fraction of total hours. Let h_t^i denote the hours worked by individual *i* at time *t*, H_t total hours at time *t*, and $s_t^i = h_t^i / H_t$. We can write the average wage measure as:

$$\bar{w}_t = \sum_{i=1}^{n_t} s_t^i w_t^i = \sum_{i=1}^{n_t} \left(h_t^i / H_t \right) w_t^i, \tag{4}$$

[6] In Appendix 1, we refer to individuals who work in period *t* but leave work prior to period *t+h* as "leavers."
[7] The aggregation term includes wage growth for individuals who stay with the same employer as well as individuals who change employers. Therefore, it combines Grigsby's (2025) "direct" effect and "reallocation" effect.
[8] 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 term" and "composition term," respectively, in the context of decomposing wage growth into a component attributable to the individual wage growths of stayers and a component attributable to movements in the wage levels of joiners and leavers and shifts in hours among stayers.
[9] Grigsby (2025) develops a Roy model where changes in skill prices over the cycle induce shifts of workers by skill types between sectors (including nonparticipation). This provides a micro foundation for composition effects. See Keane, Moffitt, and Runkle (1988) and Daly and Hobijn (2017) for a discussion of composition effects arising from unobservable worker characteristics.

As shown by (4), an equivalent way to construct $\overline{w}_t$ 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 average wage measure, $\overline{w}_t = E_t / H_t$, defines AHE.

We now consider the growth of AHE. Using the definition of $s_t^i = h_t^i / H_t$ and substituting into (2), the *h*-period growth rate in $\overline{w}_t$ and the corresponding aggregation and composition terms are given by:

$$\left(\frac{\overline{w}_{t+h}}{\overline{w}_t} - 1\right) = \left(\frac{H_t}{H_{t+h}}\right)\left(\frac{E_t^S}{E_t}\right)\sum_{i \in S}\left(\frac{h_{t+h}^i}{h_t^i}\right)\left(s_t^i\right)^e \Delta w_{t+h,t}^i + \left(\frac{\overline{w}_{t+h}^*}{\overline{w}_t} - 1\right), \tag{5}$$

where H_t and H_{t+h} denote, respectively, total hours at time *t* and time *t*+*h*, E_t^S total earnings of stayers at time *t*, E_t total earnings of all workers at time *t*, $\left(s_t^i\right)^e$ worker *i*'s earnings as a share of total earnings of stayers at time *t* $\left((s_t^i)^e = e_t^i / E_t^S\right)$, $\Delta w_{t+h,t}^i$ is worker *i's* wage growth from time *t* to time *t*+*h*, and $\overline{w}_{t+h}^*$ is the adjusted (hours-weighted) average wage at time *t*+*h* defined in (3). The exact decomposition of AHE growth in (5) is a key contribution of the paper and allows us to directly estimate the role of aggregation and composition in explaining differences in both the level and the cyclicality of AWG and AHE growth.

Note that the specific form of the aggregation method applied to the individual wage data in levels does not carry over to the aggregation term in individual wage growths. For example, the construction of the AHE version of $\overline{w}_t$ weights individual wage levels by the worker's share of hours, but the aggregation term in (5) weights individual wage growths by the worker's share of earnings.

Comparing Growth in an Average Wage to Average Wage Growth

To gain further insight into the nature and role of the weighting scheme underlying AHE growth, it is instructive to consider the special case where no individuals join or exit work and the individual hours of stayers are constant from time *t* to time *t*+*h*. Under these strong assumptions, there is no composition term and the *h*-period growth rate in $\overline{w}_t$ (AHE) is given by:

$$\left(\frac{\overline{w}_{t+h}}{\overline{w}_t}-1\right)=\sum_{i\in S}\left(s_t^i\right)^e \Delta w_{t+h,t}^i, \tag{5'}$$

where AHE growth simplifies to an earnings-weighted average of individual wage growths.

While the right-hand side of (5') will almost always differ from the aggregation term of AHE growth in (5) due to shifts in employment and hours, it provides a useful benchmark to gauge how weighting by relative earnings can impact measured wage growth. Moreover, it allows for a simple comparison to AWG. Specifically, AWG can be derived from (5') by using an alternative aggregation method that equally weights individual wage growths:

$$\overline{\Delta w_{t+h,t}}=\sum_{i\in S}\left(\frac{1}{n_{t+h,t}^S}\right)\Delta w_{t+h,t}^i, \tag{6}$$

where $n_{t+h,t}^S$ denotes the number of "stayers" reporting a wage at both time t and time $t+h$. Unlike the simplified expression for AHE growth in (5'), it is important to note that the absence of a composition term in AWG is an inherent feature of the series.

Aggregation and the Level and Cyclicality of Wage Growth

Average hourly earnings growth is often used to gauge how workers are faring over time. Here it is useful to consider how weighting by a worker's relative 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. That is, the life-cycle pattern of wages creates a negative correlation between a worker's wage (or earnings) and wage growth.[10] All else the same, this negative correlation will lower AHE growth below that of AWG.

We use the decomposition of AHE growth in (5) to examine the contributions of aggregation and composition to the difference between AWG and AHE growth. Defining notation, let ΔAHE denote AHE growth. From our decomposition we can express AHE growth as

[10] Lippi and Perri (2023) 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.

$\Delta AHE = \Delta AHE^{-A} + \Delta AHE^{-C}$, where "A" denotes the aggregation term and "C" the composition term. The level difference between AWG and AHE growth can then be expressed as:

$$AWG - \Delta AHE = \left(AWG - \Delta AHE^{-A} \right) - \Delta AHE^{-C} \tag{7}$$

The first term on the right-hand side of (7) is the contribution of aggregation to the level difference, while the second term is the contribution of composition.

From our earlier discussion, we can also explore the relative importance of aggregation and composition 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 terms in (5).

As discussed in the next section, we use an expectations-augmented wage-inflation Phillips curve model to analyze the cyclical behavior of wage growth. The specification relates wage growth to a cyclical indicator measured by an unemployment gap, expected inflation, and trend productivity growth. Let $\hat{\beta}_U^{AHE}$ denote the estimated cyclicality of AHE growth defined as the coefficient on the unemployment gap in the Phillips curve model. Because of our exact decomposition of AHE growth, we can express the overall estimated cyclicality of AHE growth as the sum of the estimated cyclicality of the aggregation term and the estimated cyclicality of the composition term:

$$\hat{\beta}_U^{AHE} = \hat{\beta}_U^{AHE\_A} + \hat{\beta}_U^{AHE\_C} \tag{8}$$

where $\hat{\beta}_U^{AHE\_A}$ and $\hat{\beta}_U^{AHE\_C}$ are defined and derived in the same manner as $\hat{\beta}_U^{AHE}$ from the Phillips curve model. The summation property of the cyclicality estimates in (8) allows us to directly estimate the relative importance of aggregation and composition to the overall cyclicality of AHE growth.

Let $\hat{\beta}_U^{AWG}$ denote the cyclicality of AWG that is also estimated from the Phillips curve model. Using (8), the difference in cyclicality between AHE growth and AWG is given by:

$$\hat{\beta}_U^{AHE} - \hat{\beta}_U^{AWG} = (\hat{\beta}_U^{AHE\_A} - \hat{\beta}_U^{AWG}) + \hat{\beta}_U^{AHE\_C} \tag{9}$$

Recall that AWG and the aggregation effect of AHE growth use the same underlying data on individual wage growths. Consequently, the first term on the right-hand side of (9), $(\hat{\beta}_U^{AHE\_A} - \hat{\beta}_U^{AWG})$, captures the difference in cyclicality of the two wage growth measures resulting from their different aggregation of individual wage growths. The balance of the overall difference is attributable to $\hat{\beta}_U^{AHE\_C}$, which measures the cyclicality of the composition term for AHE growth. We now turn to estimating the terms in (8) and (9) using the SIPP micro data.

III. Measuring Wage Growth

Aggregate wage growth measures can be constructed from group- or individual-level data. The official US AHE series uses establishment-level pay period data on payroll and hours. The SIPP uses individual-level data that involve a mixture of reported wages for those paid by the hour and inferred wages for salaried workers based on earnings and hours over one-month intervals.

Data Sources

The Bureau of Labor Statistics (BLS) publishes AHE monthly using data from the Establishment Survey, a large, stratified random sample survey of roughly 140,000 businesses and 440,000 establishments.[11] The survey covers private, nonfarm, nonsupervisory 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 then calculates AHE as aggregate payroll expenses divided by aggregate hours. An important feature of the BLS AHE is that it cannot be analyzed at the individual level because the Establishment Survey does not collect the underlying micro data.

Because the BLS AHE is computed using pay-period data, the decomposition of a micro-based AHE growth into its aggregation and composition terms would ideally require measuring worker earnings- and hours-share weights on a pay-period basis as well. Surveys like the PSID and NLSY, which have previously been used to study composition effects, require that these shares be calculated on a 12-month basis. This mismatch between survey frequency and pay periods introduces measurement error into the decomposition of AHE growth. For example, respondents who experience unemployment spells will likely have lower earnings- and hours-share weights calculated on a 12-month basis than would be calculated on a pay-period basis. This means that they

[11] See US Bureau of Labor Statistics (2018).

will be underweighted in calculating the components of AHE growth and in estimating their cyclicalities.[12]

As an alternative, we use data from the SIPP, which reports hours and earnings monthly and therefore allows for a better approximation of pay-period earnings and hour shares. The SIPP consists of a series of nationally representative short panels of individuals who are tracked across job changes as well as residence changes.[13] We use data beginning with the 1984 panel through the 2022 panel. These panels lasted between two and four years, with new panels often overlapping with previous panels.[14] 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 four-month recall period in its interviews. Starting in 2013 (the 2014 panel), the SIPP asks workers to recall information for the prior calendar year. The most recently published SIPP data that we use are based on the ongoing 2020, 2021, and 2022 panels.[15]

We restrict the SIPP sample to private, nonfarm, nonsupervisory workers who are not self-employed to align with the coverage of 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.[16]

We measure wage growth as four-quarter changes at the aggregate level. For BLS AHE growth, we compute 12-month changes and then average over the three relevant months associated with a quarter. For SIPP AHE growth and SIPP AWG, we use a trimming procedure based on three criteria to remove the influence of outliers. We initially trim observations that fall below the 1st

