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Abstract

We construct new monthly time series of U.S. labor market stocks and flows from 1976 onwards. These data reveal an upward secular trend in turnover between full-time and part-time employment, and a large cyclical component chiefly explained by fluctuations in involuntary part-time work. Both short-run and long-run reallocations occur mostly without an intervening spell of non-employment, and therefore cannot be uncovered without splitting employment into finer categories. We emphasize the importance of our findings for several active debates, such as the slowdown in U.S. labor-market dynamism, changes in job stability and security, and the assessment of labor-market slack.

Keywords: Employment; Part-time work; Labor market flows; Secular trends; Business cycles

JEL codes: E21; E32; J21.

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1 Introduction

Recent research demonstrates that part-time employment is a major channel for aggregate adjustment in hours worked and labor earnings. Borowczyk-Martins and Lalé [2016] show that the cyclical behavior of hours per worker is closely related to that of the part-time employment share, i.e. the number of part-time workers among those employed. They find that fluctuations in the part-time share are explained by individual transitions between part-time and full-time employment at the same employer. Their results support the view that firms use part-time employment to adjust the intensity with which they utilize their labor force in response to shocks to their environment. Daly and Hobijn [2016] ascribe an important role to part-time employment in dragging wage growth during the past decade, especially in the aftermath of the Great Recession. The majority of workers moving from part-time to full-time employment do so at wages below the median, and thereby exert downward pressure on overall wage growth. Last, ongoing research by Kurmann et al. [2016] finds that changes in paid hours play a predominant role in movements in firms' employment costs. The largest fraction of earnings changes of job stayers are accounted for by changes in hours; movements in the hourly wage are responsible for a smaller fraction. In light of these findings, it is surprising how little work has been done hitherto to document the part-time employment margin. Is the importance of this margin a recent labor-market phenomenon? How has part-time employment evolved in the long run? Are the forces governing its secular behavior similar to those that drive its cyclical behavior? Are they different from the sources of cyclical fluctuations in aggregate employment? These are the main questions we tackle in this paper.

We establish a number of new facts about the incidence of part-time employment in the United States (U.S.). These facts can be informative for several research areas in macroeconomics and labor economics; we outline connections to these debates momentarily. The main message of our analysis is that part-time employment plays an increasingly important role in shaping the functioning of the U.S. labor market, both in normal times and during recessions.

Our investigation is based on data from the Current Population Survey (CPS). We devise a relationship between the monthly files and the annual demographic supplement of the survey, known as the March CPS, that allows us to construct monthly time series of labor market stocks and flows from 1976 onwards. In this respect, our first contribution is a methodological one: we derive new time series based on two publicly available sets of CPS files. We then use measurement tools from the "ins and outs" literature (e.g. Fujita and Ramey [2009], Shimer [2012] and Elsby et al. [2015]) to conduct a detailed empirical analysis of these data.

The first set of results pertains to the long-run behavior of the part-time employment margin. We show that, though largely stable on average over the past decades, the share of part-time employment veils substantial trends in turnover between full-time and part-time work. From the mid-1970s to the mid-2010s, the probability to move from full-time to part-time employment increased by one-half, the probability to make the converse transition rose by one-quarter and the probability of moving from part-time to non-employment declined by one-fifth. Hence the title of our analysis: in the long run, workers have become increasingly more likely to experience spells of part-time employment. We develop a steady-state framework to analyze the sources of these low-frequency changes. In each decade, we find that, taken in isolation, the upward trends in transitions between part-time and full-time work would have entailed large changes in the part-time employment share. Since their effects offset one another, the rising importance of part-time employment is not directly observable by looking at the evolution of employment stocks. We also find that from the mid-1970s to mid-1990s, these forces *per se* could not have accounted for the whole dynamics of part-time employment: changes along the extensive margin – movements of workers between employment and non-employment – also play a role. Among the various changes in flows, the secular decline in outflows from part-time employment stands out. However, since the mid-1990s, within-employment transitions become predominant.[1] The changing importance of within-employment and non-employment reallocation underscores the advantage of using our new data (that splits employment into finer categories) to attain a richer view of recent changes in U.S. labor-market dynamics.

We then consider the short-run behavior of the part-time employment margin. We focus on its main cyclical component, involuntary part-time work, which we analyze in parallel with unemployment.[2] First, we show that the dynamics of involuntary part-time employment are fast (in particular faster than that of unemployment) and are chiefly driven by movements in inflows. Cast in terms of Darby et al. [1986]'s classic contribution, the 'ins' win over the 'outs' by a significant margin (a 60:40 split). This sharply contrasts with and ins-and-outs split for the unemployment rate of 40:60. In particular, we find that inflows from full-time work are the main source of fluctuations in involuntary part-time employment, whereas, as is well known, outflows dominate the behavior of the unemployment rate. Second, echoing our results on the long-run dynamics of the part-time share, we find that the interaction directly with full-time employment explains most fluctuations in involuntary part-time work. The changing composition of the pool of involuntary part-time workers during downturns provides concurring evidence: it shifts markedly towards those workers put on part-time work due to slack demand conditions, and away from the unemployed who take on a part-time job for lack of a better option. In sum, involuntary part-time work operates differently from unemployment, and there is little interaction between these two margins of employment adjustment.[3]

A recurrent theme in our analysis is that the period that began in the 2000s is distinct in a number of ways. While we are certainly not the first to make this observation, the facts we put forward to substantiate it have not been documented previously. Accentuating the long-term shift in the sources of its variation, the part-time employment share during that period is driven overwhelmingly by within-employment reallocation. In other words, movements in

[1]We note that, in aggregate data, the relative importance of the intensive margin (hours per worker) in explaining movements in total hours worked (hours per worker times employment) seems to remain stable in the long run (see Ohanian and Raffo [2012] and van Rens [2012]). This does not necessarily contradicts the increase in turnover between part-time and full-time work: the changes in hours experienced by workers moving from part-time to full-time employment and vice versa can cancel one another out, and thus leave the time-series standard deviations of hours per worker unchanged.

[2]In U.S. statistics an individual is considered to be working part-time involuntarily if she cannot find a full-time job or faces slack demand conditions in her job (see Section 2). We use unemployment to establish, by contradistinction, the key cyclical properties of involuntary part-time work.

[3]There is nevertheless a parallel than can be drawn with recent facts uncovered by Fujita and Moscarini [2013]. Their analysis of temporary layoffs and recalls describes a protocol to temporarily suspend the employment relationship. We find that many involuntary part-time work spells can be cast in similar terms.

and out of non-employment become irrelevant to understand the composition of employment along the part-time/full-time margin. At the same time, those movements seem to matter to account for the composition of the unemployment pool and the increase in unemployment duration. Since the 2000s an usually large fraction of the unemployed are looking for full-time jobs, and the duration of their unemployment spells is typically longer compared to the other unemployed. Finally, during the Great Recession, the cyclical response of involuntary part-time work exceeded by a large factor what was observed in previous recessions. Reflecting the long-run prevalence of within-employment reallocation, this difference is accounted for by the interaction between involuntary part-time work and full-time employment.

The facts that emerge from our analysis can be relevant for a number of actively researched issues. In particular, we think that they speak to the slowdown in U.S. labor-market dynamism, the debates surrounding changes in job stability and security, and the definition and measurement of slack in the labor market.

An extant literature documents a decline in the dynamism of the U.S. labor market. To name a few symptoms, this literature finds a decrease in the rates of job creation and destruction (e.g. Davis et al. [2006], Hyatt and Spletzer [2013]), in unemployment outflows (e.g. Figure 2c in this paper), in the separation rate (e.g. Figure 2d in this paper, and Fujita [2015]) and in job-to-job flows (e.g. Hyatt and Spletzer [2013], Mukoyama [2014]). Some of the facts that we document shed a new light on these patterns; for example, the decrease in employment separations is concentrated on part-time work. They also reveal that the decrease in turnover highlighted in this literature needs to be qualified: workers are increasingly mobile across employment states, and rotate more frequently between part-time and full-time jobs. This raises two questions for future research. First, is there a causal link between the rise of the part-time employment margin and the symptoms of dwindling labor market dynamism mentioned above? Second, compared to reallocation across employers, how does reallocation along the part-time margin, which occurs mostly at the same employer (Borowczyk-Martins and Lalé [2016]), affects labor productivity?[4] We expect the facts presented in this paper to be useful for the development of models addressing these questions.

There are recurrent concerns about changes in job stability and job security among scholars, policy-makers and the general public alike. Job stability refers to the duration of an employment relationship between a worker and a firm. Job security relates to changes in the employment relationship that are involuntary from the worker's perspective (Valletta [1999]). This distinction is important in the context of our results; in particular, we caution against interpreting the rising instability of the part-time/full-time status as a trend in job security.[5] On the one hand, the incidence of transitions from full-time employment to part-time work that are deemed 'involuntary' did not decrease during the past decades – in contrast with the

[4] The decline in U.S. dynamism raises concerns about the behavior of labor productivity, as lower worker flows suggest that the labor market fails to quickly reallocate workers from declining segments of the market to expanding ones (see Shimer [2005], Mukoyama [2014] and Galí and van Rens [2014]).

[5] In addition, we do not rule out that increased turnover between full-time and part-time work helps to prolong employment relationships. Given the limited longitudinal dimension of the CPS, and without data on job tenure, we cannot investigate how this type of turnover affects the probability of separations in long-term employment relationships. Farber [2010] argues that the incidence of such relationships has declined during the past decades.

decline in the number of unwanted job losses (Davis [2008]). On the other, we find an upward trend in turnover between *voluntary* part-time employment and full-time employment, which could be explained by changes in desired labor supply. The data are less ambivalent when we study business-cycle fluctuations: during downturns, workers who remain in employment face greater job insecurity through involuntary part-time work. The literature has often emphasized that involuntary part-time work could be used as a stepping-stone to full-time employment (e.g. Farber [1999]). In this respect, we complement existing research by showing that this mechanism plays a marginal role in the cyclicality of involuntary part-time work. A related issue concerns the impact of the rise of part-time employment reallocation on worker's labor income security and stability. Although we do not explore this dimension in our analysis, recent research shows that part-time reallocation is accompanied by large changes in hours worked (Borowczyk-Martins and Lalé [2016]), concentrated in the lower part of the wage distribution (Daly and Hobijn [2016]), and is likely associated with a penalty in hourly earnings (Canon et al. [2014]). Thus, the possible increase in job stability due to the rise of part-time employment may foreshadow greater income instability for workers, as well as lower income growth due to poorer job opportunities.

In the aftermath of the Great Recession, in the face of continued economic slack, understanding involuntary part-time employment became a priority for the Federal Reserve Board. In her 2014 address to the annual Jackson Hole Conference, Yellen [2014] listed involuntary part-time work among the top labor market 'surprises' worth worrying about. A related concern points to the difficulty in using standard statistics to measure the amount of slack in the labor market during a sluggish recovery. Blanchflower and Levin [2015] show that unemployment is less relevant for this purpose because the employment gap in the recovery is primarily explained by involuntary part-time work and by individuals who have dropped from the workforce but would rejoin in good times. Hornstein et al. [2014] propose a non-employment index that goes beyond the standard unemployment rate by taking into account workers' probability to return to employment in the near future. One version of their index includes involuntary part-time workers in order to capture more dimensions of economic slack. Our findings indicate that, in addition to those dimensions, the probability that full-time workers experience a spell of involuntary part-time employment should be part of a comprehensive assessment of the state of the labor market.

A number of recent papers document and analyze the current evolution of part-time employment in the U.S labor market based on CPS data from 1994 onwards (see e.g. Valletta and Bengali [2013], Cajner et al. [2014], Canon et al. [2014], and Valletta and van der List [2015]). Valletta et al. [2015] and Even and Macpherson [2015] analyze the post-2009 developments in light of the structural/cyclical distinction. Valletta et al. [2015] find that these changes are partly explained by shifts in the industry structure of employment, whereas Even and Macpherson [2015] show that the Affordable Care Act, which mandates the provision of health insurance for full-time employees in large firms, also contributed to the increase in part-time work. Our paper adds to this line of research. The historical perspective provided by our new series corroborates their findings that the high incidence of part-time employment could become a permanent feature of the U.S. labor market.

The paper is structured as follows. Section 2 presents the data, the main concepts of our analysis and a number of measurement issues. Section 3 describe how we address those issues. In Section 4 we analyze the secular evolution of part-time employment and the forces that shaped it. In Section 5 we turn to the cyclical behavior of part-time employment. Section 6 reports some additional facts characterizing the evolution of part-time employment, and Section 7 concludes.

2 Data and measurement issues

2.1 CPS Data

For most of the analysis we use data from the monthly files of the CPS from January 1976 to December 2015.[6] The CPS, administered by the Bureau of Labor Statistics (BLS), is a well-known labor force survey that has informed the majority of studies on worker flows in the U.S. labor market. Each month, the CPS surveys about 60,000 households and records employment information, including hours worked and workers' reasons for working part-time. CPS respondents are interviewed for 4 consecutive months, are rotated out of the survey for 8 months, and are then included in the survey again for 4 consecutive months. We use the CPS as a series of monthly cross-sections to measure labor market stocks, and we exploit the rotational structure of the survey to measure labor market flows.

In addition, we use data from the 1976-2015 March annual demographic supplement of the CPS.[7] The March CPS contains employment information that refers to the calendar year prior to the survey. We use these data to adjust certain labor market stocks derived from the monthly CPS (details follow).

2.2 Definitions

We adopt the BLS definition of part-time employment: a part-time worker is a person who reports (strictly) less than 35 total usual hours of work per week.[8] Total usual hours include both usual paid and unpaid overtime hours. We emphasize that the notion of usual hours is different from that of actual hours, and that it is the relevant metric to define part-time employment (see Borowczyk-Martins and Lalé [2016]). Actual hours measure hours worked during the reference week of the survey, and hence change due to workers' sickness, public holiday, etc., which are not relevant for our purposes.

An important theme of our analysis is the contribution of involuntary part-time work to the part-time employment margin. Our definition is also standard and based on the following question of the CPS questionnaire (see U.S. Bureau of the Census [2013]):

> Some people work part time because they cannot find full time work or because business is poor. Others work part time because of family obligations or other

[6] Available at: `http://www.nber.org/data/cps_basic.html`.

[7] Available at: `https://cps.ipums.org/cps/`.

[8] The cutoff of 35 hours is the most commonly used in U.S. labor market statistics. In Appendix B.2 we show that our results are robust to using a different threshold to define part-time employment.

personal reasons. What is (name's/your) MAIN reason for working part time?

Implicit in the question above are two broad categories of part-time workers: those who are employed part-time because of constraints originating from the demand side of the labor market, and those who work part-time for other reasons. The stock of involuntary part-time workers counts the number of workers in the first category.[9]

2.3 The 1994 redesign

In January 1994, the monthly CPS underwent a complete overhaul (Cohany et al. [1994], Polivka and Miller [1998]). Prior to the redesign, information about usual hours was very limited in the survey: it was only when a respondent reported less than 35 actual hours of work that, in addition, she would be asked whether she *usually* works less than 35 hours per week. In such circumstances, the respondent would have to select one main reason for working less than 35 hours within a list that included 'inability to find a full-time job' and 'slack work/poor business conditions', both of which are used to define involuntary part-time work.

Among the various changes that were implemented, there are at least three that improve the measurement of part-time employment, and thereby create a discontinuity around the 1994 redesign. First, the CPS started recording usual hours for all employed individuals, irrespective of actual hours worked during the reference week of the survey. Second, questions on multiple jobholding were introduced to distinguish hours worked at all jobs from hours worked at the primary job.[10] Third, the question wording to record the main reason for working part-time was changed so as to tighten the measurement of involuntary part-time employment (Cohany et al. [1994], Valletta et al. [2015]).

The 1994 survey changes pose a significant challenge to the study of part-time employment. When we compute time series for the stock of part-time and involuntary part-time workers from the monthly CPS, we observe a significant break in 1994. This problem is somewhat reinforced for time series of worker flows, especially when we distinguish involuntary from voluntary part-time employment.[11] Although the different series computed after 1994 are likely more reliable, aligning the levels of the pre-1994 series to eliminate the discontinuity at the redesign is neither straightforward nor satisfactory. Indeed, we cannot rule out that 'genuine' labor market events, in addition to the CPS redesign, create a discrepancy between values observed before and after January 1994. In the next section we lay out a different approach to tackle this problem.

[9] It should be recognized that some workers in the second category may also be working part-time *involuntarily*. For example, individuals who are constrained to work part-time because they cannot arrange childcare. The conventional definition of involuntary part-time work may be justified on the grounds that it isolates those components of involuntary employment that are directly related to the business cycle.

[10] Throughout the analysis, we do not distinguish single jobholders from workers with multiple jobs. In Appendix B we show that our results are not different when we remove multiple jobholders from the sample in data from 1994 onwards. Multiple job holders account for 5 to 6% of employment.

[11] While the problems caused the changes introduced during the CPS redesign are very pronounced for part-time employment, they should not be ignored when looking at transition probabilities with respect to other labor market states (see Abraham and Shimer [2002], Elsby et al. [2009] and Barnichon and Figura [2015]).

3 Correction procedures

There are two insights guiding our correction procedures. First, unlike the monthly survey, the March CPS was not subjected to drastic changes over the years 1976 to 2015 – at least not for the variables we focus on. Therefore, the measurements relating to part-time employment derived from the March CPS should be consistent across periods. Second, additional cross-sectional information from the March CPS can help correct labor market stocks. In turn, corrected stocks can be informative to adjust labor market flows.

Labor market stocks The first step of our correction strategy is to reconcile the stocks of part-time workers and involuntary part-time workers computed from the monthly CPS before 1994 with their counterparts from the March CPS. These stocks are actually measured differently in the monthly and in the March surveys. For instance, in the March CPS, respondents report the number of weeks worked during the preceding calendar year, and the number of weeks working less than 35 hours. Thus, we expect, and we do observe, some discrepancy between the monthly-based and March-based figures.

Our first correction procedure, detailed in Appendix A.1, is as follows. We assume that the post-1994 monthly series of stocks for part-time and involuntary part-time workers provide reliable estimates.[12] We require that the *discrepancy* between the monthly-based and March-based estimates remains constant across the 1994 break. Using the series from the March CPS, we predict the average for labor market stocks for each year prior to 1994 that results in the same discrepancy as in the post-1994 data. Finally, in each year, we multiply the corresponding values from the monthly CPS by the same number to match the predicted annual value.[13]

Labor market flows Having obtained consistent monthly time series of labor market stocks, our second step is to reconcile labor market flows with changes observed in those stocks.[14] To this end, we implement the so-called margin-error adjustment (Poterba and Summers [1986], Elsby et al. [2015]). We compute transition probabilities that characterize the evolution of labor market stocks by means of a first-order Markov chain, and then we solve for the set of stock-consistent transition probabilities implied by the Markov chain. As is standard in the literature, in a subsequent step we adjust the data for time-aggregation bias. We draw on the continuous-time correction developed by Shimer [2012].

Robustness We provide several checks for the accuracy of our correction procedures. In Appendix B, we show that our adjusted labor market stocks before 1994 are consistent with monthly data from the Survey of Income and Program Participation for the overlapping period. We also test and discard any systematic break in 1994 in our different time series of labor market stocks and flows by using regressions against a flexible time trend and a dummy

[12]We show in Appendix B.2 that the post-1994 monthly time series of part-time employment are consistent with data from the Survey of Income and Program Participation.

