The Ins and Outs of Involuntary Part-time Employment*

Daniel Borowczyk-Martins†
Copenhagen Business School
and IZA

Etienne Lalé‡
Université du Québec à Montréal,
CIRANO and IZA

Abstract

We develop and implement a protocol to measure U.S. monthly time series of involuntary part-time employment stocks and flows from 1976 until today. Armed with these new data, we provide a comprehensive account of the cyclical dynamics of involuntary part-time work. We find that the recessionary increase in involuntary part-time employment is consistently driven by a jump in the transition probability from other employment states to involuntary part-time employment, and a drop in the reverse transition probability. We compare the dynamics of unemployment and involuntary part-time employment to argue that they reflect the operation of distinct labor-adjustment channels. While unemployment dynamics are driven by movements in job creation and destruction, the dynamics of involuntary part-time employment reflect changes in employers' labor utilization.

JEL codes: E24; E32; J21.

Keywords: Involuntary part-time employment; Unemployment; Labor market flows; Business cycles

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†Address: Copenhagen Business School, Department of Economics, Porcelaenshaven 16A, 2000 Frederiksberg, Denmark – Email: dbm.eco@cbs.dk.

‡Address: Department of Economics, Université du Québec à Montréal, C.P. 8888, Succ. centre ville, Montréal (QC) H3C 3P8, Canada – Email: lale.etienne@uqam.ca.

1 Introduction

Worker flows across labor market states are key source of empirical evidence to understand aggregate labor market dynamics. The recent research in the U.S. labor market analyzed the dynamics of unemployment (the extensive margin of labor adjustment) using a three-state model, where individuals move across employment, unemployment and nonparticipation. Borowczyk-Martins and Lalé [2019] extended this framework to encompass the intensive margin of labor adjustment. They showed that cyclical fluctuations in average hours per worker are predominantly driven by the behavior of part-time employment and used a four-state model of worker flows (by separating the employment state into part-time an full-time employment) to describe those dynamics. In this paper we extend this literature further by analyzing the dynamics of involuntary part-time employment.

The Bureau of Labor Statistics (BLS) of the United States defines involuntary part-time employment (or part-time for economic reasons) as a state in which individuals want to work full-time but currently work part-time because they cannot find a full-time job or face slack work conditions in their current job. In recent years interest in these fluctuations has mounted on both sides of the Atlantic, as the share of individuals working part-time involuntarily increased spectacularly during the Great Recession in the U.S. and in the majority of European economies (see Canon et al. [2014] and Borowczyk-Martins [2017]). Figure 1 shows the series of U.S. unemployment and involuntary part-time employment rates since 1955 until today. Both series exhibit a stable pattern of large countercyclical variation around recessions. Fluctuations in the two labor market rates capture a key aspect of the effect of the business cycle on the labor market: during recessions large number of workers supply less labor to the market than they would like to.

Our study of fluctuations in involuntary part-time employment is organized around two main questions. First, what are the cyclical patterns of worker flows in and out of involuntary part-time employment? What is their relative importance in driving the recessionary spikes and subsequent falls in involuntary part-time employment visible in Figure 1? Second, are fluctuations in the ins and outs of involuntary part-time employment different from those of unemployment? Is turnover between involuntary part-time employment and unemployment over the business cycle quantitatively important? To answer these questions, we measure transition probabilities across five labor market states (full-time employment, voluntary part-time employment, involuntary part-time employment, unemployment and nonparticipation) consistently from 1976 until today. Our analysis uncovers several results. First, we find that involuntary part-time employment is a very transitory labor market state and its cyclical variation is overwhelmingly driven by within-employment reallocation (transitions to and

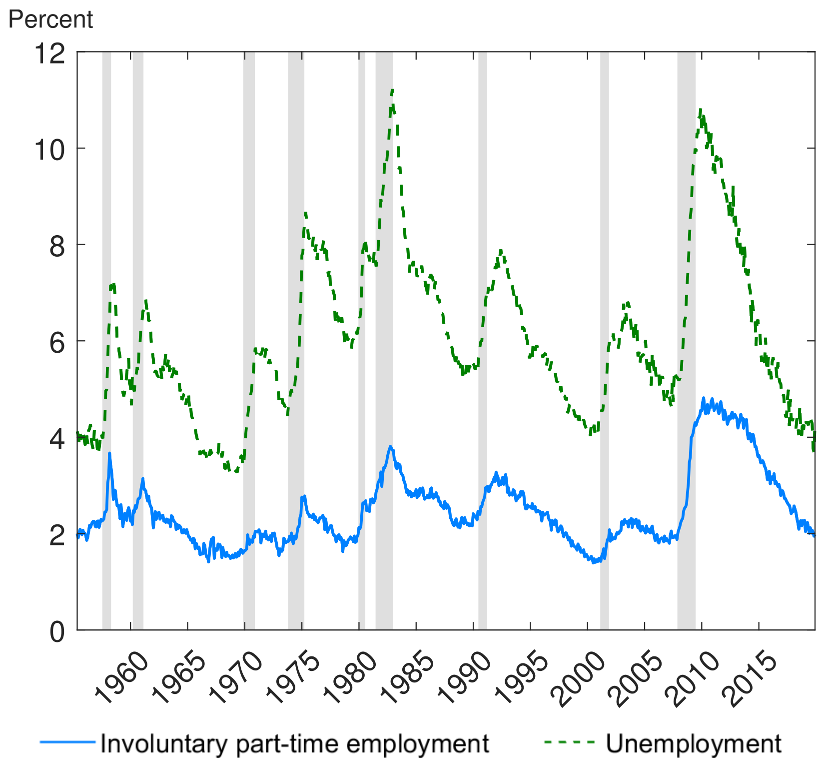

Figure 1: The involuntary part-time employment and unemployment rates

Notes: BLS data, 1955m05 – 1975m12 and CPS data, 1976m01 – 2019m12. Counts of involuntary part-time and unemployed workers divided by the civilian labor force. BLS data: ID LNS11000000 (Civilian Labor Force Level), LNS12032194 (Employment Level - Part-Time for Economic Reasons) and LNS13000000 (Unemployment Level). BLS data are aligned to post-1976 CPS data using a multiplicative adjustment factor. Post-1976 CPS data on involuntary part-time work are corrected for the 1994 break. All series are adjusted for seasonality and smoothed using a one-period, two-sided MA filter. All series are expressed in percent. The gray-shaded areas indicate NBER recession periods.

from full-time and voluntary part-time employment). Second, fluctuations in involuntary part-time employment flows exhibit systematic patterns over the business cycle. During recessions, involuntary part-time employment increases due to an increase in inflows from other employment states and by a drop in outflows to other employment states. As recoveries get underway, low outflows to other employment states become a more important driver of involuntary part-time employment dynamics. In the two most recent recessions the role of inflows from other employment states is greater compared to earlier recessions and is accompanied by a substantial increase in workers who report slack work conditions as their main reason for working part-time involuntarily. Third, turnover between involuntary part-time employment and unemployment is low and only moderately cyclical, hence, it plays no major role in the cyclical dynamics of the two labor market rates.

The point of departure of our investigation is data from the Current Population Survey

(CPS), which has informed the majority of studies on worker flows in the U.S. labor market. The distinction between voluntary and involuntary part-time work in the CPS introduces two measurement challenges that we address in this paper. The first concerns a break in the series of involuntary part-time employment stocks and flows. The basic monthly (BM) survey underwent a significant redesign in January 1994, which, among other things, introduced a tighter concept of involuntary part-time employment. From 1994 onwards to be counted as an involuntary part-time worker individuals must state that they want to work full-time. We propose a novel adjustment protocol that allows us to extend the monthly time series of involuntary part-time employment stocks and flows based on the post-1994 definitions back to 1976. Our approach can be described in two steps. In the first step, we adjust the levels of the series of BM stocks. We combine them with the series of part-time employment stocks calculated using the Annual Social and Economic Supplements (ASEC) of the CPS to predict the correct BM series prior to 1994. The underlying assumption is that the close comovement between the post-1994 ASEC and BM time series is the same in the pre-1994 period. In the second step, we adjust the series of flows. Specifically, we correct the pre-1994 flows by targeting the dynamics of the series of stocks estimated in the first step using a margin-error (or raking) procedure. Both adjustment steps work well in practice, and we conduct several exercises to assess the robustness and plausibility of our estimates.

The second measurement challenge arises from the fact that, while conceptually distinct, workers' classification between voluntary and involuntary part-time employment in the CPS is fuzzy. This opens the possibility that an individual's report of part-time employment status is misclassified. It is well-known at least since Abowd and Zellner [1985] and Poterba and Summers [1986] that small levels of misclassification, with negligible effects on the estimates of stocks, can produce large biases in estimates of worker flows. The elevated levels of flows between voluntary and involuntary part-time employment motivates us to assess the hypothesis that some transitions within part-time employment are spurious. To gauge the effects of potentially spurious transitions within part-time employment, we apply a reclassification approach similar to Elsby et al. [2015]. We find that our reclassification approach substantially reduces the amount of turnover within part-time employment, as well as its cyclicality. However, it leaves the substantive conclusions of our analysis largely unchanged.

Having established our main empirical findings and assessed their robustness, we discuss how they relate to, and can be informative for, research in macroeconomics of the labor market. The main takeaway from our analysis is that fluctuations in involuntary part-time employment provide different, and hence complementary, information on labor market adjustment compared to unemployment fluctuations. In a typical recession, involuntary part-time employment increases, and remains elevated during the recovery, mainly because employed workers are more likely to move to involuntary part-time work and less likely to do the reverse transition. Using post-1994 data, we further show that turnover between other employment states and involuntary part-time employment takes place overwhelmingly at the same employer. In other words, the cyclical dynamics of involuntary part-time employment seems to be, not only a *within-employment* phenomenon, but mostly a *within-employer* one. Therefore, we argue that cyclical fluctuations in involuntary part-time employment reflect the operation of a distinct labor-adjustment channel compared to job creation and destruction, which drives the cyclical dynamics of unemployment. This cautions against a popular interpretation that high levels of involuntary part-time work during and after recessions are a sign of weak creation of new full-time employment opportunities. In contrast, our analysis points to elevated involuntary part-time employment as evidence of continued fragility of ongoing employment relationships.

Related literature. This paper contributes to the empirical literature on U.S. labor market dynamics. Our findings on unemployment fluctuations reinforce the main conclusions of the more recent literature (see Elsby et al. [2009], Fujita and Ramey [2009], Shimer [2012] and Elsby et al. [2015]). While our substantive findings on involuntary part-time employment fluctuations were documented by Canon et al. [2014] in post-1994 data (and have since been confirmed independently by us, Lariau [2017] and Warren [2017]), we show that they are also present in earlier recessions and that they are robust to adjustments for potentially spurious transitions and time aggregation bias.[1] Furthermore, different from those papers, we decompose the cyclical variation of involuntary part-time employment using the method developed by Elsby et al. [2015], which also accounts for out-of-steady-state dynamics. Borowczyk-Martins and Lalé [2019] (BML19) quantified the importance of the *share* of involuntary part-time employment flows to the dynamics of part-time employment since 1976 by combining data from the BM files and the Outgoing Rotation Group samples of the CPS. The present paper estimates the *levels* of voluntary and involuntary part-time employment inflows and outflows before the CPS redesign break, allowing us to conduct a systematic analysis of fluctuations in involuntary part-time employment. More generally, an important motivation for this paper is to provide economists with useful information for developing, calibrating or quantitatively assessing models of cyclical labor adjustment featuring both margins of labor adjustment. To that end, we are making the dataset used in this paper available from our personal webpages. We hope that our new estimates of involuntary part-time employment stocks and flows covering several U.S. recessions, and the empirical moments produced by our variance decompositions, will be used to further advance

[1] This version of paper also improves substantially upon the first version, dated from November 2015, in which we were not yet able to address the break created by the CPS redesign to study pre-1994 data.

knowledge on cyclical labor market dynamics.