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[12] We leave it to future research to answer the question of how PSID or NLSY estimates of workers' earnings shares and hours shares, with their calculation on a 12-month basis rather than a pay-period basis, impacts the measured level and cyclicality of their respective AHE series.
[13] The monthly Current Population Survey (CPS) is an alternative source of micro data on earnings. The CPS data allow individuals to be matched over a 12-month period if the individual does not change residences. Consequently, a CPS measure of AWG will not include the individual wage growth of movers. See Neumark and Kawaguchi (2004) for a discussion of the selection bias arising from not being able to follow movers.
[14] SIPP surveys overlapped prior to the 1996 panel and after the 2014 panel (1984-1993 and 2018-present).
[15] See US Census Bureau (2024) for more information about the SIPP.
[16] Top-coded observations are difficult to ascertain after 2014 because the SIPP stopped fully disclosing its top-coding protocol. Nevertheless, we can identify probable top-coded observations by examining other related variables. For example, if a respondent has monthly earnings that exceed $200,000 in yearly income and their annual salary value is top-coded, it is likely that their monthly earnings have been top-coded as well.

percentile of reported hours at the monthly frequency. We next calculate individual 12-month changes in hours and individual 12-month changes in wages and then trim observations below the 1st percentile and above the 99th percentile in both cases. The remaining observations form the panel data used for the analysis. For SIPP AHE growth, we first compute the monthly AHE value, compute 12-month changes, and then average over the three relevant months associated with a quarter. For SIPP AWG, we retain the individual wage growths that were not dropped from the trimming procedure, average these observations by month, and then average over the three relevant months associated with a quarter.

IV. An Assessment of Aggregation and Composition Effects on Wage Growth

Our empirical analysis principally focuses on the relative importance of aggregation and composition for the behavior of AHE growth and AWG. We explore this issue by initially examining the levels of the two series and then their cyclicalities.

Level of Wage Growth

The choice of an aggregate wage growth measure can lead to very different conclusions about the extent of wage gains by workers. Figure 1 compares SIPP AWG to BLS AHE growth from 1984Q2 to 2022Q4. Average wage growth consistently exceeds BLS AHE growth by an average of 5.24 percentage points over our sample period. What explains the persistently large difference in the levels of the two wage growth series? Figure 2 demonstrates that the difference is partly attributable to the effect of earnings weighting on the level of AHE growth. Recall from (5') that AHE growth simplifies to the earnings-weighted AWG in the special case of no entry and exit from working and constant hours for individual workers—that is, when there is no composition effect. As shown in Figure 2, the earnings-weighted SIPP AWG is consistently lower than the equal-weighted SIPP AWG (5.33 percent vs. 8.16 percent), suggesting that aggregation may play a significant role in explaining the difference between the levels of AWG and AHE growth.

We previously discussed how equation (7) can be used to quantify the contribution of aggregation to the difference in levels of AWG and AHE growth, but two preliminary steps are required before we can perform this evaluation. The first step is to calculate a SIPP AHE growth series. Figure 3 compares our SIPP AHE growth series and the BLS AHE growth series. Over the sample period, the average difference in levels of BLS AHE growth and SIPP AHE growth is 0.22 percentage point, and the correlation between the two series is 0.50. However, there is a noticeable increase in the volatility of SIPP AHE growth starting with the 2014 panel due to a reduction in panel size. If we only examine the pre-2014 data, then the correlation increases to 0.71.

The second step is to apply the decomposition in (5) to the SIPP AHE growth series. Figure 4 shows the decomposition of SIPP AHE growth into its corresponding aggregation and composition terms. Over the sample period of nearly four decades, the aggregation term averages 3.93 percent, while the composition term averages –1.02 percent. This finding is consistent with the intuition that, on average, composition effects act to lower AHE growth.[17] In addition, note that the absolute size of the composition term has been declining over time. Splitting the SIPP sample roughly in half at the turn of the millennium, the composition term averages −1.51 percent from 1984-2000 and only −0.61 percent from 2001-2022.

The average values for the SIPP AWG series as well as the SIPP AHE growth series and its components provide the inputs for equation (7). The resulting expression is given by:

$$
\begin{aligned}
&AWG - \Delta AHE = (AWG - \Delta AHE^{-A}) - \Delta AHE^{-C} \\
&8.15 - 2.91 = (8.15 - 3.93) + 1.02 \\
&5.24 = 4.22 + 1.02
\end{aligned}
$$

which indicates that the aggregation effect accounts for 81 percent of the 5.24 percentage point difference between SIPP AWG and SIPP AHE growth over the sample period.

We previously demonstrated that the aggregation term captures the weighting difference between AWG and AHE growth. To gain further insight into the relationship between the alternative weighting schemes and the aggregation term, Figure 5 plots AWG disaggregated into quartiles of earnings shares. Across the four quartiles, AWG is consistently higher for workers with lower earnings shares. Figure 6 plots earnings shares and real wage growth by workers' ages, where we deflate nominal wage growth by the CPI to provide a consistent basis for comparison over time. The observed negative correlation is driven primarily by young workers who are less than 35 years of age. Taken together, these findings are consistent with early work by Mincer (1974) and Becker

[17] Mueller (2017) finds that the average skill quality of individuals transitioning to unemployment increases in recessions, which, by itself, would imply a negative composition effect. Our result that the composition effect swings from negative to positive in severe recessions suggests that Mueller's effect is being offset by changes in the wages of entrants and/or changes in the relative hours of low- and high-wage individuals who work in both periods.

(1975) and support our view that the aggregation effect is reflecting a negative interaction between individual wage growths and earnings shares that imparts a downward effect on AHE growth relative to AWG.

An important result that emerges from Figure 5 and Figure 6 is that wage growth is higher for younger, lower-earning workers. This result is closely related to job-changing. To examine the link between job-changers and strong wage growth in more detail, Figure 7 displays the nominal SIPP AWG series separated by individuals who stay with their same employer and individuals who change employers. Outside of recessions, the average wage growth of job-changers is consistently higher than that of non-job-changers, with a difference of 5.55 percentage points (12.79 percent vs. 7.24 percent) over our sample period. The strong wage growth of job-changers is consistent with the cyclical upgrading hypothesis examined in other studies (Okun (1973); Vroman and Wachter (1977); McLaughlin and Bils (2001); Devereux (2002); and Hagedorn and Manovskii (2013)). However, job-changing is more concentrated among young workers, since it is their primary source for higher wage growth.[18] Relative-earnings weighting down weights the wage growth of individuals early in their careers, illustrating one channel that can operate to lower the profile of AHE growth compared to AWG.[19]

Cyclicality of Aggregate Wage Growth

Earnings weighting also has implications for the differential cyclical behavior of AWG and AHE growth.[20] We use an expectations-augmented wage-inflation Phillips curve model to directly estimate the cyclical behavior of AWG, AHE growth, and its aggregation and composition terms. Our specification relates the growth in a wage measure (ΔW) from quarter t to $t+4$ to measures of an unemployment gap ($U - U^*$), expected inflation (π^e), and trend productivity growth (θ^*) in quarter t and is given by:

$$\Delta W_{t+4,t} = \beta_0 + \beta_1(U_t - U_t^*) + \beta_2\pi_t^e + \beta_3\theta_t^* + \varepsilon_{t+4}, \tag{10}$$

[18] 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.
[19] Job-changers also have a lower earnings share compared to job-stayers. Specifically, the average individual earnings share of a job-changer is 0.015 percent, while the average individual earnings share of a job-stayer is 0.018 percent.
[20] See Abraham and Haltiwanger (1995) for a survey of the cyclicality of wage growth.

where we measure π^e using the 10-year CPI inflation expectations from the US Survey of Professional Forecasters and proxy θ^* by applying a Hodrick-Prescott filter to quarterly (annualized) productivity growth rates from the nonfarm business sector.[21] We measure labor market conditions using an unemployment gap based on the CBO's estimate of U^*. Given the unequal sizes of the different SIPP waves, we use weighted least squares to estimate (10), 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.

Table 1 reports Phillips-curve-based estimates of wage cyclicality over the 1984Q2-2022Q4 sample period. We first revisit the question of the cyclicality of AWG compared to BLS AHE growth. Specification (1) uses the SIPP AWG as the dependent variable. A 1 percentage point decline in the unemployment gap is associated with a 60 basis point increase in SIPP AWG.[22] In specification (2), we use BLS AHE growth as the dependent variable and restrict the sample to match our SIPP sample. The results now indicate that a 1 percentage point decline in the unemployment gap is associated with a 25 basis point increase in BLS 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).

We now turn to specifications (3) through (5) of Table 1, which report the cyclicality of SIPP AHE growth as well as the cyclicality of its aggregation and composition terms. Comparing specification (3) to (2), it is reassuring that the estimates are broadly consistent, with the cyclicality of SIPP AHE growth exceeding that of BLS AHE growth by 11.4 basis points. Recall from (8) that the coefficient on the CBO unemployment gap for AHE growth is the sum of the coefficients on the CBO unemployment gap for its aggregation and composition terms. The results in columns (4) and (5) in Table 1 show that the estimated cyclicality of −0.364 for SIPP AHE growth is composed of an aggregation effect of −0.376 and a composition effect of 0.012.

The cyclicality estimates for the SIPP AWG series as well as the SIPP AHE growth series and its components provide the inputs for equation (9). Substituting the relevant estimates yields:

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[21] We follow the approach in Staiger, Stock, and Watson (2002) and use a two-sided low-pass filter to construct the measure of trend productivity growth.

[22] 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 period covered by the data.

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

$$-0.364 + 0.599 = (-0.376 + 0.599) + 0.012$$

$$0.235 = 0.223 + 0.012$$

which indicates that the aggregation effect accounts for 22.3 of the 23.5 basis point difference in cyclicality, or 95 percent. While the sign of the composition effect is positive and indicates countercyclical behavior, the magnitude is economically and statistically insignificant.