[13]We use a multiplicative factor instead of an additive one for two reasons. First, a multiplicative factor rescales not only the mean but also the variance of the time-series. Second, when we scale down a time series, a multiplicative factor prevents obtaining negative values. This issue cannot be ignored when, for instance, we compute the number of involuntary part-time workers in a small subset of the population.

[14]An intermediary step of adjustment is that we filter out potential outliers and remove seasonal variations.

for the CPS redesign. Finally, we show that the behavior of our main time series are not driven by specific sample restrictions and/or the cutoff in usual hours used to define part-time work.

4 Secular changes in part-time employment

Having obtained consistent time series of stocks and flows, we start our investigation by studying their long-term behavior. In particular, we find that the stable behavior of the part-time employment stock over the past four decades portrays a misleading picture of the secular evolution of part-time reallocation. The probability of workers to move in and out of part-time employment increased substantially during this period. This apparent contradiction is a classic example of a stock-flow fallacy. The long-run increase in part-time flows had counteracting effects on part-time employment stocks, resulting in their stability.

4.1 The aggregate picture

Our point of departure is the evolution of the part-time employment share over a period of four decades, starting in 1976 and ending in 2015, shown in Figure 1. We characterize the evolution of part-time employment controlling for potential composition effects arising from changes in the composition of labor stocks. Indeed, part-time employment affects different categories of workers differently (Valletta and Bengali [2013] and Borowczyk-Martins and Lalé [2016]) and the demographic composition of the working-age population underwent significant changes over the past decades. In order to sidestep concerns about the impact of those movements on the dynamics of part-time employment, we adjust all the series so as to keep the demographic structure of the working-age population fixed at its mean over the sample period.[15]

The first salient feature in Figure 1 is the stability of the average levels of part-time employment across the whole period. At higher frequencies, the part-time employment share displays large fluctuations around its mean. In expansions it reaches levels close to 17%, while at the peak of recessions it jumps to the vicinity of 20% of employment. The cyclical response during the Great Recession appears particularly pronounced. However, taking into account the very large magnitude of the shock, that response seems consistent with those observed in previous recessionary episodes. On the other hand, it is less clear whether the elevated levels of part-time employment that persist several years after the end of the Great Recession are an indication of a structural increase in this form of employment.[16]

In this section we are interested in identifying the sources of the long-run behavior of the part-time employment share, defined as the following ratio: $\omega_t^P = \frac{P_t}{F_t+P_t}$, where P_t and F_t denote respectively the stocks of part-time and full-time workers at time period t. To describe the behavior of those stocks we use a stock-flow framework. We measure worker flows based on a four-state model, where workers move across the states of full-time employment (F), part-time employment (P), unemployment (U) and non-participation (N). The evolution of these labor stocks is condensed in vector $\boldsymbol{s}_t = \begin{bmatrix} F & P & U & N \end{bmatrix}_t'$, which by assumption follows a

[15]Our adjustment protocol is described in Appendix A.3.

[16]See Valletta et al. [2015] for an analysis of similar changes in involuntary part-time employment.

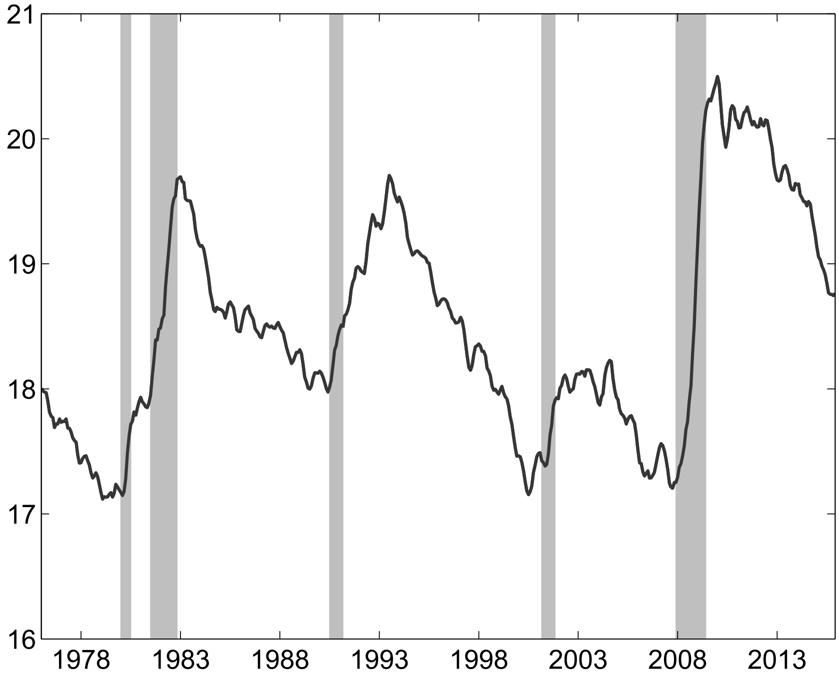


Figure 1: The part-time employment share

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A for data details). Gray-shaded areas indicate NBER recession periods.

first-order discrete Markov chain:

$$\boldsymbol{s}_t = \boldsymbol{M}_t \boldsymbol{s}_{t-1}. \tag{1}$$

In this equation, $\boldsymbol{M}_t$ is the stochastic matrix of transition probabilities $p\,(i \rightarrow j)$ across labor market states i and j.[17]

According to equation (1), the evolution of the part-time employment share is governed by movements in transitions across the four states. In principle, any of the transition probabilities can lead the evolution of the two stocks that enter the calculation of the part-time employment share. In Figure 2 we report the evolution of the transition probabilities across the two employments states (part-time and full-time), as well as the inflow and outflow transition probabilities to/from part-time and full-time employment from/to unemployment and non-participation.

The plots on the top panel concern transitions across employment states. Both exhibit a remarkably similar evolution over the sample period. The two transition probabilities trend upwards until the early 1990s, plateau from then on until the year 1995 ($p\,(P \rightarrow F)$) and 2000 ($p\,(F \rightarrow P)$), at which points both start trending upwards at a noticeable faster rate. These dynamics contrast sharply with the evolution of the part-time employment share, which as can be seen in Figure 1, exhibits no noticeable upward trend.

The remaining plots report the evolution of interactions between the two employment states and unemployment and non-participation. In these plots, dashed lines denote transitions to/from full-time employment, whereas solid lines refer to transitions to/from part-time employment.

The middle panel of Figure 2 concerns the evolution of the interactions between employment

[17] To simplify the notation, throughout the paper we omit the time t subscript from transition probabilities $p\,(i \rightarrow j)$, and later on from the corresponding flow hazard.

states and unemployment. The unemployment outflow to full-time employment is, on average, about 6 percentage points higher than the corresponding outflow to part-time employment (cf. Figure 2c). The two employment inflow probabilities display a slightly downward trend and a large and slow-moving cyclical component. The inflow to full-time employment displays greater relative low-frequency variation. Interestingly, although the two lines co-move very closely, their levels diverge in expansions (when $p\,(U \to F)$ takes off relative to $p\,(U \to P)$) and converge during recessions and their aftermath (when $p\,(U \to F)$ falls by more than $p\,(U \to P)$). The reverse transitions paint an opposite picture. The unemployment inflow from employment is much greater from part-time vs full-time (more than 2.5 times greater) and also more volatile (cf. Figure 2d). The long-run dynamics are also distinct, with unemployment inflows from part-time exhibiting a clear downward trend, while the inflows from full-time are rather stable.

The bottom panel concerns interactions between employment and non-participation. Figure 2e shows non-participation outflows. The outflows to part-time and full-time reverse roles relative to unemployment flows. Now, compared to $p\,(N \to F)$, $p\,(N \to P)$ is higher on average and more volatile, and while the former is stable over the sample period, the latter decreases steadily. Finally, non-participation inflows from employment are displayed in Figure 2f. The salient features are very similar to those concerning unemployment inflows.

4.2 A steady-state framework

The picture that emerges from Figure 2 is of complex changes in the long-run dynamics of part-time employment. To quantify more precisely the role played by the dynamics of the different transition probabilities in the evolution of part-time employment, it is to useful to consider the dynamics of the steady-state part-time employment share.[18] To this end, we consider flow hazards, the continuous-time counterparts of the discrete-time transition probabilities, which we denote by the Greek letter λ (i.e. $p\,(i \to j) = 1 - e^{\lambda^{ij}}$). Starting from the continuous-time representation of equation (1), we can express the steady-state stocks as a function of the underlying flow hazards:[19]

$$\bar{\mathbf{s}}_t = -\tilde{\mathbf{H}}_t^{-1}\mathbf{h}_t. \tag{2}$$

Accordingly, the steady-state part-time employment share, $\bar{\omega}_t^P$, is the ratio of the steady-state stocks of part-time over employed workers. To highlight the role played, on the one hand, by transitions across the two employment states and, on the other, by transitions between those

[18]It is well known that in the U.S. labor market steady-state stocks provide a very good approximation of the behavior of actual stocks. The high levels of transitions across states imply that the convergence towards steady state is nearly completed within each month. In our data the contemporaneous correlation between the actual and steady-state part-time employment shares is 88%.

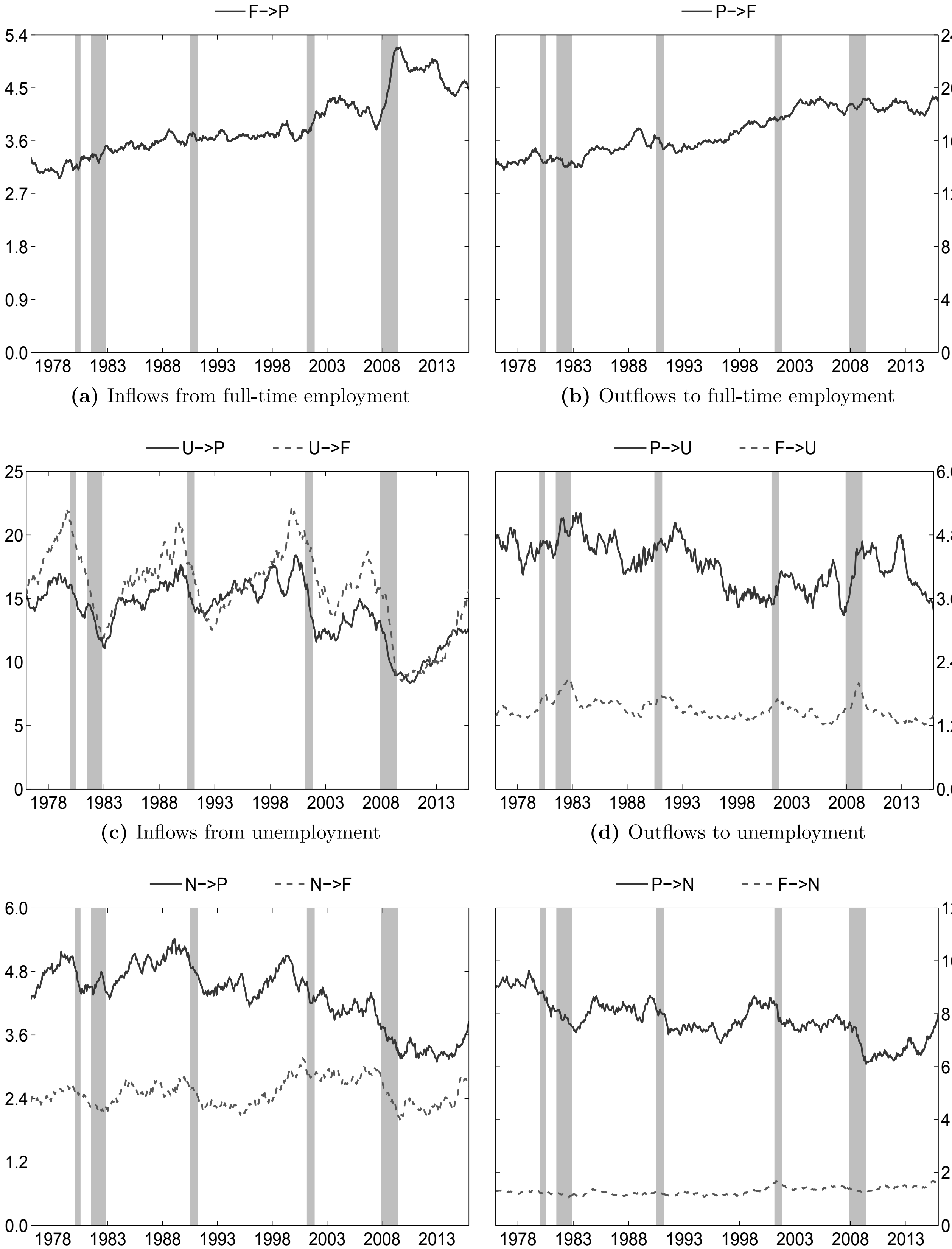
[19]Let $\tilde{\mathbf{s}}_t$ denote the vector $\boldsymbol{s}_t$ normalized by the size of the working-age population $(F_t + P_t + U_t + N_t)$, and $\tilde{\boldsymbol{M}}_t$ the matrix $\boldsymbol{M}_t$ rearranged accordingly. Equation (1) can be written as:

$$\tilde{\mathbf{s}}_t = \tilde{\boldsymbol{M}}_t \tilde{\mathbf{s}}_{t-1} + \boldsymbol{m}_t,$$

where $\boldsymbol{m}_t = \begin{bmatrix} p\,(N \to F) & p\,(N \to P) & p\,(N \to U) \end{bmatrix}_t^{'}$. The continuous-time counterpart of that equation is

$$\dot{\tilde{\boldsymbol{s}}}_t = \tilde{\mathbf{H}}_t \tilde{\mathbf{s}}_t + \mathbf{h}_t$$

where the elements of $\tilde{\mathbf{H}}_t$ and $\mathbf{h}_t$ are flow hazards.



(a) Inflows from full-time employment

(b) Outflows to full-time employment

(c) Inflows from unemployment

(d) Outflows to unemployment

(e) Inflows from non-participation

(f) Outflows to non-participation

Figure 2: Transition probabilities characterizing part-time employment

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A for data details). Gray-shaded areas indicate NBER recession periods.

states and non-employment states, we write $\bar{\omega}_t^P$ as:

$$\bar{\omega}_t^P = \frac{\bar{P}_t}{\bar{P}_t + \bar{F}_t} = \frac{\lambda^{FP} + \lambda_n^{FP}}{\lambda^{FP} + \lambda_n^{FP} + \lambda^{PF} + \lambda_n^{PF}}. \tag{3}$$

In equation (3) λ^{PF} and λ^{FP} are flows hazards between P and F, whereas λ_n^{FP} and λ_n^{PF} are flow hazards to/from part-time employment that occur through non-employment. This can be seen more clearly in the expression below:

$$\lambda_n^{ij} = \left(\lambda^{iU} + \lambda^{iN}\right) \frac{\lambda^{Uj}\bar{U}_t + \lambda^{Nj}\bar{N}_t}{\sum_{k=P,F} \lambda^{Uk}\bar{U}_t + \lambda^{Nk}\bar{N}_t} \tag{4}$$

Consider for instance inflows to part-time employment. Some occur directly from F at rate λ^{FP}. At the same time, as shown by λ_n^{FP}, some full-time workers are reallocated to non-employment at rate $\lambda^{FU} + \lambda^{FN}$. The inflows from non-employment to employment are measured by $\sum_{k=P,F} \lambda^{Uk} U_t + \lambda^{Nk} N_t$ and among those, $\lambda^{UP} U_t + \lambda^{NP} N_t$ are directed towards part-time employment. Thus, the term λ_n^{FP} captures reallocation from F to P mediated by non-employment.

This discussion underscores that the dynamics of the steady-state part-time employment share depend chiefly on the magnitude and relative variation of transitions between P and F (within-employment reallocation) and those between P, F and U, N (non-employment reallocation). In practice, and as we will show momentarily, movements at the latter margin do not play as large a role as those between employment states.

We start by noting that the identities in equation (2) hold for any portion of the variation in labor stocks. Since in this section we are interested in understanding the sources of low-frequency movements in the part-time employment share, we will inform our stock-flow framework with data that leaves out high-frequency variation.[20] To gauge the role of each flow hazard in the long-run evolution of the part-time employment share, we construct series of counterfactual movements in the part-time employment share driven by each flow hazard. Specifically, based on equation (2), we can approximate deviations at time t of each steady-state stock with respect to its sample mean, denoted $d\bar{s}_t$, in the following way:

$$d\bar{s}_t \approx \sum_{i \neq j} \frac{\partial \bar{s}_t}{\partial \lambda^{ij}} d\lambda^{ij}, \tag{5}$$

where $d\lambda^{ij}$ is the deviation of flow hazards λ^{ij} with respect to its sample mean and $\frac{\partial \bar{s}_t}{\partial \lambda^{ij}}$ are partial derivatives. Once we have obtained these steady-state stock approximations, the part-time employment share can be approximated by a first-order Taylor expansion:

$$d\bar{\omega}_t^P \approx \frac{d\bar{P}_t(1 - \bar{\omega}_t^P) - d\bar{F}_t \bar{\omega}_t^P}{\bar{F}_t + \bar{P}_t} \tag{6}$$

Note that the linearity of equation (5) allows us to construct counterfactual changes in stocks for groups of flow hazards by simply adding the individual conterfactual series.

[20] In practice, we extract the Hodrick-Prescott trend of worker flows and stocks using a standard smoothing parameter for monthly data equal to $1,600 \times 3^4$.

4.3 Decomposition of long-run changes

We use the framework developed in the previous subsection to compute two sets of results. First, we document the dynamics of the part-time employment share over each decade and compare it with the dynamics of the part-time employment share implied by the behavior of specific flow hazards or groups of flow hazards. Second, we decompose the low-frequency variation in the part-time employment share accounted for by low-frequency movements in the underlying flow hazards.

Long differences

Table 1 reports the long difference (denoted D) of alternative part-time employment shares, defined as the difference in levels of each share from the beginning to the end of the period (a decade or the whole sample period). That is, the long difference from time period t_0 to some future time period t_1 reads:

$$D\bar{\omega}^P = \sum_{\tau=t_0}^{t_1} d\bar{\omega}_\tau^P. \tag{7}$$

For convenience, in addition to part-time employment shares driven by specific flow hazards, we also aggregate changes resulting from movements in flow hazards respectively across employment states ($D\bar{\omega}_w^P$, within-employment) and non-employment states ($D\bar{\omega}_n^P$, non-employment) and, in the last row of the table, the aggregate effect of all hazards in and out of P or F. The latter is different from the actual long difference, displayed in the first row, as per the approximations entailed by equations (5) and (6).

We start with the long difference for the whole sample period (last column). The steady-state part-time employment share increased by 1.95 pp. In absolute terms, that increase is small compared to those implied exclusively by the evolution of $p\,(F \to P)$ and $p\,(F \to P)$, at 4.03 and -3.26, respectively. The remaining increase – 1.95-(4.03-3.26) – is largely accounted for by the differential behavior of outflows from employment states to non-participation.[21] Together, $p\,(P \to N)$ and $p\,(F \to N)$ implied a 1.78 pp. increase in $\bar{\omega}_t^P$, which was reverted in 0.96 pp. by the changes in $p\,(N \to P)$ and $p\,(N \to F)$. The more salient secular changes over the whole period are the declining flows between non-participation and part-time employment, especially the drop in $p\,(P \to N)$. On net, these movements led to an increase of about 1 pp. in the steady-state part-time employment share. By comparison, secular changes in reallocation between unemployment and employment states contributed with a smaller amount (about a third of a pp.), in large part due to low-frequency movements in $p\,(U \to F)$.

