

Aggregate Real Wages: Macro Fluctuations and Micro Drivers

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Using data from the Current Population Survey from 1980 through 2010 we examine what drives variation and cyclical in the growth rate of real wages over time. We employ a novel decomposition technique that allows us to divide the time series for median weekly earnings growth into the part associated with the wage growth of persons employed at the beginning and end of the period (the wage growth effect) and the part associated with changes in the composition of earners (the composition effect). The relative importance of these two effects varies widely over the business cycle. When the labor market is tight job switchers get large wage increases, making them account for half of the variation in median weekly earnings growth over our sample. Their wage growth, as well as that of job-stayers, is procyclical. During labor market downturns, this procyclicality is largely offset by the change in the composition of the workforce, leading aggregate real wages to be almost non-cyclical. Most of this composition effect works through the part-time employment margin. Remarkably, the unemployment margin neither accounts for much of the variation in nor much of the cyclical in median weekly earnings growth.

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1. Introduction

The puzzling behavior of aggregate measures of real wage growth has been a perennial topic of macro and micro economic research. Aggregate real wages exhibit less variability over time than most macroeconomic models predict. Movements that do take place appear only modestly related to the business cycle.²

Both of these patterns can be seen in Figure 1 which plots the growth in real median weekly earnings along with the unemployment rate. As the figure shows, aggregate real wage growth varies much less than the unemployment rate, failing the predictions of a variety of macro models including real business cycle models (Hansen 1985) and models of frictional unemployment (Shimer 2005).³

Even more puzzling has been the absence of any consistent comovement between wage growth and the unemployment rate.⁴ For example, visual inspection suggests that in the 1980s aggregate real wage growth was slightly procyclical, falling during the deep recessions of the first part of the decade and rising when the unemployment rate declined in middle of the decade. From the late 1980's through the mid 1990's real wage growth was countercyclical, increasing at the same time that the unemployment rate rose. In contrast, during the strong labor market of the second half of the 1990s the unemployment rate hovered near its low structural level and wages grew rapidly, statistically producing an acyclical relationship. Finally, in the most recent severe recession, real wage growth remained high while unemployment increased, suggesting that aggregate real wages responded countercyclically.

The lack of the expected variability in aggregate real wages and the absence of a consistent relationship between wage growth and unemployment have spurred a long line of research about why this is the case. Two things have been pointed out as main determinants of the observed empirical patterns. The first, which we will term the *wage growth effect*, suggests that wage setting

² Indeed, several authors have concluded that wages are only modestly tied to business cycle conditions: for example, Lucas (1977); Mankiw (1989); and Christiano and Eichenbaum (1992). See Abraham and Haltiwanger (1995) for a survey of empirical studies of real-wage growth over the business cycle.

³ The flipside of this is that unemployment, employment, and hours tend to move more than these models predict, suggesting that most of the adjustments in the labor market come through quantities rather than prices.

⁴ While most models expect wages to exhibit some cyclicality the direction depends on the model. For example, Kydland and Prescott (1982), Barro and King (1984), Rotemberg and Woodford (1992), and Bartelsman et al (1994) all posit procyclical wages while a countercyclical relationship is predicted by Classical and traditional Keynesian as well as DSGE models. See Swanson (2007) for a brief review of these issues.

practices or market imperfections limit the adjustment of wages, dampening aggregate fluctuations and cyclical responses. Examples of this line of reasoning include efficiency wage models, implicit contract models, and insider-outsider models as well as the long literature on nominal wage rigidities.⁵ Models of wage bargaining have frequently been used to explain why aggregate wages adjust much less than employment or hours; nominal rigidities are pointed to as a reason for limited cyclical responsiveness of wages in downturns.

The second, commonly known as the *composition effect*, focuses on the fact that the composition of the workforce changes over the cycle so that workers with lower wages are disproportionately laid off in downturns.⁶ The idea is that composition bias obscures the true underlying relationship between wages and economic conditions. Analysis has shown that once composition is taken into account wages are highly procyclical.⁷

Although there is a general consensus that each of these factors plays a role in the patterns displayed in Figure 1, there is less agreement or understanding about which one is more important. One reason for this is that most of the empirical work has focused on tying down one aspect of the puzzle (e.g., wage growth of particular groups, composition bias) or been restricted to aggregate or individual data with little ability to reconcile the two pieces. Another reason is that, as suggested by our discussion of Figure 1, there may not be a single answer. While the factors examined by previous authors (wage growth effect and composition effect) may always be present, Figure 1 suggests that their relative importance may change over a cycle and vary from cycle to cycle.

Netting out these effects over time and tracking their importance for both the variance of aggregate real wage growth and for aggregate real wage cyclicalities is where our paper makes a contribution. To accomplish this task we use data from the Current Population Survey (CPS) for 1980 through 2010. The CPS has the important advantage of containing data matched to regularly published aggregate wage measures as well as underlying micro data on individuals. This allows us to link our micro analysis to the macro trends. We perform a novel decomposition that allows us to

⁵ Empirical research has focused on nominal wage rigidities (e.g. Card and Hyslop, 1997, Lebow, Saks, and Wilson, 2003, Dickens et al., 2007, and Barratieri, Basu, and Gottschalk, 2010) as well as the relative size of wage fluctuations for job-stayers and job-switchers (e.g. Bils, 1985, Devereux, 2001). See Pissarides (2009) and Kudlyak (2010) for two useful overviews.

⁶ Perry (1972), Bils (1985), and Solon, Barsky, and Parker (1994).

⁷ Changes in composition can arise when employers use employment, in addition to wages, to rebalance costs, resulting in disproportionate employment losses among workers with lower than average wages. This “upskilling” implies less variation in aggregate real wages than would be implied by models where workers are homogeneous and wages adjust uniformly (Altonji and Devereux 2000).

distinguish the part of the aggregate real wage fluctuations driven by changes in workforce composition from the part related to the growth of wages among those who remain employed.

Since we have detailed micro data on labor market status we are able to perform our decomposition for subgroups of workers defined by key margins considered in macroeconomic models including those who stay on the same job, those who change jobs, and those who move into or out of unemployment or the labor force. Moreover, we can perform our decomposition on each cross-sectional sample from 1980-2010, we are able to track how these groups influence overall wage movements and to what extent they drive or obscure the cyclical changes documented in Figure 1 at different points in time.

The findings from this exercise confirm the patterns pointed out previously in the literature including the role of composition bias, the importance of employment status as an indicator of wage changes, and the relative inflexibility of wages at certain times and among certain groups (Bils 1985; Solon, Barsky, and Parker 1994). Additionally, with our decomposition we are able to show how these factors have added up over time to produce the pattern of aggregate real wages found in the data.

These findings are revealing. They show that for the variance of real wage growth, the wage growth effect is much more important than the composition effect. That is, movements in aggregate wages are driven primarily by changes in the earnings distributions of job-stayers and job-changers, rather than those of individuals who move in and out of part-time employment, unemployment, or the labor force.⁸ In fact, half of the variance of real median weekly earnings growth over our sample can be traced back to job-switchers. While individuals moving into full-time jobs from part-time employment, unemployment, or from out of the labor force pay a wage penalty, neither their share of the overall work force nor the fluctuations in their wage penalties are large enough to have a major impact on aggregate real wage growth volatility. The contribution of job-switchers to aggregate real wage growth fluctuations is mostly due to periods of tight labor markets, like the second half the 1990's in Figure 1, in which many persons change jobs in pursuit of higher pay. The result is that the wage growth effect is procyclical.

⁸This is consistent with Bils (1985) who found that job changers are responsible for most of the aggregate fluctuations in wages. Hagedorn and Manovskii (2010) emphasize the importance of on-the-job search for understanding aggregate wage dynamics.

During downturns the procyclicality of the wage growth effect is largely offset by the change in the composition of the workforce. Specifically, during economic downturns part-time employment, unemployment, and non-participation increase and do so disproportionately among individuals who make less than median earnings. The result is that aggregate real wage growth is barely cyclical. Notably, we find that a sizeable fraction of the composition effect is driven by movements of part-time workers, and that their role has increased over time. Indeed, they account for the bulk of the composition effect during the recent very severe recession that started in December 2007. In this recession the composition effect played a very large role in reducing the decline in aggregate real wage growth.

Surprisingly, just as for the variation in real wage growth, the unemployment margin does not matter much for the composition effect and thus for the cyclicity of real wage growth. The relative unimportance of the unemployment margin in the decomposition suggests that macroeconomic models that aim to match aggregate wage dynamics are most likely to be successful if they focus on job-to-job transitions and the adjustment of hours per worker rather than on unemployment dynamics.

The rest of this paper is structured as follows. In Section 2 we describe the CPS data and show that it meets our criteria as a source of a useful aggregate measure of real wage growth with available underlying microdata. In Section 3 we introduce our percentile decomposition technique that allows us to decompose the change in median wages and get around issues of top coding present in most publically available individual-level data on earnings in the U.S. We then show how this technique allows us to focus on movements in the earnings distribution related to different groups: those who enter and exit the workforce and those who stay employed and to specifically identify the relative contributions of the composition and wage growth effects that drive changes in each of the percentiles of the earnings distribution. In Section 4, we present the results of our decomposition of real median weekly earnings growth for full-time workers in the U.S. from 1980 through 2010. We conclude with Section 5. Two appendices follow: one with the details on the CPS data we use and the other detailing the mathematical derivations of our percentile decomposition.

2. Macro and Micro Analysis with the Current Population Survey

To trace business cycle fluctuations in aggregate real wages back to those of the individuals that make up the aggregate, we need a long time series of a large and representative sample of U.S. wage earners. To track wage changes of individuals according to labor market status we also need a survey administered more frequently than annually. The CPS provides monthly data on earnings for a representative sample of U.S. workers that cover the last 30 years. As such, it satisfies the data requirements for our application.⁹

The most commonly quoted aggregate measure of wages derived from the CPS, and the one we focus on in our analysis, is Median Usual Weekly Earnings (MWE) of full-time wage and salary workers. MWE is published at a quarterly frequency.

As described in BLS (2011), “Usual Weekly Earnings” are defined as

*“...earnings before taxes and other deductions and include any overtime pay, commissions, or tips usually received (at the main job in the case of multiple jobholders).”*¹⁰

Usual weekly earnings are generally reported for full-time workers.¹¹ Since our focus is on real wages, we deflate all measures of nominal wages by the Personal Consumption Expenditures Price Index.¹²

An important question is to what extent the data from the CPS match alternative aggregate wage measures, especially those used in other empirical studies. The most commonly used alternative measures of aggregate wage growth are Average Hourly Earnings (AHE) of production and non-supervisory workers in the private sector, Compensation Per Hour (CPH) in the nonfarm business

⁹Previous research on the drivers of aggregate wage dynamics have relied on smaller panel surveys which provide detailed data on individuals. For example, Bils (1985) uses the National Longitudinal Survey of Youth (NLS/Y). Solon, Barsky, and Parker (1994), Devereux (2001), and Hagedorn and Manovskii (2010) use the Panel Study of Income Dynamics (PSID). Gertler and Trigari (2009), Barattieri, Basu, and Gottschalk (2010) use data from the Survey of Income and Program Participation (SIPP). Card and Hyslop (1997), like we do here, use data from the Current Population Survey (CPS).

¹⁰The CPS survey questions related to usual weekly earnings have evolved over time: “Prior to 1994, respondents were asked how much they usually earned per week. Since January 1994, respondents have been asked to identify the easiest way for them to report earnings (hourly, weekly, biweekly, twice monthly, monthly, annually, other) and how much they usually earn in the reported time period. Earnings reported on a basis other than weekly are converted to a weekly equivalent. The term “usual” is as perceived by the respondent. If the respondent asks for a definition of usual, interviewers are instructed to define the term as more than half the weeks worked during the past 4 or 5 months” (BLS, 2011).

¹¹The focus on full-time wage earners still means that MWE is affected by fluctuations in overtime, overtime pay, as well as a trend in the average work week for full-time workers (See Perry, 1972, for a discussion of these issues)

¹²This index is published by the Bureau of Economic Analysis as part of the U.S. National Income and Product Accounts.

sector,¹³ and the Employment Cost Index (ECI).¹⁴ Figure 2 plots each of these measures along with MWE from the CPS from 1980 through 2010. As the figure shows, these measures are highly correlated and exhibit similar cyclical patterns. The correlation of real wage growth measured by MWE with the other three measures is 0.6 or higher.

Having established that the CPS MWE captures the same aggregate movements in wages as other measures of real wage growth, we now turn to the underlying individual-level microdata. The microdata come from a CPS interview structure that follows a fairly complicated pattern.

Individuals who take part in the CPS are interviewed 8 times over the course of 16 months.¹⁵ The interviews are done in a 4-8-4 sequence—respondents are interviewed for four months, drop out of the sample for eight months, and rejoin again for the final four months. Table 1 illustrates the interview structure. In interview months 4 and 8 employed respondents are asked about their earnings. In the remaining sample months, respondents are asked about their labor market status, which we use to track which labor market groups are important for aggregate wage movements.