In addition to the empirical contribution, our approach to deal with the 1994 CPS redesign adds to existing approaches proposed by Elsby et al. [2009] and Shimer [2012]. The standard approach in the literature to deal with the 1994 redesign of the CPS consists of using the adjustment factors provided in Polivka and Miller [1998] (henceforth PM98) to correct pre-1994 series.[2] PM98 estimate adjustment factors for various aggregate measures (including involuntary part-time employment) based on data from a parallel survey run by the BLS from July 1992 through May 1994 aimed specifically at estimating the effect of the 1994 CPS redesign. A limitation of this approach is the assumption that the effect of the redesign on a given series does not depend on the levels of that series during the period spanned by the BLS parallel survey. Another limitation is practical: PM98 estimated adjustment factors only for certain aggregates measures and the BLS parallel survey necessary for their approach is confidential. By contrast, at the cost of assuming that the relationship between the ASEC and the BM series remains unchanged across the 1994 redesign, our approach allows adjustment factors to vary from year to year, and it can be used to construct adjustment factors for measures not available in PM98.

Roadmap. The rest of the paper is organized as follows. Section 2 describes the data we use to measure involuntary part-time employment stocks and flows. In Section 3 we present our measurement framework and describe the two steps of our adjustment protocol to address the CPS redesign break. Section 4 establishes the basic properties of the ins and outs of involuntary part-time employment. In Section 5, we examine closely flows within part-time employment and assess the effects of removing potentially spurious transitions. Sections 6 and 7 presents our findings regarding the interaction between involuntary part-time work, unemployment and full-time employment, while Section 8 discusses the relevance of those findings for research in macroeconomics of the labor market. Section 9 concludes.

2 CPS Data on Involuntary Part-time Employment

CPS data. We use CPS data from the basic monthly files (BM) and the Annual Social and Economic Supplement (ASEC), also know as the March files. Each BM file contains information over the CPS reference week (the week containing the 12th of the month) on about 60,000 households. The ASEC files record information on individuals' labor market situation over the past calendar year. Our adjustment procedure presented in Section 3 relies on the combination of data from the BM and ASEC files.

[2]For example, BML19 used adjustment factors *à la* PM98 to estimate the series of overall part-time employment before 1994.

Definitions. We adopt the BLS definition of part-time employment: we count as part-time workers individuals who *usually* work (strictly) less than 35 hours per week.[3] Note that the definition of usual hours is different from that of actual hours, which refers to hours worked during the survey's reference week. As we explain momentarily, this distinction matters for deriving certain aggregate measures from the CPS.

Our definition of involuntary part-time employment is based on the following question posed to respondents who report less than 35 hours of weekly work:

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

(see U.S. Bureau of the Census [2017]). The first sentence of the question above singles out individuals who are counted as involuntary part-time workers.[4]

With the ASEC, we define similar concepts of part-time and involuntary part-time employment, but measure them at an annual frequency. Accordingly, individuals are classified as working part-time in the past calendar year if they report working less than 35 hours in most (i.e. more than 50 percent) of their working weeks over the preceding year. They are considered involuntary part-timers if the main reason for working part-time in at least one of the weeks of the past year was either because they could not find full-time work or due to poor business conditions.

The 1994 redesign. In January 1994, the monthly CPS underwent a complete overhaul (Cohany et al. [1994], Polivka [1996]). Among the various changes introduced in the revised version, two directly affect the measurement of part-time and involuntary part-time employment.[5] First, the CPS started recording usual hours for all employed individuals from all rotation groups, irrespective of actual hours worked during the survey's reference week. Prior to the redesign, information on usual hours worked and reasons for working part-time were only collected for individuals who reported working less than 35 actual hours per week.[6] Second, the concept of involuntary part-time work was made more precise, by explicitly including the predicate that individuals want to work full-time.

[3] The threshold of 35 hours is the most commonly used in U.S. labor market statistics. We show in the online appendix that our results are robust to using a different cutoff to define part-time employment.

[4] The 1994 redesign changed the list of reasons respondents can choose from to answer the question about reasons for working part-time. Notwithstanding, it is possible to count part-time workers due to 'slack work' and 'could not find full-time job' both before and after 1994.

[5] See the online appendix for extracts of the old and revised CPS questionnaires.

[6] The revised survey also introduced questions to distinguish hours worked at all jobs from hours worked at the primary job for individuals who work multiple jobs. In the online appendix, we use data from the revised survey to show that multiple jobholding does not drive our conclusions.

The changes introduced in the redesigned CPS pose a significant challenge to study the evolution of involuntary part-time employment over a long time period. On the one hand, the increased scope of the question on usual hours worked is likely to lead to an increase in the count of part-time workers after 1994. On the other, the more stringent definition of involuntary part-time work is likely to cause a decrease in the count of involuntary part-time workers after 1994. Consistent with this intuition, the series of stocks of overall part-time and involuntary part-time workers computed from the basic monthly survey show a prominent break in 1994. The effects on labor market stocks are compounded in the series of worker flows, but the direction of changes is more difficult to predict. Our adjustment protocol offers a solution to deal with these problems.

3 Measuring Involuntary Part-time Employment Stocks and Flows in the CPS

3.1 Framework

To uncover the sources of cyclical variation in the stock of involuntary part-time employment (I), we relate it to the evolution the stocks of individuals in two non-employment states, unemployment (U) and nonparticipation (N), and two employment states, full-time employment (F) and voluntary part-time employment (V). Formally, we condense the description of the labor market in period t in the vector

$$\boldsymbol{s}_t = \begin{bmatrix} F & V & I & U & N \end{bmatrix}_t' . \tag{1}$$

Each element of $\boldsymbol{s}_t$ denotes the stock (or count) of workers in each labor market state. Accordingly, the involuntary part-time employment rate, i_t, plotted in Figure 1, is given by:

$$i_t = \frac{I_t}{F_t + V_t + I_t + U_t}. \tag{2}$$

To analyze fluctuations in the stocks that compose i_t, we link their behavior to the evolution of transition probabilities. We assume that $\boldsymbol{s}_t$ follows a first-order Markov chain:

$$\boldsymbol{s}_t = \boldsymbol{M}_t \boldsymbol{s}_{t-1}, \tag{3}$$

where $\boldsymbol{M}_t$ is the matrix of transition probabilities $p\,(j \to k)$ across states j and k.

3.2 Addressing the CPS redesign break

In Section 2 we described the problems affecting the measurement of part-time employment stocks and flows prior to 1994. In this section, we propose a two-step adjustment protocol to overcome this issue and estimate the model described in the previous subsection.

Step 1: Adjusting stocks. To illustrate the problem and the proposed solution, Figure 2 shows alternative series of stocks of voluntary (Plot 2a) and involuntary (Plot 2b) part-time employment. In each plot, the step function (dotted line) denotes data based on the ASEC and the solid line data from the BM files. The CPS redesign entails a discontinuity in the solid lines in January 1994, and shifts the stocks in the expected directions (see Section 2). In contrast, the annual series do not show any noticeable break at 1994, as the ASEC was not subject to any substantial methodological changes during this period.[7] Our adjustment protocol uses the information on the ASEC stock of involuntary part-time workers to backcast the annual stocks implied by the monthly CPS prior to 1994. The outcome of our adjustment is depicted by the dashed lines in Figure 2. The levels of the series are well aligned with the 1994 ones, and mere visual inspection suggests their volatility is also similar.

In order to establish a clear link between our approach and PM98's, it is useful to formally describe our adjustment protocol. Let $s^{\mathrm{BM}}_{y,m}$ denote the series calculated from the BM files, where $s \in \{V, I\}$ and y and m refer, respectively, to calendar years and months. Likewise, denote by s^{ASEC}_{y} the series calculated from the ASEC. We observe s^{ASEC}_{y} throughout the whole period, but prior to 1994 we have an incorrect measurement of $s^{\mathrm{BM}}_{y,m}$, which we denote by a breve superscript $\breve{s}^{\mathrm{BM}}_{y,m}$. To obtain an estimate of $s^{\mathrm{BM}}_{y,m}$ prior to 1994, we first compute the predicted yearly average of $s^{\mathrm{BM}}_{y,m}$ before the CPS redesign, denoted $\widehat{\bar{s}}^{\mathrm{BM}}_{y}$. We regress $s^{\mathrm{BM}}_{y,m}$ on s^{ASEC}_{y} using data from the post-revision period:[8]

$$s^{\mathrm{BM}}_{y,m} = \vartheta_0 + \vartheta_1 s^{\mathrm{ASEC}}_{y} + \varepsilon_{y,m}, \quad y = 1994, \dots, 2007,\ m = 1, \dots, 12. \tag{4}$$

Having estimated ϑ_0 and ϑ_1, we use s^{ASEC}_{y} pre-1994 to generate $\widehat{\bar{s}}^{\mathrm{BM}}_{y}$ before 1994. The next step involves using $\widehat{\bar{s}}^{\mathrm{BM}}_{y}$ to derive $\widehat{s}^{\mathrm{BM}}_{y,m}$, an estimate of $s^{\mathrm{BM}}_{y,m}$ prior to 1994. We focus on

[7] It is conceivable the redesigned BM survey spilled over to the ASEC, and that computerizing of the ASEC affected estimates based on these data even if the questions were not changed. We thank Anne Polivka for raising these concerns to our attention. We have not been able to find empirical evidence demonstrating the existence of such spillover effects. In what regards data processing procedures, changes were introduced at various points in time in the ASEC with no clear documented impact on measures derived from these data. For example, the 1989 rewriting of processing programs does not seem to coincide with a change in the behavior of the ASEC series plotted in Figure 2.

[8] Note that our favorite specification excludes data after 2007, when the Great Recession hits the labor market and the correlation between the BM and ASEC time series becomes less stable. As shown in the online appendix, the results are robust to using alternative regression windows.

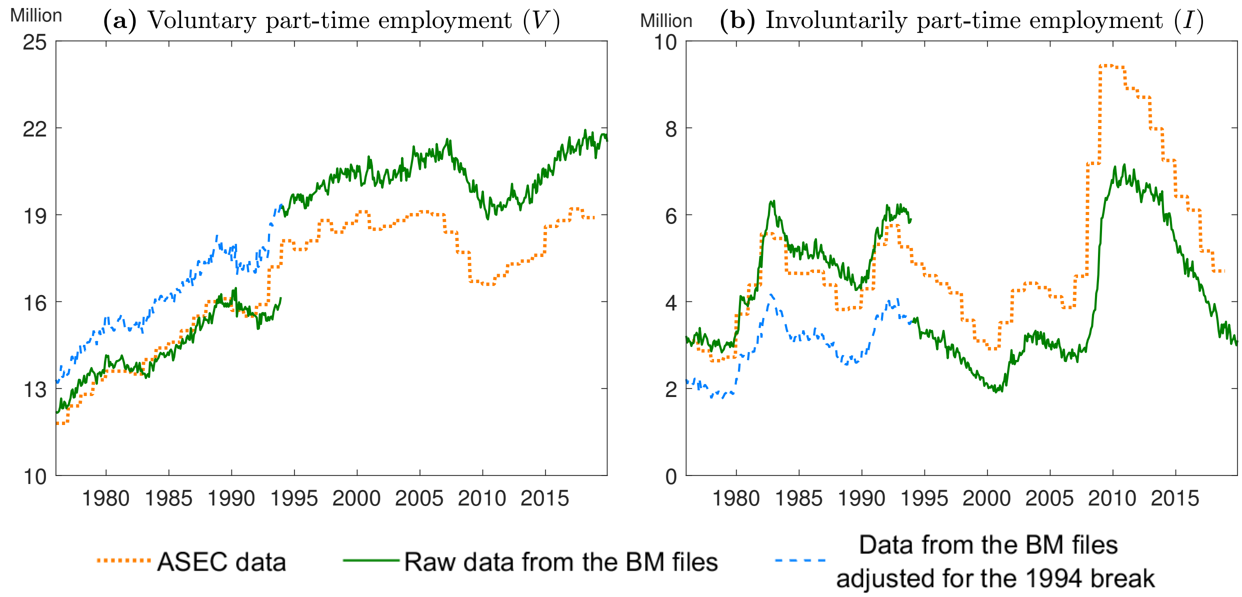

Figure 2: Labor market stocks derived from the ASEC and the BM files of the CPS

Notes: CPS Annual Social and Economic Supplement (ASEC) data, 1976 – 2018; CPS basic monthly (BM) data, 1976m01 – 2019m12. The ASEC data is annual. Data from the BM files (solid lines) is monthly and discontinued in January 1994 due to the redesign of the CPS. The dashed lines prior to 1994 show the time series obtained after implementing our adjustment protocol, which combines information contained in the ASEC and BM time series. Prior to making this adjustment, the time series based on the BM files are corrected for seasonality. The reported figures are in million workers.