Inspection of the columns (1) to (4) in Table 1 allows us to track the evolution of the part-time employment share decade by decade. With the exception of the 1996-2005 decade, the part-time employment share increased in every decade. The numbers reported in panels (i) to (iv) show the evolution of the contributions of the various flow hazards to the long difference in the part-time employment share decade by decade. There are a number of interesting facts.

[21] The attentive reader has noted that, over the whole sample period, the steady-state part-time employment share increased by 1 pp. more than the actual part-time employment share. This is because the steady-state part-time employment share underestimates the actual one during the first periods of observation.

Table 1: Long differences of the part-time employment share

	1976 – 1985 (1)	1986 – 1995 (2)	1996 – 2005 (3)	2006 – 2015 (4)	1976 – 2015 (5)
$D\bar{\omega}^P$	1.96	0.19	-1.08	0.88	1.95
(i) Within employment					
$D\bar{\omega}^P\,(F \to P)$	1.41	0.28	1.32	1.01	4.03
$D\bar{\omega}^P\,(P \to F)$	-0.54	-0.43	-2.24	-0.05	-3.26
(ii) Unemployment					
$D\bar{\omega}^P\,(U \to P)$	0.02	0.05	-0.36	0.11	-0.18
$D\bar{\omega}^P\,(U \to F)$	0.20	-0.01	0.08	0.39	0.65
$D\bar{\omega}^P\,(P \to U)$	-0.05	0.21	0.07	-0.03	0.21
$D\bar{\omega}^P\,(F \to U)$	0.28	-0.24	0.04	-0.43	-0.36
(iii) Non-participation					
$D\bar{\omega}^P\,(N \to P)$	0.37	-0.06	-0.36	-0.40	-0.45
$D\bar{\omega}^P\,(N \to F)$	-0.15	-0.02	-0.46	0.12	-0.51
$D\bar{\omega}^P\,(P \to N)$	0.69	0.36	-0.05	-0.00	0.99
$D\bar{\omega}^P\,(F \to N)$	-0.20	0.00	0.68	0.32	0.79
(iv) Aggregate					
$D\bar{\omega}^P_w$	0.88	-0.15	-0.92	0.96	0.77
$D\bar{\omega}^P_n$	1.14	0.29	-0.37	0.07	1.13
$D\bar{\omega}^P_w + D\bar{\omega}^P_n$	2.01	0.14	-1.29	1.03	1.90

NOTE: CPS data cleared from composition effects (see Appendix A for data details), covering the period 1976m01–2015m12. An entry in each column is the long difference (expressed in percentage points) of the part-time employment share indicated in the row over the period indicated in the column. In panel (iv), $D\bar{\omega}^P_w$ (resp. $D\bar{\omega}^P_n$) is the sum of within-employment changes (resp. changes through unemployment and non-participation).

First, in every decade, changes in $p\,(F \to P)$ ($p\,(P \to F)$) imply sizable positive (negative) changes in $\bar{\omega}^P_t$. The only decade in which the part-time employment share declined was mainly due to the unusual growth in $p\,(P \to F)$. Second, the impact on part-time employment of the remaining flow-hazards changes across decades is in general smaller compared to direct transitions between P and F. Third, the relative importance of within-employment vs non-employment reallocation (panel (iv)) changes across decades. While during the first two decades non-employment reallocation plays a more important role in driving the dynamics of the part-time employment share, the roles are reversed in the following two decades.

Flow variance decomposition

A second set of results concerns the variance contribution of the various flows hazards over the whole sample period. Compared to an analysis based on long differences, using variation across all periods allows a finer assessment of the contribution of the different flow hazards to the dynamics of the part-time employment share. The results are displayed in Table 2. The coefficients reported in the table are *beta coefficients*, which measure the contribution to the variance of $d\bar{\omega}_t^P$ of counterfactual part-time employment shares driven by changes in specific flow hazards.

Table 2: Variance decomposition of the low-frequency dynamics of part-time employment

Within-employment		Non-employment inflows		Non-employment outflows	
$\beta\,(P \to F)$	-38.8	$\beta\,(P \to U)$	-4.1	$\beta\,(U \to P)$	-9.1
$\beta\,(F \to P)$	106.2	$\beta\,(P \to N)$	24.6	$\beta\,(N \to P)$	-9.3
		$\beta\,(F \to U)$	0.3	$\beta\,(U \to F)$	37.0
		$\beta\,(F \to N)$	-3.2	$\beta\,(N \to F)$	5.9
$\sum_{i,j=P,F} \beta\,(i \to j)$	67.4	$\sum_{i=P,F} \sum_{j=U,N} \beta\,(i \to j)$	17.6	$\sum_{i=U,N} \sum_{j=P,F} \beta\,(i \to j)$	24.4

NOTE: CPS data cleared from composition effects (see Appendix A for data details), covering the period 1976m01–2015m12. An entry in the table is the regression coefficient of the counterfactual part-time employment share on the steady-state part-time employment share. All entries are in percent.

The left-hand side panel confirms the results that low-frequency movements in transitions between P and F are predominant. Together, they account for 67% of the variation of the part-time share, but this masks the fact they imply changes that cancel each other out. The other individual transitions that play an important role are $p\,(P \to N)$ and $p\,(U \to F)$. While outflows from part-time employment to non-participation decrease steadily over the period and likely reflect secular changes, the unemployment outflow to full-time employment seems to capture aspects associated with the business cycle.

Taking stock

A key feature of the stability of the part-time employment share over the sample period is the counteracting effects of increases in transition probabilities across part-time and full-time employment. Together these two opposing observations form a classic example of a stock-flow fallacy, whereby large and counteracting movements in flows result in a stable behavior of the stock (see Elsby et al. [2015]). Insofar as labor flows offer a richer description of the experience of labor market participants, they are more informative to gauge the rising importance of part-time employment. Using a similar measurement framework, Borowczyk-Martins and Lalé [2016] find that the cyclical dynamics of transition probabilities across the two employment states (P and F) are the main drivers of the cyclical behavior of the part-time employment share from 1994 to 2015. We reinforce that finding in the context of low-frequency variation over a longer period of time.

5 Cyclical fluctuations and involuntary part-time work

We now turn to the second set of questions under scrutiny: what are the forces that govern the cyclical behavior of part-time employment? And how different are they from those shaping fluctuations in aggregate employment? We answer these questions by focusing on involuntary part-time employment. Involuntary part-time work is the main cyclical component of part-time employment. Moreover, emphasizing its role allows us to draw a close parallel to unemployment, which drives most fluctuations in aggregate employment. We analyze the sample period as a whole, and then we shine a light on the two largest recessionary periods covered by our data.

5.1 The cyclical component of part-time employment

We extend the framework employed in the previous section and classify workers in five labor market states: full-time employment (F), part-time employment, voluntary (V) or not (I), unemployment (U) and non-participation (N).[22] Consequently, we now write the part-time employment share as the sum of the involuntary and voluntary part-time shares (respectively ω^I and ω^V):

$$\omega_t^P = \omega_t^V + \omega_t^I, \tag{8}$$

where $\omega_t^I = \frac{I_t}{F_t+V_t+I_t}$ and ω_t^V defined accordingly. Figure 3 depicts the evolution of the involuntary part-time share over the past decades. Similar to the overall part-time share, involuntary part-time work remained largely stable in the long run. Its cyclical response during the Great Recession, however, was unprecedented. It rose from 2.2% to 5.2% during the recession, reaching a historical high of 5.9% in March 2010, and by December 2015 it was still above its pre-crisis level at 3.8%.

Although, on average, involuntary part-time work accounts for "only" 15.5% of part-time employment, it explains most of its cyclical variation. The variance contribution of short-run fluctuations in the involuntary part-time share to short-run fluctuations in the overall part-time share defined below (Δ denotes first-order difference):

$$\rho = \frac{\mathbb{C}\mathrm{ov}(\Delta\omega_t^P, \Delta\omega_t^I)}{\mathbb{V}\mathrm{ar}(\Delta\omega_t^P)}, \tag{9}$$

is 59.3% over the sample period. This figure masks some large discrepancies across periods. From 1996 to 2005, ρ is "only" 28.8%, but in the 1976-1985 decade it rises to 64.1%, and to 72.1% in the 2006-2015 decade. The remainder of this section takes a close look at the sources of cyclical fluctuations in the involuntary part-time employment share, ω_t^I.

5.2 Inflows, outflows and their cyclical behavior

As already mentioned, it is relevant to analyze involuntary part-time employment in parallel with unemployment because the latter is the main source of variations in aggregate employment.

[22] See Appendix A, and in particular Subsection A.4 for details on how we construct labor market flows. We attempt to control for spurious transitions between labor market states V and I, and also between N and U like in Elsby et al. [2015].

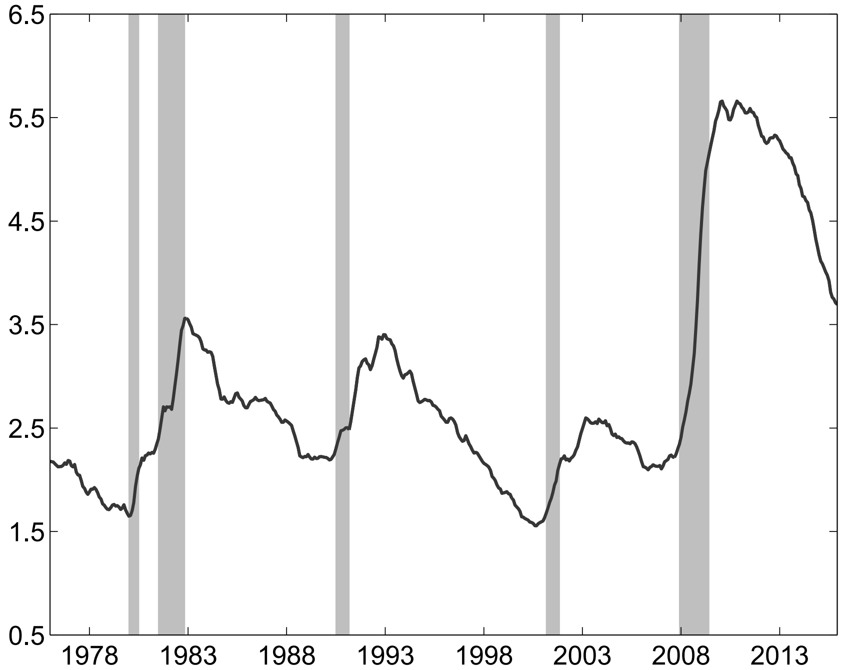


Figure 3: The involuntary part-time employment share

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A for data details). Gray-shaded areas indicate NBER recession periods.

We find that, in addition, this exercise is useful for heuristic purposes. Drawing comparisons with the dynamics of unemployment, which are well documented, helps isolate the distinctive features of involuntary part-time work. Finally, we note that both unemployment and involuntary part-time work entail a constraint on workers' desired labor supply. Thus, a natural question is whether they share the same sources of cyclical variations.

A first look at the ins and outs

The first dimension along which we want to characterize the dynamics of involuntary part-time work is that of its interaction with other labor market states. Table 3 reports sample averages of inflow and outflow transition probabilities of involuntary part-time work (left panel) and unemployment (right panel).[23] A first striking result is displayed in the bottom row of Table 3, which displays the sum of various inflow and outflow transition probabilities to involuntary part-time work and unemployment (resp. left- and right-hand side panels). Involuntary part-time employment exhibits spectacularly fast dynamics, with two-thirds of the stock entering in the previous month (67.2%) and an almost similarly large share leaving in the following one (60.3%). Over the same period, these numbers are 43.8 and 41.7% for unemployment inflows and outflows. What is more, even when we remove movements between involuntary and voluntary part-time employment from this accounting exercise, the dynamics of involuntary part-time are still higher compared to unemployment (44.9% vs. 41.7% for the outflows). This

[23]The inflow transition from state i to j at time t, denoted $q\,(i \rightarrow j)$, is the ratio of the gross flow from state i to j over the stock of workers in state j. That is, $q\,(i \rightarrow j) = {}^{\#\{i \rightarrow j\}}/_{\#\{j\}}$ (with $\#\,\{.\}$ indicating cardinality, and the numerator and denominator both measured at time t). The outflow transition probabilities are the elements of the Markov transition matrix.

is quite extraordinary given how unusually fast the dynamics of unemployment in the U.S. are in an international context.

Table 3: Inflow and outflow transition probabilities: Sample averages

Involuntary part-time work				Unemployment			
Inflows		Outflows		Inflows		Outflows	
$q(F \to I)$	28.6	$p(I \to F)$	28.9	$q(F \to U)$	17.5	$p(U \to F)$	15.7
$q(V \to I)$	16.3	$p(I \to V)$	15.4	$q(V \to U)$	6.77	$p(U \to V)$	7.56
$q(U \to I)$	16.9	$p(I \to U)$	11.6	$q(I \to U)$	4.45	$p(U \to I)$	6.41
$q(N \to I)$	5.38	$p(I \to N)$	4.43	$q(N \to U)$	15.1	$p(U \to N)$	12.0
$\sum_{i \neq I} q(i \to I)$	67.2	$\sum_{j \neq I} p(I \to j)$	60.3	$\sum_{i \neq U} q(i \to U)$	43.8	$\sum_{j \neq U} p(U \to j)$	41.7

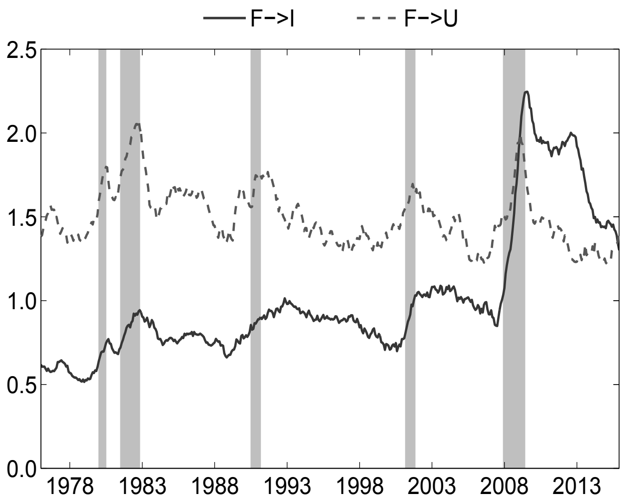
NOTE: CPS data cleared from composition effects (see Appendix A for data details), averages over the period 1976m01–2015m12. All entries in the table are reported in percent.

When looking at specific labor market states, we see that full-time employment is the most relevant state of origin and destination. On average, 28.6% of all involuntary part-timers were employed full-time in the previous month, and a similar fraction (28.9%) will enter full-time work next month. Perhaps surprisingly, movements between involuntary and voluntary part-time employment are also large (16.3 and 15.4% resp. for inflows and outflows).[24] Finally, transitions between involuntary part-time and unemployment are smaller, and those with non-participation very small. Moving on to unemployed workers, we see that, like involuntary part-timers, they are also likely to have been or become full-time employed respectively in the previous and following month (17.5% and 15.7%). Different to involuntary part-time, transitions between unemployment and non-participation are high (about the triple of the corresponding figures for transitions between I and N).

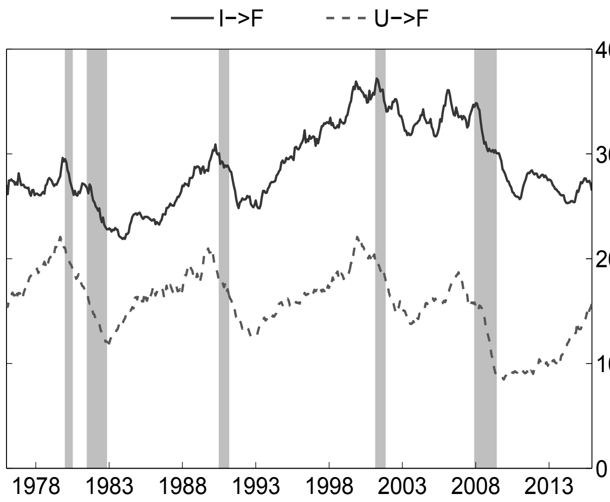
Figure 4 complements this static portrait by displaying the evolution of the most relevant transition probabilities. In each plot the same transition is shown both for involuntary part-time (solid line) and unemployment (dashed line). We first comment on the dynamic behavior of inflow transitions from full-time employment. Similar to the inflow to unemployment, the inflow probability to involuntary part-time employment spikes in recessions, and then returns to its pre-crisis level. However, its recovery is much slower, and possibly even non-existent: for instance after the 2001 recession, it never returned to its pre-crisis level. The evolution of the two probabilities is also quantitatively different during the Great Recession. The increase in $p(F \to I)$ is far greater (so much so that the two lines intersect at the end of the recessionary period), and throughout the whole post-recession period (which extends over a six year period) it remains at historically high levels.

Turning to the evolution of outflow probabilities from these two states to full-time employment, Figure 4b shows that $p(I \to F)$ and $p(U \to F)$ follow a similar trajectory to the

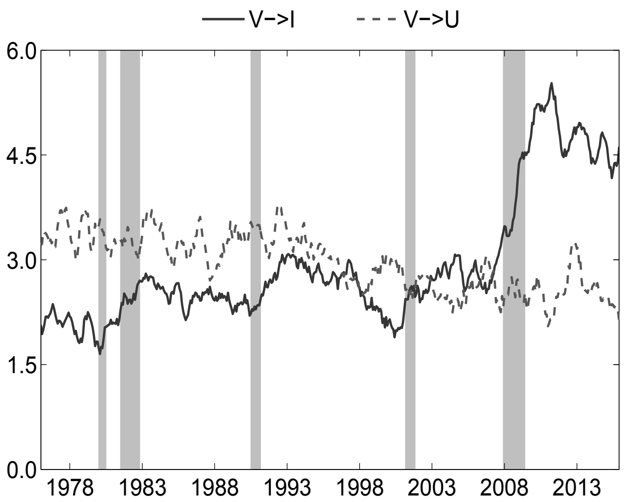
[24]This is despite the fact that we address potential measurement error in transitions between involuntary and voluntary part-time work, and discard a significant fraction of the transitions observed in the raw data.