Although the CPS interview process allows us to construct a short panel for each individual, the data are not publically provided in that format. As such, to create the panel we must match respondents across different months. We follow procedures developed by Madrian and Lefgren (1999) and Nekarda (2009) to reconstruct the longitudinal structure of the CPS. The details of this matching procedure are provided in Appendix A. Our matching procedure allows us to compute changes in labor market status and wages for relevant individuals in the CPS. With the exception of two short periods in which CPS procedures prohibit matching, our data cover 1980 through 2010.¹⁶ Figure 3 plots both the published aggregate MWE and our constructed, from the microdata, MWE series.¹⁷ The two measures are very similar with a correlation of 0.78.¹⁸ As such, we conclude that

¹³ For example, Gertler and Trigari (2009) focus on AHE for the empirical analysis in their paper while Galí (2011) focuses on CPH for his estimate of the New-Keynesian Wage Phillips Curve.

¹⁴ The ECI is part of the Principal Economic Indicators. It is identified by the Office of Management and Budget as a series that provides a timely measure of economic activity (BLS, 2009, Chapter 8). Lebow, Saks, and Wilson (2003) analyze the National Compensation Survey data on which the ECI is based.

¹⁵ The CPS is actually a household survey and the sample is a representative sample of U.S. households. This means that persons who change their residence drop out of the sample. See Nekarda (2009) for an extensive discussion of this sample design.

¹⁶ Due to the scrambling by the Census Bureau of identifiers that we use to match individuals across months, we are unable to perform this matching for two sub-periods of our sample, namely October 1985 through September 1986 and September 1995 through August 1996.

¹⁷ In any quarter, the published aggregate MWE statistic is based on respondents who are either the fourth or eighth month of the CPS survey tenure (see Table 1). This means that the 4-quarter growth rate of published MWE is based on a changing sample of individuals rather than the matched sample we construct for our analysis.

the measure of MWE growth we use for our decomposition has the same main characteristics of interest as the published MWE growth.

Having settled on a wage series, we next turn to organizing our data into groups relevant for the decomposition. In every monthly interview the CPS asks respondents about their labor market status. This means for every individual we know whether or not they were full-time employed, part-time employed, unemployed, or not in the labor force. We use repeated surveys of the same individuals over the course of a year to track movements in and out of labor market states (e.g., employed, unemployed, and out of the labor force). Unfortunately, the survey does not tell us whether or not the individual stays in the same job across the surveys. Thus, following previous researchers, we impute this. Specifically, we combine the method used by Card and Hyslop (1997) with those used by Fallick and Fleischman (2004) and Nagypál (2008). Appendix A provides the details of our imputation.

Turning to those who change jobs over the sample, we also must make some imputations. Because of the 4-8-4 CPS sampling design, we do not know whether job-changers went directly from one job to another or were temporarily unemployed, part-time or self-employed, or out of the labor force, during the 8 months that they were not part of the sample. We impute the share of NISJ transitions that are directly from one job to another (Job-to-Job or J2J). This imputation is based on a first-order Markov process approximation for labor force status and employer-to-employer flows, similar to that applied by Fallick and Fleischman (2004). We describe this approximation in detail in Appendix B. Data limitations only allow us to do this imputation from 1996 onwards.

Figure 4 shows the results of our imputation. The figure indicates that, on average, a bit less than two-thirds of NISJ flows are J2J. Just like quits as a share of separations in the Job Openings and Labor Turnover Survey, J2J flows are procyclical, increasing during the strong labor market at the end of the 1990's, with a bit of a lull during the dip in 1998, and again increasing from 2006 through 2007. Their share sharply dropped during the 2007 recession.¹⁹ This is consistent with

¹⁸ This is consistent with the analysis by Nekarda (2009), which indicates that many aggregates derived from the CPS are relatively insensitive to the household-based sampling method.

¹⁹ It is important to note that, because we count changes of the job description of a worker who stays with the same employer as a change in jobs, we find more job-to-job switches than studies, like Fallick and Fleishmann (2004) and Nagypál (2008), which consider job-to-job switches conditional on changing employers. Moreover, we only consider switches from one full-time job to another.

Akerlof, Rose, and Yellen (1988) who argue that job-to-job quits in pursuit of higher wages and job satisfaction drive a large part of U.S. labor market dynamics.

Combining these pieces of data work we are able to define five labor-market-status transition types. For persons who flow into full-time employment, that is were full-time employed at time t but not in $t-1$, there are three potential $t-1$ states: (i) part-time or self employed a year ago, (ii) unemployed, and (iii) not in the labor force. There are equivalent groups that flow out of full-time employment, full-time employed at $t-1$ but not at time t . Among those who were full-time employed in t and $t-1$ there are two potential states: (iv) persons who are full-time employed in the same job both at the beginning and end of the year, and (v) persons who are full-time employed both at the beginning and end of the year but who have changed jobs. We call these groups, respectively: part-time/self-employed, unemployed, NILF, same job, and NISJ.^{20, 21}

Basic patterns in median weekly earnings and labor force shares

To get a sense of why previous research has found both the wage growth effect and the composition effect to be important for understanding aggregate wage growth it is useful to examine the basic trends in the data on median weekly earnings by group as well as the share of the labor force each group accounts for. Figure 5 presents data on wages by group; Table 2 provides information about the shares.

Figure 5, panel (a), shows the growth rate of median weekly earnings for the two groups of individuals who are employed both at the beginning and end of the year. What stands out in this plot is the large wage gains earned by job-switchers (NISJ) during the strong labor markets of the mid-1980's and, especially, of the late-1990's. This is consistent with Hines, Hoynes, and Krueger (2001), who find that the strong labor markets during these two periods allowed workers to change to jobs with steeper wage profiles. No such period of rapid wage growth for job-switchers occurred during the 2000's. At its strongest, in 2005 and 2006, the job market during that decade

²⁰Our distinction here follows the now ample evidence that wage growth of persons who remain in the same job is less cyclical than that of persons who switch jobs See, for example, Bills (1994), Devereux (2001), Martins, Solon, and Thomas (2010), and Hagedorn and Manovskii (2010)

²¹We do not differentiate between individuals in any of these subgroups based on their observable characteristics. Hence, our composition effect is not measured based on efficiency units, as is done in Bowlus, Liu, and Robinson (2002). They, however, do not aim to decompose aggregate wage fluctuations but focus on the sensitivity of parameter estimates to composition bias.

generated relatively modest real wage gains for job-changers. Those who stayed in the same job saw even weaker real-wage growth during that period.

Panel (b) of Figure 5 shows the difference between the median earnings at which people enter and exit full-time employment, sub-divided by whether the state to or from which the transition occurs: part-time or self employment, unemployment, or not-in-the-labor-force. Consider first the series for the unemployed, which shows that the median wage for those who enter unemployment is 10 to 15 percent higher than the median wage of people who transition from unemployment to full-time status. This wage penalty paid by unemployed workers is consistent with that found for displaced workers by Farber (1997, 2005). Just like Farber (2005, Figure 10), we find that the size of these losses is affected by the condition of the economy; for instance, losses were almost non-existent during the unprecedentedly strong labor market at the end of the 1990's. During recessions, however, the earnings penalty associated with unemployment increases substantially. At the depth of each of the four recessions in our sample the median wage earned by persons after unemployment was about 25 percent lower than the median wage earned before unemployment. This is in line with evidence on the earnings losses due to mass layoffs, which are around 30 percent (Couch and Placzek, 2010).

Turning to those moving in and out of the labor force (NILF) the difference between the median earnings of persons flowing into the labor force is substantially lower than the one at which they flow out of it. Importantly, it is not very cyclical. This difference has slowly decreased during our sample period, from about 30 percent at the beginning to less than 20 percent at the end. This likely reflects the increased level of educational attainment of young workers and women flowing from out of the labor force to full-time employment. Perhaps the most surprising observation in the figure, and one we will return to later in the paper, is for the part-time and self-employed. During the 2007 recession those who ended up going from part-time employment to full-time employment actually made higher wages than those who made the opposite transition. This is a sizeable departure from the pattern observed in previous years.

Having considered the wage growth of the various groups, we now examine their shares (Table 2). The first two columns of the table reports the average shares (1980-2010) of wage earners who are in each of our five categories at the beginning and end of the year (month in sample 4 versus 8 in Table 1). The vast majority (about 90 percent) of wage earners are full-time employed

at both the beginning and the end of our individual sample frame. Of the remaining wage earners, 2.7 percent of full-time employed at the beginning of the year end up unemployed at the end of it. Conversely, 2.6 percent of those full-time employed at the end of the year were unemployed at the beginning. There are slightly larger numbers of workers moving in and out of the labor market and into or out of part-time or self-employment to or from full-time employment.²²

Although the first two columns of the table suggest that continuously full-time employed workers are likely to drive most of the movement in aggregate wages, the remaining columns of the table (III and IV) highlight why composition bias may obscure the picture. These columns show where in the wage distribution flows into and out of full-time employment are drawn for each of our five labor market states. Specifically, we consider the share of the group that is drawn from below the median wage computed across all workers. Looking first at the unemployed, on average, 63.9 percent of those full-time workers who become unemployed make less than median earnings before entering unemployment (Column III). Movements from unemployment to full-time employment occur at lower earnings levels than those in the opposite direction. Of those full-time workers who were unemployed a year ago 72.9 percent make less than the median (Column IV). Hence, the incidence of unemployment occurs disproportionately below median earnings. As a result, if unemployment goes up, workers making below median earnings lose their jobs in greater numbers than other workers. Holding wages of other workers constant, this change in the composition of the workforce increases median aggregate wages. This is the composition effect. The part-time and self-employed (Row 3 of Table 2) as well as those who move into and out of the labor force (Row 5) contribute to the composition effect in a similar way. Most of their flows into and out of full-time employment occur below the median. Hence, if outflows from full-time employment to part-time employment, self-employment, and not-in-the-labor-force increase this takes away mostly wage earners from below the median. This net exit from full-time employment then leads to an increase in aggregate MWE.

²² The shares of those in the same job and NISJ at the beginning and end of the year suggest that our dataset underestimates growth of full-time employment. Over our sample period, the number of full-time wage and salary workers grew at an average annualized rate of 1.1 percent. If that would be captured in our dataset, then we would expect, on average over that period, the sum of the shares of those in the same job and NISJ at the beginning of the year to be 1.1 percent higher than at the end of the year. This is not the case, the difference between these shares is only 0.2 percent. Thus, our sample does not seem to fully capture growth in full-time employment.

As expected, wages for those in the same job and NISJ tend to grow over time (Rows 1 and 2 of Table 2). Hence, fewer of them earn below the median at the end of the period than at the beginning.

The plots in Figure 5 and the numbers in Table 2 are only indicative of the potential importance of wage effects and composition effects for aggregate real-wage fluctuations. To quantify the importance of each and add up the effects we need a formal decomposition. We turn to this in the next section.

3. Wage Growth and Composition Effects: Percentile decomposition

Decompositions of movements in economic aggregates, most often shift-share analyses, are commonly used to account for the relative contributions of various influences in these aggregates.²³ Shift-share analyses can be applied when the aggregate being examined is a *mean*. We, however, are interested in decomposing the growth rate (log change) of the *median* of the wage distribution. Thus, we cannot apply a conventional type of shift-share analysis to MWE growth. As an alternative, we introduce a *percentile decomposition* that can be used in a similar way to a conventional shift-share analysis but applied to percentiles rather than means. We introduce the decomposition in three steps. First, we illustrate how changes in percentiles are related to shifts in the underlying distribution function. Second, we show that the changes in the distribution function can be decomposed into separate parts which in our case map to the composition and wage growth effects we are interested in. We conclude the section with a discussion of how we implement the decomposition to track the dynamics of MWE growth.

Relating changes in percentiles to changes in distribution functions

To understand how our percentile decomposition follows and differs from the traditional shift-share analysis it is useful to refer to Figure 6. The figure plots two log-earnings distribution functions, $F(W)$ and $G(W)$. The p -th percentiles associated with these two distribution functions are given by w_p and w'_p respectively. To illustrate the relationship between changes in percentiles

²³ See Juhn and Potter (2006) for an example related to the labor force participation rate and Bartelsman, Haltiwanger, and Scarpetta (2004) for an application to labor productivity growth.

and changes in the underlying distribution functions we assume, without loss of generality, that there is positive growth in the percentile over the period and that $w'_p > w_p$. These percentiles satisfy

$$p = F(w_p) = G(w'_p). \quad (1)$$

Our decomposition works as follows. We apply a shift-share type decomposition to the changes in the distribution functions. That is we decompose $F(w'_p) - F(w_p)$ and $G(w'_p) - G(w_p)$ into contributions by the different groups we identify. We then apply the mean value theorem to translate these contributions, measured along the vertical axis in Figure 6, into changes in earnings along the horizontal axis, i.e. $w'_p - w_p$. This is what yields the decomposition of the change in the percentile of log earnings.