We will again turn our attention to the aggregation term and the weighting difference between AWG and AHE growth, but now we explore the interaction by focusing on the cyclicality estimates by earnings shares. Table 2 shows the cyclicality estimates (β_1) from (10) for AWG disaggregated into earnings-share quartiles. The cyclicality is strongly declining in the earnings share, with the cyclicality for the lowest quartile more than 10 times the cyclicality of the highest quartile. This finding is consistent with prior research by Bils (1985), Blank (1990), and Topel and Ward (1992) and supports our argument that the cyclicality of AHE growth—and particularly the AHE aggregation term—will be lower than AWG cyclicality because earnings weighting assigns a lower contribution to younger, lower-earning workers whose wage growth tends to be more cyclical.

Our earlier analysis noted and documented that job-changing is associated with higher wage growth. However, there is also evidence that job-changing is associated with higher wage cyclicality (Barlevy (2001); Gertler, Huckfeldt, and Trigari (2020); and Figueiredo (2022)). Table 3 examines whether job-changing can contribute to the difference in cyclicalities of AWG and AHE growth. Table 3 reports Phillips-curve-based estimates of SIPP AWG for job-switchers and job-stayers. We restrict the sample period to 1990Q4 – 2013Q4 to match that used by Gertler, Huckfeldt, and Trigari (2020). For individuals who do not change jobs, a 1 percentage point decline in the CBO gap is associated with a 49 basis point increase in AWG. In contrast, the estimated cyclicality for job-changers is 112 basis points—more than twice as large. This result suggests that the job-changer channel can also operate to lower the cyclicality of AHE growth compared to AWG.

Taken together, our results indicate that the aggregation method underlying a wage growth measure can exert a significant influence on the level and cyclical behavior of the series. Indeed, we have not only argued that the entry and exit of workers is not a prerequisite for differences in the levels and cyclicalities of AHE growth and AWG, but we have also demonstrated the empirical insignificance of this consideration. This latter finding is in sharp contrast to earlier studies that view changes in composition as a key driver of the lower cyclicality of AHE growth. Notably, Solon, Barsky, and Parker (1994) report that composition bias accounts for roughly half of the lower cyclicality of PSID AHE growth as compared to PSID AWG. Because the evidence in Solon, Barsky, and Parker (1994) has come to be viewed as a stylized fact for wage growth, we now investigate why our findings differ from previous results.

V. Reconciling the Contrasting Findings About the Role of Composition in AHE Cyclicality

So why do our conclusions and those in Solon, Barsky, and Parker (1994) differ so dramatically? This section argues that the principal reason is that their proposed decomposition of AHE growth does not provide a valid identification of the aggregation and composition terms and, therefore, cannot be used to quantify their relative importance. In addition, Solon, Barksy, and Parker (1994) incorrectly use group-specific (male and female) AWG cyclicalities in their calibration exercise, resulting in an overstatement of the procyclicality of their aggregation term and, importantly, a concurrent overstatement of the countercyclicality of the composition term.

As a robustness check, we adopt the decomposition of Solon, Barsky, and Parker (1994) and implement their calibration exercise using the SIPP. The results now assign a much larger role to composition, supporting our view about the source of the discrepancy with our findings. We also discuss some additional, albeit more minor, issues and show how they might affect the estimated cyclicality of the composition term.

Estimating the Importance of Composition Effects Using the Approach of Solon, Barsky, and Parker (1994)

Solon, Barsky, and Parker (1994) begin their empirical investigation into the importance of composition bias by constructing an AHE series from the PSID and then comparing it to the BLS AHE series. Using the change in the unemployment rate as their cyclical indicator, they note that the estimated cyclicality of −0.57 for PSID AHE growth is very similar to the estimate of −0.60 for BLS AHE growth over the period 1967/68 – 1986/87. If they were to follow our methodology, their next step would be to use our equation (5) and decompose PSID AHE growth into its aggregation and composition terms. This would allow them to directly estimate the cyclicality of these terms, where the two cyclicalities sum to the cyclicality of PSID AHE growth.

Instead, Solon, Barsky, and Parker (1994) propose a simple calibration exercise to derive the cyclicality of their version of an aggregation term and then use this to back out the implied cyclicality of the composition term. They start with the following decomposition of AHE growth:[23]

$$\frac{d\ln \overline{w}_t}{dU_t} = \left(\frac{1}{\overline{w}_t}\right)\left(\frac{d\overline{w}_t}{dU_t}\right) = \sum_{j=1}^{J}(s_t^j)^e\left(\frac{d\ln \overline{w}_t^j}{dU_t}\right) + \sum_{j=1}^{J}\left(\frac{\overline{w}_t^j}{\overline{w}_t}\right)\left(\frac{d(s_t^j)^h}{dU_t}\right) \tag{11}$$

where there are *J* different groups of individuals, $\overline{w}_t^j$ denotes AHE for individuals in group *j* at time *t*, $(s_t^j)^h$ denotes their share of hours, $(s_t^j)^e$ denotes their share of earnings, and U_t denotes the unemployment rate.

Solon, Barsky, and Parker (1994) consider the first term of the decomposition as the aggregation term and the second term as the composition term. They then simplify (11) by disaggregating the population of workers into two groups—men and women—as well as into two groups within each gender—low- and high-skill workers. They also assume that the difference in wage cyclicality between skilled and unskilled workers is the same across groups and that the hours of skilled workers are not cyclically marginal. With this selection of groups and these additional assumptions, they provide the following specification for their calibration exercise:

$$\begin{aligned}\beta_U^{AHE} = &\left\{\left[1-(s^F)^e\right]\alpha_M + \left[(s^F)^e\right]\alpha_F\right\} + \delta_1 (s^F)^h\left[1-(s^F)^h\right]\left[\frac{d\ln H^F}{dU} - \frac{d\ln H^M}{dU}\right] \\ &+\delta_2\left[\left[1-(s^F)^e\right]\frac{d\ln H^M}{dU} + (s^F)^e\frac{d\ln H^F}{dU}\right]\end{aligned} \tag{12}$$

where α_M and α_F denote, respectively, the cyclicalities of AWG for men (M) and women (F), H^M denotes the group's (j=M, F) total hours, and $(s^j)^e$, $(s^j)^h$, and U remain as previously defined.

Solon, Barsky, and Parker (1994) use the PSID to obtain estimates of the first two terms in (12), which represent, respectively, their aggregation effect and the gender composition effect, with the estimate of the skill composition effect backed out as a residual. They report an estimate of −1.16 for the aggregation effect and an estimate that is close to zero for the gender composition

[23] See Appendix 2 for a more detailed discussion of Solon, Barsky, and Parker (1994) and the derivation of equations discussed in this section.

effect.[24] With an estimated cyclicality of −0.60 for BLS AHE growth, the implied cyclicality of the skill composition effect is 0.56, which Solon, Barsky, and Parker (1994) view as evidence of a substantial countercyclical bias in the BLS AHE statistic.

A closer inspection of Solon, Barsky, and Parker (1994) suggests there are two problematic aspects to their approach. The first aspect concerns the viability of the decomposition in (11) to generate a term that is free of composition effects. While Solon, Barsky, and Parker (1994) consider the first term as an aggregation effect, this term involves cyclicalities of group-specific AHE growths. These AHE growths will reflect both within-group aggregation and composition effects. Consequently, their decomposition cannot separately identify aggregation and composition effects, which precludes its ability to quantify the composition bias in the cyclicality of AHE growth.

A second aspect concerns the implementation of the calibration exercise. Abstracting from the concern just raised, the translation of the decomposition into the calibration exercise requires that the estimated cyclicalities of male and female AHE growth be used for the first term in (12). Instead, Solon, Barsky, and Parker (1994) use α_M and α_F, which are, respectively, the estimated cyclicalities of male and female AWG. While the cyclicalities of male and female AWG in (12) are free of composition effects, they involve an equal weighting of the underlying individual wage growths rather than the relative-earnings weightings that we have shown are relevant for the aggregation term. Because the cyclicalities of an equal weighting of male and female individual wage growths will be larger (in absolute value) than a relative-earnings weighting, this will overstate the procyclicality of the aggregation term, and, as a result, overstate the inferred countercyclicality of the composition term.

To illustrate the problem with the Solon, Barsky, and Parker (1994) calibration exercise, we obtain estimates of −0.600 and -0.598 for the cyclicality of male and female AWG from the SIPP data.[25] Using the relative-earnings share for women in 2001—which is the mid-point of our sample

[24] The empirical methodology used by Solon. Barsky, and Parker (1994) to derive these estimates is also discussed in Appendix 2. Their estimate of the average cyclicality of individual wage growths is essentially the same as the cyclicality of an average wage growth measure defined as an equally weighted average of individual wage growths.

[25] The estimation of almost identical wage cyclicalities for men and women is simply coincidental. If we split the SIPP sample at the turn of the millennium, we see somewhat higher female wage cyclicality in both time periods (-1.05 versus -0.88 from 1984-2000 and -0.23 versus -0.17 from 2001-2022). In contrast, Solon, Barsky, and Parker (1994) found higher male wage cyclicality in their sample. One explanation for the

period—of 0.409, the cyclicality of the earnings-share-weighted average is –0.599. If we use the estimate of −0.599 instead of our previous estimate of −0.376 for the cyclicality of the aggregation term, then the inferred cyclicality of the composition term increases by a factor of almost 20, from 0.012 to 0.235. This result is similar to that of Solon, Barsky, and Parker (1994) and would lead us to conclude that the composition effect plays a significant role in the observed lower cyclicality of AHE growth as compared to AWG.

Other Specification Choices When Estimating the Relative Importance of Composition Effects

We view the methodological and calibration issues discussed above as the principal reasons for the different conclusions between Solon, Barsky, and Parker (1994) and our study. However, two other considerations bear upon the analysis. The first relates to the choices of the cyclical measure to gauge labor market conditions and the sample period used in the estimation. The second concerns the use of a logarithmic approximation instead of the actual percentage change to measure individual wage growths. We use our estimation approach to illustrate how these two considerations would impact the estimated cyclicality of AHE growth and the roles of aggregation and composition.