linear specifications, i.e. we posit the following relationship: $\widehat{s}^{\text{BM}}_{y,m} = \phi_{0,y} + \phi_{1,y}\breve{s}^{\text{BM}}_{y,m}$. Though simple, this relationship allows the coefficients $\phi_{0,y}$ and $\phi_{1,y}$ to vary across years. To find $\phi_{0,y}$ and $\phi_{1,y}$, we minimize the distance between the predicted yearly average and the yearly average of the adjusted time series, i.e. we solve

$$\min_{\phi_{0,y},\phi_{1,y}} \sum_{y=1976}^{1993} \left(\widehat{\overline{s}}^{\text{BM}}_{y} - \frac{1}{12}\sum_{m=1}^{12} \left(\phi_{0,y} + \phi_{1,y}\breve{s}^{\text{BM}}_{y,m}\right) \right)^2 . \tag{5}$$

At this level of generality, the minimization problem has too many free parameters. Therefore, we explore two alternative sets of restrictions: (i) using multiplicative coefficients only (i.e., $\phi_{0,y} = 0$ for all y) and (ii) using additive coefficients only (i.e., $\phi_{1,y} = 1$ for all y). Our preferred model involves using multiplicative factors. The multiplicative adjustment factors rescale, not only the mean, but also the variance of the time series. Moreover, multiplicative factors cannot, by construction, predict negative values when a time series is scaled down, which is an important advantage in practice, since the stock of involuntary part-time workers is a small number. Solving the problem above under restriction (i), we get

Table 1: Adjustment coefficients for voluntary and involuntary part-time employment

	A. Voluntary part-time employment			**B. Involuntary part-time employment**		
	All	Men	Women	All	Men	Women
1976	1.215	1.226	1.212	0.863	0.763	0.964
1977	1.206	1.225	1.194	0.803	0.743	0.863
1978	1.186	1.194	1.184	0.779	0.751	0.806
1979	1.204	1.238	1.177	0.790	0.761	0.819
1980	1.184	1.208	1.166	0.843	0.735	0.951
1981	1.202	1.249	1.161	0.875	0.785	0.959
1982	1.207	1.255	1.166	0.826	0.758	0.888
1983	1.234	1.272	1.204	0.805	0.781	0.818
1984	1.208	1.212	1.211	0.764	0.755	0.766
1985	1.209	1.238	1.187	0.778	0.731	0.819
1986	1.190	1.188	1.199	0.784	0.756	0.806
1987	1.179	1.190	1.176	0.770	0.721	0.811
1988	1.176	1.190	1.169	0.706	0.656	0.754
1989	1.157	1.181	1.139	0.760	0.750	0.764
1990	1.133	1.138	1.134	0.789	0.740	0.829
1991	1.145	1.150	1.146	0.810	0.733	0.880
1992	1.186	1.203	1.176	0.819	0.728	0.901
1993	1.212	1.185	1.247	0.749	0.669	0.816

Notes: The table reports the multiplicative adjustment coefficients used to correct the monthly stocks of voluntary (Panel A) and involuntary (Panel B) part-time employment for each year of the 1976-1993 period. 'All': All working-age individuals; 'Men': working-age men; ; 'Women': working-age women.

$\phi_{1,y} = \widehat{\bar{s}}_y^{\text{BM}} / \frac{1}{12}\sum_{m=1}^{12} \breve{s}_{y,m}^{\text{BM}}$. To obtain the adjusted series of V_t and I_t we simply multiply each of them by the relevant multiplicative adjustment factor. After adjusting V_t and I_t in the manner just described, we recover F_t by using the accounting identity $E_t = F_t + V_t + I_t$ and the fact that total employment (E_t) is correctly measured in the BM files prior to 1994.

Table 1 reports the multiplicative adjustment coefficients (the $\phi_{1,y}$'s from our preferred specification) delivered by our adjustment protocol, and that we used to correct the monthly series of voluntary (V_t) and involuntary (I_t) part-time employment stocks prior to the redesign of the CPS. For researchers interested in using our coefficients to adjust data separately by gender, the table also provides the coefficients obtained for men and women (the dataset available from our webpages also provides series disaggregated by gender).

Comparison to Polivka and Miller [1998]. PM98 provide two types of adjustment factors: multiplicative and additive. The multiplicative adjustment factors depend on the values taken by the adjusted series ($\breve{s}^{\mathrm{BM}}_{y,m}$) during the period spanned by the confidential BLS parallel survey (July 1992 to May 1994). The additive adjustment factors do not, but are valid only under the assumption that the difference between the unadjusted and adjusted series remains the same over time. We find this assumption less plausible, and conjecture that researchers tend to use PM98's multiplicative factors for this same reason. Indeed, when working with time series for which there exist no adjustment factor in PM98, researchers typically compute an alternative multiplicative weight by taking the ratio of the January 1994 to the December 1993 observation of the relevant time series (see e.g. Elsby et al. [2009] and Shimer [2012]).[9]

To assess the plausibility of our approach, we find it useful to compare our results covering the period spanned by the BLS parallel survey with PM98's. In Table 7.7 of PM98, they report that the CPS-based series of overall part-time employment should be multiplied by 1.098 prior to 1994 to remove the discrepancy caused by the redesign. When putting together the adjusted series of voluntary and involuntary part-time employment, we obtain a multiplicative adjustment coefficient of 1.119 in 1993. Similarly, PM98 estimate adjustment factors of 1.074 for men and 1.125 for women, and our corresponding 1993 figures by gender are respectively 1.056 and 1.182. Last, PM98's multiplicative coefficient for involuntary part-time work is 0.806, while our coefficient in 1993 for that series is 0.749.[10] In sum, our adjustment factors in 1993 line up well with those estimated by PM98, which gives us confidence that our approach can be used to adjust series not included in PM98.

Robustness checks and additional estimates. We subjected our series of adjusted stocks to several robustness checks. First, we compared them to similar series derived from the Survey of Income and Program Participation (SIPP). Second, we ran a regression model designed to detect any remaining 1994 break in the adjusted series. Both checks support the robustness of our series of adjusted stocks. We also used our adjustment protocol to obtain estimates of involuntary part-time employment stocks by different subgroups (i.e., by gender, age, etc.) and by reason (i.e. workers reporting “slack work/business conditions” and “could only find part-time work”). Further details are provided in Appendix B.

Step 2: Adjusting flows. Having obtained consistent monthly time series of labor market stocks, we use them to correct the series of flows. Our adjustment of flows relies on the fact that, put together, the series of corrected stocks and the properties of our Markovian framework (viz. equation (3)) impose sufficient restrictions to correct the transition

[9] It should be clear that this approach suffers from the same limitations as PM98's.

[10] PM98 do not report adjustment factors separately for men and women for this time series.

probabilities. We use these restrictions by implementing a margin-error adjustment. In standard applications, this adjustment is used to make transition probabilities (computed from longitudinally-linked data, which are affected by rotational sample attrition) consistent with changes in stocks (computed from cross-sectional data). The insight from applying it in this specific context is that, by targeting changes in the corrected stocks from step 1, it addresses in addition the mismeasurement in worker flows prior to the CPS redesign.[11] In practice, we adapt the margin-error correction procedure proposed by Elsby et al. [2015]. A formal description of the margin-error adjustment calculations is provided in Section A.1 of the Appendix.

3.3 Full protocol to adjust transition probabilities

In addition to the 1994 break, we adjust transition probabilities to deal with other measurement issues well-know in the literature. To offer a clear picture of how we construct our final time series of transition probabilities, we now shortly describe the sequence of steps of our adjustment protocol.

To measure individual transitions, we start by longitudinally matching CPS respondents across two consecutive months using household and personal CPS identifiers.[12] To construct the gross flows data, we aggregate individual transitions using the longitudinal weights provided in the CPS files. Next, we remove potential outliers and seasonal variation from both stocks and flows using the U.S. Census Bureau's X-13ARIMA-SEATS program. Combining those series of stocks and flows we obtain an estimate of seasonally adjusted transition probabilities. Armed with time series of seasonally adjusted stocks obtained in step 1 of our correction procedure for the 1994 break, we use the margin-error procedure to obtain time series of seasonal and margin-error adjusted transition probabilities. In the last step we implement a procedure to account for time aggregation. Time-aggregation bias arises when the true processes of worker mobility occur at a higher frequency than the frequency of measurement. Given the high levels of worker turnover rates in the U.S. labor market, time aggregation can impart a substantial bias on the levels and cyclicality of worker flows. We deal with this source of bias by adapting the continuous-time correction proposed in Shimer [2012], which we apply to the series of seasonally adjusted and margin-error corrected transition probabilities.[13]

[11]We implement margin-error adjustment for all periods covered by our data. That is, prior to 1994 the adjustment addresses both the biases induced by the old CPS and rotational sample attrition, while after 1994 it deals only with the latter issue.

[12]As is standard when working with the CPS, we check the validity of the longitudinal links against the age/sex/race filter prescribed by Madrian and Lefgren [2000].

[13]Since time aggregation bias is well understood, and the method we employ to address it is standard,

4 The Ins and Outs of Involuntary Part-time Employment

In this section we use our newly constructed time series of transition probabilities to characterize the dynamics of the ins and outs of involuntary part-time employment.

We begin with plots of the time series of transition probabilities in Figure 3. In each plot, three series are reported: seasonally adjusted series, seasonally and margin-error adjusted series and our preferred series which in addition are adjusted for time aggregation. The three series are reported to unpack the impact of the various steps of our adjustment protocol. Two patterns stand out. First, there is a salient difference between the dotted and the dashed lines in the pre-1994 period, but with no apparent differential impact on the evolution of the series at high or low frequencies across 1994. In the post-1994 period there is almost no visible difference between the two series, which is consistent with previous studies that showed that correcting for margin error has a limited impact on the levels of transition probabilities. We take both observations as evidence that step 2 of our correction procedure for the 1994 break works well in practice. The second observation is that in all plots the solid lines lie well above or below the dashed lines, indicating that adjusting for time aggregation has a large effect on the levels of transition probabilities. The effect is negative for transitions between involuntary part-time employment and nonparticipation, and positive for the remaining transitions. The adjustment for time aggregation seems to preserve the cyclical patterns of unadjusted transition probabilities, with the exception of transitions between involuntary part-time and unemployment that seem to gain variation around recessions.

Next, we focus on the evolution of the solid lines in Figure 3 to describe the dynamics of involuntary part-time employment flows over the past four decades. The first striking feature is the strong cyclicality in transition probabilities between involuntary part-time employment and the two employment states (full-time employment and voluntary part-time employment), displayed in Plots 3a–3d. At the onset of recessions, transition probabilities from those states into involuntary part-time employment (Plots 3a and 3c) rise sharply, whereas transition probabilities out of involuntary part-time employment to the two employment states drop (Plots 3b and 3d). As the recovery gets underway, all four series return to their pre-crisis level, but at somewhat different paces. Whereas the inflows resume their pre-crisis levels rather quickly, the outflows do so more sluggishly. It is quite remarkable how the patterns of cyclical variation of these four transition probabilities remained so stable across the past

our discussion is purposefully short.

Figure 3: Transition probabilities in and out of involuntary part-time employment

Notes: CPS data, 1976m01 – 2019m12. The dotted lines show series adjusted for seasonality; the dashed lines show series adjusted for seasonality and margin error; the solid lines show series adjusted for seasonality, margin error and time aggregation bias. All series are smoothed using a one-period, two-sided moving-average. All series are expressed in percent. The vertical line in each plot indicates January 1994. Gray-shaded areas indicate NBER recession periods.

four decades.

The second salient feature concerns the properties of transition probabilities between involuntary part-time employment and unemployment, shown in the third panel of Figure 3. Unlike transitions with employment states, the cyclical patterns of transitions between unemployment and involuntary part-time employment are not immediately visible to the naked eye. Both series seem to behave procyclically, but variation around recessions is not much larger compared to non-recessionary periods. Both lines exhibit a downward trend, which is especially marked for the outflow transition probability (see Plot 3f). The last feature concerns transitions between involuntary part-time employment and nonparticipation, displayed in the bottom-panel plots of Figure 3. Despite the clear cyclical patterns and large variation around recessions, the levels of both transition probabilities are very low.