As we show in Appendix B, rearranging (1) allows us to write

$$\left(F(w'_p) - F(w_p)\right) + \left(G(w'_p) - G(w_p)\right) = \left(F(w_p) - G(w_p)\right) + \left(F(w'_p) - G(w'_p)\right). \quad (2)$$

This result implies that the sum of the changes in each of the distribution functions evaluated between w'_p and w_p equals the sum of the difference in the value of the distribution functions in w'_p and w_p . In the figure, the vertical lines *I* and *II* correspond to the left-hand side terms of (2) while the lines *A* and *B* correspond to the right-hand side terms.

The left-hand side terms in the above equation can be translated into changes in the percentile by the application of the mean value theorem. If the distribution functions $F(W)$ and $G(W)$ are continuously differentiable, then there exists a w^* , such that $w_p \leq w^* \leq w'_p$, and

$$\left(F(w'_p) - F(w_p)\right) + \left(G(w'_p) - G(w_p)\right) = [f(w^*) + g(w^*)](w'_p - w_p). \quad (3)$$

This allows us to express the change in the percentile from the beginning to the end of the period, $(w'_p - w_p)$, in terms of shifts in the distribution function from $F(W)$ to $G(W)$. In particular, we can write

$$(w'_p - w_p) = \frac{1}{f(w^*) + g(w^*)} \left\{ \left(F(w_p) - G(w_p)\right) + \left(F(w'_p) - G(w'_p)\right) \right\}. \quad (4)$$

This generalizes to the case in which the population from which W is drawn is made up of various subgroups. In that case we can apply a shift-share type decomposition to the right-hand side of the above equation.

Decomposing changes in distribution functions

Equation (1) can be rewritten in terms of conditional distribution functions as

$$p = \int \varphi(s)F(w_p|s)ds = \int \gamma(s)G(w'_p|s)ds. \quad (5)$$

As we derive in detail in Appendix B, this can be rearranged to obtain a generalization of equation (2) of the form

$$\begin{aligned} & \int \varphi(s)\{F(w'_p|s) - F(w_p|s)\} ds + \int \gamma(s)\{G(w'_p|s) - G(w_p|s)\} ds \\ &= \int \varphi(s)\{F(w_p|s) - G(w_p|s)\} ds + \int \gamma(s)\{F(w'_p|s) - G(w'_p|s)\} ds \\ & \quad - \int [\{F(w'_p|s) - p\} + \{G(w_p|s) - p\}]\{\gamma(s) - \varphi(s)\} ds. \end{aligned} \quad (6)$$

Similar to equation (2), the left-hand side of the above equation is expressed in terms of the changes in each of the conditional distribution functions evaluated between w'_p and w_p . The first two terms on the right-hand side of (6) are similar those on the right-hand side of (2) in that they reflect changes in the distribution functions at w'_p and w_p . The final term on the right-hand side captures the effect of the changes in the shares of the different sub-groups.

Just like in the example in the previous subsection, we can use the mean value theorem to translate the left-hand side into changes in the percentile. That is, there exists a w^* , such that $w_p \leq w^* \leq w'_p$, and

$$\begin{aligned} & \int \varphi(s)\{F(w'_p|s) - F(w_p|s)\} ds + \int \gamma(s)\{G(w'_p|s) - G(w_p|s)\} ds \\ &= \left[\int \varphi(s)f(w^*|s) ds + \int \gamma(s)g(w^*|s) ds \right] (w'_p - w_p) = q_p(w'_p - w_p). \end{aligned} \quad (7)$$

This then allows us to express the change in the percentile, $(w'_p - w_p)$, as

$$\begin{aligned} (w'_p - w_p) &= \frac{1}{q_p} \left\{ \int \varphi(s)\{F(w_p|s) - G(w_p|s)\} ds + \int \gamma(s)\{F(w'_p|s) - G(w'_p|s)\} ds \right\} \\ & \quad - \frac{1}{q_p} \left\{ \int [\{F(w'_p|s) - p\} + \{G(w_p|s) - p\}]\{\gamma(s) - \varphi(s)\} ds \right\}. \end{aligned} \quad (8)$$

Thus, we are able to decompose the change in the percentile in terms of (i) a part that is due to *shifts* in the distribution functions for each of the subgroups that make up the population and (ii) a part due to the changes in the *shares* of these subgroups in the population.

However, these shifts and shares parts do not directly correspond to the *composition* and *wage growth effects* that are the focus of our analysis. Extracting these two effects requires an additional reshuffling of the right-hand side terms of (8). In order to disentangle the composition effect from the wage growth effect, we have to divide the population of wage earners into three types of subgroups. The first type consists of those who earn a wage both at the beginning and end of the period. They are subgroups that are part of S_S . The two subgroups in this set are those who are in the same job and who are *NISJ*. They correspond to rows 1 and 2 of Table 2. The second type consists of individuals who are full-time wage and salary workers at the beginning of the year and who flow out of these jobs and become either part-time or self employed, unemployed, or drop out of the labor force. These groups are exiters, denoted by the set S_X , and are in columns I and III and rows 3 through 5 of Table 2. The final type consists of those who flow into full-time wage and salary jobs and were either part-time or self employed, unemployed, or not in the labor force at the beginning of the period. These groups of entrants into full-time jobs are part of S_N . They correspond to columns II and IV and rows 3 through 5 of Table 2.

By explicitly defining who enters and exits the group of full-time wage earners we are able to rewrite (8) as

$$\begin{aligned}
 (w'_p - w_p) = & \frac{1}{q_p} \left\{ \int_{s \in S_S} \varphi(s) \{F(w_p|s) - G(w_p|s)\} ds + \int_{s \in S_S} \gamma(s) \{F(w'_p|s) - G(w'_p|s)\} ds \right\} \\
 & + \frac{1}{q_p} \left\{ \int_{s \in S_X} \varphi(s) [\{F(w'_p|s) - p\} + \{F(w_p|s) - p\}] ds \right\} \\
 & - \frac{1}{q_p} \left\{ \int_{s \in S_N} \gamma(s) [\{G(w'_p|s) - p\} + \{G(w_p|s) - p\}] ds \right\} \\
 & - \frac{1}{q_p} \left\{ \int_{s \in S_S} [\{F(w'_p|s) - p\} + \{G(w_p|s) - p\}] \{\gamma(s) - \varphi(s)\} ds \right\}.
 \end{aligned} \tag{9}$$

The right-hand side of (9) consists of four terms. The first term captures the effect of the shift in the earnings distribution for those who are full-time employed both at the beginning and at the end of the period on the change in the percentile. The first part of this term captures this effect by quantifying how much the percentile would have shifted if the distribution of the population over different groups in S_S is held constant at the one that prevailed at the beginning of the period, i.e. at $\varphi(s)$. The second *shift* term captures the same effect, but instead holding the distribution constant at the one observed at the end of the period, $\gamma(s)$.

Thus, the first term on the right-hand side quantifies how much the percentile changed because of the wage growth of the individuals who were observed working in both periods. This is the *wage growth effect*. If, for all groups in S_s , $F(w_p|s) > G(w_p|s)$ as well as $F(w'_p|s) > G(w'_p|s)$, then, just like in Figure 6, there has been a rightward shift in the distribution of weekly earnings of those employed at both the beginning and end of the period and this contributes positively to the change in the percentile of weekly earnings. In that case, the wage growth effect would be positive.

The second term on the right-hand side of (9) measures the effect of flows out of full-time employment on the change in the percentile. Two things contribute to this effect. The first is what fraction of full-time wage and salary workers flow out of full-time employment, measured by $\varphi(s)$ for $s \in S_X$. The second is where in the earnings distribution they were before leaving their jobs. If a disproportionate share of them made below the percentile, such that $F(w'_p|s) > p$ and $F(w_p|s) > p$, then because exit occurs at the low end of the earnings distribution this raises the percentile. This is the *exit component* of the *composition effect*.

The third term on the right-hand side of (9) measures the effect of flows into full-time employment on the change in the percentile. Similar to the second term, two things contribute to this effect. The first is the fraction of full-time wage and salary workers at the end of the period who are newly employed, measured by $\gamma(s)$ for $s \in S_N$. The second is where in the earnings distribution the newly employed locate. If a disproportionate share of newly employed make less than a certain percentile, such that $G(w'_p|s) > p$ and $G(w_p|s) > p$, then the percentile itself declines. This is the *entry component* of the *composition effect*.

As for the last term, if there is more exit than entry, then there is no full replacement of outflows. That is, the share of those in S_s is higher at the end of the period than at the beginning of the period. In that case, it matters for the change in the percentile where those who are part of S_s are in the earnings distribution. If they are disproportionately making more than the percentile, such that $F(w'_p|s) < p$ and $G(w_p|s) < p$ for $s \in S_s$, then the shortfall of replacement of outflows actually leads to an increase in the percentile because this shortfall is effectively replaced by stayers whose earnings are relatively high. This mechanism is captured by the fourth term, which we call the *replacement component* of the *composition effect*.

Our decomposition then yields *exit and entry components* for the *composition effect* for those who move along (i) the part-time and self-employment margin, (ii) the unemployment margin, and

(iii) the participation margin. It yields a *wage growth effect* as well as a *replacement component* for the *composition effect* for those (iv) persons who remained in the same job, and (v) persons who changed jobs (*NISJ*).

One final detail is worth noting. Since we do not observe the actual distribution and density functions needed to construct the right-hand side of equation (9), we estimate them. The estimation procedure that we use is consistent with the one used to construct Median Usual Weekly Earnings, as published by the BLS. The BLS rounds the weekly earnings values reported by individuals to the nearest multiple of 50.²⁴ The linear interpolation of the interval in which the quantile boundary lies implicitly assumes that the earnings of those who report in the interval that gets rounded to a particular multiple of 50 are uniformly distributed over that interval. To be consistent with this methodology we estimate the distribution and density functions, F , G , f , and g , in (9) the same way. That is, we group all earnings observations on the nearest multiple of fifty and assume that earnings are uniformly distributed over the intervals that get rounded to each of these points.

This way of estimating the distribution functions, however, implies that they are not continuously differentiable and that, as a result, the mean value theorem that we applied to derive (9) is not applicable. This does not mean we cannot use the percentile decomposition. Instead we replace $f(w^*|s)$ and $g(w^*|s)$ by

$$f(w^*|s) = \frac{F(w'_p|s) - F(w_p|s)}{w'_p - w_p}, \text{ and } g(w^*|s) = \frac{G(w'_p|s) - G(w_p|s)}{w'_p - w_p}. \quad (10)$$

In that case (9) still holds and we can thus decompose changes in earnings percentiles.²⁵ This method is applicable to any percentile of the earnings distribution. Since we focus in particular on the median in the rest of our analysis, we will drop the subscript p when we present the results.

²⁴ According to the BLS: “The estimation procedure places each reported or calculated weekly earnings value into \$50-wide intervals which are centered around multiples of \$50. The actual value is estimated through the linear interpolation of the interval in which the quantile boundary lies.” (BLS, 2011)

²⁵ This estimation method works if $w'_p \neq w_p$. If $w'_p = w_p$ then we use the value of the density implied by the assumption that earnings are uniformly distributed over the intervals that are rounded to the same multiple of 50. The case where $w'_p = w_p = 50i - 25$ for $i = 1, 2, 3, \dots$ and in which this does not work because of the kinked distribution function does not occur in our data.

4. Results

In the remainder of the paper we present the results of our decomposition of the log changes in the median weekly earnings from the CPS from 1980 through 2010. We begin by reviewing the time series movements of each of the components that go into our analysis. Recall from the derivation above that what matters for our decomposition of the log change in median earnings are the shares of each subgroup and the (changes) in their earnings distributions. These are the two things displayed in Figures 7 and 8.

Figure 7 shows the time series plots of the shares of the full-time employed made up by each subgroup in the sample, namely same job (SJ), not in the same job (NISJ), part-time/self-employed (PT), unemployed (U), and not in the labor force (NILF). Panel (a) of the figure shows the share of those classified as “same job” and NISJ as a fraction of the full-time employed.²⁶ Taking into account that the data are normalized at the end of the year and that the figure plots the 4-quarter moving average, panel (a) suggests that NISJ transitions are procyclical—they go up when the labor market is strong and then decline during labor market downturns. Based on our imputation results of the composition of NISJ over the business cycle (Figure 4), this procyclical pattern is consistent with the view that when the labor market is strong workers quit more frequently and leave for higher paid jobs (Akerlof, Rose, and Yellen 1988) and when the labor market is weak, layoffs increase and a higher number of persons lose their full-time job, go through unemployment, and end up in a different full-time job a year later.²⁷

The remaining panels of the figure (panels b-d) plot the time series of entry into and exits out of full-time employment by our three other labor market status variables: unemployed, part-time/self employed, and not in the labor force. On average, flows into and out of unemployment are smaller than those along the part-time and self-employment margin as well as the labor force margin. However, as expected, flows into unemployment (exits from full-time employment into unemployment, panel b) are much more cyclical than those to part-time and self employment or out

²⁶ The sudden shift in 1983 is a data anomaly due to the change in occupation codes in the CPS. In particular after 1983 these codes were more detailed, allowing us to be more precise about our “same job” versus “not-in-the-same-job” imputation.