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.[26] However, Phillips curve models use an unemployment gap as the cyclical measure, with the change in the unemployment rate (if this variable is included at all) used to capture a "speed limit" effect. Speed limit effects are motivated by the possibility that the response of wage growth (or another variable of interest) may also depend on how quickly the unemployment rate is changing.[27]

Figure 8 plots the CBO unemployment gap and the four-quarter change in the CBO unemployment gap from 1950 through the end of our SIPP sample period (2022Q4).[28] While the purpose of both series is to measure the cyclical component of the unemployment rate, their behavior can be quite different. The correlation between the two series is only 0.42. The measures

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different gender estimates of wage cyclicality is that our sample period is more recent and could reflect ongoing gender convergence in labor market outcomes (Goldin, 2014).

[26] This choice is a consequence of their analyses starting with a log wage specification that includes the unemployment rate as its cyclical control. Because they use a 12-month difference to approximate individual wage growth, the cyclical variable is transformed into the 12-month change in the unemployment rate.

[27] See Fuhrer (1995), Turner (1995), Debelle and Vickery (1998), and Malikane (2014).

[28] As noted earlier, the change in the CBO unemployment gap is essentially the same as the change in the unemployment rate. A positive (negative) value of the gap suggests a weak (strong) labor market.

also focus on different aspects of the unemployment rate. While the gap conveys information about the proximity of unemployment to the natural rate of unemployment and, therefore, the degree of slack or tightness in the labor market, the change in the gap is more informative about the directional change in unemployment. Consequently, the measures can provide conflicting views about labor market conditions, with positive (negative) values of the gap shown on occasion to be associated with falling (rising) unemployment. These differences in the measures and their assessment of labor market conditions could result in notable differences in estimation results.

Table 4 offers insights into the use of the CBO unemployment gap versus the change in the CBO unemployment gap as the cyclical measure for our various wage growth measures. Specification (1) repeats our earlier findings for ease of comparison. Specification (2) replaces the CBO unemployment gap with the four-quarter change in the CBO unemployment gap. The change in the CBO unemployment gap produces an estimated cyclicality for AWG and SIPP AHE growth that is, respectively, 43 percent lower and 62 percent lower compared to the CBO unemployment gap. Moving further down the column, we observe that the lower cyclicality of AHE wage growth is driven largely by a meaningful composition effect. The cyclicality of the composition effect increases by a factor of about 18, while the cyclicality of the aggregation effect declines by roughly 7 percent. Consequently, the relative contribution of the composition effect to the reduced cyclicality of AHE growth compared to AWG increases from about 5 percent using the CBO unemployment gap to 103 percent using the change in the CBO unemployment gap.

Specification (3) of Table 4 reports the results from expanding our Phillips curve model to include both the CBO unemployment gap and the change in the CBO unemployment gap. For both AWG and SIPP AHE growth, the CBO unemployment gap displays comparable behavior across specification (1) and specification (3), as there is little change in estimated cyclicality and statistical significance. However, when we examine the change in the CBO unemployment gap for AWG and SIPP AHE growth across specification (2) and specification (3), we observe a marked difference in estimated cyclicality. Specifically, controlling for the CBO unemployment gap, the change in the CBO unemployment gap experiences a loss in both economic and statistical significance. This comparison of the CBO unemployment gap to its change provides strong evidence that the former is a preferred and more robust cyclical measure.

As we continue down the column for specification (3), we see that there is a positive relationship between the change in the CBO unemployment gap and the composition effect on

AHE growth. This finding is consistent with the Roy model in Grigsby (2025), where rapid swings in the unemployment rate are associated with significant labor flows that typically induce larger composition effects. However, an important consideration is that the sharp changes in the unemployment rate associated with composition effects were much more prevalent prior to the mid-1980s, which includes the 1967/68 – 1986/87 sample period analyzed by Solon, Barsky, and Parker (1994). This can be seen in Figure 8, which shows the "Great Moderation" beginning in the mid-1980s that was characterized by a reduction in the volatility of unemployment (McConnell and Perez-Quiros, 2000). The two exceptions are the 2008 financial crisis and the COVID-19 pandemic, which both resulted in large spikes in the unemployment rate.

A second issue that bears upon the evaluation of composition effects is that the prior literature on the cyclicality of AWG estimates individual wage growths using the difference in log wages. This approximation to the percentage change in a worker's wage is poor for large positive and negative wage growth and affects the calculation of AWG. For example, this approach would differentially impact job-changers, who, as we have shown, have higher wage growth cyclicality. Using this approximation to calculate SIPP AWG reduces its estimated cyclicality from −0.599 to −0.407, a decline of 32 percent. Because the calculation of SIPP AHE growth and its composition term do not involve individual wage growths, their cyclicality estimates would not be affected by the approximation. As a result, the log wage approximation of AWG would lower the gap in cyclicality between AWG and AHE growth to just 0.043 and, consequently, the (unchanged) composition term would now account for 28 percent of this reduced gap.

The results from Table 4 and Figure 8 demonstrate that choices of the cyclical variable, the sample period, and the measure of individual wage growths have important implications for gauging the roles of aggregation and composition in AHE growth. Our investigation uses the unemployment gap as the cyclical variable, includes more recent data, and measures individual wage growths as exact percentage changes. In contrast, prior studies use the change in the unemployment rate as the cyclical variable, principally draw data from earlier decades, and measure individual wage growths using a logarithmic approximation. We show that using the change in the unemployment rate as the cyclical variable increases the relative contribution of composition effects. In addition, the volatility in the unemployment rate was higher during the 1970s and 1980s, a factor that our analysis indicates would also contribute to the relative importance of composition effects. There is also evidence that using a logarithmic difference to approximate individual wage growth lowers the estimated cyclicality of AWG, which would also act to raise the relative contribution of composition effects. Taken together, these considerations provide additional insights into why prior studies would have assigned greater importance to composition effects in AHE growth even if they used our decomposition.

VI. Conclusion

As we noted at the outset of this paper, it has been widely accepted that the cyclicality of aggregate wage growth measures is influenced by changes in the composition of workers over the business cycle. While several studies have contributed to this view, it has been principally shaped by the evidence in Solon, Barsky, and Parker (1994) that the procyclicality of AHE growth is understated due to composition bias. They argue that composition bias arises from the construction of AHE placing more weight on low-skill workers during expansions than during recessions.

While we agree that the construction of AHE leads to its lower estimated cyclicality, we contend that this lower cyclicality is not linked to "joiners" and "leavers" but instead arises from "stayers," a group that has largely remained outside of previous consideration. Specifically, the lower cyclicality is due to AHE placing more weight on older, higher-earning workers who typically exhibit less cyclical wage growth. Because older, higher-earning workers also tend to experience lower wage growth, this same consideration accounts for the lower level of AHE growth as compared to AWG.

This paper's contribution is an explicit decomposition of the growth of an average wage into an aggregation term and a composition term. We use this decomposition to assess the relative importance of aggregation and composition for explaining differences in the level and cyclicality of AWG and AHE growth. Over our four-decade sample period, AHE growth compared to AWG is lower on average by 5.24 percentage points and less cyclical by 24 basis points. The results indicate that aggregation effects—the weighting of individual wage growths—largely account for these differences. Moreover, as we move through our sample period, aggregation explains relatively more of the level difference between AWG and AHE growth, as the composition effect has been trending toward zero.

We also explore the reasons why Solon, Barsky, and Parker (1994) report a significant composition effect and show that it is principally due to their using a simple but improper calibration of the cyclicality of their aggregation term rather than directly estimating its cyclicality. We also identify the sample period, the choice of the cyclical indicator, and the approximation of individual wage growths as other factors that increase the relative contribution of composition effects. It is important to note that our results should not be interpreted as evidence that composition effects should be ignored. We recognize that composition effects can at times exert a very strong influence on AHE growth. This occurs when the unemployment rate changes rapidly, such as at the onset of the COVID-19 pandemic. Rather, our results suggest that composition effects are less prevalent and less relevant than previously thought. Similarly, researchers should focus more on aggregation effects when comparing the level and cyclicality of different average wage growth measures.

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Table 1. Decomposition of Cyclicality of AHE Growth

Variable	SIPP Average Wage Growth	BLS AHE Growth	SIPP AHE Growth		
			Overall	Aggregation	Composition
	(1)	(2)	(3)	(4)	(5)
CBO unemployment gap	–0.599***	–0.250**	–0.364***	–0.376***	0.012
	(0.171)	(0.097)	(0.073)	(0.078)	(0.069)
Obs.	127	127	127	127	127
R-squared	0.416	0.207	0.513	0.612	0.317

Notes: Coefficient estimates in specifications (1) and (3)-(5) are weighted by the number of individual wages used to construct an aggregate wage growth relative to the total number of individual wages in the estimation sample; specification (2) is estimated using OLS. All specifications control for expected inflation and trend productivity growth. Newey-West (1987) standard errors are reported in parentheses and are calculated using a bandwidth=4.

Sample period is 1984Q2 to 2022Q4.