Variance decomposition. Inspection of Figure 3 suggests that transitions within employment play an important role to understand the countercyclicality of involuntary part-time employment. The role of transitions from and to unemployment is less clear, and whatever its importance, it has been steadily declining over the past decades. As for transitions from and to nonparticipation, their very low levels suggest they play a limited role in the cyclical dynamics of involuntary part-time employment. In order to make these statements more precise, we quantify the relative importance of the various transitions probabilities for the cyclical dynamics of involuntary part-time employment. For that purpose, for each transition probability we compute its contribution to the short-run variation of involuntary part-time employment. Specifically, we calculate the following so-called beta coefficients (Fujita and Ramey [2009]):

$$\beta\left(j \to k\right) = \frac{\mathbb{C}\text{ov}\left(\Delta i_t, \Delta \widetilde{i_t}^{jk}\right)}{\mathbb{V}\text{ar}(\Delta i_t)}. \tag{6}$$

$\Delta \widetilde{i_t}^{jk}$ denotes changes in the counterfactual involuntary part-time employment rate whose evolution is based on past and contemporaneous changes in the flow hazard λ^{jk}.[14] The results are reported in Panel A of Table 2.

The estimated beta coefficients confirm our analysis of Figure 3. The cyclical dynamics of involuntary part-time employment is overwhelmingly accounted for by movements in transition probabilities into/out of involuntary part-time employment from/to full-time employment (17.2 and 21.9, respectively) and voluntary part-time employment (25.3 and 22.2, respectively).[15] Conversely, transitions between unemployment and nonparticipation

[14]The statistical decomposition is based on flow hazards λ^{jk}, which map one-to-one to transition probabilities $p\left(j \to k\right)$ via the identity $p\left(j \to k\right) = 1 - e^{-\lambda^{jk}}$. Appendix A.2 provides formal details on the variance decomposition.

[15]The sum of the two cells in the bottom row of Panel A is close to 100 percent ($51.5 + 48.6 = 100.1$),

Table 2: Involuntary part-time employment inflow and outflow probabilities

A. Variance contributions				**B. Sample averages**			
Inflows		Outflows		Inflows		Outflows	
$\beta\,(F \to I)$	17.2	$\beta\,(I \to F)$	21.9	$q\,(F \to I)$	32.3	$p\,(I \to F)$	31.1
$\beta\,(V \to I)$	25.3	$\beta\,(I \to V)$	22.2	$q\,(V \to I)$	36.8	$p\,(I \to V)$	31.4
$\beta\,(U \to I)$	5.54	$\beta\,(I \to U)$	3.91	$q\,(U \to I)$	19.3	$p\,(I \to U)$	14.0
$\beta\,(N \to I)$	3.44	$\beta\,(I \to N)$	0.68	$q\,(N \to I)$	2.75	$p\,(I \to N)$	2.89
$\sum_{i \neq I} \beta\,(i \to I)$	51.5	$\sum_{j \neq I} \beta\,(I \to j)$	48.6	$\sum_{i \neq I} q\,(i \to I)$	91.2	$\sum_{j \neq I} p\,(I \to j)$	79.4

Notes: CPS data, 1976m01 – 2019m12. Transition probabilities are corrected for the 1994 break, and adjusted sequentially for seasonality, margin error and time aggregation. Panel A reports the variance contributions of flows hazard λ^{jk} to the dynamics of involuntary part-time employment (see equation (6)). Panel B reports the averages of monthly transition rates and probabilities over the sample period. The inflow rate from state j to k at time t, denoted $q\,(j \to k)$, is the ratio of the gross worker flow from j to k over the stock of workers in state k, i.e. $q\,(j \to k) = {}^{\#\{j \to k\}}/_{\#\{k\}}$ with $\#\{.\}$ indicating cardinality, and the numerator and denominator both measured at time t. The outflow probabilities are the elements of the Markov transition matrix (see equation 3). All table entries are expressed in percent.

account, altogether, for less than 10 percent of the dynamics of involuntary part-time employment. To tease out the role of the average level of flows across these states and their variation at high frequencies, Panel B of Table 2 reports the sample averages of flows in and out of part-time employment normalized by the stock of involuntary part-time employment. They indicate that, by and large, flows with higher variance contributions are also the ones that have greater relative cyclical variation. The exception concerns unemployment flows, which are large on average, but have low relative cyclical variation, which explains their low beta coefficients. A last observation concerns the numbers reported in the bottom row of Panel B, which are the column sums of inflow and outflow probabilities. Both values are very high (by construction they cannot be greater than 100 percent). They imply that spells of involuntary part-time employment are extremely short lived: on average from 1976 to 2019, 91.2 percent of the stock of involuntary part-time workers was in a different state last month and 79.4 percent of workers in that stock will move to another state the following month. This observation is an important motivation for the analysis conducted in the following section.

which indicates that each $\beta\,(j \to k)$ can be interpreted as the relative contribution of flow hazard λ^{jk} to changes in the involuntary part-time employment rate.

5 Transitions within Part-time Employment

The previous section established that transitions between voluntary and involuntary part-time employment are very large and are one of the major drivers of the countercyclicality of involuntary part-time employment. In this section we assess the hypothesis that some transitions within part-time employment are spurious. We motivate this hypothesis on two observations. First, although conceptually distinct, the measurement of voluntary and involuntary part-time employment in the CPS generates some fuzziness in the classification of workers across the two states. This fuzziness may lead to classification error which, in turn, generates spurious transitions, i.e. a worker's reported labor force state changes from month to month even when the 'true' labor force state is unchanged. The very elevated levels of flows between these two states documented in the previous section are consistent with such classification errors. Unfortunately, the redesigned CPS interview is unlikely to have eliminated that fuzziness.[16] Second, there is direct and systematic evidence of reporting error in workers' classification between unemployment and nonparticipation in the CPS (see e.g. Abowd and Zellner [1985] and Poterba and Summers [1986]). While we are not aware of similar evidence concerning classification errors between voluntary and involuntary part-time employment, the underlying fuzziness of the two states is analogous to (if not more pronounced than) the one between unemployment and nonparticipation. These observations prompt us to implement a procedure to control for the effect of misclassification.[17]

We quantify the role of potentially spurious transitions between voluntary (V) and involuntary (I) part-time employment in our empirical results by subjecting our data to a 'deVIVification' procedure.[18] To implement it, we begin by longitudinally matching CPS

[16] As shown by the CPS questionnaire extracts reported in the online appendix, after 1994 workers can be classified as voluntary part-time workers in two ways. First, the worker wants to work full-time but indicates a reason for working part-time that is neither 'slack work conditions' nor 'could not find a full-time job'. Second, the worker does not want to work full-time and, per force, indicates a reason for working part-time that is neither 'slack work conditions' nor 'could not find a full-time job'. Consistent with the very distinct dynamics of I and V stocks and flows, the share of V workers who want to work full-time is small. On average over the sample period (i.e. from 1994 onwards, the period during which this distinction is made), 9.7 percent of V workers report that they want to work full-time and another 12.1 percent report that their regular hours are full-time hours. We thank an anonymous referee for drawing our attention to this aspect of the measurement of involuntary part-time employment post-1994.

[17] We do not think the same fuzziness applies to classification between part-time and full-time employment, since it is based on a question that should elicit an objective answer: "*How many hours per week do you usually work at all job(s)?*" (pre-1994) and "*How many hours per week do you usually work at your (main) job?*" (post-1994). Our reading finds support in the large average differences in working hours across part-time and full-time employment, and the large average changes in working hours for workers who move between full-time and part-time employment (see Borowczyk-Martins and Lalé [2019] and Section 7).

[18] The name is inspired by Elsby et al. [2015]'s 'deNUNification' adjustment, from which we heavily borrow. Elsby et al. [2015] have demonstrated that deNUNified data allow for a cleaner assessment of the sources of fluctuations in the unemployment rate.

Table 3: Description of deVIVification procedure

Observed	Adjusted	Share (%)	Observed	Adjusted	Share (%)
$F \to V \to I \to V$	$F \to V \to \boldsymbol{V} \to V$	7.60	$F \to I \to V \to I$	$F \to I \to \boldsymbol{I} \to I$	14.2
$V \to V \to I \to V$	$V \to V \to \boldsymbol{V} \to V$	35.9	$I \to I \to V \to I$	$I \to I \to \boldsymbol{I} \to I$	31.0
$U \to V \to I \to V$	$U \to V \to \boldsymbol{V} \to V$	2.19	$U \to I \to V \to I$	$U \to I \to \boldsymbol{I} \to I$	5.00
$N \to V \to I \to V$	$N \to V \to \boldsymbol{V} \to V$	3.36	$N \to I \to V \to I$	$N \to I \to \boldsymbol{I} \to I$	3.54
$V \to I \to V \to F$	$V \to \boldsymbol{V} \to V \to F$	7.91	$I \to V \to I \to F$	$I \to \boldsymbol{I} \to I \to F$	13.4
$V \to I \to V \to V$	$V \to \boldsymbol{V} \to V \to V$	38.6	$I \to V \to I \to I$	$I \to \boldsymbol{I} \to I \to I$	27.2
$V \to I \to V \to U$	$V \to \boldsymbol{V} \to V \to U$	1.41	$I \to V \to I \to U$	$I \to \boldsymbol{I} \to I \to U$	2.95
$V \to I \to V \to N$	$V \to \boldsymbol{V} \to V \to N$	3.06	$I \to V \to I \to N$	$I \to \boldsymbol{I} \to I \to N$	2.76

Notes: Each row describes sequences of individual labor market statuses over four consecutive months targeted by the adjustment procedure. The columns 'Observed' describe sequences from the raw CPS data. The columns 'Adjusted' show the final sequences of labor market statuses. The columns 'Share (%)' reports the percent share of each row in the row sum of each panel of the table.

respondents across four consecutive months. Our measurements of individual transitions in these matched data are based on the labor market states in the second and third months.[19] The deVIVification procedure identifies particular sequences of labor market states in the raw data as suspicious (those displayed in columns 'Observed' in Table 3) and then recodes them to another sequence that is deemed more plausible (those denoted 'Adjusted' in Table 3). To fix ideas, consider the following individual sequence reported in the raw data: full-time work in month 1, voluntary part-time work in month 2, involuntary part-time work in month 3, voluntary part-time work in month 4, i.e. $F \to V \to I \to V$. DeVIVifying entails changing the status in month 3 to 'voluntary part-time work', resulting in the sequence $F \to V \to V \to V$. Since we measure transitions by looking at months 2 and 3, this means that we discard some transitions between V and I observed in the raw data.

Inspection of columns titled 'Share' in Table 3 indicates that the vast majority of suspicious transitions occur within part-time employment (i.e. in sequences only involving V and I). When looking at the shares of discarded transitions, we find that deVIVification turns down 44.2 percent of the raw $V \to I$ transitions and 48.3 percent of $I \to V$ transitions. It is quite remarkable that these numbers are so similar, in spite of the very large difference between the levels of $p(V \to I)$ and $p(I \to V)$ – in the unadjusted data they average 6.76 and 31.4 percent, respectively. The shares of discarded transitions exhibit no clear cyclical patterns, and remain stable around their sample means (see Figure B2 in the Appendix). These

[19] In the CPS, respondents are interviewed for four consecutive months, rotated out of the survey for eight months, and then included in the survey again for an additional four months. By second and third months, we refer to those from the four-month period of consecutive interviews. In other words, although perhaps not apparent in this terminology, we do use information from respondents who are either in their first or their second round of four consecutive CPS interviews.