²⁷ This contrasts somewhat with Hall (2005) who argues that the behavior of quits and layoffs offset such that overall separations are barely cyclical. Our findings suggest that these opposing forces do not cancel out to the same extent for the sample of those transitioning from full-time to full-time employment; for these movements the cyclicity of quits seems to dominate. The result is that NISJ transitions in our full-time employed sample are procyclical.

of the labor force (panels c and d). That said, flows from full-time to part-time employment spiked in the 2007 recession, leading to about 6 percent of the labor force being part-time employed for economic reasons during 2009 and 2010. The last time that this rate was so high was in October 1982. What seems to be different about the run-up of the rate of part-time employment in the 2007 recession compared to that in 1982 is that it consisted more of persons whose full-time status changed to part-time, rather than the unemployed and labor force entrants being unable to find full-time employment.²⁸ Exits from full-time employment to NILF vary little with the business cycle being mostly determined by demographic factors and retirement norms. Entry into full-time employment from NILF is, not surprisingly, slightly more procyclical.

In Figure 8 we plot the shifts in the earnings distributions for each of our subgroups. Panel (a) of the figure plots the fraction of full-time employed, classified as either “same job” or NISJ, that moves from below median weekly earnings to above it. In terms of our notation, it is calculated as

$$\frac{1}{2}(F(w'|s) - G(w'|s)) + \frac{1}{2}(F(w|s) - G(w|s)) \text{ for } s \in \{SJ, NISJ\}. \quad (11)$$

As can be seen from the panel, during strong labor markets a larger share of job-switchers than job-stayers break through the median. In downturns and recoveries, however, this pattern is reversed and a larger fraction of those in the same job break through the median. These findings are consistent with the previous discussion that highlighted the importance of quits in NISJ during expansions versus layoffs in contractions.

Panels (b-d) of Figure 8 show where in the earnings distribution exit and entry for different subgroups occurs. In terms of our notation, these are calculated as

$$\frac{1}{2}(F(w|s) + F(w'|s)) \text{ and } \frac{1}{2}(G(w|s) + G(w'|s)) \text{ for } s \in \{U, PT, NISJ\} \quad (12)$$

for exiters from and entrants into full employment respectively. The first thing to note from each of these panels is that the vast majority of those who enter full-time employment from any of these states earn less than MWE. This can also be seen in Table 2, rows 3-5. Surprisingly, entry into and exit from unemployment takes place at a higher part of the income distribution than do movements from and to part-time and self-employment and not-in-the-labor-force.

²⁸ This finding is consistent with changes in UI rules in several states that allowed individuals to claim benefits when reducing hours of work as well as when losing jobs.

Turning to the dynamics of the earnings of these flows, panel (b) shows that there is considerable cyclicity in the composition of those exiting (entering) full-time employment into (from) unemployment. During recessions, the fraction of workers moving from full-time employment to unemployment from below MWE falls. This is consistent with Mueller (2010), who finds that during recessions the incidence of unemployment among high-income earners increases. This pattern is reversed in expansions, when the share of workers entering full-time employment with earnings below MWE rises, suggesting that expansions bring in a larger pool of workers from across the skill and wage distribution. To a lesser degree, the same pattern is observed for entries into full-time employment from unemployment; the fraction making this transition from below MWE falls during recessions and rises during expansions.

Relative to the unemployment subgroup, there is very little cyclicity in where in the earnings distribution those who flow into NILF or part-time and self-employment originate. The main pattern in both series is that the gaps between the entries and exits to (from) full-time employment narrow over time, suggesting that in the decomposition most of the cyclical variation in the contributions from the part-time and self-employment and NILF margins will come through their shares rather than shifts in the earnings distributions.

Decomposition of median weekly earnings growth by subgroup

The next step in our analysis is to combine the parts plotted in Figures 7 and 8 using equation (9) to decompose the log-change of median weekly earnings into the wage growth effect and the composition effect. From this we obtain composition effects for all of the subgroups and wage effects for the same job and NISJ subgroups; these are displayed in Figure 9. Panel (a) plots the composition effect which is the *replacement components* for the “same job” and NISJ subgroups and the net contribution of the *entry and exit components* for the other subgroups. Panel (b) plots the wage growth effect for those in the same job and NISJ.

Given the number of moving parts underlying the decomposition we begin our discussion with a detailed description of how the components displayed in Figures 7 and 8 produce the net composition effect for the unemployment margin shown in panel (a) of Figure 9 and for the NISJ wage growth effect shown in panel (b) of the same figure.

In equation (9), up to the scaling factor, $1/q$, the net composition effect of the unemployment margin is given by

$$\varphi(U)\{(F(w'|U) - \frac{1}{2}) + (F(w|U) - \frac{1}{2})\} - \gamma(U)\{(G(w'|U) - \frac{1}{2}) + (G(w|U) - \frac{1}{2})\}. \quad (13)$$

Here, $\varphi(U)$ is the share of full-time employed at the beginning of the year exiting to unemployment and $\gamma(U)$ is the share of full-time employed at the end of the year who were unemployed at the start. Both these shares are in panel (b) of Figure 7. $F(w'|U)$ and $F(w|U)$ reflect the share of those exiting full-time employment to unemployment who make less than median wage, measured either at the end and the beginning of the year respectively. $G(\cdot|U)$ measures the same share, but for those entering full-time employment from unemployment.

Recall from panel (b) of Figure 8 that unemployed workers pay a displacement penalty such that $G(w'|U) > F(w'|U)$ and $G(w|U) > F(w|U)$. In terms of equation (13), this implies that when $\varphi(U) \cong \gamma(U)$ the composition effect of unemployment pulls down median wage growth since the distribution of earnings for those transitioning from full-time employment to unemployment is higher than for those transitioning from unemployment to full-time employment. Looking at the line for the unemployment margin in Figure 9 (panel a), this is exactly what happens on average; the unemployment margin reduces aggregate wage growth. In general then, the composition effect of the unemployed is negative.

However, as the figure shows, during, and around, recessions this effect is reduced and the composition effect of unemployment is less negative than normal. Returning to Figures 7 and 8 it is easy to see how this happens. In economic downturns $\varphi(U)$ goes up and $\gamma(U)$ goes down so that unemployment increases. Since unemployment occurs disproportionately among workers earning less than MWE, in the sense that more than half of them make less than the median wage, the earnings distribution terms in (13) are both positive. This means that the cyclical movement in the flows $\varphi(U)$ and $\gamma(U)$ makes the net composition effect of unemployment less negative than it normally is. This is what drives the countercyclical movements in the composition effect for the unemployed.

However, this countercyclicity of the composition effect of the unemployed is partly offset by the shifts in the earnings distributions. This effect comes from the increased earnings penalty of unemployment during recessions. In our notation, this earnings penalty is represented by the difference between $\frac{1}{2}(G(w|U) + G(w'|U))$ and $\frac{1}{2}(F(w|U) + F(w'|U))$, both displayed in panel

(b) of Figure 8. On average, these two effects work against each other in recessions and limit the composition effect of unemployment discussed in the literature.

Importantly, all of the remaining subgroups also contribute to the countercyclicality of the composition effect. Though small, even the *replacement components* turn out to move countercyclically. In terms of contributions to the composition effect, the part-time and self employment margin contributes more to the composition effect for median weekly earnings growth and cyclicalities than the unemployment margin. The magnitude of the part-time and self employment effect relative to other margins owes to the fact that a larger fraction of flows into and out of part-time and self-employment occur below MWE (Figure 8, panel (c)). Unlike the unemployment margin, the part-time and self-employment effect does not have offsetting components. In business cycle downturns, the share of exits from full-time to part-time rises and there is little change in the earnings difference between entrants to and exits from full-time employment from (to) part-time employment. In line with the shares presented in panel (c) of Figure 7, the importance of the part-time and self-employed for the composition effect increased significantly during the 2007 recession.

Panel (b) of Figure 9 shows the wage growth effect for both the same job and NISJ subgroups. We focus on the one for NISJ here. The wage growth effect for NISJ is obtained by combining the information in panel (a) of Figures 7 and 8 in the context of equation (9), ignoring the scaling coefficient, to obtain

$$\varphi(NISJ)\{F(w|NISJ) - G(w|NISJ)\} + \gamma(NISJ)\{F(w'|NISJ) - G(w'|NISJ)\}. \quad (14)$$

In particular, the terms in (14) are the share of full-time employed who are NISJ, $\frac{1}{2}(\varphi(NISJ) + \gamma(NISJ))$, from Figure 7 and the movements in the earnings distribution of NISJ at the median from Figure 8, $\frac{1}{2}\{F(w|NISJ) - G(w|NISJ)\} + \frac{1}{2}\{F(w'|NISJ) - G(w'|NISJ)\}$. Combining these terms reveals that those who change jobs over the year contribute more to the wage growth effect than those who remain in the same job. This owes to the fact that the NISJ share of full-time employed is larger and on average the earnings changes of NISJ and same job are similar. When labor markets are tight, the NISJ is amplified by an increase in the share and an increase in the fraction moving from below to above the MWE. In labor market downturns the wage growth effect of NISJ and same job groups converge as both the share of NISJ falls and their earnings gains relative to the

same job group subside. In general, during labor market expansions the strong performance in terms of wages of those who are in the “same job” and NISJ (displayed in Figure 8) is accentuated by an increase in their share as shown in Figure 7. The result is that the wage growth effect shows large procyclical fluctuations.

Adding it all up

Figure 10 summarizes our results for the full sample and shows how the *wage growth* and *composition* effects vary over time. Three things stand out from this figure.

First, fluctuations in the wage growth effect are much larger than those of the composition effect. In order to gauge the average importance of the different effects over our sample period we present the variance decomposition reported in Column I of Table 3. This decomposition works as follows. Our method allows us to represent real MWE growth as the sum of the 7 parts shown in Figure 9. The variance of real MWE growth is thus the sum of the covariance of real MWE growth with each of these 7 components. From Column I of Table 3 it can be seen that the wage growth effect accounts for more than 90 percent of wage fluctuations. The majority of these 90 percentage points is due to job-switchers, who alone account for almost half of the fluctuations in real wage growth. Off the entry and exit components, it is the part-time and self employment margin, not the unemployment margin, that is most important for the contribution of the composition effect to real wage fluctuations.

Second, the wage growth effect dominates the composition effect in almost every period of the sample and contributes to the general procyclicality of median weekly earnings growth. The composition effect normally is a drag on median weekly earnings growth since entrants into full-time employment tend to earn lower wages than those who exit from full employment. During recessions however, this differential falls and the composition effect becomes less of a drag on median weekly earnings, offsetting part of the procyclicality of the wage growth effect.

Column II of Table 3 reports the average effect of the 7 parts that make up real MWE growth displayed in Figure 9 on the cyclicity of aggregate wages. It decomposes the regression coefficient of a regression of real MWE growth on the unemployment rate, both measured in percentage points, into the parts that are due to each of the subcomponents. The aggregate regression yields an insignificant negative coefficient of -0.082. This suggests that aggregate real wage growth, as measured by MWE, is only mildly procyclical. The small value and insignificance of this

coefficient is because the composition effect of 0.109, reported in row 7, offsets the total wage growth effect of -0.191, in row 10. The offsetting nature of the composition effect is mainly due to the part-time and self employment margin. Interestingly, the unemployment margin plays virtually no role in this.

Finally, the average cyclicity results reported in column II of Table 3 hide the change in the relative importance of the composition effect over different business cycles. During the first three of the four recessions in our sample, the offsetting countercyclicity of the composition effect was not particularly large. However, during the 2007 recession the composition effect turned from negative to positive, something previously unseen in the data. This large increase in the composition effect means that real wage growth in 2008 and 2009 was greatly affected by changes in the composition of the workforce. In terms of the importance of the composition effect for growth in median usual weekly earnings the 2007 recession is an outlier compared to the three recessions before.

5. Conclusion

Using data from the Current Population Survey from 1980 through 2010 we examined what drives the variation and cyclicity in the growth rate of real wages over time. To do this we employed a novel decomposition technique that allows us to divide changes in percentiles of aggregate usual weekly earnings growth into the part associated with the wage growth of persons employed at the beginning and end of the period (the wage growth effect) and the part associated with changes in the composition of earners (the composition effect).

Our results show that the relative importance of these two effects varies widely over the business cycle. When the labor market is tight job-changers get high wage changes, making them account for about half of the variation in median weekly earnings growth over our sample. Their wage growth as well as that of job stayers is procyclical. During labor market downturns this procyclicity is partly offset by the change in the composition of the workforce. As a result, aggregate wages exhibit only limited cyclicity. Surprisingly, the composition effect works primarily through the part-time employment margin. Remarkably, the unemployment margin neither accounts for much of the variation nor much of the cyclicity of median weekly earnings.