* p<0.1, **p<0.05, ***p<0.01

Table 2. AWG Cyclicality by Earnings Quartile

	AWG	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
CBO unemployment gap	−0.599***	−1.213***	−0.897***	−0.612***	−0.105
	(0.171)	(0.264)	(0.254)	(0.184)	(0.131)
Obs.	127	127	127	127	127
R-squared	0.416	0.479	0.426	0.381	0.279

Notes: All coefficient estimates are weighted by the number of individual wages used to construct an aggregate wage growth relative to the total number of individual wages in the estimation sample. All specifications control for expected inflation and trend productivity growth. Newey-West (1987) standard errors are reported in parentheses and are calculated using a bandwidth=4. The first column displays information on the entire sample. Subsequent columns display information limited to the referenced earnings quartile subsample.
Sample period is 1984Q2 to 2022Q4.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 3. Average Wage Growth – Job-Stayers vs. Job-Changers

	SIPP Average Wage Growth	Job-Stayer	Job-Changer
Variable	(1)	(2)	(3)
CBO unemployment gap	–0.660*	–0.493	–1.121**
	(0.380)	(0.326)	(0.551)
Obs.	76	76	76
R-square	0.443	0.495	0.251

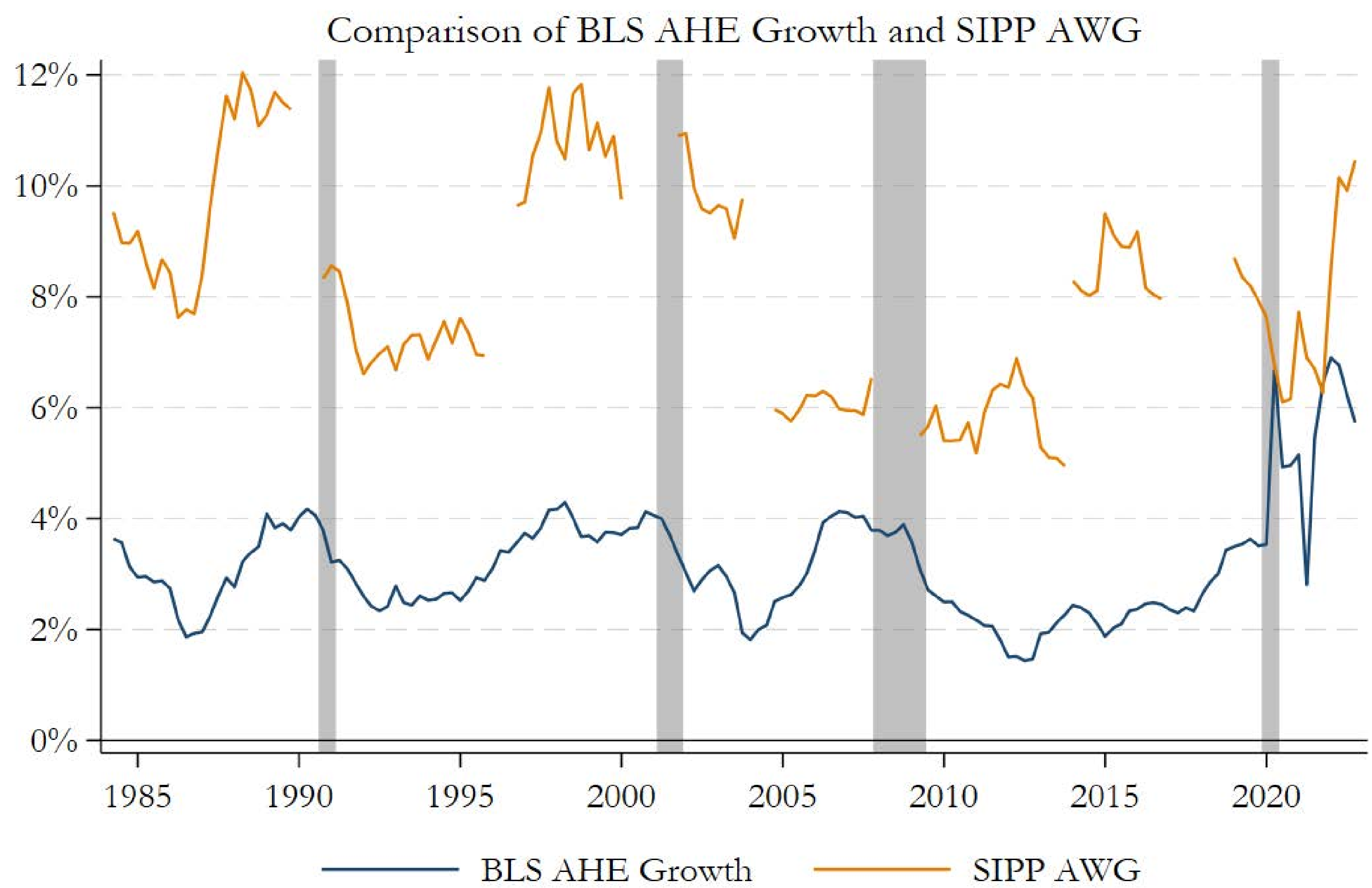
Notes: All coefficient estimates are weighted by the number of individual wages used to construct an aggregate wage growth relative to the total number of individual wages in the estimation sample. All specifications control for expected inflation and trend productivity growth. Newey-West (1987) standard errors are reported in parentheses and are calculated using a bandwidth=4. Sample period is 1990Q4 to 2013Q4, which aligns with the period used in the literature (e.g. Gertler, Huckfeldt, and Trigari (2020)).
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 4. Alternative Wage-Inflation Phillips Curve Estimates

	(1)	(2)	(3)
SIPP AWG			
CBO gap	−0.599***		−0.569***
	(0.171)		(0.203)
ΔCBO gap		−0.344*	−0.066
		(0.175)	(0.202)
SIPP AHE			
CBO gap	−0.364***		−0.388***
	(0.073)		(0.082)
ΔCBO gap		−0.137*	0.053
		(0.077)	(0.073)
SIPP AHE Aggregation			
CBO gap	−0.376***		−0.280***
	(0.078)		(0.102)
ΔCBO gap		−0.350***	-0.213
		(0.131)	(0.154)
SIPP AHE Composition			
CBO gap	0.012		−0.108
	(0.069)		(0.074)
ΔCBO gap		0.213	0.266*
		(0.132)	(0.151)
Contribution of composition effect to reduction in wage growth cyclicality	5.1%	103%	

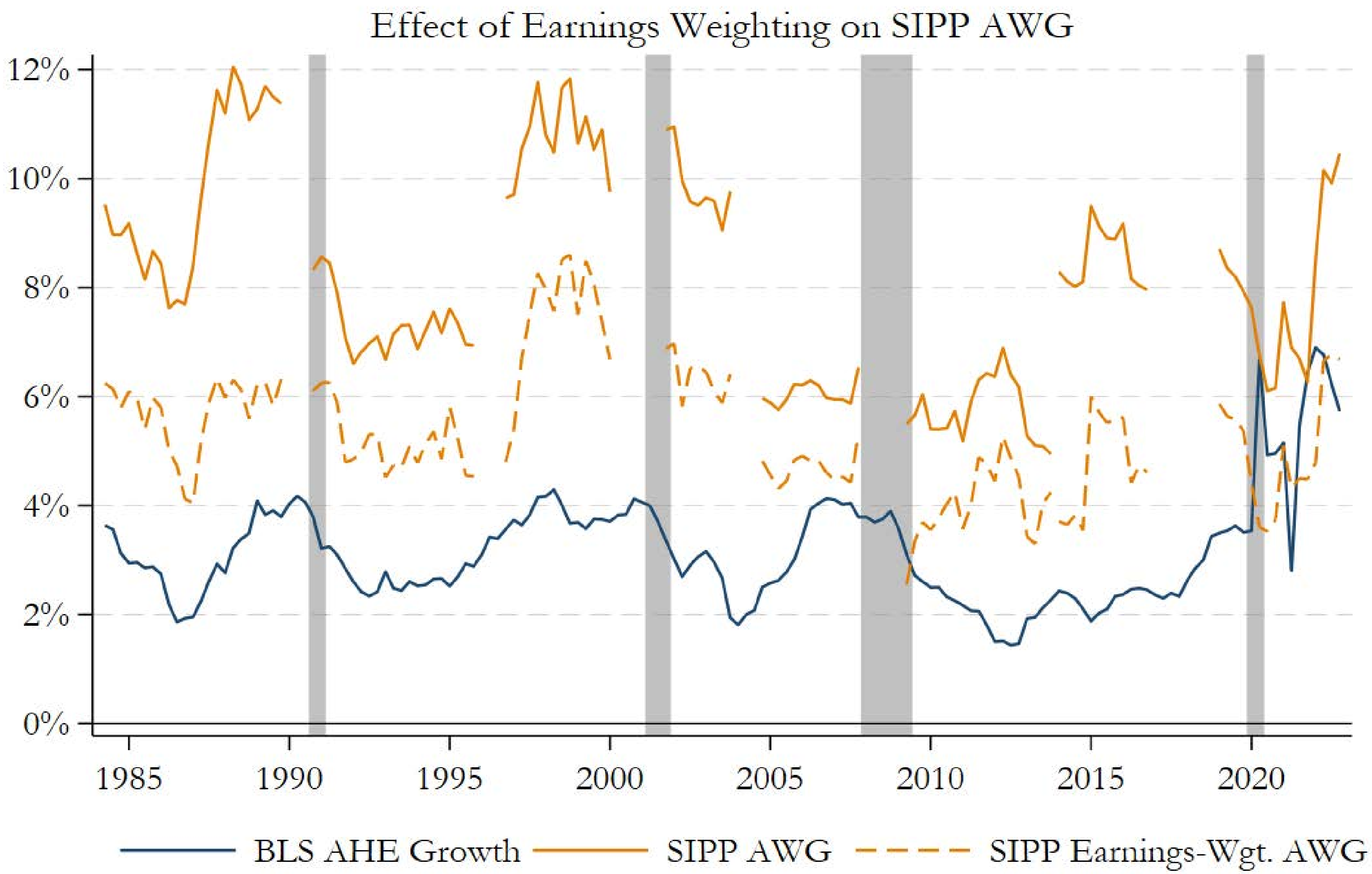
Notes: All coefficient estimates are weighted by the number of individual wages used to construct an aggregate wage growth relative to the total number of individual wages in the estimation sample. All specifications control for expected inflation and trend productivity growth. Newey-West (1987) standard errors are reported in parentheses and are calculated using a bandwidth=4.
Sample period is 1984Q2 to 2022Q4.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Figure 1