Table 4: Accounting for potentially spurious transitions within part-time employment

A. Variance contributions				**B. Sample averages**			
Inflows		Outflows		Inflows		Outflows	
$\beta\,(F \to I)$	27.4	$\beta\,(I \to F)$	24.0	$q\,(F \to I)$	28.5	$p\,(I \to F)$	28.8
$\beta\,(V \to I)$	15.6	$\beta\,(I \to V)$	11.9	$q\,(V \to I)$	16.2	$p\,(I \to V)$	15.2
$\beta\,(U \to I)$	11.6	$\beta\,(I \to U)$	4.79	$q\,(U \to I)$	17.5	$p\,(I \to U)$	11.9
$\beta\,(N \to I)$	1.82	$\beta\,(I \to N)$	2.14	$q\,(N \to I)$	3.66	$p\,(I \to N)$	3.46
$\sum_{i \neq I} \beta\,(i \to I)$	56.4	$\sum_{j \neq I} \beta\,(I \to j)$	42.8	$\sum_{i \neq I} q\,(i \to I)$	65.9	$\sum_{j \neq I} p\,(I \to j)$	59.4

Notes: CPS data, 1976m01 – 2019m12. Transition probabilities are constructed based on reclassified stocks and flows, corrected for the 1994 break, and adjusted sequentially for seasonality, margin error and time aggregation. Panel A reports the variance contributions of flows hazard λ^{jk} to the dynamics of involuntary part-time employment (see equation (6)). Panel B reports the averages of monthly transition rates and probabilities over the sample period. The inflow rate from state j to k at time t, denoted $q\,(j \to k)$, is the ratio of the gross worker flow from j to k over the stock of workers in state k, i.e. $q\,(j \to k) = {}^{\#\{j \to k\}}/_{\#\{k\}}$ with $\#\,\{.\}$ indicating cardinality, and the numerator and denominator both measured at time t. The outflow probabilities are the elements of the Markov transition matrix (see equation 3). All table entries are expressed in percent.

two results suggest a stable pattern of measurement error. Consistent with this, we find (not reported here) that workers' observable characteristics (gender, age, education, marital status) are mostly uncorrelated with the probability of appearing in columns 'Observed' vs. appearing in columns 'Adjusted' of Table 3.

Table 4 reports the same statistics as Table 2 but based on the series of reclassified flows. As expected, the main effect of the reclassification approach is a very substantial reduction in the levels of $p\,(V \to I)$ and $p\,(I \to V)$ (respectively of 20 and 15 percentage points, see Panel B). Consequently, the relative contributions of those flows to the dynamics of involuntary part-time employment decrease, and inspection of Panel A of Table 2 indicates that their weight is mostly *transferred* to transitions between involuntary part-time and full-time employment. Figure B3 in the Appendix plots the series of reclassified transition probabilities along with the baseline series reported in the previous section. Two additional observations are worth making. One, reclassification seems to reduce the cyclicality of $p\,(V \to I)$ and $p\,(I \to V)$, while for the remaining transitions both their high and low frequency dynamics are largely unchanged. Two, for some of the remaining transitions, reclassification has a more pronounced effect in the pre-1994 period. This is not surprising, given the different definitions of voluntary and involuntary part-time employment across the 1994 break.

Taking stock. Addressing potential misclassification leaves our main substantive conclusions largely unchanged. Workers in involuntary part-time employment are extremely likely to have been in another employment state in the previous month, and to move to another employment state in the next month. Over the business cycle, fluctuations in transition probabilities between involuntary part-time employment and other employment states account for the bulk of those cyclical movements. The main impact of the reclassification approach is to lower the levels and cyclicality of transitions within part-time employment. While the statistics on discarded transitions are consistent with the hypothesis that most of them are the result of classification error, this does not imply that reclassification discards all, and only those, transitions that are spurious. Indeed, some of the additional analyses that we have done lead to more mixed results (available upon request), and we have not been able to gather sufficient evidence that could confirm or reject that interpretation.

6 Comparison to Unemployment Turnover

In this section we use our estimates of transition probabilities to characterize fluctuations in and out of unemployment. First, we use them to bring out the distinctive features of involuntary part-time employment turnover. Second, we investigate more closely the dynamic interaction between the two labor market states during recessionary episodes and their aftermaths.

Table 5: Unemployment inflow and outflow probabilities

A. Variance contributions				**B. Sample averages**			
Inflows		Outflows		Inflows		Outflows	
$\beta(F \to U)$	15.6	$\beta(U \to F)$	16.3	$q(F \to U)$	19.0	$p(U \to F)$	17.8
$\beta(V \to U)$	3.85	$\beta(U \to V)$	7.36	$q(V \to U)$	6.20	$p(U \to V)$	7.88
$\beta(I \to U)$	1.20	$\beta(U \to I)$	3.74	$q(I \to U)$	5.52	$p(U \to I)$	7.64
$\beta(N \to U)$	21.8	$\beta(U \to N)$	27.9	$q(N \to U)$	36.2	$p(U \to N)$	28.0
$\sum_{i \neq U} \beta(i \to U)$	42.4	$\sum_{j \neq U} \beta(U \to j)$	55.2	$\sum_{i \neq U} q(i \to U)$	66.9	$\sum_{j \neq U} p(U \to j)$	61.3

Notes: CPS data, 1976m01 – 2019m12. Transition probabilities are corrected for the 1994 break, and adjusted sequentially for seasonality, margin error and time aggregation. Panel A reports the variance contributions of flows hazard λ^{jk} to the dynamics of involuntary part-time employment (see equation (6)). Panel B reports the averages of monthly transition rates and probabilities over the sample period. The inflow rate from state j to k at time t, denoted $q(j \to k)$, is the ratio of the gross worker flow from j to k over the stock of workers in state k, i.e. $q(j \to k) = {}^{\#\{j \to k\}}/_{\#\{k\}}$ with $\#\{.\}$ indicating cardinality, and the numerator and denominator both measured at time t. The outflow probabilities are the elements of the Markov transition matrix (see equation 3). All table entries are expressed in percent.

To fix ideas, Table 5 reports the same statistics reported in Table 2 but for flows in and out unemployment. Several observations emerge from comparing the two tables. We start by focusing on the sample averages of transition probabilities displayed in Panel B of Table 5. First, the bottom row indicates that unemployment exhibits much slower dynamics compared to involuntary part-time employment (cf. bottom row of panel B of Table 2). Put differently, spells of involuntary part-time employment are, on average, about 30 percent shorter than those of unemployment.[20] Second, different from involuntary part-time employment, transitions between unemployment and nonparticipation are very large. Third, the average levels of turnover between unemployment and full-time and voluntary part-time employment are considerably smaller compared to involuntary part-time employment. In sum, a fundamental feature of involuntary part-time employment dynamics compared to unemployment is the much larger size of within-employment transitions. Compared to involuntary part-time workers, the unemployed are much less likely to return to another employment state in the next month.

Panel A of Table 5 reports the variance contributions to unemployment dynamics. Consistent with findings uncovered by Elsby et al. [2015], the dynamics of nonparticipation turnover account for half of the cyclical variation in the unemployment rate $(21.8 + 27.9 = 49.7)$.[21] The contribution of the dynamics of full-time employment turnover $(15.6 + 16.3 = 31.9)$ is at similar levels to those reported in Table 2 on involuntary part-time employment dynamics. On the other hand, the dynamics of transitions between unemployment and part-time employment play a negligible role in the cyclical dynamics of unemployment. In the context of unemployment dynamics, much attention has been devoted to the relative contributions of cyclical variation in inflow and outflow transitions (see e.g. Darby et al. [1986] and Shimer [2012]). Consistent with the more recent literature (e.g. Elsby et al. [2009]), we find that both inflows and outflows from other employment states are quantitatively important to understand the dynamics of unemployment (20.7 and 27.4). The same can be said about the dynamics of involuntary part-time employment, where the ins and outs from other employment states respectively account for 42.5 and 44.1 percent of its short-run dynamics.

Figure 4 complements the static picture provided in Table 5 by showing time series of unemployment (dashed line) and involuntary part-time employment (solid line) transition probabilities to and from full-time employment, voluntary part-time employment and nonparticipation. The plots on the top panel highlight that, at a first pass, transition probabilities in and out of full-time employment behave similarly across unemployment and involuntary part-time employment. However, a closer look reveals two important differences.

[20]Calculated as the ratio of the outflow probability of U over that of I, i.e. 61.3/79.4=77.2 percent. That is, we take the ratio of the average expected duration of an I spell over that of a U spell under the assumption of a constant exit flow rate.

[21]Elsby et al. [2015] show that reclassifying transitions between unemployment and nonparticipation reduces the relative role of nonparticipation to about one third.

Figure 4: Transition probabilities in and out of unemployment

Notes: CPS data, 1976m01 – 2019m12. The dashed lines denote transition probabilities to and from unemployment. The solid lines denote transition probabilities to and from involuntary part-time employment. Transition probabilities are adjusted sequentially for seasonality, margin error and time aggregation. All series are smoothed using a one-period, two-sided moving-average. All series are expressed in percent. The vertical line in each plot indicates January 1994. Gray-shaded areas indicate NBER recession periods.

First, $p(F \to I)$ is more persistent than $p(F \to U)$. The spike in $p(F \to U)$ at the onset of recessions is sharper and more short-lived compared to that in $p(F \to I)$, which remains elevated well into the recovery. Second, the recessionary drop in $p(U \to F)$ is more pronounced and more persistent than that in $p(I \to F)$. Put together, the two features imply that the cyclical dynamics of $p(F \to I)$ and $p(I \to F)$ are more closely aligned compared to their unemployment counterparts.[22]

Having shown the distinctiveness of the ins and outs of involuntary part-time employment, we now turn our attention to the interaction between unemployment and involuntary part-time employment during recessions and their recoveries. Specifically, we want to assess the relevance of the hypothesis that involuntary part-time employment offers a path for workers to escape unemployment during recessions and their aftermaths. Consistent with this view, we expect $p(U \to I)$ to contribute positively to elevated levels of i_t during recoveries. To assess this hypothesis, the four plots in Figure 5 display the contributions of the evolution of $p(U \to I)$ and $p(I \to U)$ for changes (in levels) in i_t around each recession. The gross contributions of $p(I \to U)$ (crossed lines) and $p(U \to I)$ (dash-dotted lines) to changes in i_t are basically zero during recessions and remain negligible during recoveries.[23] Contrary to the stepping-stone hypothesis, the behavior of $p(U \to I)$ during recoveries contributes negatively to the persistence in involuntary part-time employment. On the other hand, the drop in $p(I \to U)$ contributes to maintain i_t at high levels.

Taking stock. The cyclical behavior of the ins and outs of involuntary part-time employment differs in important respects to their unemployment counterparts. Three seem particularly important. One, at any point of the business cycle, involuntary part-time workers are much more likely to move in and out of full-time and voluntary part-time employment. Two, the cyclical increase in inflows from other employment states to involuntary part-time employment is much more persistent. Three, the cyclical dynamics of flows in and out of full-time employment are more closely aligned. As we argue in Section 8, we find these patterns consistent with the notion that the interaction between involuntary part-time employment flows and full-time employment reflects the workings of a distinct labor adjustment channel compared to the one driving flows between unemployment and full-time employment. Last, our analysis of the dynamics of transitions between unemployment and involuntary part-time

[22]The plots on the middle panel of Figure 4 reinforce this distinctive aspect of the dynamics between involuntary part-time employment and other employment states. While $p(V \to I)$ and $p(I \to V)$ track the dynamics of $p(F \to I)$ and $p(I \to F)$ very closely, the same is not true of the unemployment flows. Indeed, $p(V \to U)$ is largely acyclical and $p(U \to V)$ displays much lower variation compared to $p(U \to F)$. The bottom panel of Figure 4 shows how negligible flows between involuntary part-time work and nonparticipation are compared to flows between unemployment and nonparticipation.

[23]The dashed and dotted lines show respectively the contributions of $p(F \to I)$ and $p(I \to F)$. They are much larger. We will comment on their behavior in Section 7.