Our conclusion that job switchers are more important for understanding real wage growth than flows in and out of unemployment has an important implication for studies that try to reconcile real wage cyclicality in macroeconomic models with search frictions. Such studies often, for simplicity, assume that the separation rate from employment is exogenously given.²⁹ However, our results suggest that such an assumption would mean discarding the cyclical fluctuations in the composition of these separations that drive the bulk of U.S. wage growth.³⁰

²⁹ This is consistent with Hall's (2005) analysis that shows that this rate is not very cyclical in the U.S.

³⁰ Hagedorn and Manovskii (2010) drop this assumption and show how job-to-job transitions in their model of frictional unemployment are important to match the observed cyclicality of real wages.

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A. Description of Data

Matching individuals across CPS interviews in different months

Our match criteria are the following. Individuals must match on age (+3 or -1 between subsequent interviews), race, household ID, and line number. This is the same matching criteria employed by Madrian and Lefgren (1999), matching the outgoing rotations; Moscarini and Thomsson (2008), matching month-to-month transitions; and is similar to Fallick and Fleischman (2004) and Card and Hyslop (1997)³¹. After 1994, when additional record-keeping variables are added, we still use the (now-redundant) demographic constraints.³²

We implement this match strategy with a simple data step. First, we figure out the date that each observation would have entered the sample if it was continuously interviewed (interview date minus month in sample). Then, we sort the data set by all of the constraints.³³ We start off our CPS panel series at one, and increment it by one each time one of these criteria changes. Each time a match is successful, we store the age from the previous matched observation to compare with the next observation using the +3/-1 criteria. Note that if an observation is missing for a single month, our match automatically skips to the next month to check for a match, since we are using the starting date as our reference date.

Our results are very similar to other papers that have matched the CPS. Fallick and Fleischman (2004) match 94.9 percent of men, and 95.4 percent of women between MIS 2 and 3 of 1998. We match an identical number of observations over this time period. Card and Hyslop (1997) match 74.5 percent of the individuals in MIS 4 in 1979 to their MIS 8 observations in 1980 and 74.4 percent from 1992-1993. Our match rate is 74.3 percent and 72.6 percent, respectively. Nagypál (2008) matches 94.82 percent of observations to their subsequent month in the time period 1994-2007. Our match yields 92.76 percent of observations matching within the same time period. Moscarini and Thomsson (2008) match MIS2 to MIS3 on average, 92.20 percent before 1994, and

³¹ Fallick and Fleischman (2004) require age to be decreased by no more than one year or increased by no more than two years. Card and Hyslop (1997) use age plus or minus one year.

³² Within 1994 and 1995, HHID's are only consistent within state, so we add a state constraint within those years. For 2003-2004 we don't use the *HRSAMPLE* and *HRSERSUF* variables, since they seem to be randomized, and HHID coupled with the demographic variables successfully matches individuals.

³³ The CPS variables on which we base our match are *starting_date hhid state hnum lino race sex hhid2 hrsample hrsersuf age*.

93.88 percent between 1994 and 2006. We match 91.91 percent and 93.74 percent over these time periods, respectively.

One thing to note is that our match procedure could introduce some bias into our results due to geographic mobility. Our results are conditional on staying within the same household, and people within the unemployment, NILF, and NISJ margin are more likely to move. However, Nekarda (2009) shows that the effect of geographic mobility on aggregate CPS measures such as the job finding rate and the separation rate is small. Nekarda (2009) also incorporates a match similar to ours, which allows for households to non-report or misreport in months between valid matches.

Some months are impossible to match due to the census scrambling the household identifiers for incoming groups. These household identifiers were scrambled in June 1995³⁴ and July 1985³⁵. BLS documentation claims that household identifiers were also scrambled in 2005, but matching on demographics results in some successful matches for this time period³⁶. The scrambling of household identifiers means that we cannot match one year forward for July 1984 to September 1985, and June 1994 to August 1995. Because of this limitation, Card and Hyslop (1997) match only 37.0 percent of all individuals in the 1984 outgoing rotation groups and 18.3 percent in 1985. Our match rate over these periods is 36.3 and 18.4 percent, respectively. Other studies do not disclose the exact months that are unmatchable.

Constructing the not-in-same-job variable

Various researchers have used strategies to identify when individuals switch jobs in the CPS. Card and Hyslop (1997) compare 2-digit industry and occupation codes between MIS4 and MIS 8³⁷. In 1994, new variables were introduced to the CPS to help identify month-to-month changes in employment. Fallick and Fleishmann (2004) and Nagypál (2008) use one of these variables - whether an individual still works for the same employer as last month, providing the employer's

³⁴ Fallick and Fleischman (2004, page 9)

³⁵ Card and Hyslop (1997, page 40)

³⁶ Nagypál (2008) also matches over this time period, with a reduced match rate.

³⁷ From their appendix: "The industry and occupation are matched using detailed (2-digit) industry and occupation codes for all years except 1982-83, 1983-84, and 1988-89. Matching for the 1983-84 sample is based on 3-digit 1980 census codes; for the 1982-83 sample, industry is matched using the detailed (2-digit) codes which are comparable across years, while occupation was matched using an algorithm devised to convert 1970 census 3-digit5 occupation codes to their 1980 census counterparts; and for the 1988-89 sample, occupation was matched using the detailed codes, and an algorithm was devised to match the detailed industry codes."

name. Both of these studies look at month-to-month transitions. This is also touched on in Moscarini and Thomsson (2008)'s study of occupational mobility.

Our "Same Job" definition can be considered a combination of the month-month SJ calculation of Fallick and Fleischman (2004), Nagypál (2008) and the year-to-year SJ calculation of Card and Hyslop (1997). We want to use all available information on a matched individual, but we are also constrained by missing data between MIS 4 and MIS5. After 1994, we define a job stayer as an individual observed as employed in MIS 4, 5, 6, 7, and 8, with the same detailed industry and occupation in each of these months, and who reports being with the same employer, with the same job description, and the same job duties, or who have missing values for these dependent-coding variables in MIS 6, 7, and 8. Nagypál (2008) and Fallick and Fleischman (2004) only use the "same employer" variable, so including these three variables enables a wider definition of job renegotiation. After 1994, industry and occupation data, as well as the tests for employer, description, and duties, are available for the prior month in MIS 6, 7, and 8. These tests are not available for comparing MIS 4 and 5, however, so we rely on industry and occupation being reliably reported between MIS 4 and 5, as Card and Hyslop (1997) do between MIS 4 and 8. Thus, our same job test applies Card and Hyslop's (1997) method to matching MIS 4 and MIS 5, and then applies a slightly more restrictive month-to-month match for the remaining MIS.

Prior to 1994, we do not have the dependent coding variables, and industry and occupation data is reported anew each month. In order to get a reasonable "same job" measure, we match industry and occupation between MIS 4 and 8, and at least 2 out of the 3 months in MIS 5, 6, and 7, keeping the constraint of employment throughout MIS 4-8.. This gives us a reasonably consistent same job rate across the 1994 boundary, and a slightly more restrictive test than Card and Hyslop (1997), who only constrained industry, occupation, and labor status in MIS 4 and MIS 8.

There are three different components to our same job definition. The first is the month-to-month match between MIS 5, 6, 7, and 8 post-1994. The second is the industry and occupation match across MIS 4 and 5 post-1994. Finally, pre-1994 we are matching on industry and occupation only. Each component of this match roughly corresponds to both to other definitions in the literature, and to each other component.

Our "Same Job" rates are consistent with these other estimates in the literature. Card and Hyslop (1997) average 54.5 percent of matched, hourly workers from 1979-1980. In our sample, for hourly

workers employed in MIS 4, 5, 6, 7, and 8, 52.4 percent are in the same job. Note that since we have access to labor status outcomes in MIS 5, 6, and 7, our overall same job rate is lower by definition. Fallick and Fleischman (2004) report that 97.3 percent of E->E workers stay in the same job. Over the same time period, our month-to-month test yields 93.6 percent of E->E workers are classified as job stayers. This difference is the result of our more restrictive month-to-month test. While Fallick and Fleischman (2004) test only for staying in the same employer, we test for staying in the same employer with the same job description and same job duties. This also corresponds with Moscarini and Thomsson (2008)'s observation that 40 percent of individuals who change occupations from month to month stay with the same employer, with 33 percent of month-to-month job movers keeping the same occupation, suggesting that promotions and demotions are not considered in an individual's response to the "Same Job" question.

B. Mathematical details

Derivation of equation (2)

Equation (2) can be derived by realizing that

$$\begin{aligned}
0 &= F(w_p) - G(w'_p) \\
&= (F(w_p) - F(w'_p)) + (F(w'_p) - G(w'_p)) = (F(w_p) - G(w_p)) + (G(w_p) - G(w'_p)) \quad (15) \\
&= (F(w_p) - F(w'_p)) + (G(w_p) - G(w'_p)) + (F(w_p) - G(w_p)) + (F(w'_p) - G(w'_p)).
\end{aligned}$$

Moving the first two terms in this expression from the right-hand side to the left-hand side yields equation (2).

Derivation of equation (6)

The version of (2) for more than one subgroup, s , reads

$$\begin{aligned}
&\int \varphi(s)[F(w'_p|s) - F(w_p|s)]ds + \int \gamma(s)[G(w'_p|s) - G(w_p|s)]ds \\
&= \int \varphi(s)F(w_p|s)ds - \int \gamma(s)G(w_p|s)ds + \int \varphi(s)F(w'_p|s)ds - \int \gamma(s)G(w'_p|s)ds. \quad (16)
\end{aligned}$$

The right-hand side of this expression can be rewritten as

$$\begin{aligned}
 & \int \varphi(s)F(w_p|s)ds - \int \gamma(s)G(w_p|s)ds + \int \varphi(s)F(w'_p|s)ds - \int \gamma(s)G(w'_p|s)ds \\
 &= \int \varphi(s)[F(w_p|s) - G(w_p|s)]ds - \int (\gamma(s) - \varphi(s))G(w_p|s)ds + \\
 & \quad \int \gamma(s)[F(w'_p|s) - G(w'_p|s)]ds - \int (\gamma(s) - \varphi(s))F(w'_p|s)ds.
 \end{aligned} \tag{17}$$

Combining terms, we obtain equation (6).

Derivation of equation (9)

Equation (9) follows from

$$\begin{aligned}
 (w'_p - w_p) &= \frac{1}{q_p} \left\{ \int_{s \in S_S} \varphi(s) \{F(w_p|s) - G(w_p|s)\} ds + \int_{s \in S_S} \gamma(s) \{F(w'_p|s) - G(w'_p|s)\} ds \right\} \\
 & \quad - \frac{1}{q_p} \left\{ \int_{s \in S_S} [\{F(w'_p|s) - p\} + \{G(w_p|s) - p\}] \{\gamma(s) - \varphi(s)\} ds \right\} \\
 & \quad + \frac{1}{q_p} \left\{ \int_{s \in S_X} \varphi(s) \{F(w_p|s) - G(w_p|s)\} ds \right\} \\
 & \quad - \frac{1}{q_p} \left\{ \int_{s \in S_X} [\{F(w'_p|s) - p\} + \{G(w_p|s) - p\}] \{\gamma(s) - \varphi(s)\} ds \right\} \\
 & \quad + \frac{1}{q_p} \left\{ \int_{s \in S_N} \gamma(s) \{F(w'_p|s) - G(w'_p|s)\} ds \right\} \\
 & \quad - \frac{1}{q_p} \left\{ \int_{s \in S_N} [\{F(w'_p|s) - p\} + \{G(w_p|s) - p\}] \{\gamma(s) - \varphi(s)\} ds \right\} \\
 &= \frac{1}{q_p} \left\{ \int_{s \in S_S} \varphi(s) \{F(w_p|s) - G(w_p|s)\} ds + \int_{s \in S_S} \gamma(s) \{F(w'_p|s) - G(w'_p|s)\} ds \right\} \\
 & \quad + \frac{1}{q_p} \left\{ \int_{s \in S_X} \varphi(s) \{F(w_p|s) + F(w'_p|s) - 2p\} ds \right\} \\
 & \quad - \frac{1}{q_p} \left\{ \int_{s \in S_N} \gamma(s) \{G(w_p|s) + G(w'_p|s) - 2p\} ds \right\} \\
 & \quad - \frac{1}{q_p} \left\{ \int_{s \in S_S} [\{F(w'_p|s) - p\} + \{G(w_p|s) - p\}] \{\gamma(s) - \varphi(s)\} ds \right\}.
 \end{aligned} \tag{18}$$

This is the equation we are supposed to derive.

Not-in-the-same-job (NISJ) versus job-to-job (J2J) transitions

What we are interested in is to derive the fraction of persons who we classify as *NISJ* who moved directly from one full-time job to another, i.e. job-to-job (*J2J*) transitions. What we would like to weed out are the persons who changed jobs and in between were either unemployed, out of the labor force, or part-time or self employed. Just like Fallick and Fleischman (2004) and Nagypál (2008) we consider a job-to-job transition as one in which a CPS respondent reports to be employed in a particular job in one month and another job in the next month. Hence, this definition does not include an adjustment for time aggregation. That is, it does not correct for the possibility of such a worker having moved through a short spell of unemployment or part-time or self employment during the month in between the two responses.