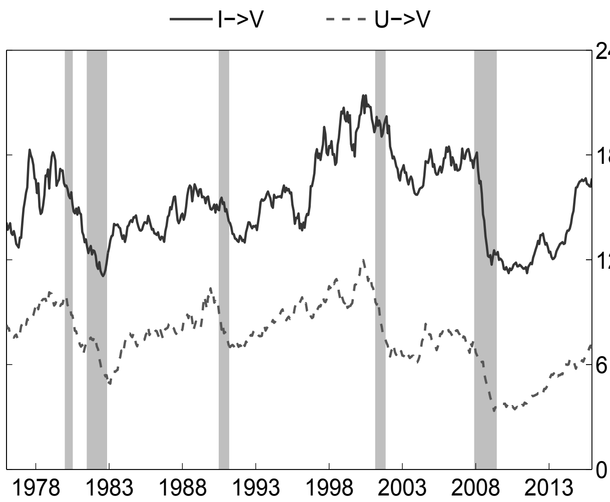
(a) Inflows from full-time employment



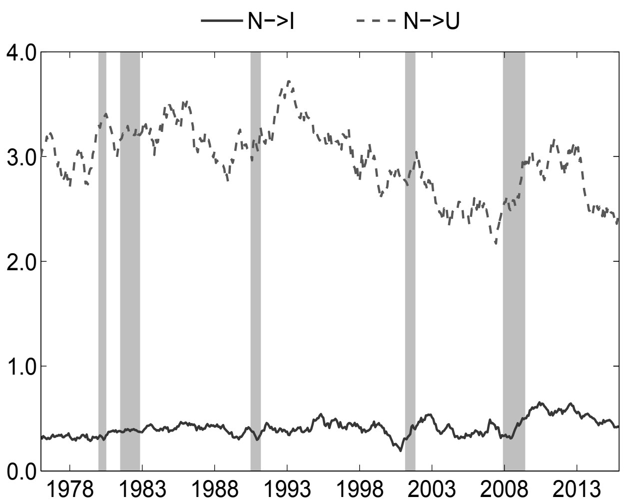
(b) Outflows to full-time employment



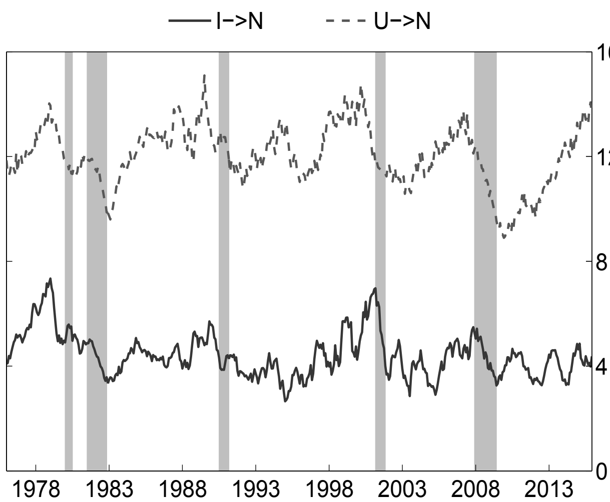
(c) Inflows from voluntary part-time employment



(d) Outflows to voluntary part-time employment



(e) Inflows from non-participation



(f) Outflows to non-participation

Figure 4: Transition probabilities comparing involuntary part-time work and unemployment

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A for data details). Gray-shaded areas indicate NBER recession periods.

aggregate job-finding rate. Both probabilities rise steadily in normal times and fall slowly starting just before, or at the very beginning of recession, and extending over a period that goes beyond the end of the recession. It is noticeable that the solid line exhibits lower variation in both upturns and downturns. As for the aftermath of the Great Recession, by the end of 2015 unemployment outflows towards full-time employment have not fully recovered (hence the term *jobless recovery*) but they are close to their pre-crisis level. In contrast, outflows from involuntary part-time work only seem to start increasing in 2014, leaving them well below their pre-crisis level. These responses underscore the magnitude and persistence of the shock and the ongoing slack in the labor market.

The two figures in the middle panel of Figure 4 plot transition probabilities between the two labor market states of interest (I and U) and voluntary part-time employment (V). Like full-time jobs, voluntary part-time jobs become scarcer in recessions, leading to a decrease in the voluntary part-time rate. However, there are some notable differences between the cyclical dynamics of the associated flow rates. While $p\,(V \to U)$ is surprisingly acyclical and exhibits a downward trend, the recessionary behavior of $p\,(V \to I)$ is just like the one displayed by other employment outflow rates (jumping at the onset of the recession), and is even more persistent than that of $p\,(F \to I)$. For instance in the 2010s, it remains close to its recessionary peak six years later. As can be seen by comparing Figures 4d and 4b, the outflows to voluntary part-time behave no differently from their counterparts to full-time employment. However, it is apparent that $p\,(I \to V)$ recovered faster compared to $p(U \to V)$ in the 2010s, whereas the opposite was true in outflow rates to full-time employment.

Finally, Figures 4e and 4f track the evolution of flow rates to non-participation. Consistent with the picture provided by a comparison of sample means, and in spite of similar comovements with the cycle, the cyclicality of non-participation flows is more pronounced with unemployment. In fact, there is almost no interaction between involuntary part-time work and non-participation, which dovetails with the idea that non-participants would not take *any* job if they were to work. On the other hand, we will confirm below that non-participation plays a prominent role in the dynamics of unemployment – confirming *the importance of the participation margin*, in the words of Elsby et al. [2015].

A business-cycle framework

A convenient way to assess the importance of fluctuations in the different transition probabilities to the dynamics of the involuntary part-time employment share is to decompose its variation into the individual contributions of the various flow hazards associated with each transition probability. Again, we consider a set of beta coefficients defined as follows:

$$\beta^{ij} = \frac{\mathbb{C}\mathrm{ov}\left(\Delta\omega_t^I, \Delta\breve{\omega_t^I}^{ij}\right)}{\mathbb{V}\mathrm{ar}(\Delta\omega_t^I)} \tag{10}$$

$\Delta\breve{\omega_t^I}^{ij}$ denotes changes in the counterfactual involuntary part-time employment share whose evolution is only based on the past and contemporaneous changes in a particular flow hazard λ^{ij}. It can be shown that the variation in ω_t^I is approximated by the sum of variance contributions of each flow hazard.[25] That is:

$$\sum_{i \neq j} \beta^{ij} \approx 1 \tag{11}$$

The results are reported in Table 4.[26] By and large, the estimated beta coefficients confirm the picture we have been constructing thus far. The ins and outs of full-time employment are quantitatively very important, but much more so for involuntary part-time vis-a-vis unemployment (52.3 vs 35.7%). In line with our comments of Figure 4, the inflow from full-time employment plays a prominent role in the cyclicality of the involuntary part-time employment share (29.5%). If we add to that the contribution of λ^{VI}, transitions from employment states explain 47.1% of the variation in ω_t^I. On the other hand, the main drivers of unemployment fluctuations during this period are fluctuations in and out of non-participation (40.4%), followed closely by full-time employment (35.7%). Finally, we assess the relative importance of the 'ins' and 'outs' for the evolution of both labor market states. Interestingly, the outs dominate the variation in the unemployment rate, with a split of roughly 40:60, whereas a similar breakdown of the variation of the involuntary part-time employment share yields a 60:40 split.

Table 4: Variance contributions: Comparing involuntary part-time work and unemployment

Involuntary part-time share				Unemployment rate			
Inflows		Outflows		Inflows		Outflows	
$\beta\,(F \to I)$	29.5	$\beta\,(I \to F)$	22.8	$\beta\,(F \to U)$	13.5	$\beta\,(U \to F)$	22.2
$\beta\,(V \to I)$	17.6	$\beta\,(I \to V)$	12.7	$\beta\,(V \to U)$	1.72	$\beta\,(U \to V)$	6.06
$\beta\,(U \to I)$	6.20	$\beta\,(I \to U)$	2.31	$\beta\,(I \to U)$	5.63	$\beta\,(U \to I)$	8.85
$\beta\,(N \to I)$	4.30	$\beta\,(I \to N)$	1.27	$\beta\,(N \to U)$	20.1	$\beta\,(U \to N)$	20.4
$\sum_{i \neq I} \beta\,(i \to I)$	57.6	$\sum_{j \neq I} \beta\,(I \to j)$	39.1	$\sum_{i \neq U} \beta\,(i \to U)$	40.9	$\sum_{j \neq U} \beta\,(U \to j)$	57.4
$\sum_{i \neq I} \beta\,(i \to I) + \sum_{j \neq I} \beta\,(I \to j) = 96.7$				$\sum_{i \neq U} \beta\,(i \to U) + \sum_{j \neq U} \beta\,(U \to j) = 98.3$			

NOTE: CPS data cleared from composition effects (see Appendix A for data details), covering the period 1976m01–2015m12. All entries in the table are reported in percent.

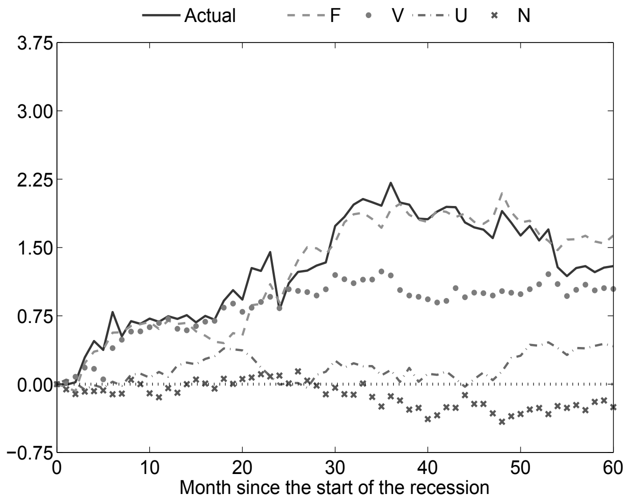
5.3 A closer look at two large recessions

To conclude this investigation, we look more closely at the two main recessionary episodes covered by our data: the twin recessions of 1980-1982 and the Great Recession of 2007-2009.

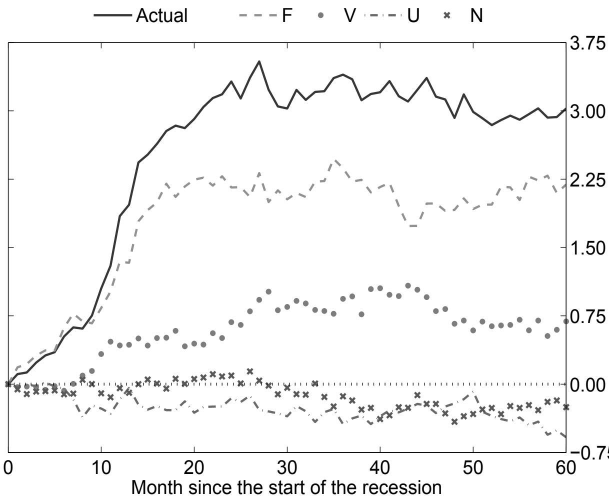
[25] Unlike the variance decomposition in the previous section, here we use a different method to approximate each labor market stock. See Elsby et al. [2015] for a complete formal treatment, and appendix A in Borowczyk-Martins and Lalé [2016] for an application to a five-state Markov chain.

[26] Notice that the left-hand side panel reports results for the involuntary part-time *share* whereas the right-hand side panel is for the unemployment *rate*. In Appendix B.2 we show that our conclusions are unchanged when we decompose the variation of the involuntary part-time rate, defined as the number of involuntary part-time workers divided by the size of the labor force. This is not surprising because, as shown in Table 4, non-employment plays a negligible role in the dynamics of the involuntary part-time share.

Our analysis of long-run changes demonstrates that the part-time employment margin plays a more active role by the end of the sample period. The analysis of short-run fluctuations shows that it operates mainly through the interaction between full-time employment and involuntary part-time work. Consequently, the question we ask is whether full-time employment explains the stronger cyclical response of involuntary part-time work during the Great Recession, as shown on Figure 3.



(a) Twin recessions of the 1980s



(b) Great Recession

Figure 5: Contributions to the recessionary increase in involuntary part-time work

NOTE: The solid line shows the actual change in the involuntary part-time employment share. The other lines show counterfactual shares based on the contribution of each labor market state. All figures are percentage point differences from the value at time 0, the last month before the NBER recession episode.

The answer to this question is an overwhelming 'yes'. In Figure 5, we report for each recession the contribution of the various labor market states to the evolution of involuntary part-time employment since the start of the recession. In line with our earlier analysis, unemployment and non-participation play a negligible role in those dynamics. The dotted lines in 5a and 5b reveals that, surprisingly, in both episodes voluntary part-time work increased the involuntary part-time share by a similar amount, i.e. 0.75 pp. during the months following the initial shock. Therefore, the lion's share of the different cyclical response across recession comes from full-time employment. In the Great Recession it accounts for a persistent 2.25 pp. rise in involuntary part-time work.

6 Additional facts on part-time employment

6.1 The contribution of slack work to part-time employment

We summarize several facts about the contribution of slack work/poor business conditions to the recessionary increase in involuntary part-time work. We refer the reader to the case study of the Great Recession conducted in Appendix B.1 for details.

As highlighted in Section 2, involuntary part-time employment encompasses two categories: workers who face slack work conditions in their current job and workers unable to find a full-time job. First, since the late 1990s, slack work conditions explain a relatively larger share of involuntary part-time work (between 50% and 70%). Second, during the Great Recession, the increase in slack work is the predominant force driving the surge in involuntary part-time employment: it explains three-quarters of the increase during the first year of the recession. Slack work also contributes to the elevated levels of involuntary part-time employment during the recovery period. These facts corroborate the strong interaction between full-time employment and involuntary part-time work documented in the previous section. In particular, we discard an explanation for the recessionary increase in part-time employment based on the behavior of job-seekers who would temporarily work part-time for lack of a better option. We find, nonetheless, that workers who cannot find a full-time job contribute to the sluggish behavior of involuntary part-time employment after the Great Recession (see also Cajner et al. [2014] and Valletta and Bengali [2013]). Third, the incidence of slack work in explaining involuntary part-time work is very pronounced at the occupation level. For instance, in executive, administrative, managerial and management-related occupations, it explains most of the dynamics of involuntary part-time employment, since almost no individual in these occupations is working part-time for lack of a full-time job opportunity during non-employment spells.

6.2 Unemployment duration, job search and part-time employment

Using information from the CPS pertaining to workers' stated job search behavior, we document a statistical correlation between the share of unemployed workers looking for full-time employment and the duration of unemployment.[27] Figure 6 reports the share of these job-seekers in the unemployment pool (left axis), along with the average duration of unemployment (in weeks, reported on the right axis).[28]

The share of workers who report looking for a full-time job is very high: it accounts for 82.7% of the pool of unemployed in the average month. As can be observed in Figure 6, it has a sizable cyclical component and varies substantially from trough to peak (over 5 pp. in the largest recessions covered by our data). We find that the average duration of unemployment is larger for workers reporting to look for a full-time job: 9 weeks more, on average. Consequently, there is a large and positive statistical association between the average duration of unemployment and the share of unemployed looking for full-time work, which leads the former in a time-series sense. The contemporaneous correlation in levels is 68.1%, and as high as 78.3% between the one-year lag of the fraction of full-time job-seekers and unemployment duration.

Up until the mid 2000s unemployment duration was rather stable, at which point a break sets the average unemployment duration on an upward course.[29] After the mild recession in

[27]Specifically, the survey asks unemployed persons whether they are looking for full-time work. In the CPS interview manual this question is coded LKFT (cf. `https://www.census.gov/cps/`).

[28]To avoid a discontinuity around the redesign of the CPS, we follow Abraham and Shimer [2002] and use only CPS respondents in rotation groups 1 and 5 to compute unemployment duration.

[29]A number of papers have documented a long-run increase in unemployment duration in the U.S. labor market (see e.g. Mukoyama and Şahin [2009] and Abraham and Shimer [2002]). Using our data, and consistent with more recent analyses (e.g. Valletta [2011]), we find no evidence of such a long-run change from the mid-

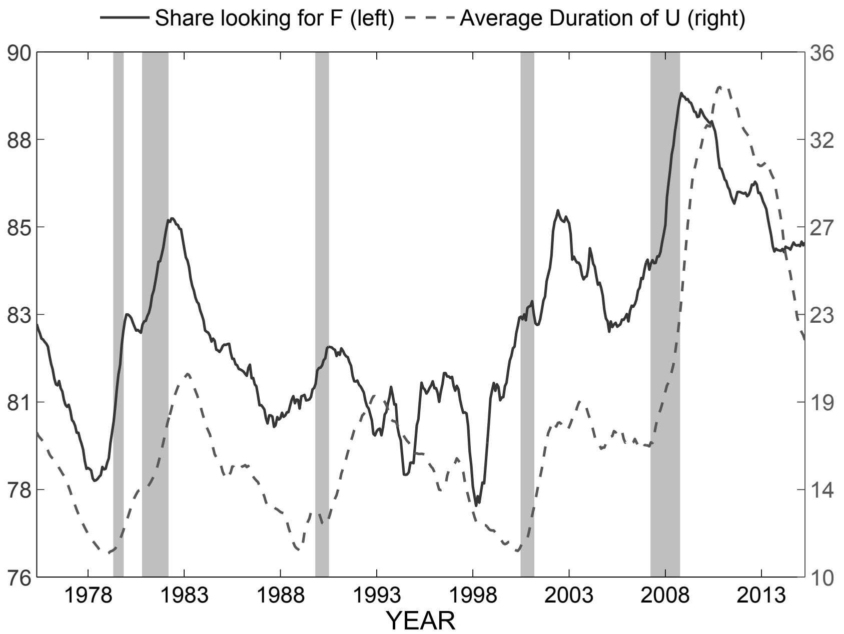


Figure 6: Unemployment duration and workers seeking full-time work

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A for data details). Gray-shaded areas indicate NBER recession periods.

2001, average unemployment duration starts falling, but that process is interrupted by mid-2006; so much so that at the onset of the Great Recession unemployment duration is high by historical standards. Then, following the spectacular response during the Great Recession, elevated levels of unemployment duration persist until the end of 2015, despite the ongoing recovery. Interestingly, we observe that the fraction of unemployed job-seekers looking for full-time work exhibits a very similar behavior during the last decade (viz. break in mid 2006 which initiates an upward trend). This fact reinforces the correlation discussed above.

It is beyond the scope of our analysis to analyze the joint dynamics of the two variables, but nevertheless we can provide some observations. One possible interpretation is that the share of unemployed job-seekers looking for full-time work mirrors the behavior of the part-time employment share: it increases during downturns because those looking for part-time work become relatively more likely to be employed. This, however, is inconsistent with the short-run dynamics of part-time employment uncovered in the previous section. Another interpretation is that job-seekers looking for part-time work may display lower attachment to the labor market, and drop from the unemployment pool during downturns. An alternative to these explanations based on composition effects is that individuals' desired labor supply increases in periods of slack labor market and/or greater economic uncertainty due, for example, to couples' joint forward-looking optimizing behavior (e.g. the added worker effect).[30] Future work could analyze whether the data reflects composition effects or actual changes in the behavior of job-seekers. As

1970s until the mid-2000s. This statement is true whether or not we correct for unemployment composition and for the changes introduced by the CPS redesign. Using the official series published by the BLS (LNS13008275) leads to the same conclusion.

[30]A different hypothesis is that stated job search behavior may simply reflect individuals' adjustment to perceived aggregate economic conditions: individuals who would normally search for part-time jobs only may report that they are willing to take on a full-time job in face of a slack labor market.

for the consequences, the countercyclicality of the share of workers seeking full-time employment can contribute to the decrease in measured matching efficiency in the Great Recession. Ceteris paribus, if a fraction of the pool of unemployed job-seekers becomes more choosy in recessions (by not being available to take a part-time job), then their matching probabilities will decrease as a result of the increase in the part-time employment share.