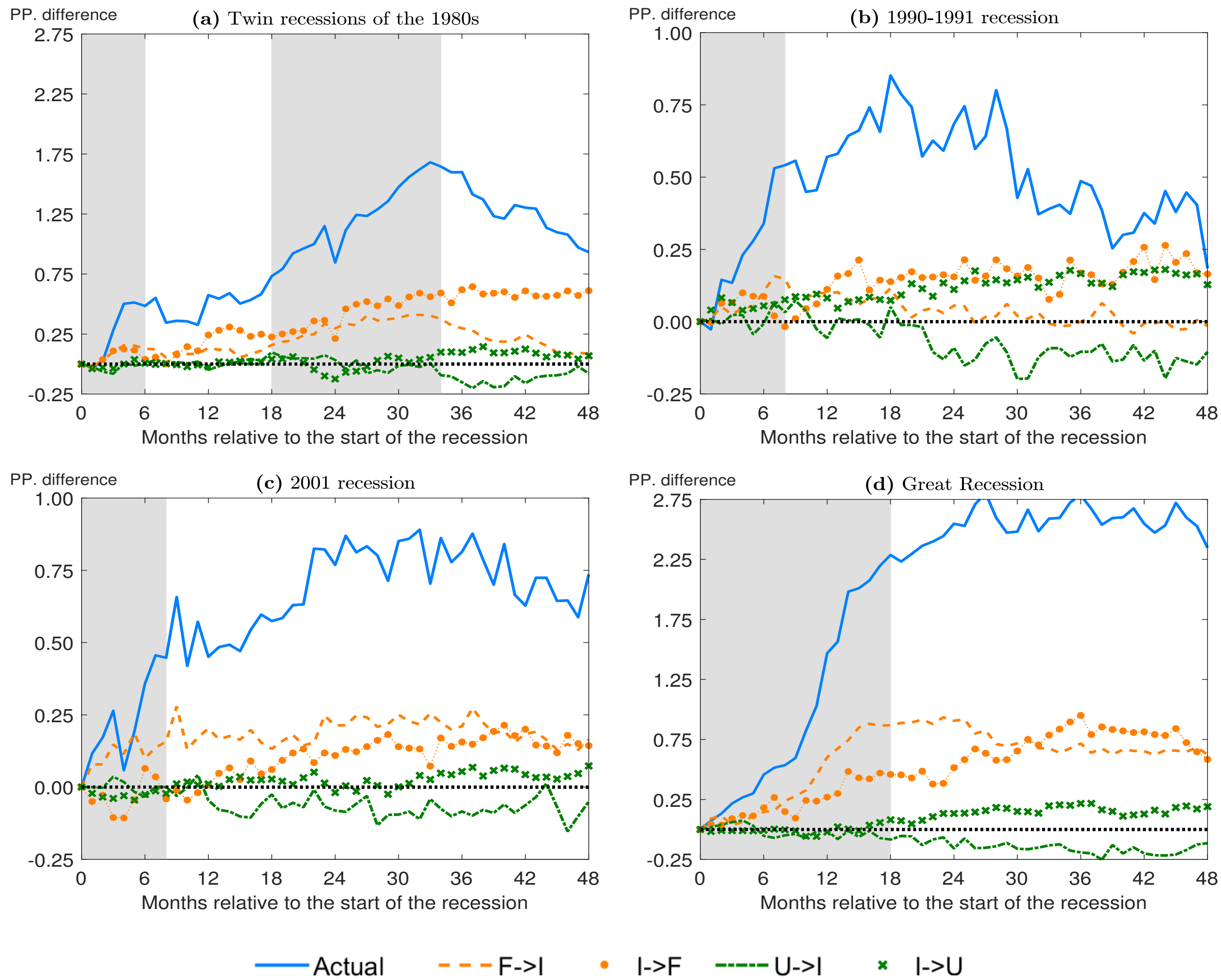

Figure 5: Contributions to the recessionary increase in involuntary part-time employment

Notes: CPS data. Each solid line shows the change in the involuntary part-time employment rate from its value at time 0, the starting month of the corresponding recession. The other lines report counterfactual changes in the involuntary part-time employment rate predicted by specific transitions probabilities, i.e. time series $\sum_{\tau=0}^{t} \Delta \widetilde{i_\tau}^{jk}$ where the $\Delta \widetilde{i_t}^{jk}$'s are the series defined in equation (6). All series are expressed in percentage points difference. The scale on the vertical axis is different across mild (Plots 5b and 5c) and large recessions (Plots 5a and 5d). Gray-shaded areas indicate NBER recession periods.

employment strongly rejects the view that involuntary part-time employment helps workers escape unemployment during downturns.

7 Turnover with Full-time Employment

In this section we explore in more detail transitions between involuntary part-time and full-time employment. Despite the quantitative importance of turnover within part-time employment, and setting aside the measurement issues discussed in Section 5, turnover between involuntary part-time and full-time employment lends itself to a more straightforward interpretation. Borowczyk-Martins and Lalé [2019] document that, not only are average hours worked different across part-time and full-time employment, but they also show that transitions between them entail, on average, large changes in weekly hours (a difference that ranges between 11 and 20 hours depending on the sample). In contrast, in our dataset average hours worked are very similar across voluntary and involuntary part-time employment (around 1.5 hours more among involuntary part-time workers), and workers who move from voluntary to involuntary part-time employment experience an average reduction in working hours of about one hour, whereas transitions in the reverse direction entail an average increase of one hour.

When analyzing turnover with full-time employment, we focus on the role of workers' stated reasons for working part-time involuntarily ("slack work/business conditions" and "could only find part-time work"). We interpret the former as indicative of greater attachment to the current employer. To assess this hypothesis, we quantify the interaction between turnover at the same employer and the two stated reasons for working part-time involuntarily in transitions between full-time and involuntary part-time employment. The results of our analysis are reported in Table 6. Note that in this analysis we rely on post-1994 data only.[24]

To fix ideas, the first row of Table 6 shows that at least 90 percent of the cyclical variation in the probabilities $p(F \to I)$ and $p(I \to F)$ (measured by the variance of first-differenced data) is driven by transitions at the same employer. While this number may seem elevated, it is consistent with the patterns of within-employment transitions documented in BML19.[25] The second and third rows focus on workers' stated reasons for working part-time involuntarily. Respectively 66.8 and 61.4 percent (65.9 and 63.3 percent if we limit the analysis to post-1994 data) of the cyclical variation of $p(F \to I)$ and $p(I \to F)$ is driven by slack work conditions. The next set of rows shows the interaction between within-employer transitions and involuntary part-time employment by reason. They show a strong overlap between changes at the same employer and transitions reflecting slack work conditions. More than 50 percent of the variation in $p(F \to I)$ and $p(I \to F)$ is explained by the conjunction of these two factors. Indeed, when we combine the numbers with results from Table 2, we

[24]Information on job-to-job transitions is available only in the revised (i.e. post-1994) CPS. Like Fallick and Fleischman [2004], we use the following dependent interviewing question of the CPS to identify employer changes: "*Last month, it was reported that (name's/you) worked for (input company name). (Do/Does) (you/he/she) still work for (input company name) at (your/his/her) main job?*".

[25]In BML19 we documented that 85 percent of the dynamics of U.S. *quarterly* transitions between full-time and *overall* part-time employment is driven by changes occurring at the same employer.

Table 6: Further decomposition of within-employment flows

A. Inflow $F \to I$			**B. Outflow** $I \to F$		
	1976-2019	1994-2019		1976-2019	1994-2019
β (SAME)		92.6	β (SAME)		90.1
$\beta\,(F \to S)$	66.8	65.9	$\beta\,(S \to F)$	61.4	63.3
$\beta\,(F \to C)$	33.2	34.1	$\beta\,(C \to F)$	38.8	36.6
			β (SHARE)	-0.17	0.14
$\beta\,(F \to S$, SAME)		62.6	$\beta\,(S \to F$, SAME)		59.6
$\beta\,(F \to C$, SAME)		30.7	$\beta\,(C \to F$, SAME)		30.2
			β (SHARE, SAME)		0.12

Notes: CPS data, 1976m01 – 2019m12. Transition probabilities are corrected for the 1994 break, and adjusted sequentially for seasonality, margin error and time aggregation. The table reports the variance contributions of within-employer transitions and of reason-specific involuntary part-time work to the dynamics of the transition probabilities $p\,(F \to I)$ and $p\,(I \to F)$. 'SAME': Transitions at the same employer (data cover the period 1994m02 to 2019m12); 'S': Slack work conditions; 'C': Cannot find full-time job; 'SHARE': Changes in the shares of reason-specific involuntary part-time work (see equation (A.7) in Appendix A). All table entries are expressed in percent.

find that almost one quarter ($62.6 \times 17.2 + 59.6 \times 21.9 = 23.8$ percent) of the variation of i_t is driven solely by within-employer fluctuations between full-time and involuntary part-time employment due to slack work conditions.

The close association between involuntary part-time employment due to slack work and turnover at the same employer is useful to speculate whether there have been significant changes in the importance of within-employer turnover across recessions spanning the past four decades. Figure 6 speaks to this by showing the composition of involuntary part-time employment by reason in each recessionary episode in our dataset. Two observations stand out. First, in all recessionary episodes, the main driver of the initial increase in involuntary part-time employment is "slack work". Two, while in the earlier recessionary episodes "could only find part-time work" is the main driver of the persistently elevated involuntary part-time employment during the recovery, that is no longer the case in the most recent recessions, which are completely dominated by "slack work". These patterns are very closely aligned with those shown in Figure 5, namely the contributions of $p\,(F \to I)$ and $p\,(I \to F)$ to the dynamics of involuntary part-time employment. It is quite remarkable that the counterfactual changes shown in Figure 5, which are the outcomes of a sophisticated calculation, line up so closely with workers' stated reasons for working part-time hours. Overall, Figure 6 reinforces the notion that the composition of the dynamics of involuntary

Figure 6: Reasons for involuntary part-time employment during recessions

Notes: CPS data. The solid line shows the actual involuntary-part-time employment rate. Each solid line shows the change in the involuntary part-time employment rate from its value at time 0, the starting month of the corresponding recession. The other lines report changes in the involuntary part-time employment rate due to slack work conditions (dashed lines) and workers who cannot find a full-time job (dotted lines). All series are expressed in percentage points difference. The scale on the vertical axis is different across mild (Plots 6b and 6c) and large recessions (Plots 6a and 6d). Gray-shaded areas indicate NBER recession periods.

part-time employment has changed in the two most recent recessions, with within-employer turnover playing a more prominent role.

8 Discussion

In this section we discuss the implications of our empirical findings for macroeconomic analysis of labor markets.

Internal vs external labor market adjustment. Our results strongly reinforce the characterization of the intensive margin of labor adjustment put forward in BML19. Specifically, following a negative shock, some employed workers are "turned down" by their employers into working lower hours (which results in F to I transitions) with the understanding that they will be brought back to higher working hours when business conditions improve (I to F transitions). Consistent with this interpretation, a key source of cyclical variation in flows between involuntary part-time and full-time employment is accounted for by changes within the same employer. For workers undergoing those transitions, this means that they remain within the internal market of their employer. A (permanent) separation to unemployment, on the other hand, implies that the worker can only regain employment through the external labor market. The distinction between mechanisms governing these outcomes is particularly sharp when we consider movements in $p\,(I \to F)$ and $p\,(U \to F)$. On the one hand, changes in $p\,(U \to F)$ are explained primarily by shifts in job creation. On the other, we find that changes in $p\,(I \to F)$ entail, in the majority of cases, a return to a full-time work schedule at the same employer.[26] To paraphrase Bell and Blanchflower [2019], involuntary part-time employment is personal in a way that unemployment is not.

More broadly, our analysis points to a form of job/match heterogeneity that determines whether the adjustment in response to a given adverse economic shock occurs through involuntary part-time employment or through unemployment. Indeed, some of the dynamics that we uncover suggest that the same impulse shocks drive involuntary part-time work and unemployment fluctuations. These findings resonate closely the analysis of temporary layoffs and recalls by Fujita and Moscarini [2017], albeit with some noticeable differences. They show that in the U.S. unemployed workers face a very high probability of being recalled by their previous employer, and that the probability of being recalled is much less cyclical than the job-finding rate. Their main interpretation of recalls is that they are not mediated by search frictions and that, therefore, they impose smaller costs on both workers and

[26] In preliminary analyses based on SIPP data, we condition the transition probability $p\,(F \to I)$ on job tenure, and verify that full-time workers at risk of working part-time involuntarily in recessions' aftermaths are workers with a long-established relationship with their employer. This fact dovetails with the analysis of the dynamics of involuntary part-time work within subgroups of the population (see Borowczyk-Martins and Lalé [2016]). During downturns, the composition of full-time employment and involuntary part-time employment shifts towards older and better educated workers, and these subgroups also experience higher relative increases (decreases) in their group-specific $p\,(F \to I)$ ($p\,(I \to F)$). However, these composition effects play a limited role in the cyclical behavior of aggregate $p\,(F \to I)$ and $p\,(I \to F)$.

firms. Our findings show that the workings of this type of labor adjustment channel (i.e. not mediated by search frictions and hiring/firing costs) is even more pervasive than Fujita and Moscarini [2017]'s analysis suggests. More importantly, we find that both transitions between involuntary part-time and full-time employment are as large and as cyclical as their unemployment counterparts. This indicates that involuntary part-time reallocation is used more intensively in bad times and, therefore, it constitutes an important element to understand labor adjustment during recessions. An interesting avenue for future work is to develop macro-search models with a margin of involuntary part-time work that can be activated in response to shocks that are otherwise responsible for unemployment fluctuations.