In the following we describe how we impute the fraction of *NISJ* transitions that are *J2J*. Our imputation method relies heavily on the gross worker flows measurement methodologies used in Shimer (2005) and Fujita and Ramey (2009). The reason we need to impute this fraction is that we do not observe an individual's labor market status in the eight months that he or she drops out of the CPS in between the first reported level of earnings in MIS4 and MIS5 and for some individuals their labor market status is missing in MIS5, MIS6, or MIS7.

Given this survey structure, the individuals that we classify as *NISJ* consist of four groups: (i) Those who have missing data for MIS5, MIS6, or MIS7 (ii) employed in MIS4 and employed in another job in MIS8 but either unemployed, not in the labor force, or part-time or self employed in MIS5, MIS6, or MIS7, (iii) not in (i) and (ii) and employed in MIS4 in the same job in MIS5 and in a different job at MIS8, (iii) not in (i) and (ii) and employed in MIS4 and in a different job in MIS5.

Those in (ii) are not part of *J2J* transitions. These are individuals who have not been employed for the whole 12-month period between the two levels of earnings they report. For our imputation, we ignore temporary layoffs and assume that everyone who reports to have the same job as 8 months earlier has remained in that job over the intervening period. Hence, we classify those in (iii) as part of *J2J* transitions.

The imputation is made complicated by those in (iv) and (i). We discuss the imputation for those in (iv) first. Some of the individuals in that group who changed jobs between MIS4 and MIS5 actually went through unemployment, dropped out of the labor force, or were part-time or self employed. However, these episodes are not observed because they occurred during the eight months

when the individuals were not part of the CPS sample. Hence, we have to impute what share of those in group (iii) did not experience any episodes of unemployment, part-time employment, or self employment and did not drop out of the labor force.

We impute this share by assuming that labor market status transitions follow a first-order Markov process.³⁸ We denote the different labor market statuses as: (i) E full-time employed in the same job as at the beginning of the period, (ii) E' full-time employed in a different job as at the end of the period, (iii) U unemployed, (iv) N not in the labor force, and (v) PT part-time or self employed. The arrow $\xrightarrow{4,5}$ denotes the transition during the 9 months between MIS4 and MIS5.

The first-order Markov assumption allows us to write transition probabilities over multiple months in terms of monthly transition probabilities. We define these monthly transition probabilities in month t as

$$m_{l,k}(t), \text{ where } l, k \in \{E, E', U, N, PT\}. \quad (19)$$

Here $m_{l,k}(t)$ is the fraction of persons with labor market status l at the beginning of the period that end up in k at the end of the period.

As we discussed above, we assume that persons who are in the same job in MIS5 as in MIS4 have been continuously employed in that job. This implies that

$$m_{l,E}(t) = 0, \text{ for } l \in \{E', U, N, PT\}. \quad (20)$$

Note that $m_{E,E}(t)$ is the probability of remaining full-time employed in the same job during the month and $m_{E,E'}(t)$ is the probability of a job-to-job transition.³⁹

We construct the Markov transition matrix that is associated with these probabilities based on monthly matched CPS data, similar to Shimer (2007), Fujita and Ramey (2009), and Elsby, Hobijn, and Şahin (2010).

The share we are imputing is the ratio of two probabilities. The numerator is the probability that an individual reports to have changed jobs in MIS5 relative to nine months before in MIS4 and has not flown through U , N , or PT . This probability can be written as

³⁸ This assumption means that, due to data-limitations, we do not account for duration dependence of unemployment outflow rates, or tenure duration dependence of worker separation rates. Consequently, our imputations should only be interpreted as indicative of cyclical fluctuations of the composition of the *NISJ* group in our sample rather than a precise estimate.

³⁹ This job-to-job transition is slightly different from that reported in Fallick and Fleischman (2004) and Nagypál (2008) because it is conditional on full-time employment.

$$Pr[E \xrightarrow{4,5} E' \cap \text{not through } U, N, \text{ or } PT] = \prod_{t=2}^{10} \{m_{E,E}(t) + m_{E,E'}(t)\} - \prod_{t=2}^{10} m_{E,E}(t). \quad (21)$$

The denominator is much harder to impute. It is the probability that an individual reports to have changed jobs in MIS5 relative to eight nine months before in MIS4 irrespective of what she or he did in the meanwhile. It is

$$Pr[E \xrightarrow{4,5} E'] = [0 \ 1 \ 0 \ 0 \ 0](\prod_{t=2}^{10} \mathbf{M}(t))[1 \ 0 \ 0 \ 0 \ 0]'. \quad (22)$$

Here, the Markov transition matrix $\mathbf{M}(t)$ is given by

$$\mathbf{M}(t) = \begin{bmatrix} m_{E,E}(t) & 0 & 0 & 0 & 0 \\ m_{E,E'}(t) & (m_{E,E}(t) + m_{E,E'}(t)) & m_{PT,E}(t) & m_{U,E}(t) & m_{N,E}(t) \\ m_{E,PT}(t) & m_{E,PT}(t) & m_{PT,PT}(t) & m_{U,PT}(t) & m_{N,PT}(t) \\ m_{E,U}(t) & m_{E,U}(t) & m_{PT,U}(t) & m_{U,U}(t) & m_{N,U}(t) \\ m_{E,N}(t) & m_{E,N}(t) & m_{PT,N}(t) & m_{U,N}(t) & m_{N,N}(t) \end{bmatrix}. \quad (23)$$

Thus, only a fraction

$$Pr[E \xrightarrow{4,5} E' \cap \text{not through } U, N, \text{ or } PT] / Pr[E \xrightarrow{4,5} E'] \quad (24)$$

of those in the third group of individuals classified as *NISJ* will be imputed as having gone directly from job to job rather than flowing through unemployment, part-time or self employment, or temporarily leaving the labor force.

As for those in group (i) we can do the same as for those in (iv). The share of this group that we attribute to *NISJ* is given by

$$Pr[E \xrightarrow{4,8} E' \cap \text{not through } U, N, \text{ or } PT] / Pr[E \xrightarrow{4,8} E']. \quad (25)$$

The numerator and denominator for this group are calculated in a very similar way as for group (iv).

In particular

$$Pr[E \xrightarrow{4,8} E' \cap \text{not through } U, N, \text{ or } PT] = \prod_{t=2}^{13} \{m_{E,E}(t) + m_{E,E'}(t)\} - \prod_{t=2}^{13} m_{E,E}(t), \quad (26)$$

and

$$Pr[E \xrightarrow{4,8} E'] = [0 \ 1 \ 0 \ 0 \ 0](\prod_{t=2}^{13} \mathbf{M}(t))[1 \ 0 \ 0 \ 0 \ 0]'. \quad (27)$$

That is, if one or more observations in MIS5, MIS6, and MIS7 are missing for an individual we treat all these observations as missing and impute the share of such individuals that are *J2J* through the assumed first-order Markov transition process.

The first-order Markov assumption in our imputation method assumes that a person flowing through unemployment is just as likely to become unemployed later in the year as someone that did not. In actuality, this person is more likely to become unemployed (again) but the CPS data do not allow us to correct for this. Not correcting for this leads to an overestimate of the number of persons flowing through unemployment (and non-participation and part-time and self-employment for the same reason). Hence, it is best to interpret our imputed fraction of NISJ flows that are *J2J* as a lowerbound estimate.

Table 1. CPS sampling design

Calendar month	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4
Month in sample (MIS)	1	2	3	4									5	6	7	8
Labor force status	✓	✓	✓	✓									✓	✓	✓	✓
Earnings data				✓												✓

Table 2. Summary statistics by subgroup of full-time wage and salary earners

	I	II	III	IV
	Share of wage earners in subgroup		Share of subgroup below the median	
	$\varphi(s)$	$\gamma(s)$	$\frac{1}{2}(F(w s) + F(w' s))$	$\frac{1}{2}(G(w s) + G(w' s))$
	Beginning of period	End of period	Beginning of period	End of period
1. Same Job	40.8	40.9	45.3	43.9
2. Not in the Same Job	48.4	48.3	50.2	48.4
	Exit	Entry	Exit	Entry
3. Part Time / Self Employed	3.9	5.1	76.4	80.8
4. Unemployed	2.7	2.6	63.9	72.9
5. Not in the Labor Force	4.3	3.2	65.7	80.7

Note: All shares reported are average shares over our 1980-2010 and are reported in percentages.

Table 3. Decomposition of variance and cyclicity of real MWE growth.

		I	II
Measure		Variance	Cyclicity
1.	Total	1.9	-0.082 (-1.06)
<u>A. Composition Effect</u>			
<i>Replacement component</i>			
2.	Same job	0.6	0.013 (4.47)
3.	Not in the same job	0.2	0.003 (2.97)
<i>Exit and entry components</i>			
4.	Part-time or self employed	4.3	0.067 (3.34)
5.	Unemployed	3.7	-0.005 (-0.33)
6.	Not in the labor force	0.9	0.030 (2.08)
7.	Total	9.7	0.109
<u>B. Wage Growth Effect</u>			
8.	Same job	41.0	-0.073 (-1.94)
9.	Not in the same job	49.2	-0.118 (-2.42)
10	Total	90.3	-0.191

Note: Rows 2 through 10 in column I are reported in percent of the total variance reported in row 1 in squared percentage points. Totals do not add up to 100 due to rounding. Column II reports regression coefficients, β , of cyclicity regression, $\Delta w = \alpha + \beta u + \varepsilon$, for total real MWE growth measured in percentage points and its subcomponents. *t*-values are in parentheses.

Figure 1. Real wage growth and changes in the unemployment rate

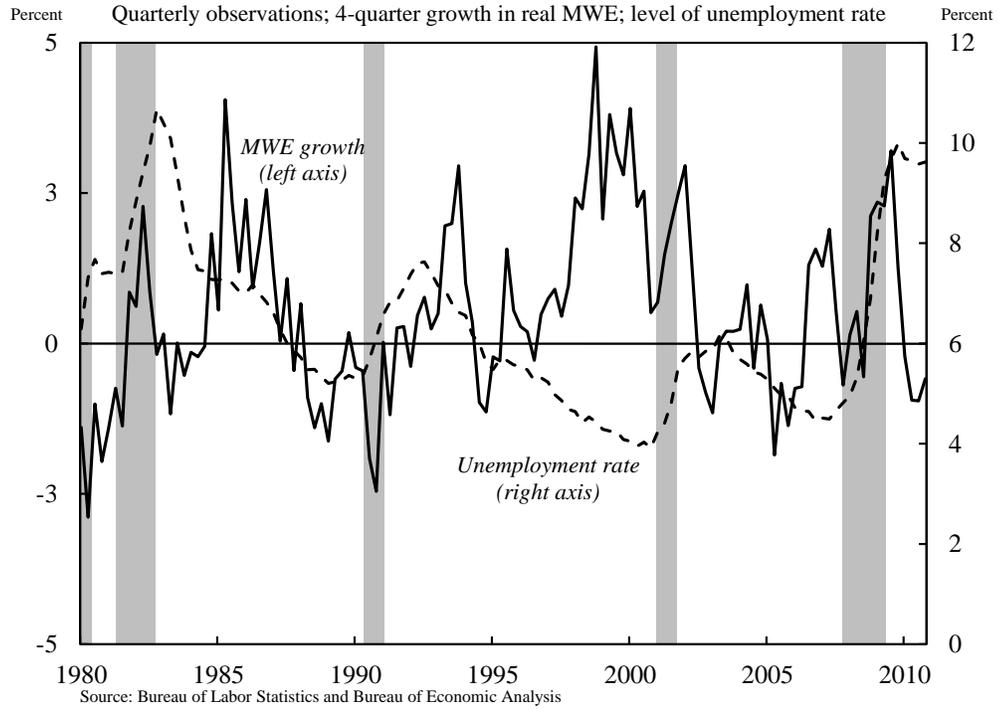


Figure 2. Four aggregate measures of real wage growth

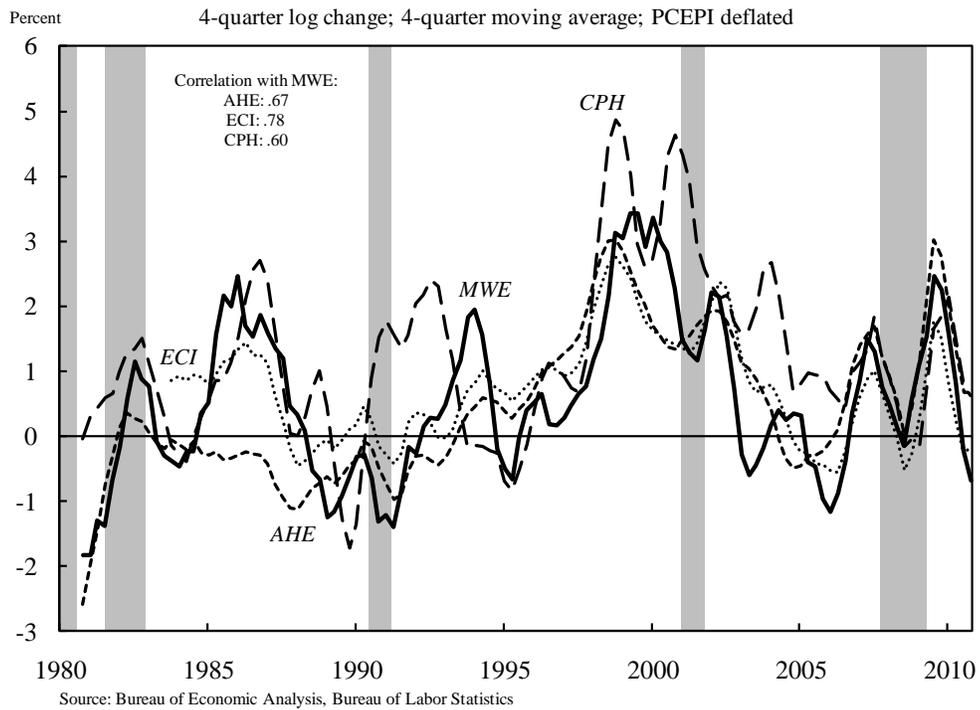


Figure 3. MWE growth for Published, MIS4-MIS8, and matched CPS samples.