6.3 Rising turnover and involuntary vs. voluntary part-time work

We decompose the long-run increase in turnover between full-time (F) and part-time employment (P) into changes attributable to voluntary (V) and involuntary (I) part-time work. The analysis of $p\,(F \to P)$ is straightforward because this transition probability is the sum of $p\,(F \to V)$ and $p\,(F \to I)$.[31] On the other hand, changes in $p\,(P \to F)$ depend not only on transition probabilities $p\,(V \to F)$ and $p\,(I \to F)$ but also on the relative shares of voluntary and involuntary part-time workers in part-time employment. Therefore, we perform a 'shift-share' analysis whereby the cumulated changes attributable to the share of involuntary part-time workers between two periods t_0 and t_1 are computed as:

$$\sum_{\tau=t_0}^{t_1-1}\left(\frac{\omega^I_{\tau+1}}{\omega^P_{\tau+1}}-\frac{\omega^I_{\tau}}{\omega^P_{\tau}}\right)\frac{p_{\tau+1}\,(I \to F)+p_{\tau}\,(I \to F)}{2}. \tag{12}$$

Panel (i) of Table 5 reports the cumulative change in transitions from full-time to part-time work and its underlying components, decade by decade and for the whole period (last column). Panel (ii) reports the corresponding numbers for transitions from part-time to full-time employment. The sub-columns labeled $D\omega$ display the changes explained by variations in the relative shares of voluntary and involuntary part-time workers calculated using equation (12). The sub-columns labeled Dp display the changes explained by variations in transition probabilities.[32]

During the past four decades, the probability to move from full-time to part-time employment increased by 1.41 pp. (a 50% increase in relative terms). Until the mid-1990s, voluntary and involuntary part-time work play a similar role in those dynamics: they explain respectively around 42 and 58% of the increase. In contrast, the period from the year 1996 until 2005 is characterized by a large increase in the role of $p\,(F \to V)$, which accounts for almost 80% of the rise in turnover from full-time to part-time employment. The role of transition probabilities is reversed in the decade that follows, when $p\,(F \to I)$ explains all of the increase in $p\,(F \to P)$. In sum, transitions to involuntary part-time work slightly dominate those towards voluntary part-time work on average, and the dispersion in their relative role increased markedly in the last two decades.

[31] However, note that the transition probability $p\,(F \to P)$ based on the four-state Markov-chain of Section 4 does not match the sum of $p\,(F \to V)$ and $p\,(F \to I)$ obtained from the five-state chain of Section 5 due to time-aggregation adjustments. The analysis in this subsection is based on the five-state Markov chain. We reconstruct $p\,(F \to P)$ and $p\,(P \to F)$ to make them consistent with their underlying components.

[32] For example, in sub-columns labeled Dp in the row beginning with I, the displayed coefficient is:

$$\sum_{\tau=t_0}^{t_1-1}\left(p_{\tau+1}\,(I \to F)-p_{\tau}\,(I \to F)\right)\frac{1}{2}\left(\frac{\omega^I_{\tau}}{\omega^P_{\tau}}+\frac{\omega^I_{\tau+1}}{\omega^P_{\tau+1}}\right).$$

Next, we analyze the probability to move from part-time to full-time employment, which increased by 4.47 pp. since 1976 (a 25% increase in relative terms). During the first thirty years of the sample period, changes in this time series are to a large extent driven by changes in the transition probability from voluntary part-time to full-time employment ($p(V \to F)$). This feature is especially present in the 1996-2005 decade: much of the increase (2.60 pp.) in $p(P \to F)$ is concentrated during this period and driven by the behavior of $p(V \to F)$. A closer look at the data shows that this pattern masks some discrepancies between male and female workers. While for men two-thirds of changes in $p(P \to F)$ are caused by changes in $p(I \to F)$, $p(V \to F)$ explains about 80% of the changes for women. Since the latter account for a greater fraction of overall part-time employment, transitions from *voluntary* part-time to full-time employment play a more important role in the aggregate.

Table 5: Rising turnover: Contributions of voluntary and involuntary part-time work

	1976 – 1985		1986 – 1995		1996 – 2005		2006 – 2015		1976 – 2015	
	(1)		(2)		(3)		(4)		(5)	
(i) Change in $F \to P$										
Actual	0.34		0.17		0.47		0.43		1.41	
$Dp(F \to V)$	0.15		0.07		0.37		-0.01		0.58	
$Dp(F \to I)$	0.19		0.10		0.10		0.44		0.83	
(ii) Change in $P \to F$										
Actual	0.77		0.29		2.60		0.28		4.47	
	Dp	$D\omega$	Dp	$D\omega$	Dp	$D\omega$	Dp	$D\omega$	Dp	$D\omega$
V	0.94	-0.32	-0.56	0.10	2.50	0.25	0.07	-1.16	3.51	-1.28
I	-0.63	0.78	0.90	-0.16	0.38	-0.53	-1.24	2.61	-0.81	3.05

NOTE: CPS data cleared from composition effects (see Appendix A for data details), covering the period 1976m01–2015m12. See the text for definitions and computations of the different contributions. All entries in the table are reported in percent.

The last decade, which includes the Great Recession, stands out. Both $p(V \to F)$ and $p(I \to F)$ dropped during the 2010s, but the increase in the relative share of involuntary part-time workers was so large that it counteracted these changes (recall that $p(I \to F)$ is about twice as large as $p(V \to F)$). In a nutshell, the long-run increase in transitions from part-time to full-time work is mostly explained by voluntary part-time employment, except during the past ten years when the recessionary increase in involuntary part-time work generates a large composition effect in the dynamics of this transition probability.

7 Conclusion

In this paper we documented the rising incidence of part-time employment in the U.S. labor market. In the long run, workers have become increasingly likely to switch between full-time and part-time positions. This trend is not driven by compositional changes, sample selection or other measurement artifacts. Our analysis therefore suggests a genuine transformation in the functioning of the U.S. labor market.

We found that both the short-run and long-run dynamics of part-time employment are dominated by within-employment reallocation. That is, low and high-frequency movements in the incidence of part-time employment operate mainly through changes in the frequency with which workers move between part-time and full-time employment without an intervening spell of non-employment. In the long-run, increases in these transitions produce a stock-flow fallacy: their effects on the part-time employment share offset one another, leaving it largely stable across decades. At business-cycle frequencies, within-employment reallocation generates large movements in the part-time share, especially through involuntary part-time employment. We think there is a close connection between the long-run and short-run patterns we documented. Indeed, the rising significance of part-time employment came to the fore during the Great Recession and its aftermath: since the crisis of 2007-09, employed workers are at a higher risk of becoming part-time employed involuntarily than put in unemployment.

A key contribution of this paper was to construct a new time series dataset combining information from the CPS monthly files and the annual demographic supplement of the survey. This procedure allowed us to overcome inconsistencies in the time series triggered by the CPS redesign. The recent burgeoning empirical research on part-time employment only covers the past two decades of U.S. labor market activity. By adding another two decades of monthly data, our paper allows researchers to construct a broader and richer view of the evolution of part-time employment, and of the U.S. labor market more generally. We are making these data publicly and readily available, and we hope that they will be used in future empirical and theoretical research on the functioning of labor markets.

This paper is primarily intended to provide a set of empirical facts and raise new questions. We close the analysis by outlining a number of research questions which we think are important avenues for future work in macroeconomics and labor economics. What explains the increase in turnover between part-time and full-time employment? Does reallocation along this margin help workers and firms avoid destroying good matches in the face of economic shocks? How does this greater flexibility affect the reallocation rate towards new and more productive jobs? Is involuntary part-time work an alternative to becoming unemployed? What are the implications of rising part-time reallocation for workers earnings stability and security? As spells of involuntary part-time work become more frequent, should U.S. states expand short-time compensation schemes and related insurance programs?

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Appendix

A Data

Our time series of labor market stocks and gross flows are subject to a number of adjustments outlined in Section 3 and Subsection 5.2 of the paper. We describe these in turn below.

A.1 Labor market stocks

We use annual data from the March CPS to adjust the stocks of part-time and involuntary part-time workers computed from the monthly files of the CPS. A respondent is classified as a part-timer in the March CPS is she reports to work part-time more than 50 percent of her annual number of working weeks. An involuntary part-time worker is a part-timer who reports that the main reason for working less than 35 hours (for at least one week) in the preceding calendar year was because she could not find a full-time job or due to slack work conditions.

The charts displayed in Figure A1 help illustrate the first of our correction procedures. In each plot, the step function (dotted line) is the value of the stock derived from the annual March CPS.[33] The solid line, which is discontinued in January 1994, shows the corresponding stock from the monthly files of the CPS. For instance, in the lower panel, we notice that the stocks of involuntary part-time workers became systematically lower from 1994 onwards. This observation is consistent with the revised version of the survey questionnaire.

To obtain the dashed lines (adjusted data) before 1994, we proceed as follows. First, we regress the monthly time series after 1994 on the annual series from the March CPS.[34] [35] Second, we apply the OLS coefficients to the March series to predict the annual level of the time series for each year prior to 1994. Thus, before 1994 we obtain a step function (not shown on the graphs) which is an affine transformation of the March series. Third, we multiply the values from the monthly CPS series by a common factor, such that the average matches the annual value derived from the March CPS. Note that the stock of full-time workers is computed as the difference between total employment and the corrected stock of part-time workers.

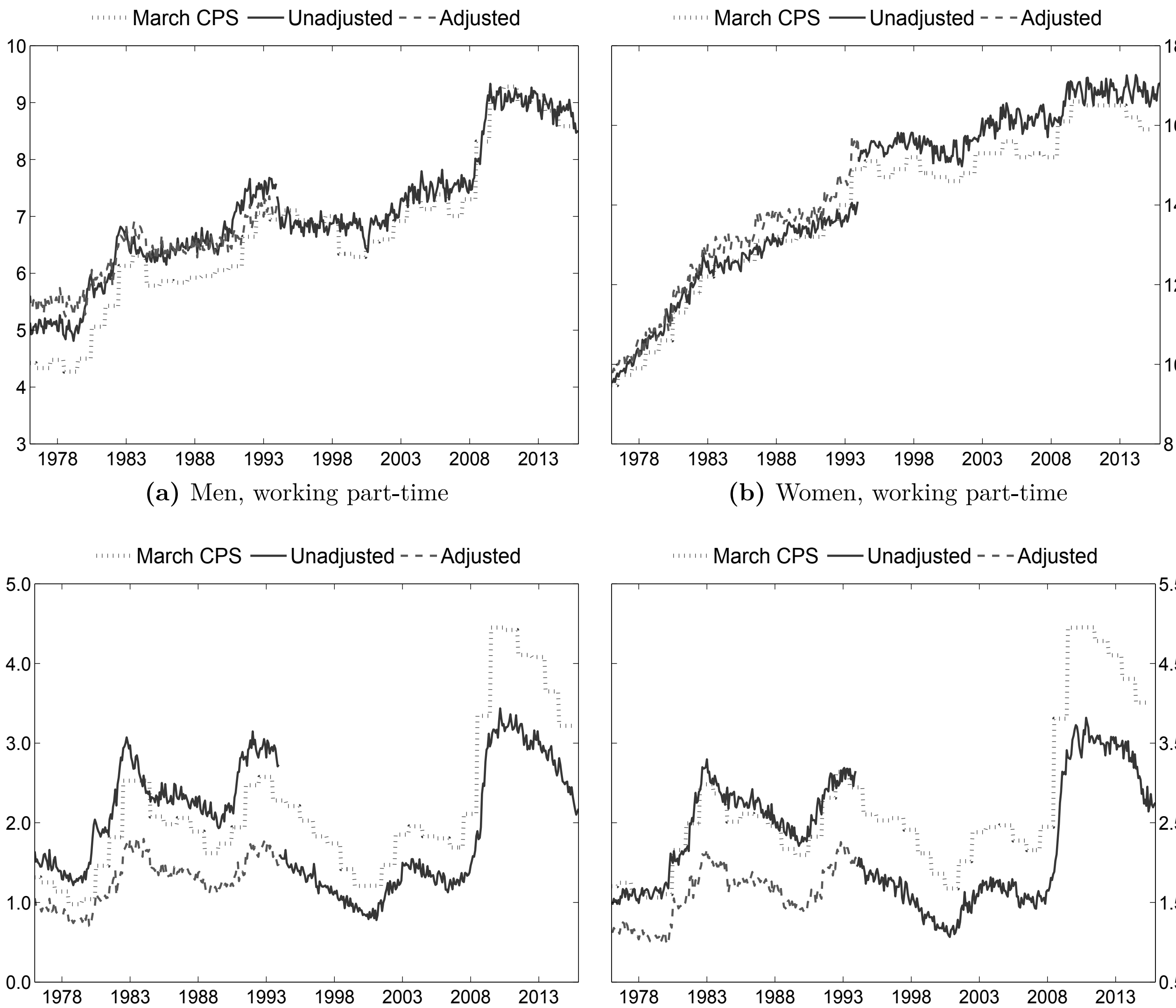
A.2 Labor market flows

To construct labor market flows, we start by linking CPS respondents in 2 consecutive months using household and personal identifiers from the non-rotation groups combined with a standard

[33] Although in principle information in the March CPS refers to the whole calendar year that precedes the survey, several authors find that the information it contains likely refers to the end of the previous year (e.g., Kambourov and Manovskii [2013], Lalé [2016]). We interpret the March CPS as providing information from July of the previous year to March of the survey year, and we extrapolate that information to April, May and June of the survey year. We find that these assumptions yield the best fit between the March CPS and annual averages of the monthly CPS data after 1994.

[34] To run these regressions, we use data only from 1994 to 2007, i.e. we exclude the Great Recession and its aftermath. The predictive power of the annual series is higher when we remove the period from 2008 onwards. To a large extent, this can be gauged by visual inspection of Figure A1.

[35] For consistency with the figures presented in the rest of the paper, in these plots all series are computed using cross-sectional weights controlling for composition effects.



(a) Men, working part-time **(b)** Women, working part-time

(c) Men, working part-time involuntarily **(d)** Women, working part-time involuntarily

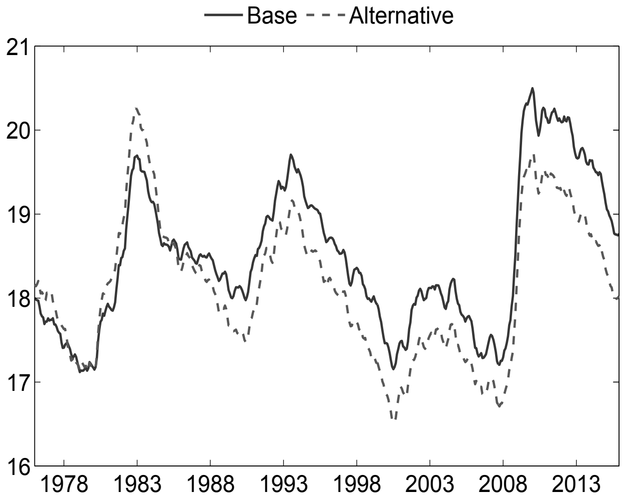
Figure A1: Labor market stocks derived from the March CPS and from the monthly CPS

NOTE: The time series based on the monthly CPS are seasonally adjusted. Figures are reported in million workers.

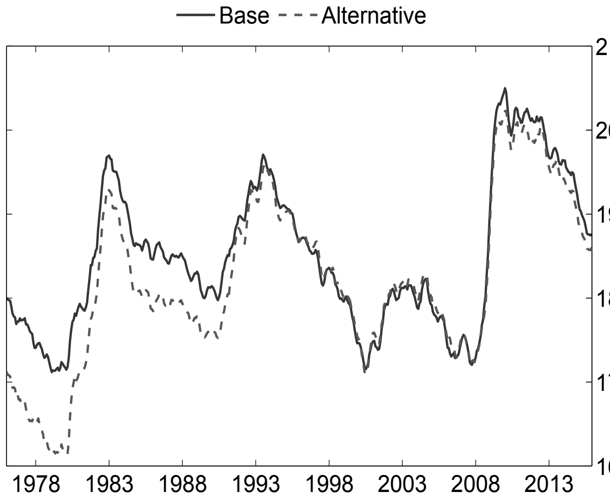
age/sex/race filter. We then remove potential outliers and adjust both labor market stocks and flows to control for seasonality using the Census Bureau's X-13ARIMA-SEATS program.[36]

The subsequent step is to adjust the time series of labor market flows to account for margin error. This adjustment is described in the main text. It should be noted that margin error is particularly important for the analysis conducted in Section 5 of the paper: in that section our cleaning procedure implies matching CPS respondents over four consecutive months, which amplifies sample attrition and hence potential discrepancies between stocks and flows (see Appendix A.4). The last adjustment addresses time-aggregation bias (Shimer [2012]). In all our applications, the conditions on the eigenvalues of the discrete-time transition matrix describing labor market dynamics are always satisfied. This enables us to recover and report bias-adjusted transition probabilities.

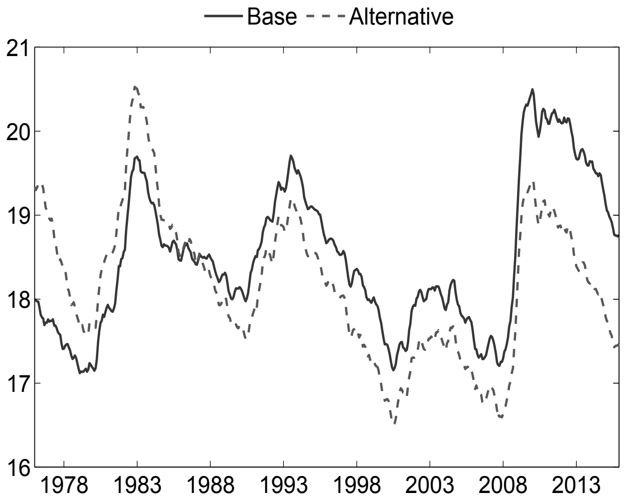
[36]See: `https://www.census.gov/srd/www/x13as/`.



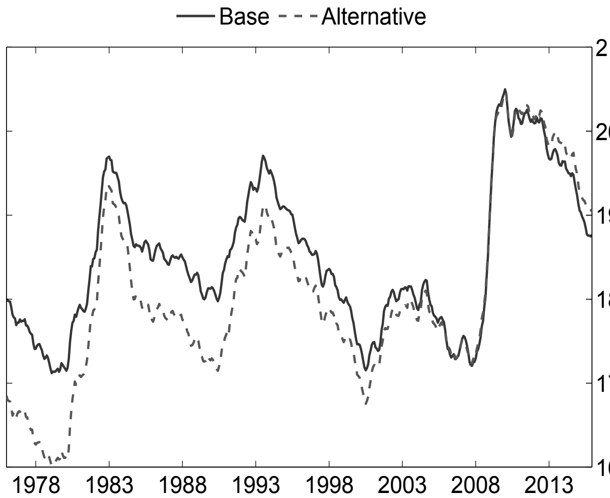
(a) Base vs. unadjusted cross-sectional weights



(b) Base vs. cross-sectional weights adjusted for age



(c) Base vs. cross-sectional weights adjusted for sex and marital status



(d) Base vs. cross-sectional weights adjusted for education

Figure A2: Part-time employment share adjusted for composition effects

NOTE: Seasonally-adjusted time series. The solid line is the part-time employment share based on adjusted weights, as shown in Figure 1 in the main text. The dashed lines show part-time employment shares based on alternative version of the cross-sectional weights.

A.3 Composition effects

To enhance the comparability of the figures we report, throughout the analysis we work with adjusted cross-sectional weights. The purpose of these weights is to hold a set of demographic characteristics constant at their average value over the whole sample period.

We use the March CPS data to obtain adjusted cross-sectional weights. For each year of the sample period, we define an indicator that takes the value of one for observations in that year and is zero for observations in any other year. We run a Logistic regression of the indicator against a set of demographic controls, and use this model to compute the predicted probability of being surveyed in that specific year. Thus, for each individual i we obtain the probability γ_i that she was included in her survey year vs. any other year. As for the 12 monthly CPS files of a given year, we use the coefficients from the Logistic regression ran on March CPS data of that year to retrieve this probability. Finally, we multiply the cross-sectional weight by $(1-\gamma_i)\,\gamma_i^{-1}$ to re-weigh observation i.