U-6, non-employment index or underemployment rate? Our findings uncover a clear relationship between involuntary part-time employment and the fragility of full-time employment relationships, with very pronounced and stable patterns over the business cycle. Therefore, fluctuations in involuntary part-time employment carry additional information on the impact of the business cycle on the labor market. This point is best illustrated in the large and persistent contribution of $p(F \to I)$ to elevated levels of involuntary part-time employment during recessions and their aftermaths. Its greater persistence relative to $p(F \to U)$ shows that, long after job destruction rates have returned to pre-crisis levels (usually a few months after the recession's trough), a large fraction of full-time employment relationships remains unstable (Figure 4). The episode of the Great Recession is elucidative. Thirty months after the recession's trough, the contributions of flows from F to I remained comparable to those of transitions in the reverse direction. This conclusion goes against a common view that high recessionary levels of involuntary part-time employment reflect "hidden unemployment", so that adding up the involuntary part-time employment and unemployment rates would provide a relevant metric for measuring labor market slack. According to this view, a high level of this indicator means that too few jobs are being created (which is why unemployment remains elevated), and that, amongst newly-created jobs, too many positions are part-time instead of full-time (which is why involuntary part-time employment remains elevated). But Figure 5 shows that high rates of involuntary part-time employment during recessions are not fueled by large inflows of unemployed workers. The composition of involuntary part-time work inflows by reason (Table 6), which is dominated by slack work conditions, reinforces this conclusion.

The view described in the previous paragraph is often used to interpret the levels and dynamic behavior of the BLS's U-6 measure.[27] The evolution of the U.S. labor market after

[27] See `https://www.bls.gov/lau/stalt.htm`. The U-6 is the sum of total unemployment, all marginally attached workers, and all involuntary part-time workers, divided by the civilian labor force plus all marginally attached workers.

the Great Recession has generated great interest in developing measures of labor utilization that go beyond U-6. Hornstein et al. [2014] propose a Non-Employment Index (NEI) that counts the number of non-employed workers weighted by their probability of becoming employed (calculated to account for observational differences across various segments of the workforce).[28] The extended version of the NEI includes involuntary part-time workers weighted by their hours as well as by their probability of moving to full-time work. Our analysis strongly supports this weighting strategy. Bell and Blanchflower [2019] develop an underemployment rate that counts the unemployed and employed workers who are dissatisfied with their working hours given their current pay rate. They are able to identify the latter by using information available in the European Labor Force surveys. Similar information is not available for the U.S., which is unfortunate, especially because Bell and Blanchflower [2019] show that involuntary part-timers are not the only workers who wish to work different hours. Ours and Hornstein et al. [2014]'s analyses suggest that extending the underemployment rate to account for the probability that employed workers attain their desired hours would provide an even more accurate picture of labor market slack in Europe.[29]

9 Concluding Remarks

This paper addresses methodological breaks in data collection on involuntary part-time employment to construct U.S. monthly time series of stocks and flows from 1976 until today. We use these new data to analyze the role of involuntary part-time work in U.S. labor market dynamics, and more broadly to describe cyclical labor adjustment on the intensive and extensive margins.

An important by-product of our analysis is a new dataset of U.S. worker flows. We think this data can be useful not only to calibrate and assess quantitatively models of cyclical labor adjustment, but also to explore other empirical questions. For example, we do not explore the long-run perspective afforded by our dataset to study how the risks of involuntary part-time employment and unemployment have evolved over time. A question that has received considerable attention in the literature concerns evidence on dwindling U.S. business and employment dynamics (see e.g. Davis et al. [2010] and Hyatt and Spletzer [2013]). Interestingly, over the same period involuntary part-time employment inflows and outflows show no visible declining trend. These observations indicate that, relative to the risk of

[28] See `https://www.richmondfed.org/research/national_economy/non_employment_index`.

[29] Measuring whether the economy is at full capacity in terms of labor utilization is key for fiscal and monetary policy. The underemployment rate is also particularly important to understand the behavior of wages: Bell and Blanchflower [2019] show that its impact on wage growth (and the lack thereof) has become more important than the impact of the unemployment rate.

becoming unemployed, employed workers in the U.S. labor market face an increasing risk of working part-time and to do it involuntarily during recessions. Future work could use our data to investigate whether there is a common explanation for these long-run trends.

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Appendices

A Measurement Details

This appendix provides details on the margin-error adjustment procedure used in Section 3 and on the variance decomposition used in Sections 4 to 7.

A.1 Margin-error adjustment

Let $\breve{\boldsymbol{p}}_t$ denote the vector of outflow transition probabilities measured using the raw data from the BM files. The margin-error procedure involves adjusting $\breve{\boldsymbol{p}}_t$ to make it consistent with the series of changes in stocks obtained in step 1 denoted as $\Delta \boldsymbol{s}_t$, where Δ is the first-difference operator. Starting from equation (3), i.e. $\boldsymbol{s}_t = \boldsymbol{M}_t \boldsymbol{s}_{t-1}$, we re-write it as

$$\Delta \boldsymbol{s}_t = \boldsymbol{S}_{t-1} \boldsymbol{p}_t, \tag{A.1}$$

or, written in explicit form,

$$\underbrace{\begin{bmatrix} \triangle F_t \\ \triangle V_t \\ \triangle I_t \\ \triangle U_t \\ \triangle N_t \end{bmatrix}}_{\Delta \boldsymbol{s}_t} = \underbrace{\begin{bmatrix} -F_{t-1} & F_{t-1} & 0 & 0 & 0 \\ -F_{t-1} & 0 & F_{t-1} & 0 & 0 \\ -F_{t-1} & 0 & 0 & F_{t-1} & 0 \\ -F_{t-1} & 0 & 0 & 0 & F_{t-1} \\ V_{t-1} & -V_{t-1} & 0 & 0 & 0 \\ 0 & -V_{t-1} & V_{t-1} & 0 & 0 \\ 0 & -V_{t-1} & 0 & V_{t-1} & 0 \\ 0 & -V_{t-1} & 0 & 0 & V_{t-1} \\ I_{t-1} & 0 & -I_{t-1} & 0 & 0 \\ 0 & I_{t-1} & -I_{t-1} & 0 & 0 \\ 0 & 0 & -I_{t-1} & I_{t-1} & 0 \\ 0 & 0 & -I_{t-1} & 0 & I_{t-1} \\ U_{t-1} & 0 & 0 & -U_{t-1} & 0 \\ 0 & U_{t-1} & 0 & -U_{t-1} & 0 \\ 0 & 0 & U_{t-1} & -U_{t-1} & 0 \\ 0 & 0 & 0 & -U_{t-1} & U_{t-1} \\ N_{t-1} & 0 & 0 & 0 & -N_{t-1} \\ 0 & N_{t-1} & 0 & 0 & -N_{t-1} \\ 0 & 0 & N_{t-1} & 0 & -N_{t-1} \\ 0 & 0 & 0 & N_{t-1} & -N_{t-1} \end{bmatrix}'}_{\boldsymbol{S}_{t-1}} \times \underbrace{\begin{bmatrix} p_t^{FV} \\ p_t^{FI} \\ p_t^{FU} \\ p_t^{FN} \\ p_t^{VF} \\ p_t^{VI} \\ p_t^{VU} \\ p_t^{VN} \\ p_t^{IF} \\ p_t^{IV} \\ p_t^{IU} \\ p_t^{IN} \\ p_t^{UF} \\ p_t^{UV} \\ p_t^{UI} \\ p_t^{UN} \\ p_t^{NF} \\ p_t^{NV} \\ p_t^{NI} \\ p_t^{NU} \end{bmatrix}}_{\boldsymbol{p}_t}. \tag{A.2}$$

$\boldsymbol{S}_{t-1}$ is a conformable matrix of labor market stocks in the previous month and $\boldsymbol{p_t}$ is the 'true' vector of outflow transition probabilities (the transition probabilities $p\,(j \to k)$ across states j and k at time t have been written as p_t^{jk} in order to lighten the notation). $\boldsymbol{p_t}$ is recovered by minimizing the weighted sum of squares of the margin-error adjustments:

$$\min_{\boldsymbol{p}_t} \left(\boldsymbol{p}_t - \breve{\boldsymbol{p}}_t\right)' \boldsymbol{W}_t^{-1} \left(\boldsymbol{p}_t - \breve{\boldsymbol{p}}_t\right) \text{ s.t. } \triangle \boldsymbol{s}_t = \boldsymbol{S}_{t-1} \boldsymbol{p}_t, \tag{A.3}$$

where $\boldsymbol{W}_t$ is a weighing matrix proportional to the covariance matrix of $\breve{\boldsymbol{p}}_t$. Specifically, by virtue of Markov chain properties, the diagonal elements of the covariance matrix of $\breve{\boldsymbol{p}}_t$ have the form, $\breve{p}_t^{jk}\left(1 - \breve{p}_t^{jk}\right)$, whereas non-diagonal elements with the same departing state have the form, $-\breve{p}_t^{jk}\breve{p}_t^{j\ell}$, for all j and with $j \neq k, \ell$. $\boldsymbol{W}_t$ is a 20×20 matrix with those values (scaled by the respective departing labor stock j_{t-1}) on its main 4×4 diagonal blocks, and with blocks of zeros in the remaining entries. For instance the first four rows of $\boldsymbol{W}_t$ are

$$\begin{bmatrix} \frac{\breve{p}_t^{FV}\left(1-\breve{p}_t^{FV}\right)}{F_{t-1}} & -\frac{\breve{p}_t^{FV}\breve{p}_t^{FI}}{F_{t-1}} & -\frac{\breve{p}_t^{FV}\breve{p}_t^{FU}}{F_{t-1}} & -\frac{\breve{p}_t^{FV}\breve{p}_t^{FN}}{F_{t-1}} & \mathbf{0_{16}} \\ -\frac{\breve{p}_t^{FI}\breve{p}_t^{FV}}{F_{t-1}} & \frac{\breve{p}_t^{FI}\left(1-\breve{p}_t^{FI}\right)}{F_{t-1}} & -\frac{\breve{p}_t^{FI}\breve{p}_t^{FU}}{F_{t-1}} & -\frac{\breve{p}_t^{FI}\breve{p}_t^{FN}}{F_{t-1}} & \mathbf{0_{16}} \\ -\frac{\breve{p}_t^{FU}\breve{p}_t^{FV}}{F_{t-1}} & -\frac{\breve{p}_t^{FU}\breve{p}_t^{FI}}{F_{t-1}} & \frac{\breve{p}_t^{FU}\left(1-\breve{p}_t^{FU}\right)}{F_{t-1}} & -\frac{\breve{p}_t^{FU}\breve{p}_t^{FN}}{F_{t-1}} & \mathbf{0_{16}} \\ -\frac{\breve{p}_t^{FN}\breve{p}_t^{FV}}{F_{t-1}} & -\frac{\breve{p}_t^{FN}\breve{p}_t^{FI}}{F_{t-1}} & -\frac{\breve{p}_t^{FN}\breve{p}_t^{FU}}{F_{t-1}} & \frac{\breve{p}_t^{FN}\left(1-\breve{p}_t^{FN}\right)}{F_{t-1}} & \mathbf{0_{16}} \end{bmatrix}$$

where $\mathbf{0_{16}}$ is a 1×16 vector of zeros.

A.2 Variance decomposition

A complete formal treatment of the variance decomposition is provided in Borowczyk-Martins and Lalé [2019] (BML19). Here we provide a detailed description and key equations from BML19 to explain the workings of this decomposition.