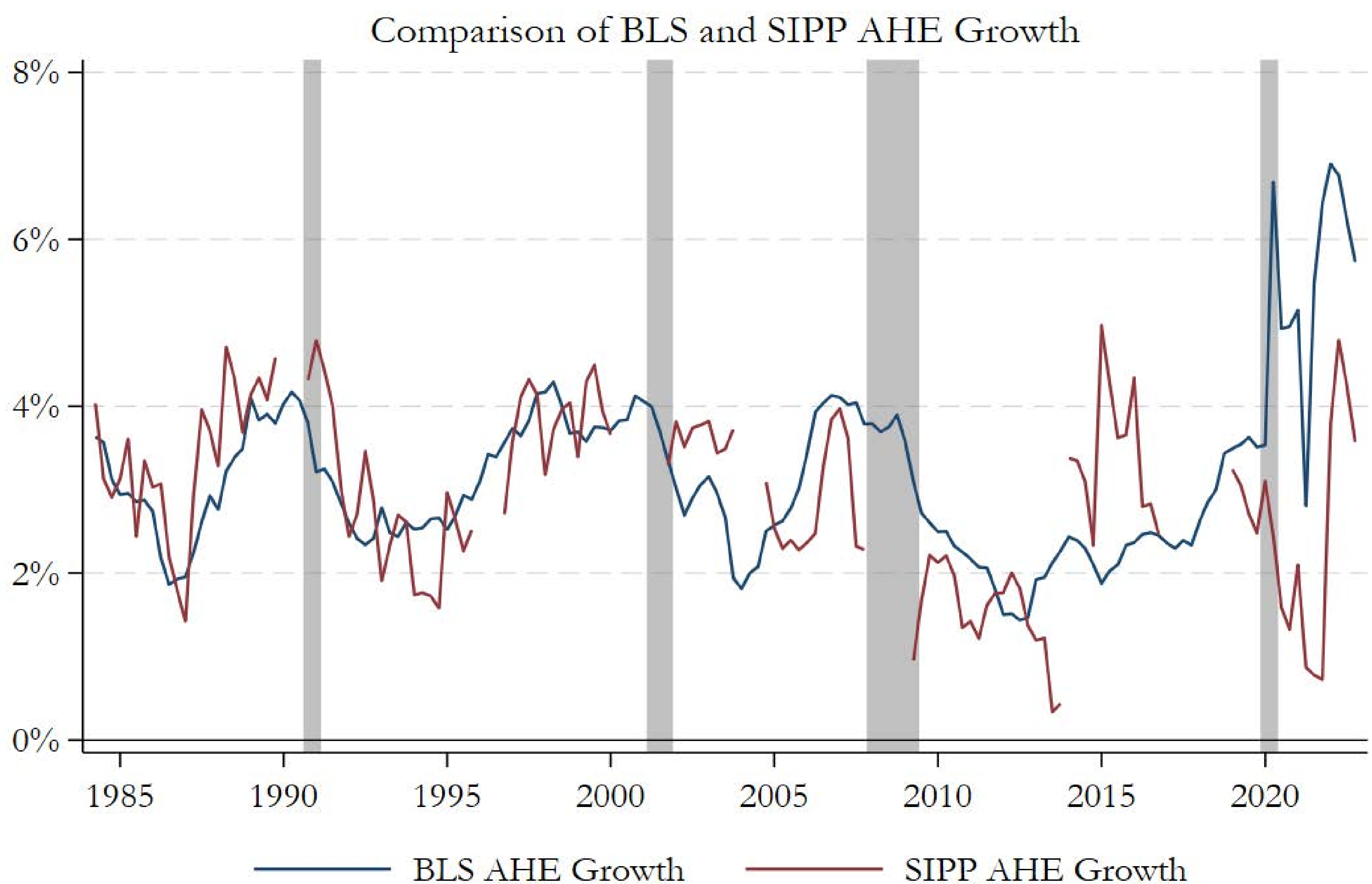
Grey bars indicate recessions.
Growth measured in actual percent change from quarter *t* to quarter *t*+4.

Figure 2



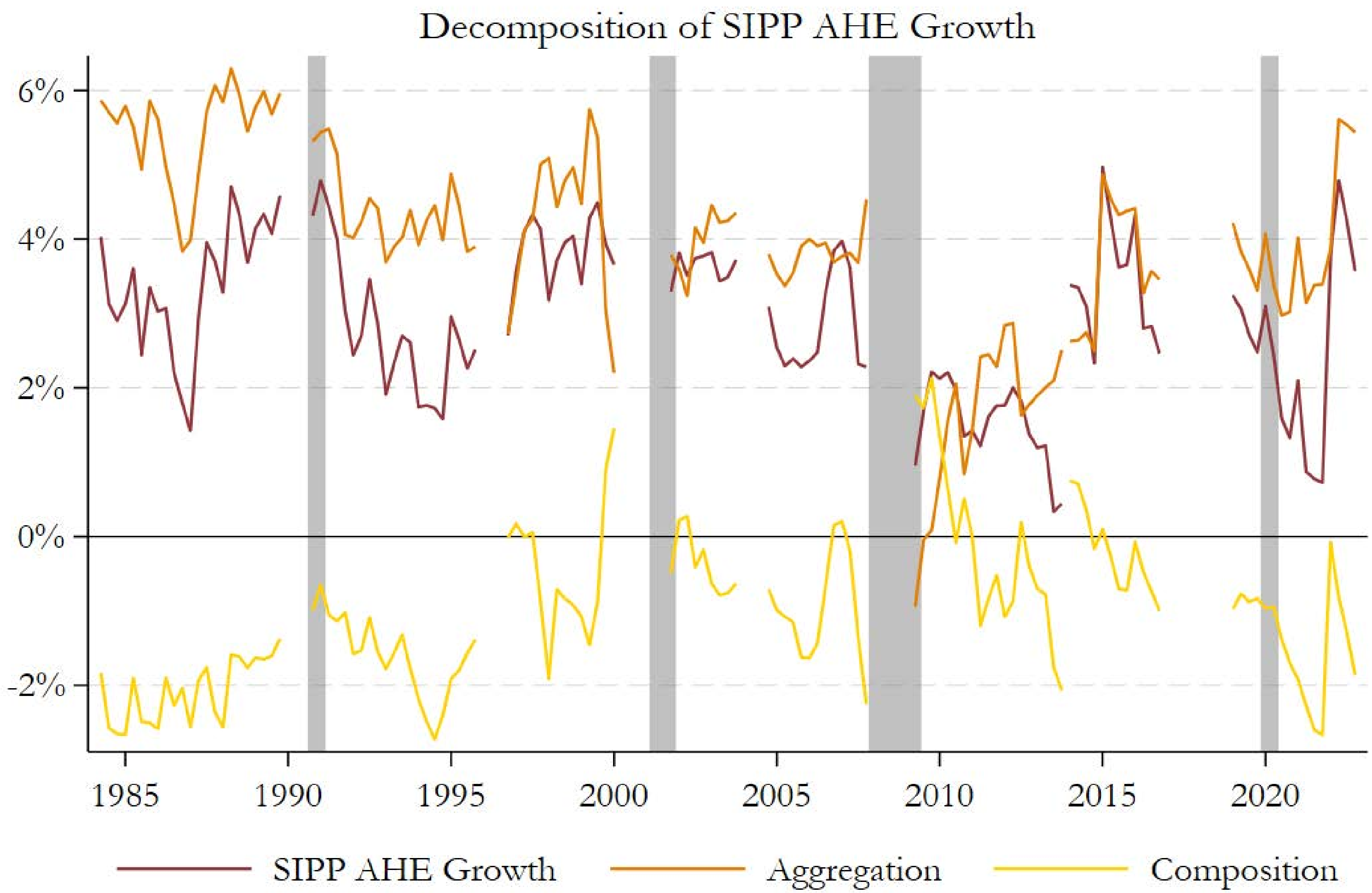
Grey bars indicate recessions.
Growth measured in actual percent change from quarter *t* to quarter *t*+4.

Figure 3



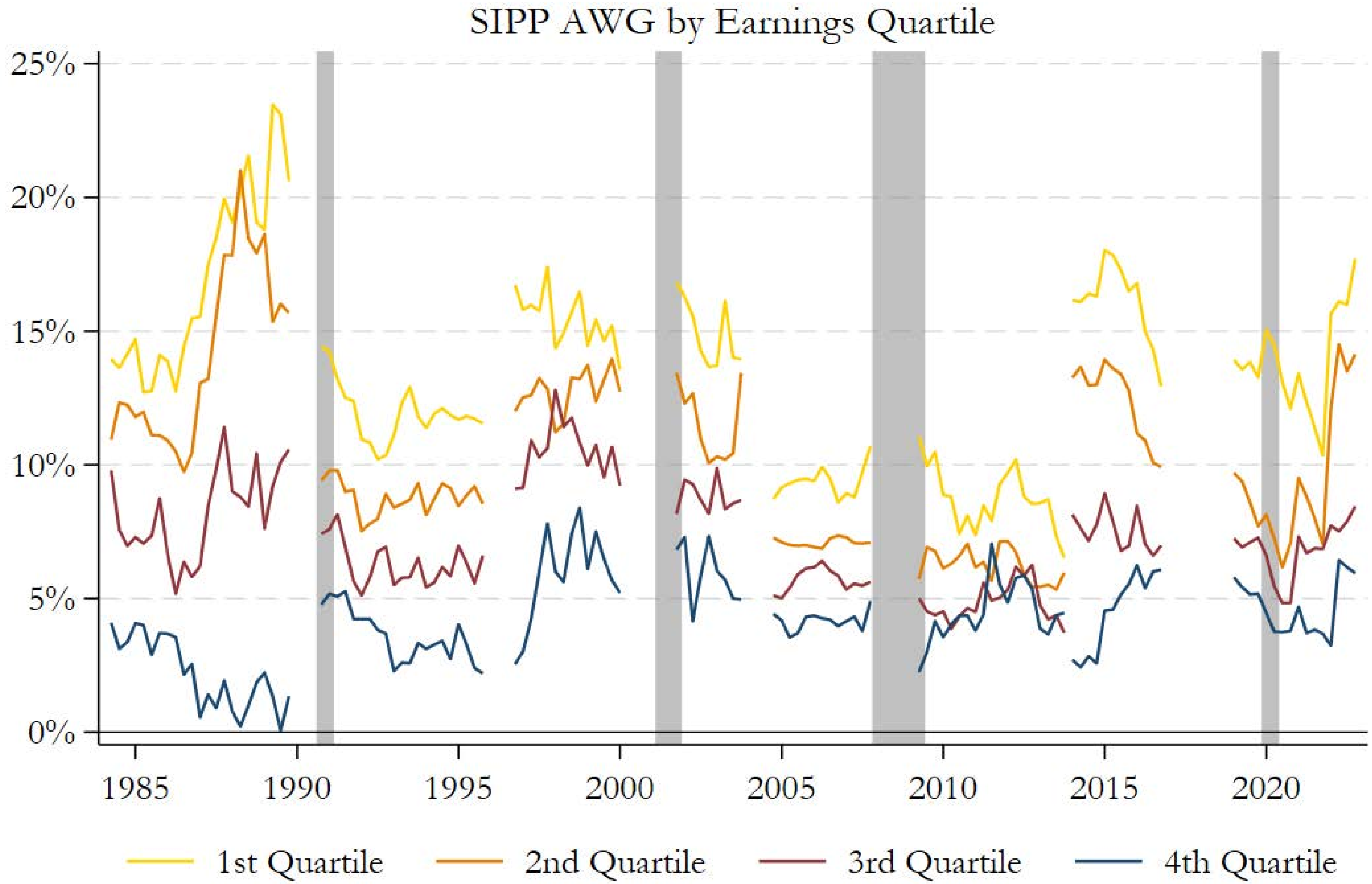
Grey bars indicate recessions.
Growth measured in actual percent change from quarter t to quarter t+4.