Our preferred specification controls for changes in age, sex, marital status and education attainment in the working-age population. The baseline Logistic regression includes dummies for young (aged 16 to 24) and older (aged 55 to 64) individuals, a quartic in age, a dummy for sex interacted with a dummy for married individuals, educational dummies and their interaction with the polynomial in age.[37] To compute worker flows in the monthly CPS, we use the average of adjusted cross-sectional weights as our longitudinal weights.

To see how reweighting affects the data, Figure A2 compares the part-time employment share based on our baseline specification (solid line) with the part-time shares obtained in various alternatives. In Figure A2a, the dashed line uses the cross-sectional weights of the CPS without adjustment. The line matches remarkably well the annual estimates of part-time employment displayed in Figure 1 of Valletta and Bengali [2013]. The authors used the adjustment factors proposed by Polivka and Miller [1998] to address the 1994 redesign of the CPS. Our own strategy to tackle this issue seems to work well in light of the close fit between their estimates and ours. In graph A2b, the dashed line adjusts the data for changes in age only. As can be seen, when one controls for aging of the working-age population over the past decades, there is a modest upward trend in part-time employment caused by the prevalence of part-time work among younger workers. Holding constant gender and marital status, as in graph A2c, yields a trend in the opposite direction. These results are consistent with Valletta and Bengali [2013]. Finally, the increase in educational attainment dampened the rise in part-time employment that would have obtained otherwise, as illustrated by graph A2d. Like young workers, workers with lower educational attainment are often employed part-time. Our baseline adjusted weights compound these different effects.

A.4 Flows between V and I

In Section 5, we construct labor market flows by matching individuals across 4 consecutive months (the longest period of time in which CPS respondents are interviewed consecutively). We use the longitudinal information from the 1st to the 4th month of the interview to minimize measurement error in recorded transitions between months 2 and 3 of the interview.[38] Indeed, as is well known, small amounts of reporting error in individual labor market status at the cross-section can produce large changes in measured flows. We are especially concerned with transitions between voluntary (V) and involuntary (I) part-time employment, which appear spuriously common in the raw data.

To deal with this issue we adapt the practical approach suggested by Elsby et al. [2015]. We use a rule of thumb to detect and correct suspicious labor market status in months 2 and 3 of

[37] We consider four educational categories: "less than high school", "high school graduates", "some college" and "college or higher education".

[38] By months 1, 2, 3 and 4, we refer to those from the four-months period of consecutive interviews. Thus, although not apparent in this terminology, we use respondents from rotation groups 1 and 3 as well as rotation groups 5 to 7. This implies that an individual who remains in the survey for a complete 16-months period (2 periods of 4 consecutive interviews with a 8-months break period between them) can contribute to our computations twice.

the interview. Specifically, we discard transitions between V and I in the following instances:

Observed	Corrected	Observed	Corrected
$F \to V \to I \to V$	$F \to V \to V \to V$	$F \to I \to V \to I$	$F \to I \to I \to I$
$V \to V \to I \to V$	$V \to V \to V \to V$	$I \to I \to V \to I$	$I \to I \to I \to I$
$U \to V \to I \to V$	$U \to V \to V \to V$	$U \to I \to V \to I$	$U \to I \to I \to I$
$N \to V \to I \to V$	$N \to V \to V \to V$	$N \to I \to V \to I$	$N \to I \to I \to I$
$V \to I \to V \to F$	$V \to V \to V \to F$	$I \to V \to I \to F$	$I \to I \to I \to F$
$V \to I \to V \to V$	$V \to V \to V \to V$	$I \to V \to I \to I$	$I \to I \to I \to I$
$V \to I \to V \to U$	$V \to V \to V \to U$	$I \to V \to I \to U$	$I \to I \to I \to U$
$V \to I \to V \to N$	$V \to V \to V \to N$	$I \to V \to I \to N$	$I \to I \to I \to N$

Like Elsby et al. [2015], we correct transitions between N and U (the procedure amounts to replacing V by N and U by I in the above table) in order to improve the analysis of fluctuations in the unemployment rate. Notice that we make no attempt to correct "cycles" such as $V \to I \to V \to I$ and $I \to V \to I \to V$ (likewise, $N \to U \to N \to U$ and $U \to N \to U \to N$).

On average, about 48% of the transitions between V and I observed between months 2 and 3 are deemed suspicious when checked against the information provided in months 1 and 4 of interview. This figure seems relatively high, yet it is in line with estimates of measurement error in other labor market transitions computed using the monthly CPS. For example, Moscarini and Thomsson [2007] report that the unadjusted occupational mobility rate in the monthly CPS files for the years 1979–1993 is 34%, whereas the adjusted rate is less than 4%. Second, and interestingly, the amount of noise is roughly identical for $I \to V$ and $V \to I$ transitions, although the levels of the raw transition probabilities are very different (31.7% vs. 6.68%). Finally, there is little to no evidence of cyclicality in the amount of measurement error. As a result, the cyclical patterns of the raw transition probabilities are also present in their adjusted counterparts (see Borowczyk-Martins and Lalé, 2016).

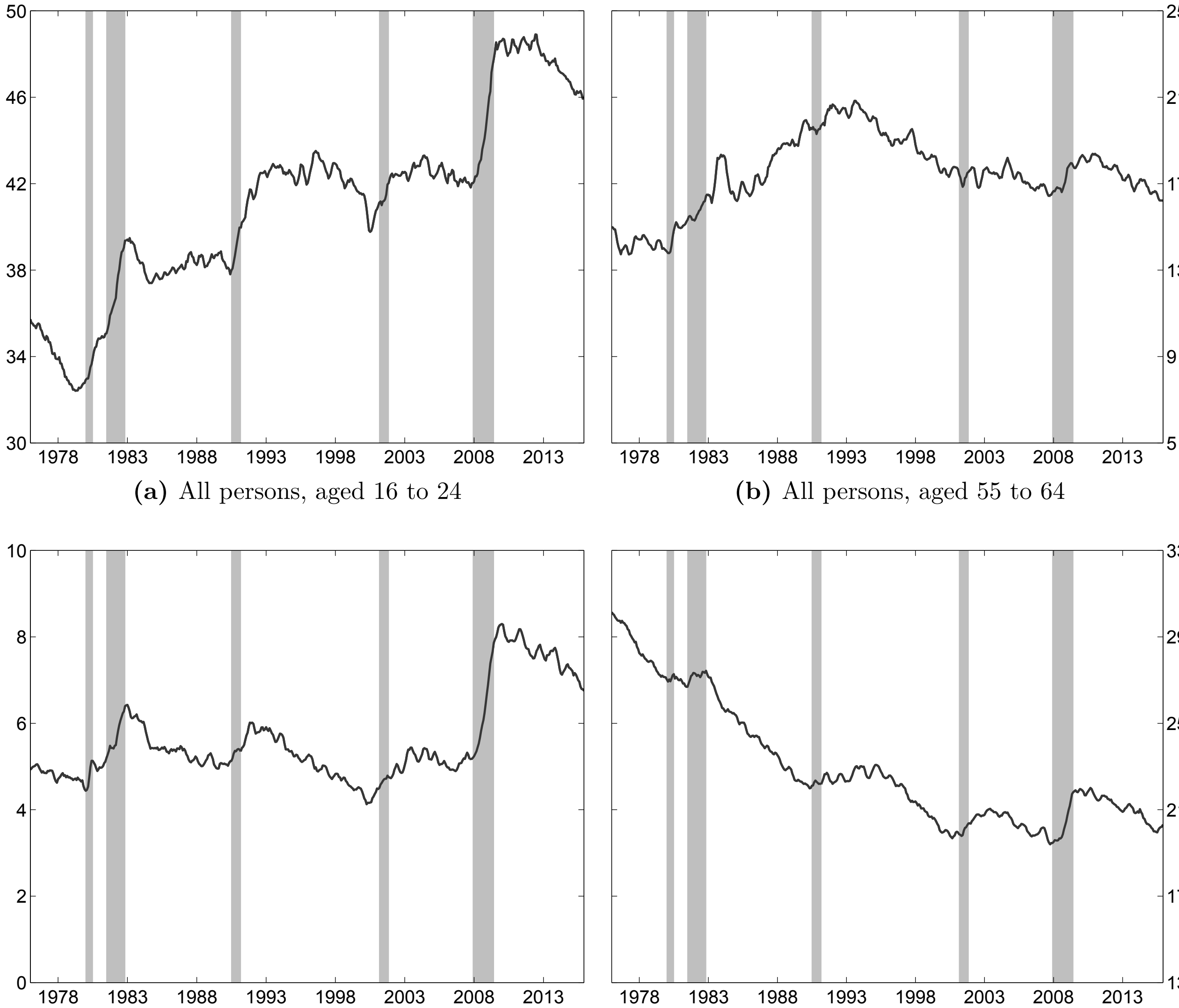
B Online appendix

B.1 More facts

We provide more detailed results for some subgroups of the population and a number of facts that substantiate the points made in Section 6 of the paper.

Trends in part-time employment and transition probabilities

The charts in Figure B1 show the part-time employment share in four subgroups of the employed population: workers aged 16 to 24, workers aged 55 to 64, prime-age (i.e., aged 25 to 54) male and female workers. We notice a number of trends in all plots, except for prime-age men. For younger workers, there is a large increase in the part-time employment share during the first



(a) All persons, aged 16 to 24

(b) All persons, aged 55 to 64

(c) Men, aged 25 to 54

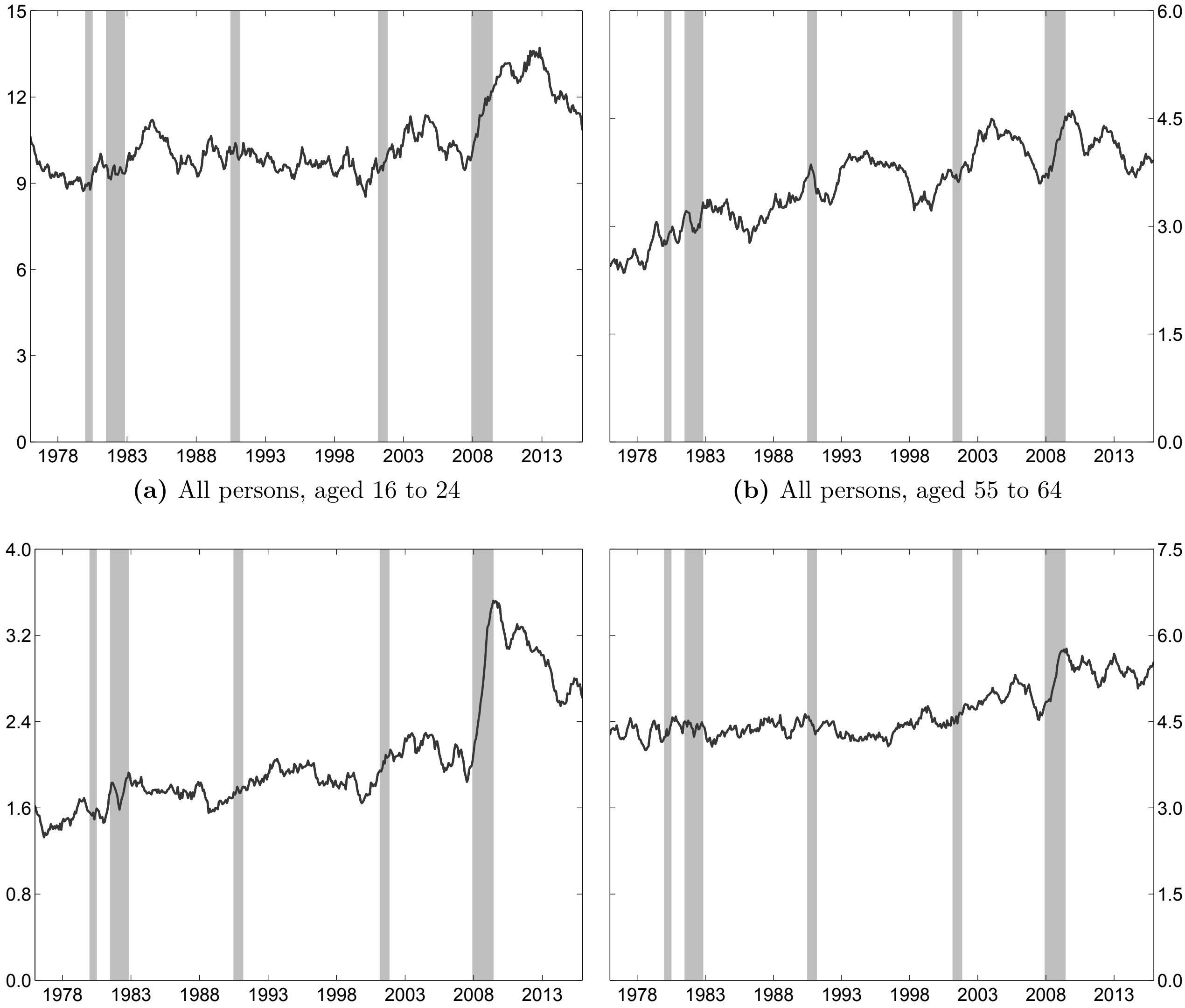
(d) Women, aged 25 to 54

Figure B1: Part-time employment share in selected subgroups

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A). Gray-shaded areas indicate NBER recession periods.

decades of the period under study. The share then stays roughly constant from the mid-1990s until the start of the Great Recession, and rises to almost 50% after the downturn. Among workers aged 55 to 64, there is an upward trend during the first part of the sample period, but the trend is largely reverted in the 20-year period that follows. Without the rebound observed during the last recession, it seems that this part-time employment share would have returned to its 1976 level. Finally, for female workers there is a large downward trend during the first two decades. The part-time employment share in this group plateaus at the beginning of the 1990s, then resumes its decreases and stays in the vicinity of 20-21% in the 2000s.

We continue our description with a study of transition probabilities within the same demographic groups. We find that, in spite of different trends in the part-time share displayed in Figure B1, the behavior of transition probabilities between part-time and full-time employment is qualitatively similar across all four groups: they increase in most years of the sample period. In light of the analysis conducted in Section 4, the *relative* increase in these transition



(a) All persons, aged 16 to 24

(b) All persons, aged 55 to 64

(c) Men, aged 25 to 54

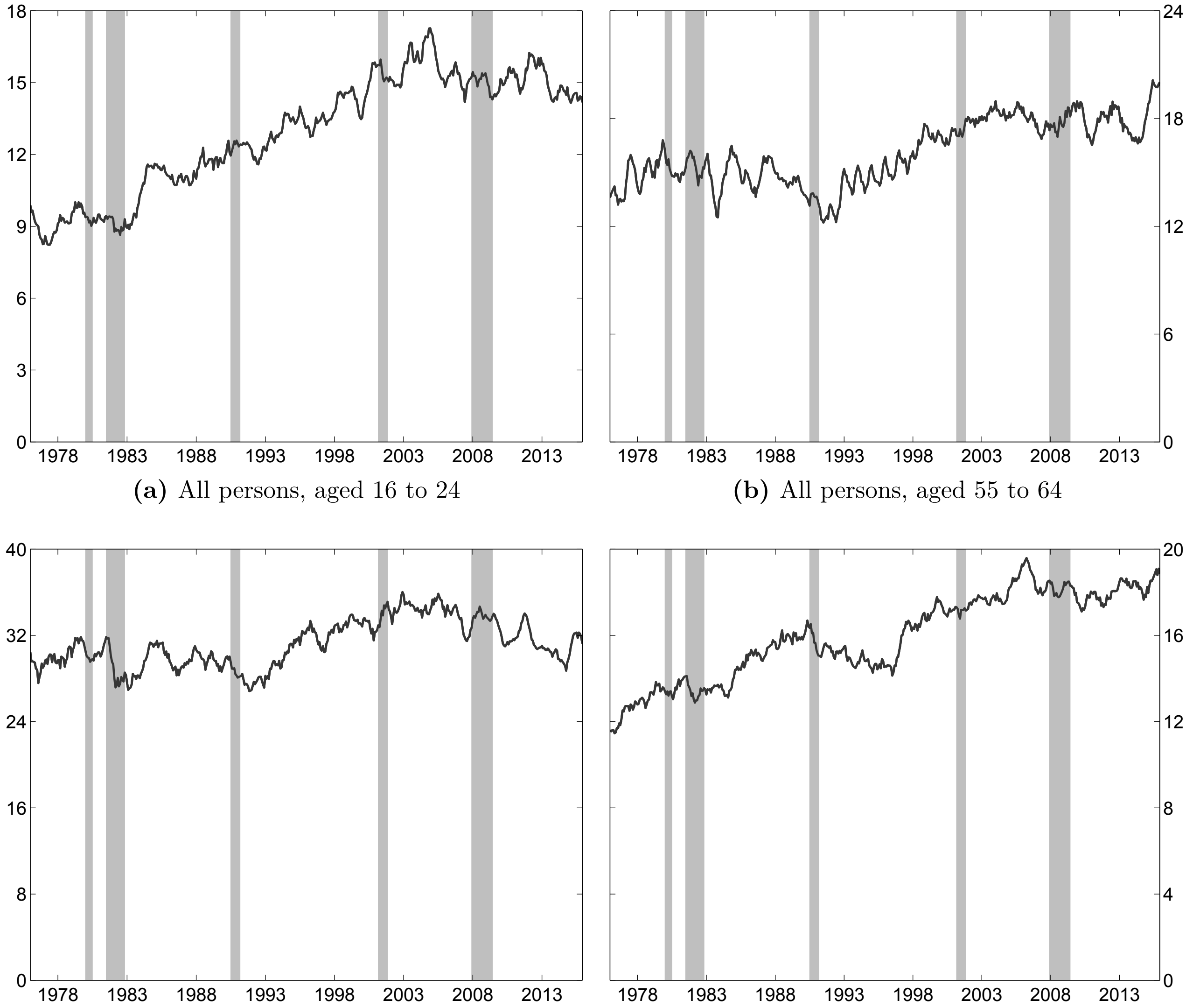
(d) Women, aged 25 to 54

Figure B2: Transition probabilities from full-time to part-time work in selected subgroups

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A). Gray-shaded areas indicate NBER recession periods.

probabilities is key to explain the part-time employment shares presented in Figure B1.

With the exception of younger workers, before the Great Recession the different groups under study experience an increase in the probability to switch from full-time to part-time employment (Figure B2). We also notice some differences in the timing of those changes. For instance, among older workers, the increase is more pronounced before the mid-1990s while the converse is true for prime-age female workers. A similar picture is conveyed by transition probabilities from part-time to full-time employment in Figure B3. Among workers aged 16 to 24, the large increase in part-time employment is accompanied by an *increase* in the probability to move from part-time to full-time employment. For older workers, we observe a slight decrease in this transition probability in the earlier period. The probability increases after 1990, which partly explains the decrease in part-time employment for this group. Finally, prime-age workers (both male and female) experience a rise in turnover from part-time to full-time work throughout most of the period.