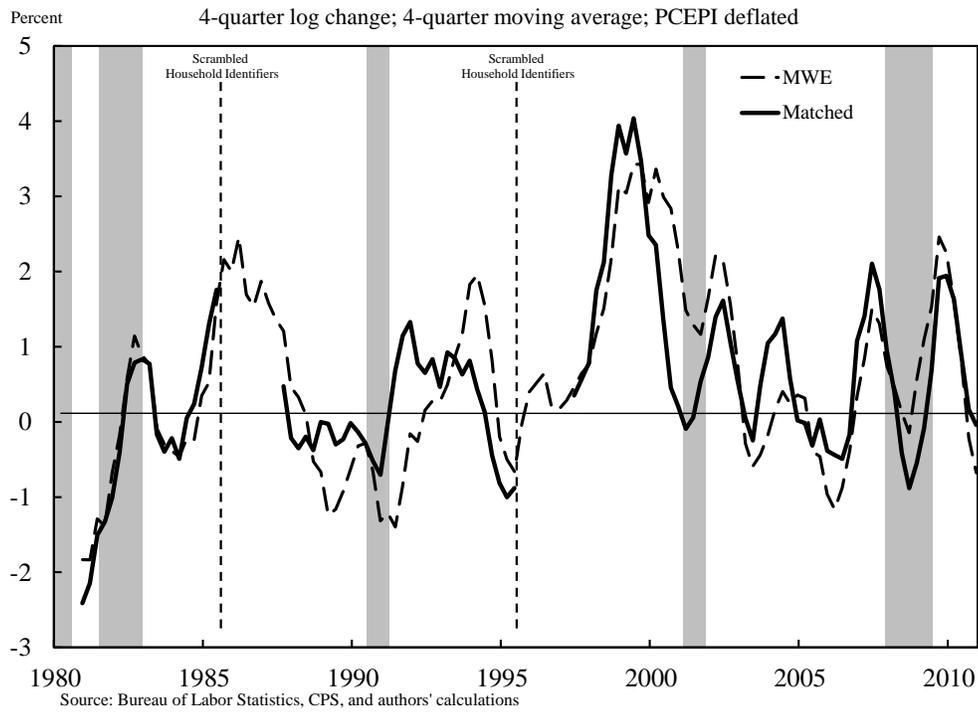
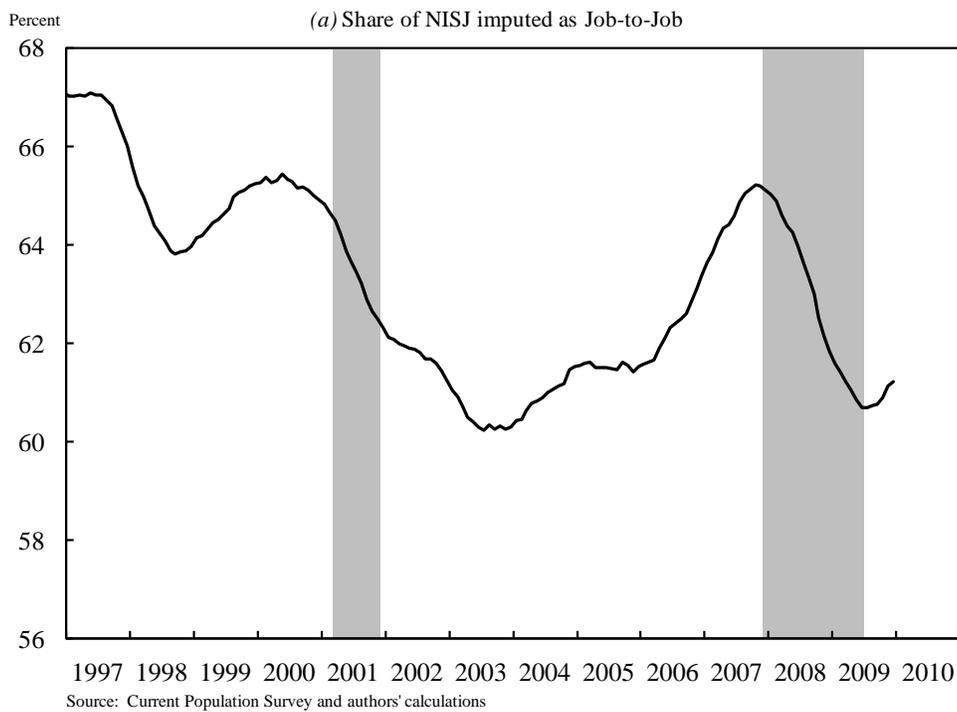
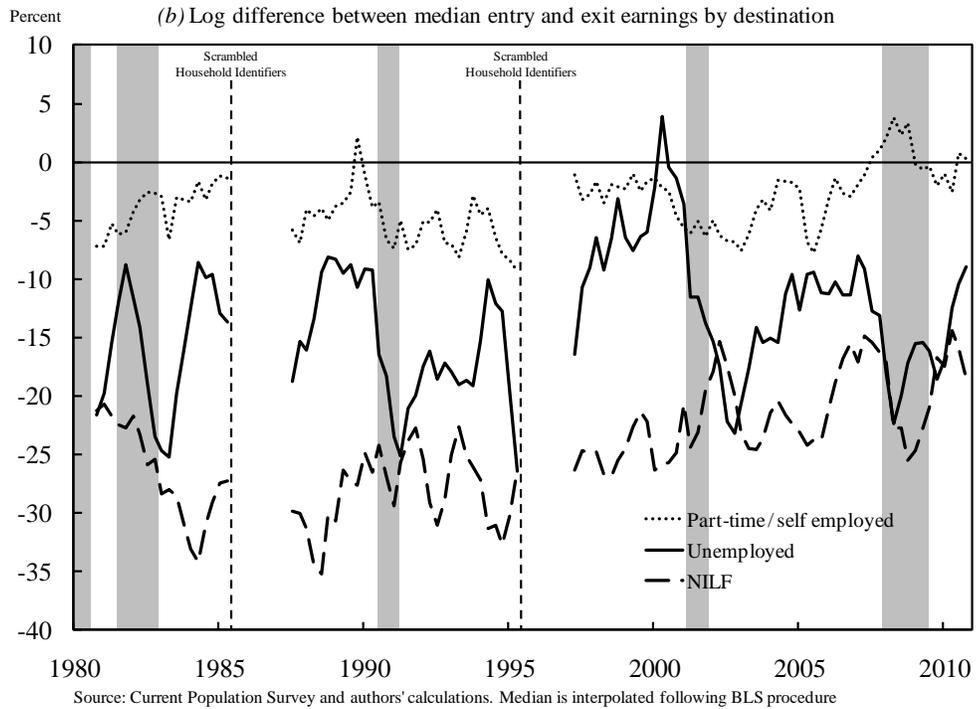
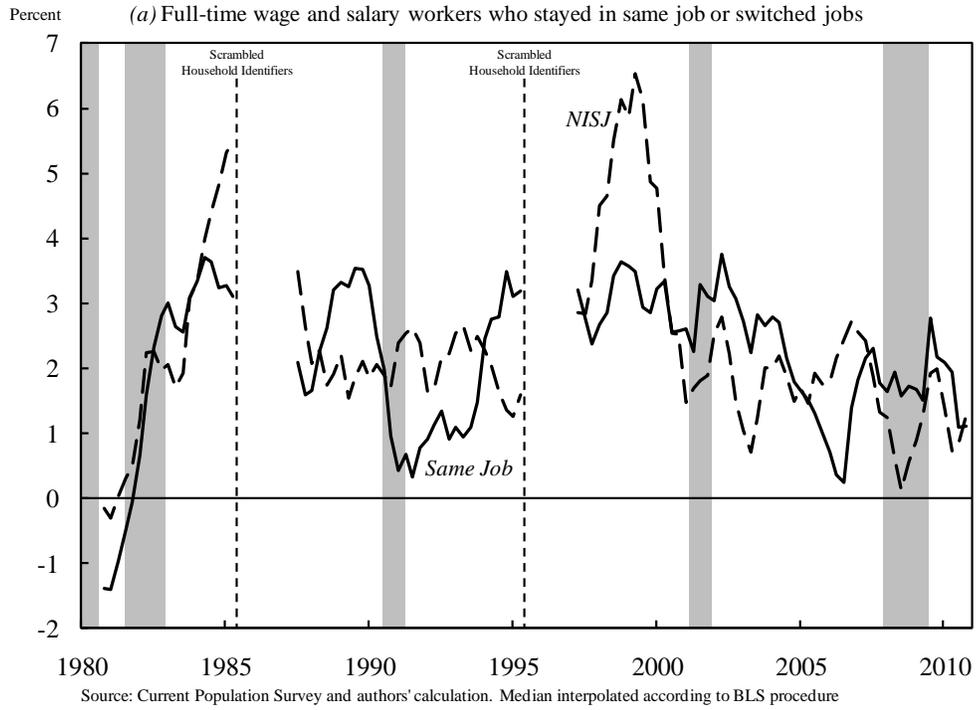


Figure 4. Not-in-the-same-job and imputed job-to-job transitions.



Note: 12-month moving averages

Figure 5. Growth of median weekly earnings by subgroup of CPS.



Note: All panels contain 4-quarter moving averages of 4-quarter log-changes

Figure 6. Graphical representation of equation (2).