Figure 4



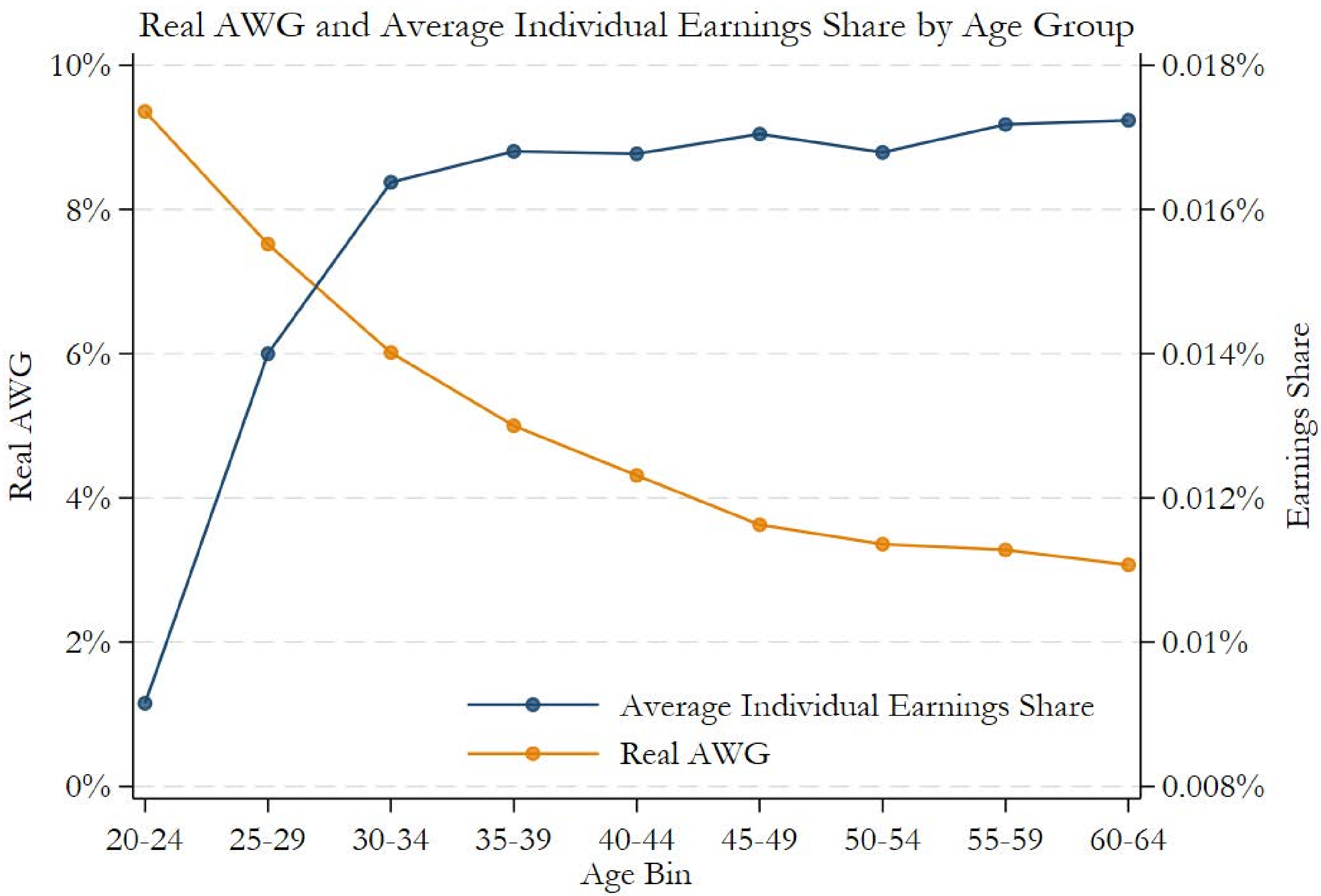
Grey bars indicate recessions.
Growth measured in actual percent change from quarter *t* to quarter *t*+4.

Figure 5



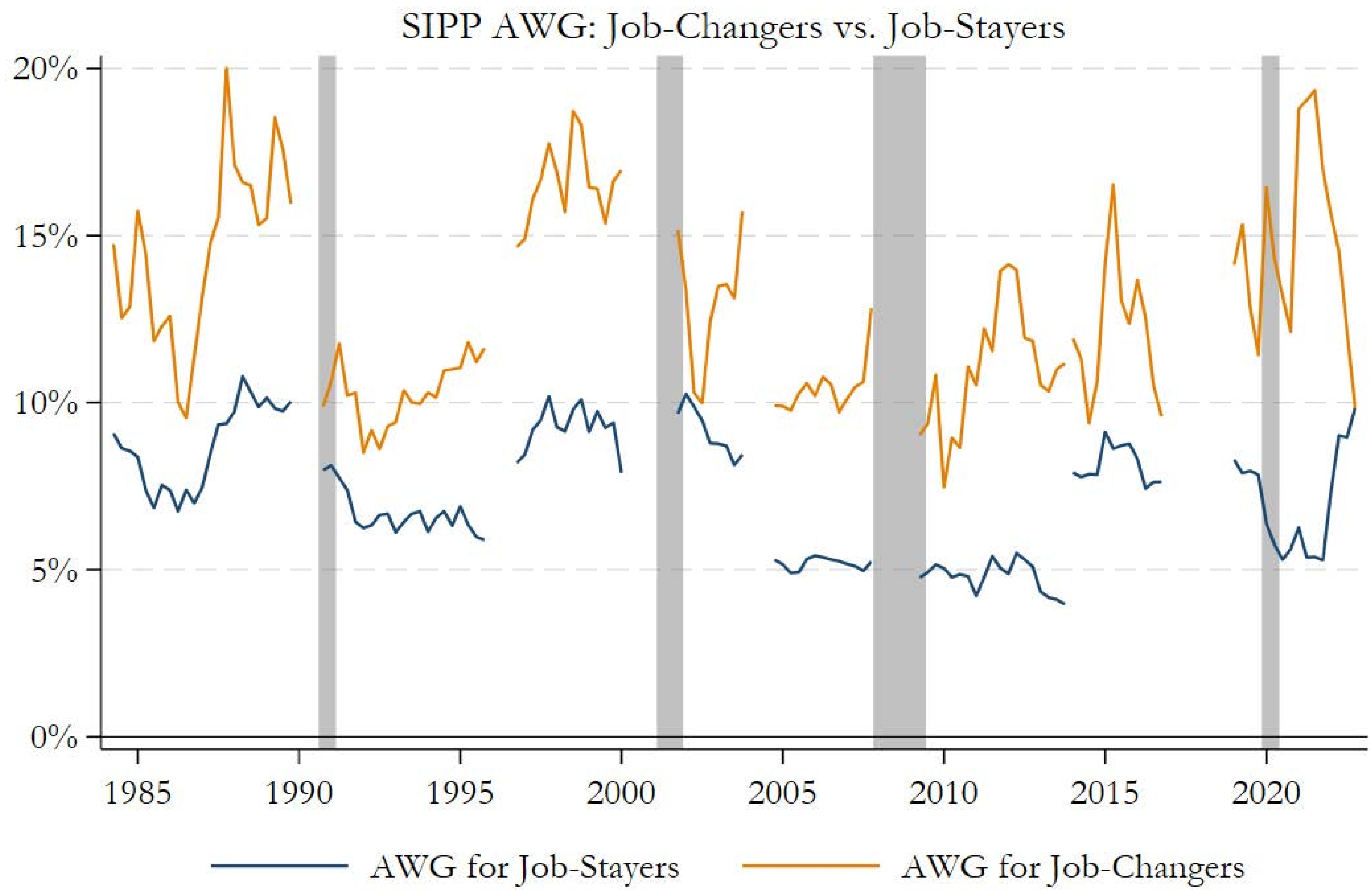
Grey bars indicate recessions.
Growth measured in actual percent change from quarter *t* to quarter *t*+4.