(a) All persons, aged 16 to 24

(b) All persons, aged 55 to 64

(c) Men, aged 25 to 54

(d) Women, aged 25 to 54

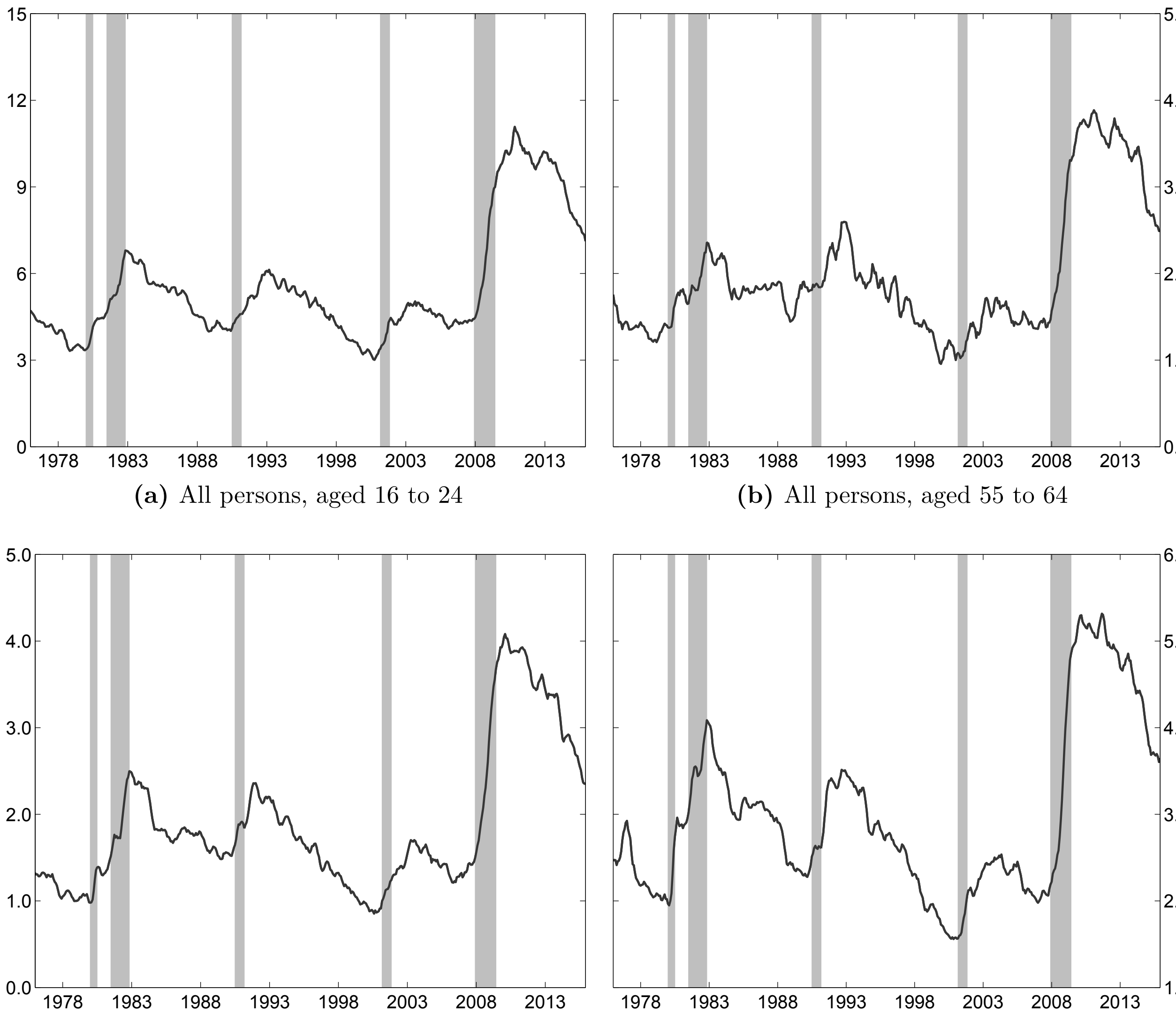
Figure B3: Transition probabilities from part-time to full-time work in selected subgroups

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A). Gray-shaded areas indicate NBER recession periods.

It must be noted that, unlike overall part-time employment, the involuntary part-time work share remains largely stable in all subgroups studied in this section (Figure B4). For prime-age male workers, this share is close to the part-time employment share in levels. This indicates that part-time employment for men is predominantly involuntary. Conversely, involuntary part-time work explains a smaller share of part-time work for women on average across periods. These male-female differences are consistent with our analysis of the components driving the dynamics of $p\,(P \rightarrow F)$ in Subsection 6.3.

Slack work and recessionary increases in involuntary part-time work

We examine changes in the composition of involuntary part-time by reason during the Great Recession and its aftermath. We seek to determine whether the recessionary increase is mostly the result of employed workers who are working part-time hours due to slack work, or if instead



(a) All persons, aged 16 to 24

(b) All persons, aged 55 to 64

(c) Men, aged 25 to 54

(d) Women, aged 25 to 54

Figure B4: Involuntary part-time employment share in selected subgroups

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A). Gray-shaded areas indicate NBER recession periods.

it is due to job seekers not being able to find full-time work. To perform this decomposition, we start by writing the involuntary part-time share as the sum of the part-time share due to slack work (ω_t^s) and the part-time share of workers who cannot find a full-time job (ω_t^f):

$$\omega_t^I = \omega_t^s + \omega_t^f \tag{13}$$

Then, the change from the beginning of the Great recession, denoted t_0, to some subsequent period t_1, can be expressed in this way:

$$\omega_{t_1}^I - \omega_{t_0}^I = \sum_{\tau=t_0}^{t_1-1} \left(\omega_{\tau+1}^s - \omega_\tau^s\right) + \sum_{\tau=t_0}^{t_1-1} \left(\omega_{\tau+1}^f - \omega_\tau^f\right) \tag{14}$$

and the ratio of $\sum_{\tau=t_0}^{t_1-1}\left(\omega^s_{\tau+1}-\omega^s_{\tau}\right)$ to $\omega^I_{t_1}-\omega^I_{t_0}$ quantifies the share of the increase in ω^I_t accounted for by the increase in ω^s_t. Table B1 reports this ratio for various periods during and after the Great Recession. The top row considers the aggregate involuntary part-time share, whereas the remaining ones are computed in specific groups stratified by demographics and, in panel (v) of the table, by occupations.[39]

Table B1: Contribution of "slack work" to changes in the involuntary part time share

	During the Great Recession			After the Great Recession		
	6 months (2008m06)	12 months (2008m12)	18 months (2009m06)	1.5 years (2010m12)	3 years (2012m06)	4.5 years (2013m12)
Total	74.6	77.6	76.5	66.5	63.3	58.1
(i) Gender						
Men	80.4	84.1	82.4	71.4	68.6	62.8
Women	70.7	75.2	72.1	65.6	59.6	55.1
(ii) Age						
16 to 24 years	65.3	67.2	64.9	50.4	48.0	44.4
25 to 54 years	76.7	81.3	80.2	71.9	68.1	61.6
55 to 64 years	78.0	79.4	84.7	72.2	73.8	70.4
(iii) Education						
Less than high-school	74.0	79.6	81.4	73.9	71.0	65.9
High-school graduates	74.9	80.4	75.0	64.2	63.8	60.9
Some college	64.8	68.2	72.8	63.8	58.2	50.5
College or higher education	65.8	79.0	72.4	59.8	54.5	57.4
(iv) Marital status						
Married	72.9	76.6	79.2	70.6	67.9	63.2
Widowed; divorced; separated	62.9	80.3	74.5	69.5	64.6	65.6
Single	76.4	77.5	72.0	60.0	55.0	53.2
(v) Occupations						
Group 1	103.7	97.6	87.4	81.2	77.0	72.7
Group 2	109.2	82.1	78.5	76.3	71.3	61.1
Group 3	80.1	82.2	68.9	60.2	59.0	59.2
Group 4	65.1	67.7	69.4	58.7	55.2	51.5
Group 5	42.2	61.7	71.4	60.4	54.4	50.2

NOTE: CPS data for the period 2007m12–2013m12. Occupational groups are defined as: 1. Farming, forestry and fishing, Precision production, craft, and repairers; 2. Executive, administrative, and managerial occupations, Management-related occupations; 3. Professional specialty occupations; 4. Technical, sales and administrative support occupations; 5. Service Occupations. An entry in the table is the contribution of the share of workers who were working part-time involuntarily due to slack work to the evolution of the involuntary part-time employment share since the beginning of the Great Recession. Contributions are reported in percent.

On impact, the increase in the aggregate involuntary part-time employment share is mostly accounted for by the increase in the share of workers who report slack work/poor business conditions (about 75%). As time goes by, failure to find a full-time job grows in relative importance, although slack work still explains more than 58% of changes in involuntary part-time employment 4.5 years after the end of the Great Recession.[40] Historically, slack work and

[39]Results by industry of employment are available upon request. The findings are similar but not as clear-cut as the results by occupations. The reason is that some broad industry categories lump together occupations that differ substantially with respect to their involuntary part-time work shares.

[40]In Borowczyk-Martins and Lalé [2016], we note that 'slack work conditions' indicate a broader phenomenon that includes, among other symptoms, the lack of full-time jobs. In spite of this potential overlap, we find that the stated reasons 'slack work' and 'could not find a full-time job' seem reasonably linked to actual labor market trajectories. For instance, 74.1% of workers who move from full-time employment to involuntary part-

the inability to find a full-time job have been on a par in explaining the incidence of involuntary part-time employment (see for example Figure 4 in Valletta and Bengali [2013]).

The dynamics of involuntary part-time work within specific subgroups of workers is similar to its behavior in the aggregate: the recessionary increase is mostly explained by slack work conditions, while the share of workers who cannot find a full-time job increases slowly and contributes to high involuntary part-time employment shares mostly during the sluggish recovery. Interestingly, we find more differences in the trajectory of involuntary part-time work when looking at the data by occupational groups. On the one hand, in executive, administrative, managerial and management-related occupations (group 2), the involuntary part-time employment share is low (less than 1%) and very few individuals work part-time because they cannot find a full-time job. In fact, the share of the latter decreases slightly at the beginning of the Great Recession, while slack work predominantly explains the increase in involuntary part-time work. On the other hand, in service occupations (group 5) where involuntary part-time work is common (6.5% of employment), the share of workers who cannot find a full-time job increases early on in the recession. Consequently, the peak in the relative importance of 'slack work' occurs later during the recession episode.

B.2 Sensitivity checks

We report a number of robustness checks for the time series shown in the paper, and additional results based on a variance decomposition of these time series.

Correction procedure: Cross-validation using SIPP data

By construction, our procedure to adjust labor market stocks tends to align pre-1994 data to the levels of the time series after the CPS redesign. To detect a discrepancy around January 1994, we compare our time series to data from the Survey of Income and Program Participation (SIPP).[41] Specifically, we use the 1990, 1991, 1992 and 1993 panels of the SIPP to construct monthly labor market stocks of part-time employed workers that span the period from December 1989 to October 1995.[42] [43] In Figure B5 we plot these data for different subgroups of the working-age population, and we also report the corresponding time series based on the monthly CPS using our adjutment protocol. To provide a clear picture of the data before making further adjustments, we do not control for seasonality or for any composition effect.

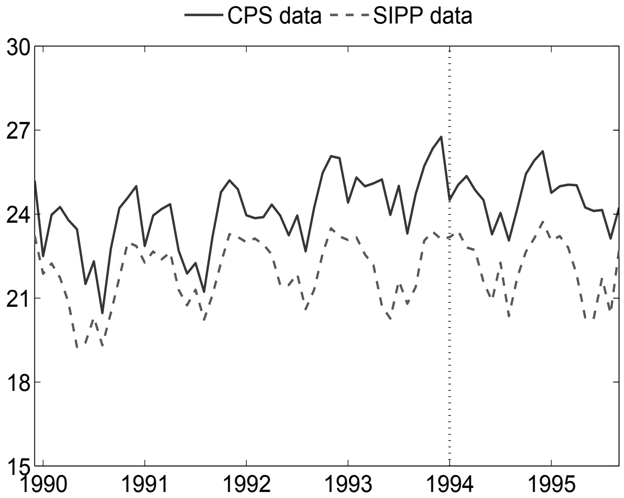
As can be observed, there are some discrepancies in levels between the SIPP-based and CPS-based estimates. This affects data for younger and older workers and, to a lesser extent,

time work without an intervening spell of non-employment report 'slack work' as the main reason for their change in employment category. 61.7% of workers who were unemployed report 'could not find a full-time job' as the main reason for working part-time hours when they move into employment.

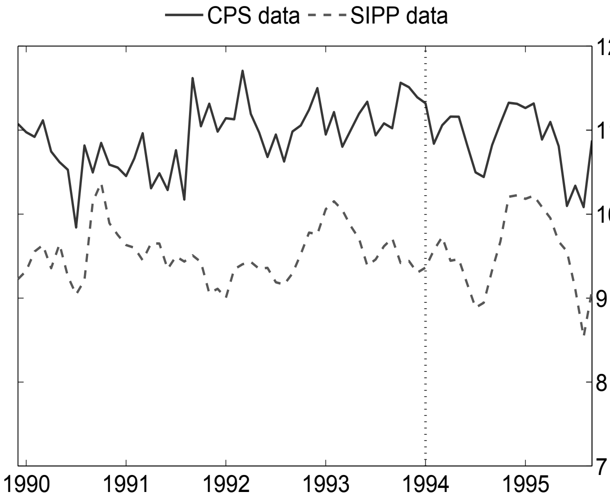
[41]See: http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html.

[42]Although the SIPP came into existence before the 1990 panel, there were important changes introduced in the SIPP files after 1989. Our goal in this section is to construct time series with a sufficient window of time to scrutinize January 1994, not to obtain long time series before this period. We use the 1990-1993 panels because the structure of these files is comparable and they are sufficient for our purposes.

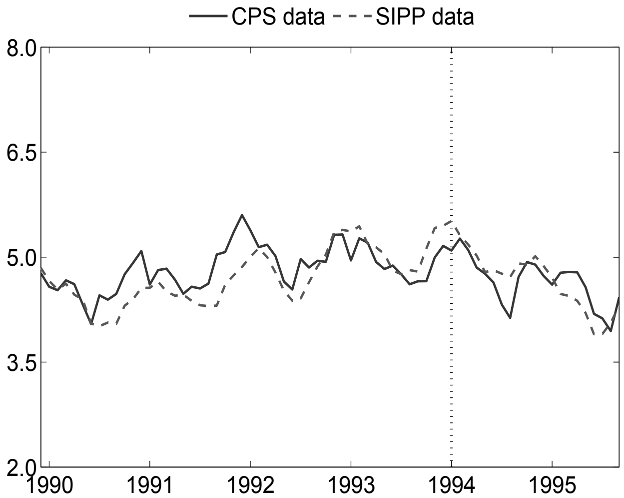
[43]In principle, the 1990–1993 panels data span the period from October 1989 to December 1995. We drop the first and last two months of the period because these contain less than three SIPP rotation groups, which result in very large discrepancies in the estimates of labor market stocks.



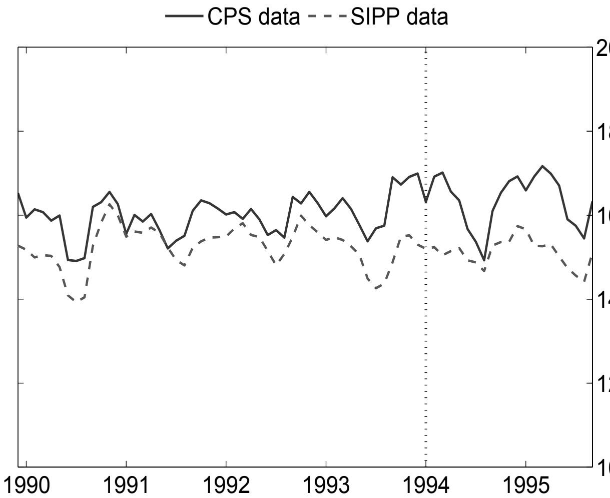
(a) All persons, aged 16 to 24



(b) All persons, aged 55 to 64



(c) Men, aged 25 to 54



(d) Women, aged 25 to 54

Figure B5: Part-time employment stocks in the monthly CPS and in the SIPP

NOTE: The solid line show part-time employment stocks based on the monthly CPS. The dashed lines show part-time employment stocks based on the SIPP. Figures are reported as a share (in pp.) of the civilian population of the corresponding age/gender group. The vertical line in each plot indicates January 1994.

data for prime-age female workers. The figures for prime-age men, on the other hand, are very consistent across the two surveys. More importantly, we see that the behavior of the SIPP-based and CPS-based time series remain similar across the 1994 break (denoted by the vertical line). Thus, the adjustment protocol presented in Appendix A.1 does not seem to generate any spurious trend in the CPS-based time series. This is noteworthy because, as suggested by Figure A1, its does introduce a trend in some of the stocks when these are measured in levels (i.e., not normalized by the size of the civilian population).

The fact that the discrepancy between any of our SIPP-based and CPS-based stocks remains constant across the 1994 break gives us confidence in the reliability of our estimates. In addition to this external validation, we find no evidence of systematic breaks in January 1994 in the different time series displayed in the figures of the paper.

Sensitivity to definitions and sample restrictions

In order to check for the robustness of our main results, we estimate the transition probabilities in the Markov-chain models in equation (1) and its extended version for business-cycle analysis in alternative samples. More precisely, for each of the two models we compute transition probabilities for three samples: private firm salaried workers (we exclude government workers, unincorporated self-employed workers and unpaid family workers), employed workers with the hours cutoff defining part-time employment lowered to 30 usual hours per week, and no single jobholders (we exclude workers who hold more than one job at any point in time).

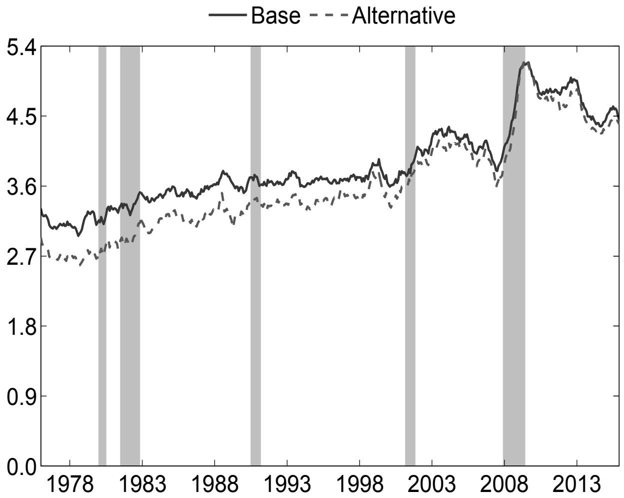
Figure B6 reports the main transition probabilities ($p(F \to P)$ and $p(P \to F)$) for each of the three samples respectively in the top, middle and bottom panels. In each plot the solid and dashed lines denote the transition probability computed respectively in the baseline sample and in one of the alternative samples. For plots (c), (d), (e) and (f), our robustness checks can only be carried out with post-1994 CPS data.[44] As can be seen by inspecting the various plots in Figure B6, the sample restrictions entail changes in the levels of some transitions probabilities, but have little or no effect on the time-series dynamics. In that sense our main results concerning the sources of long-run variation of part-time employment are robust to changes in the sample definition.

We reach a similar conclusion concerning the robustness of our findings on the short-run dynamics of part-time employment. Since our analysis of the short-run dynamics focuses on involuntary part-time employment and emphasizes the role of the inflows from employment, in Figure B7 we display the transition probabilities $p(F \to I)$ and $p(V \to I)$ computed in the baseline sample and in each of the three robustness samples. It is clear that their cyclical behaviors are not driven by any of the sample restrictions considered or by the definition of part-time employment.