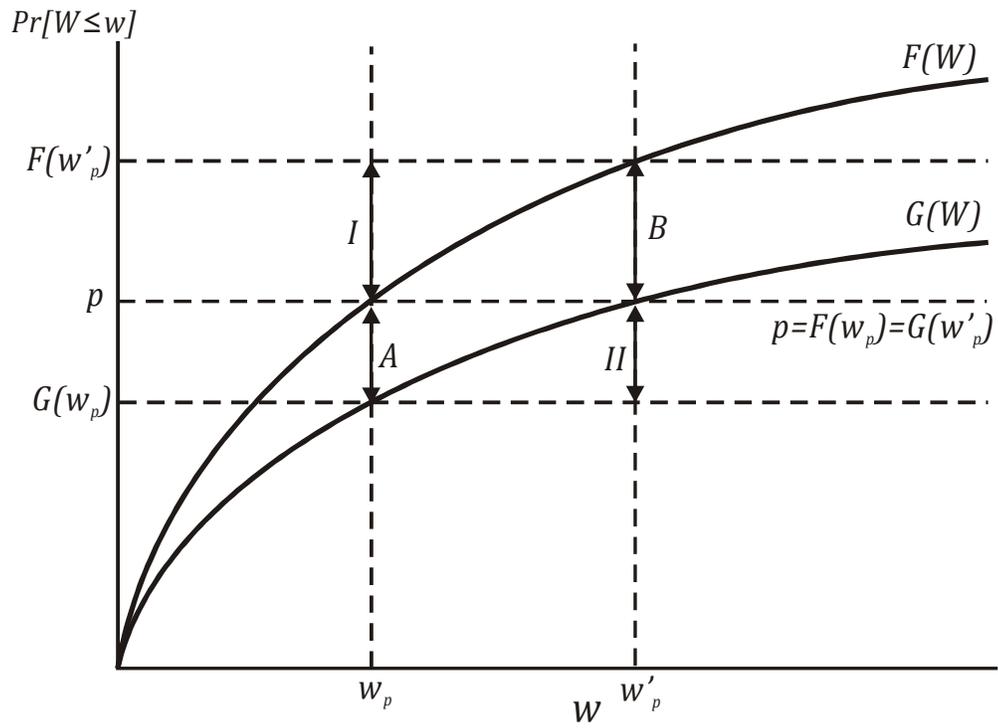
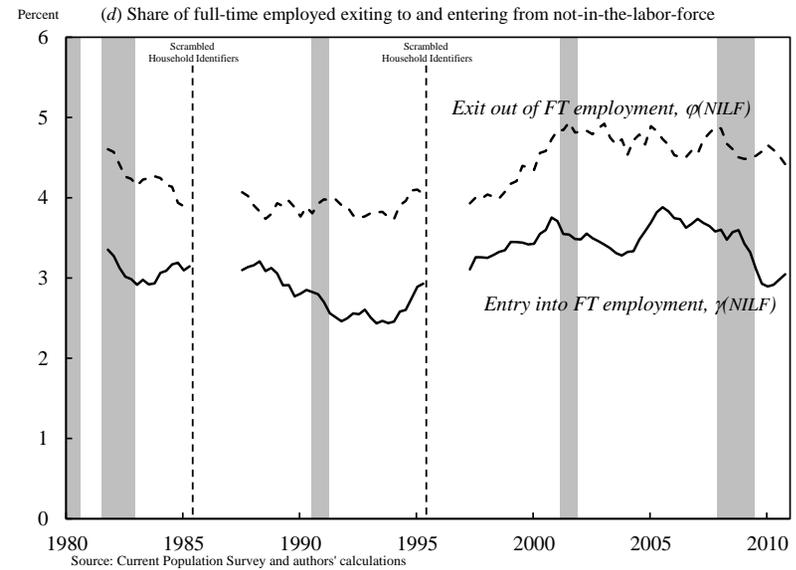
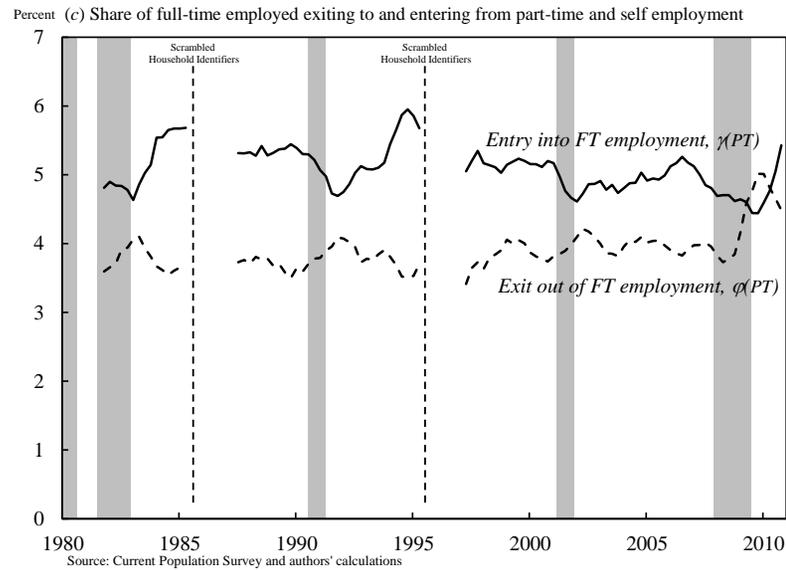
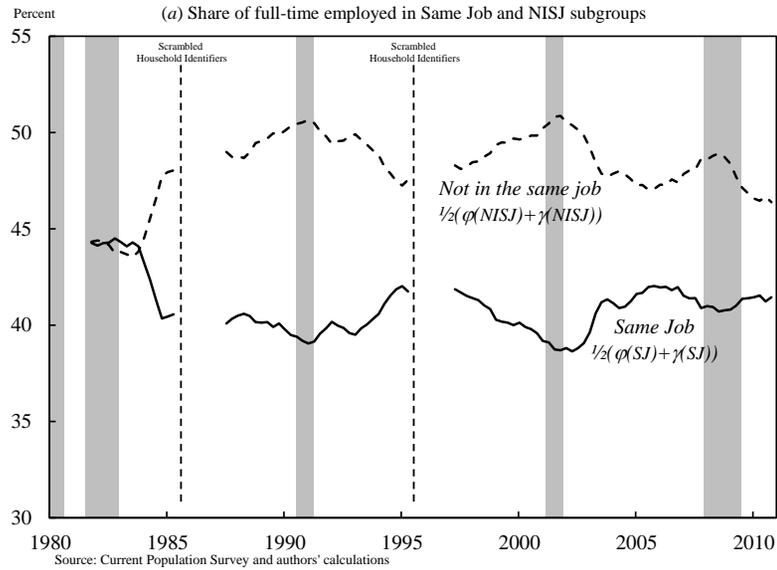
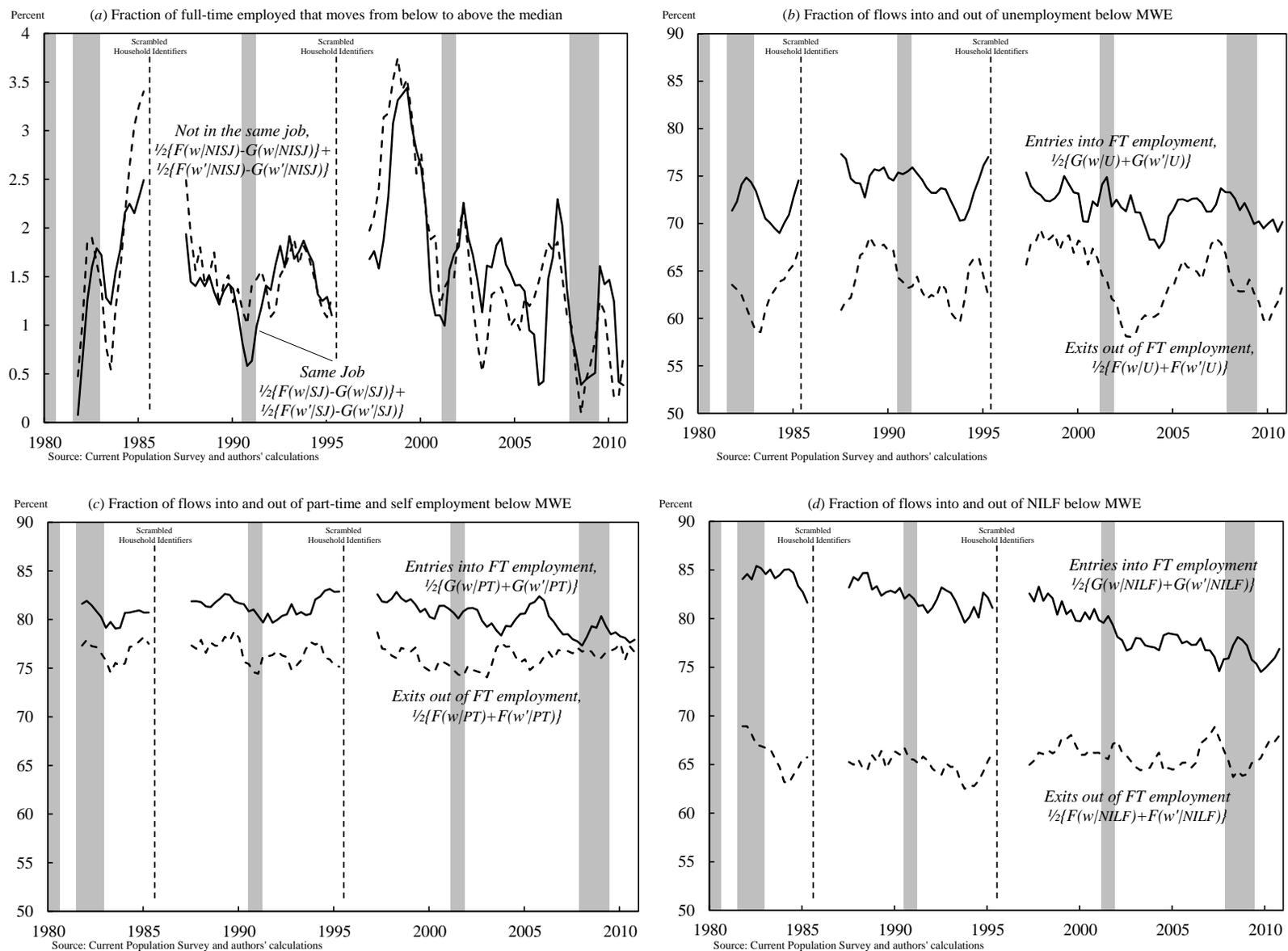


Figure 7. Subgroups as shares of the full-time employed.



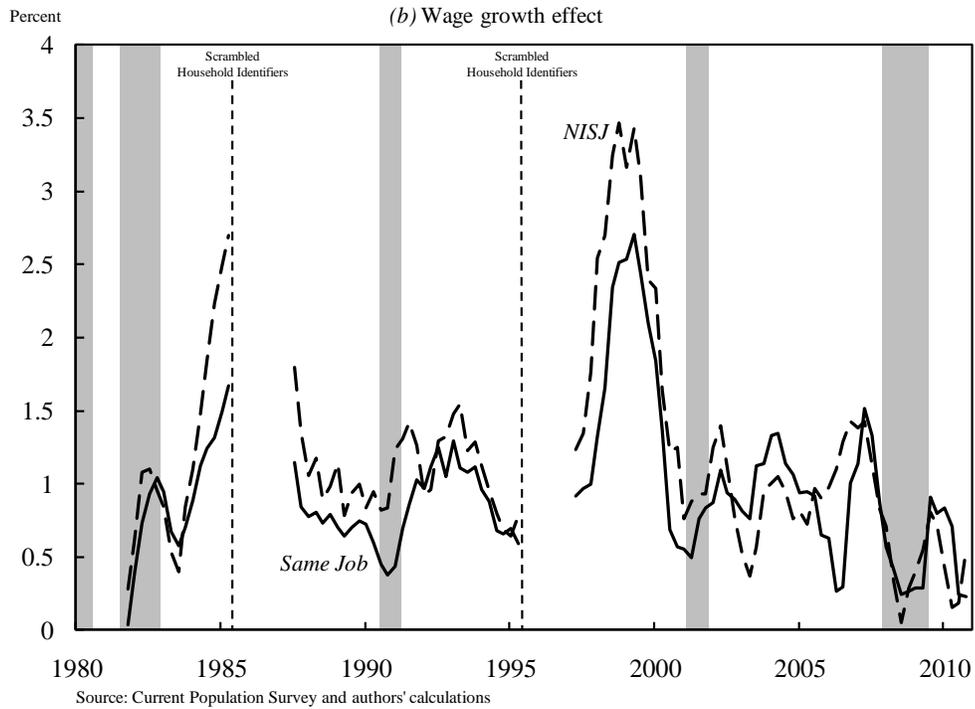
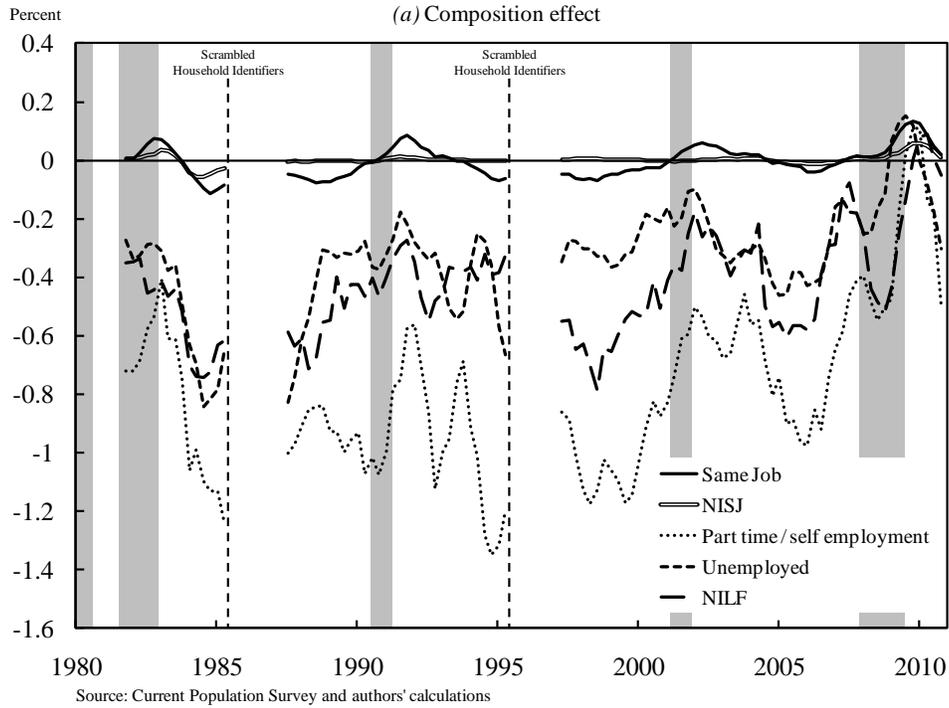
Note: All panels contain 4-quarter moving averages. Panel (a) contains the average of the shares at the beginning and end of the year. Other panels show shares indexed at end of year.

Figure 8. Shifts in earnings distribution function at median for different subgroups.



Note: All panels contain 4-quarter moving averages

Figure 9. Decomposition of composition effect and wage growth effect by subgroup.



Note: All panels contain 4-quarter moving averages

Figure 10. Contributions of changes in shares and shifts in earnings distributions to log change of MWE.