Figure 6



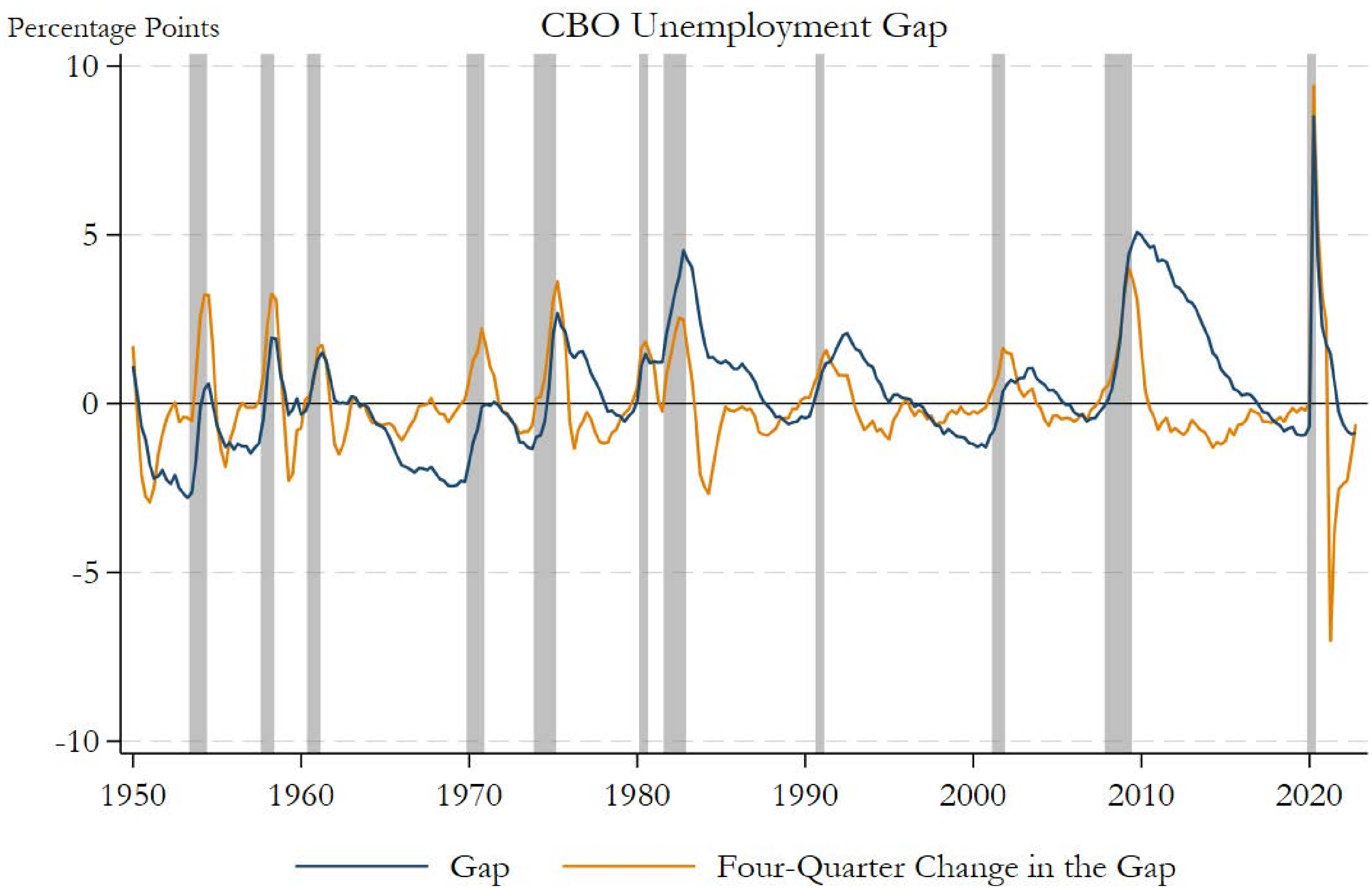
Growth measured in actual percent change from quarter *t* to quarter *t*+4.

Figure 7



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

Figure 8



Grey bars indicate recessions.

Appendix 1:

Let w_t^i denote the wage paid to individual *i* in period *t* and s_t^i denote the weight attached to that wage where $0 < s_t^i < 1$ and $\sum_{i=1}^{n_t} s_t^i = 1$ Let $\Delta w_{t+h,t}^i$ be the h-period wage growth for individual *i*. Define an average wage in period *t* as $\bar{w}_t = \sum_{i=1}^{n_t} s_t^i w_t^i$ and similarly for $\bar{w}_{t+h}$. 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+h* ("leavers"), and let *J* denote the set of individuals who are not working in period *t* but enter work by period *t+h* ("joiners").

The h-period growth in the average wage is given by:

$$\begin{aligned}
\frac{\bar{w}_{t+h}}{\bar{w}_t} - 1 &= \frac{\sum_{i\in S} s_{t+h}^i w_{t+h}^i + \sum_{i\in J} s_{t+h}^i w_{t+h}^i - \sum_{i\in S} s_t^i w_t^i - \sum_{i\in L} s_t^i w_t^i}{\bar{w}_t} \\
&= \frac{\sum_{i\in S} s_{t+h}^i w_{t+h}^i - \sum_{i\in S} s_{t+h}^i w_t^i + \sum_{i\in S} s_{t+h}^i w_t^i + \sum_{i\in J} s_{t+h}^i w_{t+h}^i - \sum_{i\in S} s_t^i w_t^i - \sum_{i\in L} s_t^i w_t^i}{\bar{w}_t} \\
&= \frac{\sum_{i\in S} s_{t+h}^i \left(w_{t+h}^i - w_t^i\right) + \left(\sum_{i\in S} s_{t+h}^i w_t^i + \sum_{i\in J} s_{t+h}^i w_{t+h}^i\right) - \left(\sum_{i\in S} s_t^i w_t^i + \sum_{i\in L} s_t^i w_t^i\right)}{\bar{w}_t}
\end{aligned} \qquad \text{(A1.1)}$$

Define $\bar{w}_{t+h}^* = \sum_{i\in J} s_{t+h}^i w_{t+h}^i + \sum_{i\in S} s_{t+h}^i w_t^i$, which is the "adjusted" average wage in period *t+h* calculated using the wages and weights for joiners at time *t+h* and the wages at time *t* and the weights at time *t+h* for stayers for the two periods. Substituting this expression into (A1.1) yields:

$$\begin{aligned}
\frac{\bar{w}_{t+h}}{\bar{w}_t} - 1 &= \frac{\sum_{i\in S} s_{t+h}^i w_t^i \left(\frac{w_{t+h}^i}{w_t^i} - 1\right)}{\bar{w}_t} + \left(\frac{\bar{w}_{t+h}^*}{\bar{w}_t} - 1\right) \\
&= \sum_{i\in S} \left(\frac{s_{t+h}^i}{s_t^i}\right)\left(\frac{s_t^i w_t^i}{\bar{w}_t}\right) \Delta w_{t+h,t}^i + \left(\frac{\bar{w}_{t+h}^*}{\bar{w}_t} - 1\right)
\end{aligned} \qquad \text{(A1.2)}$$

Appendix 2:

Solon, Barsky, and Parker (1994) use PSID data to investigate the importance of composition bias for the cyclicality of AHE growth. They start by assuming that the relevant worker population can be divided into J different groups of individuals. Using our notation, let $\overline{w}_t^j$ denote AHE for individuals in group *j* at time *t*, $(s_t^j)^h$ their share of hours, and $(s_t^j)^e$ their share of earnings. The aggregate AHE measure can then be derived as an hours-weighted average of the J group's specific AHEs:

$$\overline{w}_t = \sum_{j=1}^{J} (s_t^j)^h \, \overline{w}_t^j \tag{A2.1}$$

The overall cyclicality of AHE growth and its components can then be expressed as:

$$\frac{d\overline{w}_t}{dU_t} = \sum_{j=1}^{J} \frac{d\left((s_t^j)^h \, \overline{w}_t^j\right)}{dU_t} = \sum_{j=1}^{J} (s_t^j)^h \left(\frac{d\overline{w}_t^j}{dU_t}\right) + \sum_{j=1}^{J} \overline{w}_t^j \left(\frac{d(s_t^j)^h}{dU_t}\right) \tag{A2.2}$$

or, in logarithms,

$$\frac{d\ln \overline{w}_t}{dU_t} = \left(\frac{1}{\overline{w}_t}\right)\left(\frac{d\overline{w}_t}{dU_t}\right) = \sum_{j=1}^{J} (s_t^j)^e \left(\frac{d\ln \overline{w}_t^j}{dU_t}\right) + \sum_{j=1}^{J} \left(\frac{\overline{w}_t^j}{\overline{w}_t}\right)\left(\frac{d(s_t^j)^h}{dU_t}\right) \tag{A2.3}$$

where U_t denotes the unemployment rate. 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 that wage cyclicality is the same for skilled and unskilled individuals within each group. Suppressing time subscripts in (A2.3), let δ_1 denote the proportional between-gender AHE gap $\left[(\overline{w}^F - \overline{w}^M)/\overline{w}\right]$ and let δ_2 denote the proportional gap between AHE of skilled and unskilled workers $\left[(\overline{w}^F_{Unskilled} - \overline{w}^F_{Skilled})/\overline{w}^F\right] = \left[(\overline{w}^M_{Unskilled} - \overline{w}^M_{Skilled})/\overline{w}^M\right]$. Under these assumptions, the cyclicality of AHE growth can be written as:

$$\beta_U^{AHE} = \left\{\left[1-(s^F)^e\right]\alpha_M + \left[(s^F)^e\right]\alpha_F\right\} + \delta_1 (s^F)^h \left[1-(s^F)^h\right]\left[\frac{d\ln H^F}{dU} - \frac{d\ln H^M}{dU}\right]$$
$$+\delta_2\left[\left[1-(s^F)^e\right]\frac{d\ln H^M}{dU} + (s^F)^e\frac{d\ln H^F}{dU}\right] \quad \text{(A2.4)}$$

where Solon, Barsky, and Parker (1994) interpret α_M and α_F, respectively, as the wage cyclicalities for men and women that are free of composition bias.[29] The first term on the right-hand side of (A2.4) represents an aggregation effect, with the second and third terms representing, respectively, the cyclical variation in the gender composition of total work hours and the cyclical variation in the skill composition of each gender's hours.

In their analysis, Solon, Barsky, and Parker (1994) 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. Drawing from the results of other studies and the PSID data, Solon, Barsky, and Parker (1992) calculate a value of 0.27 for $(s^F)^e$, which, when combined with their earlier estimates for $\alpha_M = -1.40$ and $\alpha_F = -0.53$ yields an estimate of −1.16 for the aggregation effect.

The authors then estimate the cyclicality of BLS AHE growth β_U^{AHE} over their sample period and obtain a value of −0.60. Given the estimates for β_U^{AHE} and the aggregation effect, 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, indicating a strong countercyclical impact on AHE growth that can mask the cyclicality of wage growth.

Solon, Barsky, and Parker (1994) then proceed to decompose the 0.56 estimate of the composition bias. Using the previously reported values of δ_1 and $(s^F)^e$ as well as estimates of the cylicality of per capita hours worked from Solon, Barsky, and Parker (1992), they obtain an estimate for the gender composition bias term that is quantitatively small: -0.04. The skill composition bias

[29] See Solon, Barsky, and Parker (1992) for a more detailed discussion of the derivation.

term can then be calculated as a residual from (A2.4) and is estimated to have a value of 0.60, which is essentially the same as the entire composiiton bias term.