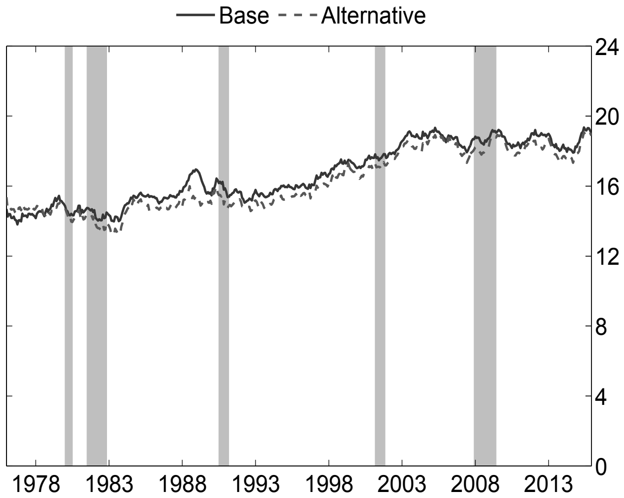
Variance decomposition: Involuntary part-time share vs. rate

We show that the involuntary part-time *share* behaves very similarly to the involuntary part-time *rate*, defined as the ratio between involuntary part-time workers and the size of the labor force. In so doing, we highlight that the different dynamics between the involuntary part-time share and the unemployment rate in Table 4 are not driven by differences in the denominator of those two statistics. The right-hand side panel in Table B2 displays the beta coefficients of the variance decomposition of the involuntary part-time rate. The left-hand side panel reproduces results from Table 4. As can be observed, the sources of variations and relative importance of inflows and outflows are virtually identical for employment states (F and V) and the differences for non-employment states (U and N) are quantitatively negligible.

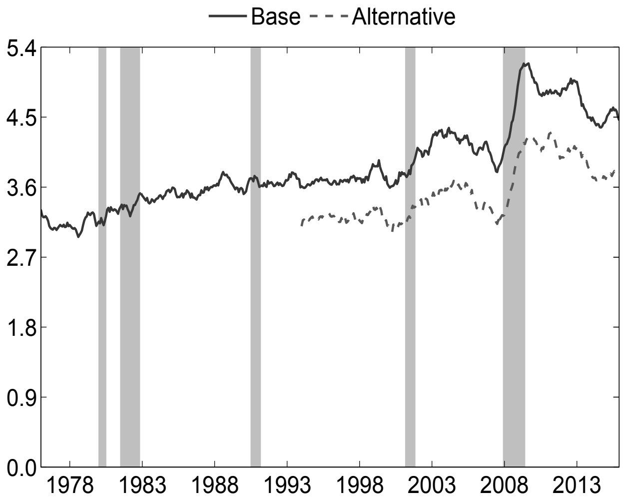
[44] Recall that before the 1994 redesign of the survey, CPS respondents do not report usual hours (they indicate whether they usually work less than 35 hours per week only when they did work less than 35 hours during the reference week of the survey) and there is no information on multiple jobs.



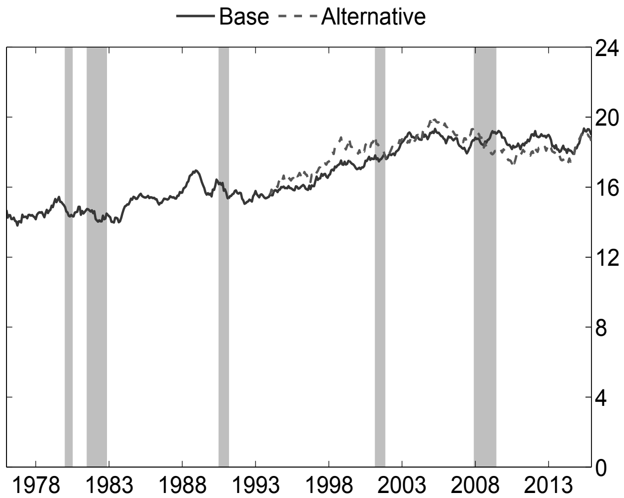
(a) Base vs. Private sector salaried workers



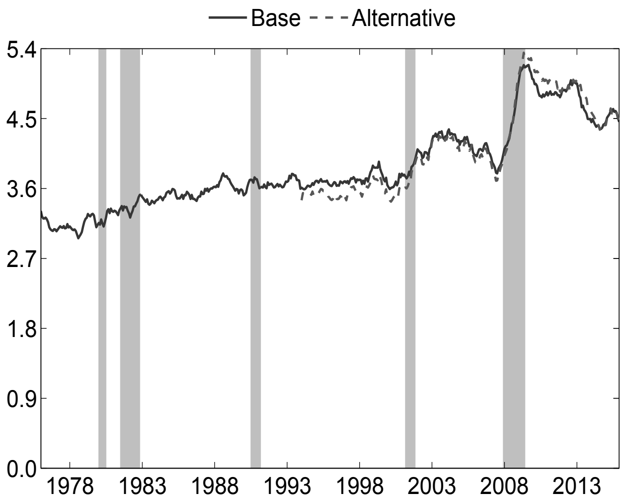
(b) Base vs. Private sector salaried workers



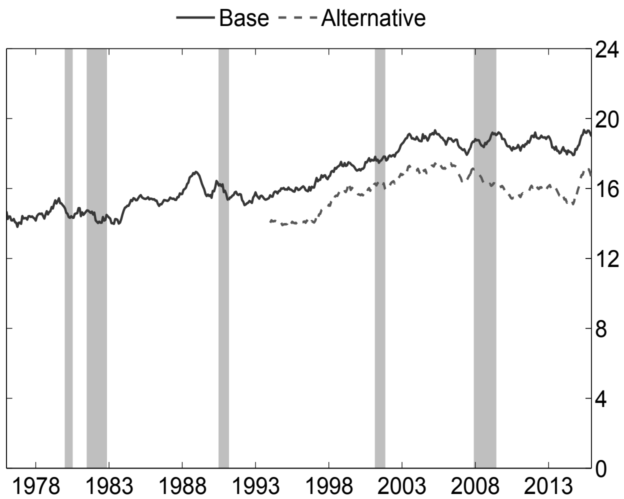
(c) Base vs. Part-time less than 30 hours



(d) Base vs. Part-time less than 30 hours



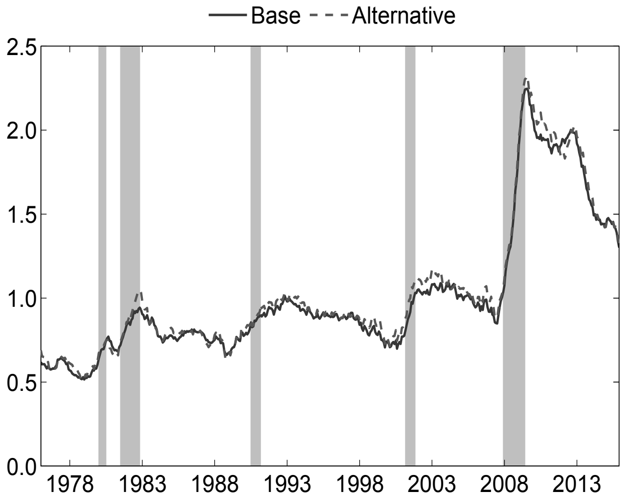
(e) Base vs. No multiple jobholders



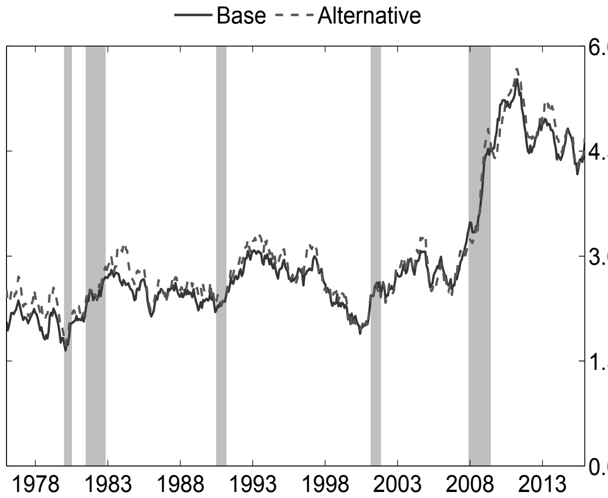
(f) Base vs. No multiple jobholders

Figure B6: Sensitivity checks: Transition probabilities $F \rightarrow P$ (left) $P \rightarrow F$ (right)

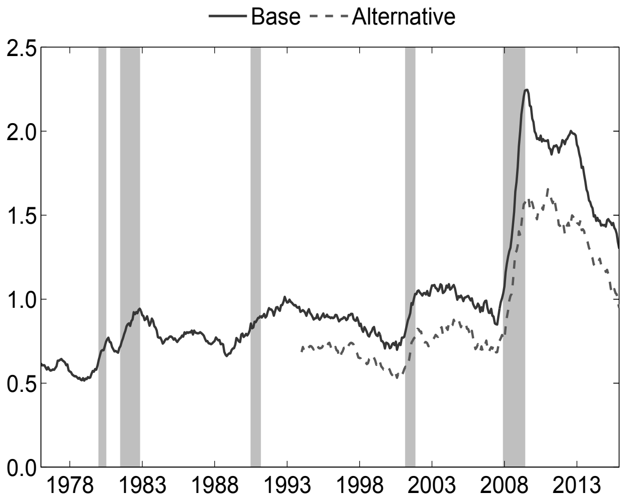
NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A for data details). Gray-shaded areas indicate NBER recession periods. The solid lines show transition probabilities from the base sample, also displayed in Figure 2 in the main text. The dashed lines show part-time the transition probabilities based on different sample restrictions or different definition of part-time employment.



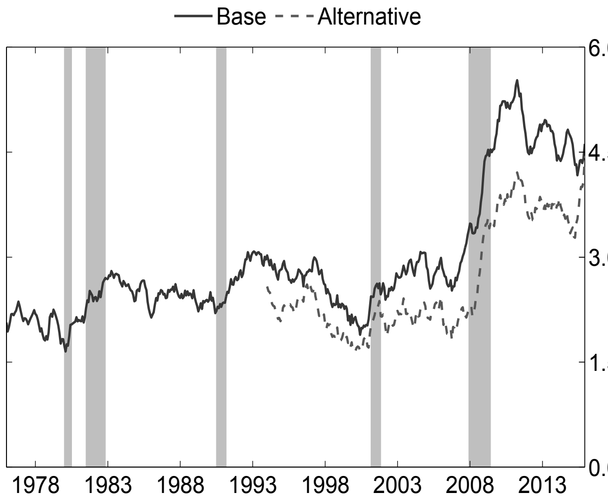
(a) Base vs. Private sector salaried workers



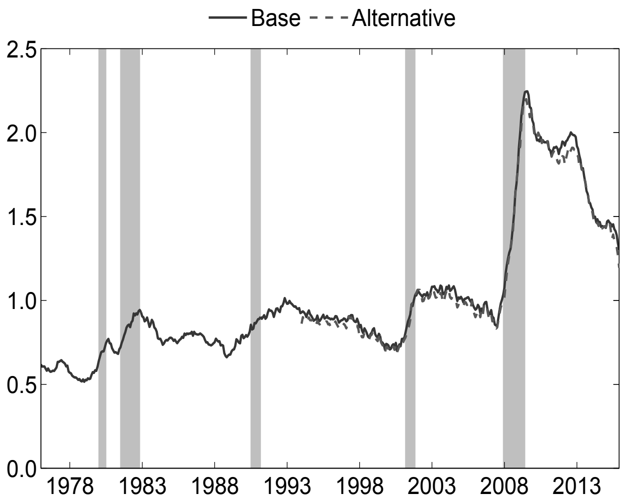
(b) Base vs. Private sector salaried workers



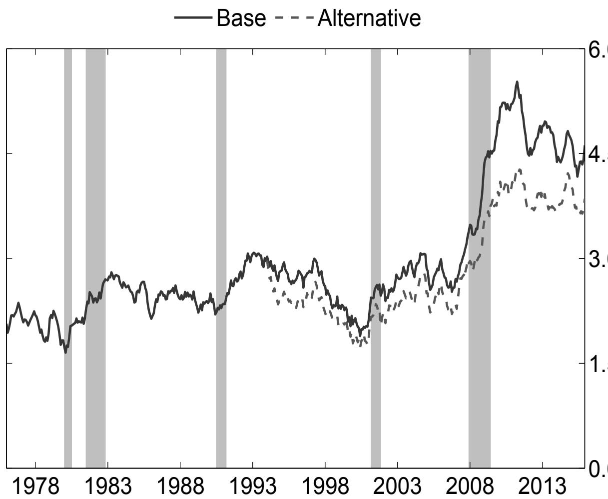
(c) Base vs. Part-time less than 30 hours



(d) Base vs. Part-time less than 30 hours



(e) Base vs. No multiple jobholders



(f) Base vs. No multiple jobholders

Figure B7: Sensitivity checks: Transition probabilities $F \rightarrow I$ (left) $V \rightarrow I$ (right)

NOTE: Seasonally-adjusted, MA-smoothed time series cleared from composition effects (see Appendix A for data details). Gray-shaded areas indicate NBER recession periods. The solid lines show transition probabilities from the base sample, also displayed in Figure 4 in the main text. The dashed lines show part-time the transition probabilities based on different sample restrictions or different definition of part-time employment.

Table B2: Variance contributions: Involuntary part-time share vs. rate

Involuntary part-time share				Involuntary part-time rate			
Inflows		Outflows		Inflows		Outflows	
$\beta(F \to I)$	29.5	$\beta(I \to F)$	22.8	$\beta(F \to I)$	29.4	$\beta(I \to F)$	22.2
$\beta(V \to I)$	17.6	$\beta(I \to V)$	12.7	$\beta(V \to I)$	17.9	$\beta(I \to V)$	12.7
$\beta(U \to I)$	6.20	$\beta(I \to U)$	2.31	$\beta(U \to I)$	8.22	$\beta(I \to U)$	3.13
$\beta(N \to I)$	4.30	$\beta(I \to N)$	1.27	$\beta(N \to I)$	3.67	$\beta(I \to N)$	0.58
$\sum_{i \neq I} \beta(i \to I)$	57.6	$\sum_{j \neq I} \beta(I \to j)$	39.1	$\sum_{i \neq I} \beta(i \to I)$	59.2	$\sum_{j \neq I} \beta(I \to j)$	38.7
$\sum_{i \neq I} \beta(i \to I) + \sum_{j \neq I} \beta(I \to j) = 96.7$				$\sum_{i \neq U} \beta(i \to I) + \sum_{j \neq U} \beta(I \to j) = 97.9$			

NOTE: CPS data cleared from composition effects (see Appendix A), covering the period 1976m01–2015m12. All entries in the table are reported in percent.

Variance decomposition: Other definitions and sample restrictions

To demonstrate the robustness of the results of Subsection 5.2, in Table B3 we report the results from the variance decomposition conducted with different data. We assess the effects of: (i) correcting spurious transitions across labor market states, (ii) using different definitions of part-time employment and (iii) using different sample restrictions. Since (ii) and (iii) can be implemented only with post-1994 CPS data, we restrict attention to this period. Columns 1a and 1b give the baseline results in data from 1994 onwards. In columns 2a and 2b, we define part-time work as less than 30 total usual hours of work per week. Columns 3a and 3b revert to the definition of part-time work based on a cutoff of 35 hours, but removes multiple jobholders from the sample. Finally, in columns 1a, 2a, 3a we do not correct spurious transitions between V and I and also between N and U (therefore we match individuals only across two consecutive periods). Columns 1b, 2b, 3b are based on the correction strategy presented in Appendix A.4.

In all instances, we note that adjusting transitions between V and I lowers the variance contribution of transitions to and from V. A similar result holds for spurious transitions between N and U and the variance contribution of N to the unemployment rate. This effect is much less pronounced in columns 2a and 2b; these columns indicate that transitions between V and I that contribute to cyclical variations in involuntary part-time work occur among workers who report 30 to 34 usual hours per week. The fit of the dynamic variance decomposition remains very high in all instance, with the exception of the unemployment rate in columns 3a and 3b: without multiple jobholders, the decomposition explains a significantly lower fraction of variations in the unemployment rate. The results presented in columns 2b and 3b confirm the baseline results reported in Column 1b. The results in Column 1b are consistent with the results displayed in Table 4 for the period from January 1976 onwards.

Table B3: Variance contributions: Results from sensitivity checks

	Benchmark (1a)	(1b)	< 30 hours (2a)	(2b)	No multiple jobs (3a)	(3b)
			Involuntary part-time share			
Inflows						
$\beta(F \to I)$	30.2	34.5	31.6	33.9	27.2	29.5
$\beta(V \to I)$	23.9	18.0	8.84	8.07	22.6	13.8
$\beta(U \to I)$	-0.27	1.68	3.64	9.57	6.61	5.64
$\beta(N \to I)$	1.81	6.75	7.12	10.9	2.98	10.2
$\sum_{i \neq I} \beta(i \to I)$	55.6	60.9	51.2	62.4	59.4	59.1
Outflows						
$\beta(I \to F)$	15.3	21.0	15.9	14.7	11.6	22.5
$\beta(I \to V)$	22.3	12.8	21.6	12.1	21.6	8.48
$\beta(I \to U)$	3.70	1.25	7.91	5.20	7.91	9.51
$\beta(I \to N)$	0.65	0.70	0.54	5.54	0.55	2.75
$\sum_{j \neq I} \beta(I \to j)$	41.9	35.7	45.9	37.5	41.7	43.2
$\sum_{(i,j), i \neq j} \beta(i \to j)$	97.5	96.7	97.1	99.9	101.1	102.3
			Unemployment rate			
Inflows						
$\beta(F \to U)$	13.0	15.5	13.7	17.6	15.3	21.0
$\beta(V \to U)$	2.23	2.05	3.07	2.11	2.60	1.25
$\beta(I \to U)$	4.33	6.74	3.99	6.32	4.35	8.59
$\beta(N \to U)$	25.6	20.9	28.4	19.8	18.4	15.0
$\sum_{i \neq U} \beta(i \to U)$	45.2	45.2	50.1	45.8	40.6	45.9
Outflows						
$\beta(U \to F)$	16.3	20.8	15.2	20.6	20.7	24.9
$\beta(U \to V)$	3.85	6.36	3.22	5.42	1.86	0.95
$\beta(U \to I)$	5.89	7.80	3.86	5.19	7.44	9.68
$\beta(U \to N)$	30.4	19.2	29.0	19.3	20.1	11.3
$\sum_{j \neq U} \beta(U \to j)$	56.4	54.2	51.3	50.5	50.1	46.8
$\sum_{(i,j), i \neq j} \beta(i \to j)$	101.5	99.3	100.5	96.3	90.7	92.7

NOTE: CPS data for the period 1994m01–2015m12. All entries are reported in percent. Columns 1x: baseline definition; all civilians of working-age. Columns 2x: part-time employment is defined as less than 30 total usual hours of work per week; all civilians of working-age. Columns 3x: baseline definition; civilians of working-age who do not hold more than one job. Columns Xa: Data unadjusted for spurious transitions between V and I and between N and U. Columns Xb: Data adjusted for spurious transitions between V and I and between N and U.