To begin with, we normalize the size of the labor force in each period t (i.e. the sum $F_t + V_t + I_t + U_t + N_t$) to one and rewrite the Markov chain (1) accordingly. We denote by $\tilde{\boldsymbol{s}}_t$ the vector of the re-arranged Markov chain. Working backwards from period t, it can be shown that its first difference, denoted as $\triangle\tilde{\boldsymbol{s}}_t$, is the sum of current and past changes in each flow hazard (the λ^{jk}'s) starting from the initial conditions of the Markov chain. Combining this with a Taylor expansion around the steady state of labor market stocks, we have

$$\mathbb{V}\text{ar}\left(\triangle\tilde{\boldsymbol{s}}_t\right) \approx \sum_{j\neq k} \mathbb{C}\text{ov}\left(\triangle\tilde{\boldsymbol{s}}_t, \sum_{\tau=0}^{t-2} \mathbf{E}_{\tau,t-\tau} \frac{\partial \bar{\tilde{\boldsymbol{s}}}_{t-\tau}}{\partial \lambda_{t-\tau}^{jk}} \triangle\lambda_{t-\tau}^{jk}\right) \tag{A.4}$$

(equation (B9) in BML19). That is, the variance-covariance matrix of changes in $\tilde{\boldsymbol{s}}_t$ is the sum of 20 variance-covariance matrices, each of which measures the contribution of a specific flow hazard to changes in labor market stocks. For each λ^{jk}, this measurement is based on the specific time series of counterfactual changes in stocks driven by current and past changes of $\triangle\lambda_t^{jk}$, denoted as $\sum_{\tau=0}^{t-2} \mathbf{E}_{\tau,t-\tau} \frac{\partial \bar{\tilde{\boldsymbol{s}}}_{t-\tau}}{\partial \lambda_{t-\tau}^{jk}} \triangle\lambda_{t-\tau}^{jk}$ in equation (A.4).[30] By looking at the diagonal

[30]The term $\mathbf{E}_{\tau,t-\tau}$ is the matrix formed of current and past values of the transition probabilities p_t^{jk} via the distributed lag form expression of $\triangle\tilde{\boldsymbol{s}}_t$ (see equation (B5) in BML19).

elements of the matrices on both side of equation (A.4), we obtain a variance decomposition of changes in each labor market stock of the Markov chain $\tilde{\boldsymbol{s}}_t$.

For the next step of the calculation, recall that we are interested in the dynamics of the involuntary part-time employment rate i_t. This is a *ratio* between labor market stocks. We use the following first-order linear approximation:

$$\triangle i_t \approx \frac{\triangle \tilde{I}_t \left(1 - i_{t-1}\right) - \left(\triangle \tilde{F}_t + \triangle \tilde{V}_t + \triangle \tilde{U}_t\right) i_{t-1}}{\tilde{F}_{t-1} + \tilde{V}_{t-1} + \tilde{I}_{t-1} + \tilde{U}_{t-1}} \tag{A.5}$$

to express the variance $\mathbb{V}\text{ar}\left(\triangle i_t\right)$ as the sum of the variances of changes in each labor market stocks. Since we have decomposed the latter into the contribution of current and past changes in each flow hazard λ^{jk}, we obtain the counterfactual series $\Delta \widetilde{i_t}^{jk}$ used to conduct a similar decomposition of the dynamics of the involuntary part-time employment rate.

Decomposition of transition probabilities by reason. In Table 6, we decompose the dynamics of transition probabilities into the contribution of reason-specific involuntary part-time employment. Denoting by S part-time work due to slack work conditions, and by C part-time work because the worker cannot find a full-time job, we have: $I_t = S_t + C_t$ and $i_t = i_t^S + i_t^C$. It is then straightforward to decompose changes in p_t^{FI}. We do so by using:

$$\underbrace{p_t^{FI} - p_{t-1}^{FI}}_{F \to I} = \underbrace{p_t^{FS} - p_{t-1}^{FS}}_{F \to S} + \underbrace{p_t^{FC} - p_{t-1}^{FC}}_{F \to C}. \tag{A.6}$$

For instance, $\beta\left(F \to S\right)$ in the top panel of Table 6 is the covariance between $\triangle p_t^{FI}$ and $\triangle p_t^{FS}$ divided by the variance of $\triangle p_t^{FI}$.

For changes in p_t^{IF}, we must account for compositional changes in the pool of involuntary part-time employment, in addition to changes in transition probabilities. Indeed, we have $p_t^{IF} = \frac{i_t^S}{i_t} p_t^{SF} + \frac{i_t^C}{i_t} p_t^{CF}$, meaning that we must rely on the following 'shift-share' equation:

$$\begin{aligned}\underbrace{p_t^{IF} - p_{t-1}^{IF}}_{I \to F} = {} & \underbrace{\frac{\frac{i_t^S}{i_t} + \frac{i_{t-1}^S}{i_{t-1}}}{2}\left(p_t^{SF} - p_{t-1}^{SF}\right)}_{S \to F} + \underbrace{\frac{\frac{i_t^C}{i_t} + \frac{i_{t-1}^C}{i_{t-1}}}{2}\left(p_t^{CF} - p_{t-1}^{CF}\right)}_{C \to F} \\ & + \underbrace{\frac{p_t^{SF} + p_{t-1}^{SF}}{2}\left(\frac{i_t^S}{i_t} - \frac{i_{t-1}^S}{i_{t-1}}\right) + \frac{p_t^{CF} + p_{t-1}^{CF}}{2}\left(\frac{i_t^C}{i_t} - \frac{i_{t-1}^C}{i_{t-1}}\right)}_{\text{SHARE}}.\end{aligned} \tag{A.7}$$

Interpreting the variance contribution of changes in the shares of reason-specific involuntary part-time employment is not easy. Fortunately for us, this component accounts for less than 1 percent of the dynamics of p_t^{IF}.

In addition to reason-specific involuntary part-time employment, we also study the contribution of transitions at the same employer to the dynamics of inflows and outflows. We are able to do so because all the transitions listed above (FI, FS, FC, IF, SF, CF) imply that the individual remains employed in two consecutive months. In the revised CPS, an individual who is observed in two consecutive months or more reports in the second month of interview whether s/he is employed with the same employer as in the previous month (SAME = 1). Thus, we can use the fact that, for example, $p_t^{IF} = p_t^{IF,\text{SAME}=1} + p_t^{IF,SAME=0}$ and measure the variance contribution of $p_t^{IF,\text{SAME}=1}$.

B Robustness Checks

B.1 Adjustment of stocks for the CPS 1994 break

We have proposed a protocol to address the discontinuity triggered by the CPS redesign. In this section, we describe the results of several checks of our adjustment protocol.

B.1.1 Comparison to other data sources. As we have explained in the introduction, in BML19 we constructed series of *overall* part-time employment before 1994 using the Earner Study questions administered to the CPS Outgoing Rotation Group samples. We can compare the *sum* of our time series V_t and I_t to those data. The differences between them are negligible (details available upon request).

The Survey of Income and Program Participation (SIPP) provides another source of data against which we can check the robustmess of our adjustment protocol. Based on the SIPP, we can construct monthly labor market stocks for both voluntary and involuntary part-time employment. We do so using the 1990, 1991, 1992 and 1993 panels, which are homogeneous in terms of their structure and span the period from October 1989 to December 1995, hence including the period of the break in the CPS.[31] Comparison of the dynamics of the CPS-based adjusted series and their SIPP counterparts around the 1994 break in Figure B1 shows they are remarkably similar.[32] In particular, the slight upward trend in involuntary part-time employment in the early 1990s is also visible in the time series based on the SIPP data. We view this as an important external source of validation of the protocol, given that the data underlying the dashed lines in Figure B1 are not based on the CPS.

B.1.2 Testing for the 1994 break. Since the goal of our procedure is to remove any discontinuities in the series of stocks and flows fabricated by the 1994 redesign, we test for the presence of a 1994 break in the adjusted series. We do so by running the following type of regressions:

$$s_t = \alpha \mathbb{1}\left\{y\left(t\right) < 1994\right\} + \sum_n \gamma_n t^n + \sum_m \delta_m \mathbb{1}\left\{m\left(t\right) = m\right\} + \upsilon_t. \qquad \text{(B.1)}$$

[31]Using the SIPP to construct longer time series of part-time employment is difficult. The SIPP came into existence before the 1990 panel, but the structure of its files changes drastically from this point on. The structure evolves again in 1996, and in addition the number of categories used to classify part-time workers changes between the 1990-1993 panels (variable 'WKSPTR') and the 1996 panel (variable 'EPTRESN'). The 1990-1993 panels are sufficient for our purpose, which is to scrutinize January 1994 with data that are not based on the CPS.

[32]In Figure B1 the time series span the period from December 1989 to October 1995: we drop the first and last two months of the SIPP data because these contain less than three SIPP rotation groups, which results in very large discrepancies in the estimates of labor market stocks.

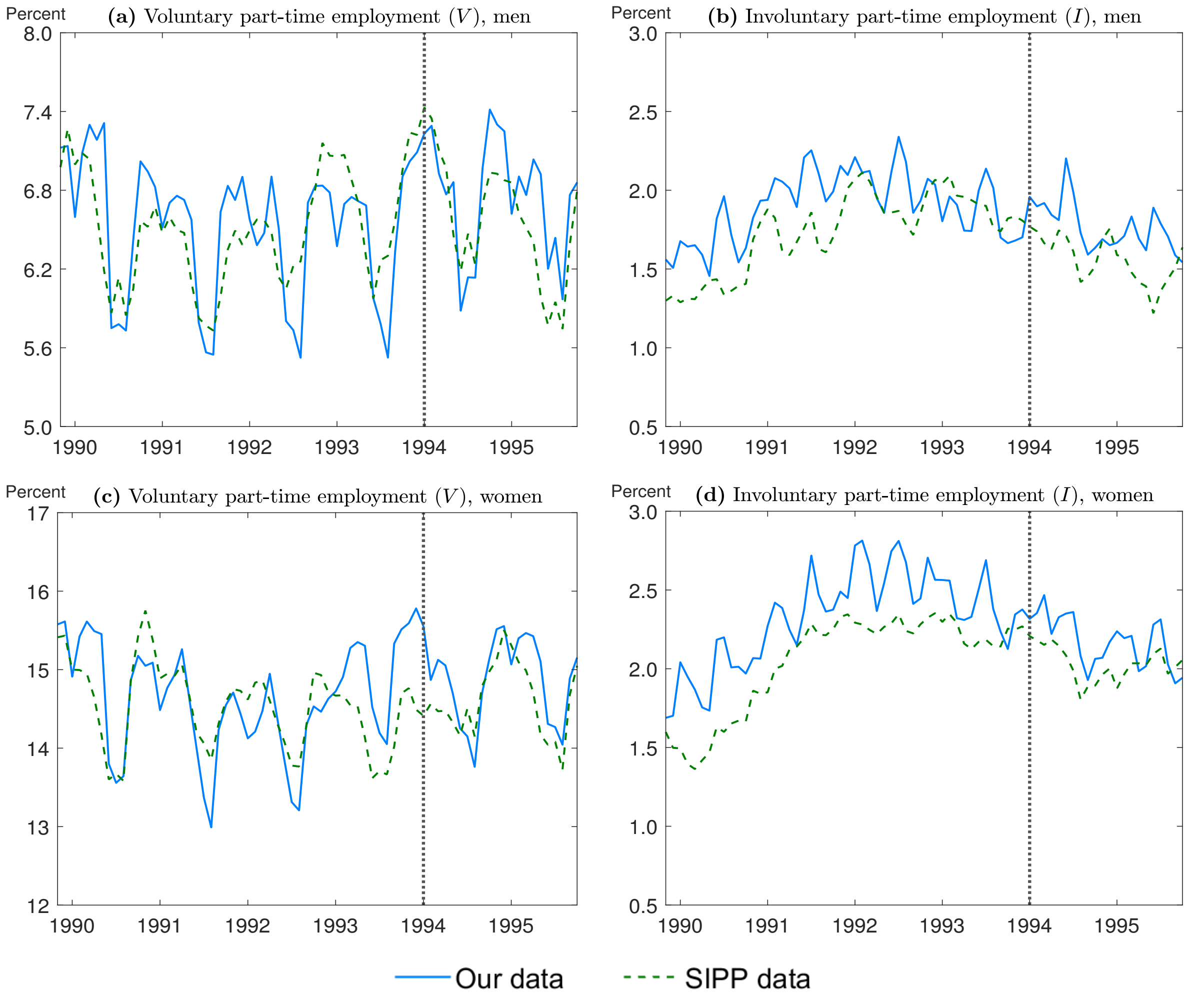

Figure B1: Stocks of voluntary and involuntary part-time workers: Our vs. SIPP data

Notes: CPS and SIPP data, 1989m12 – 1995m10. The plots show the (not seasonally adjusted) series of stocks of voluntary (Plots B1a and B1c) and involuntary (Plots B1b and B1d) part-time employment based on our adjustment protocol (solid lines) and those computed using data from the SIPP (dashed lines). Stocks are normalized by the corresponding working-age population and expressed in percent. The vertical line in each plot indicates January 1994.

In this equation, s_t denotes a series of stock or flow transition probability, $\mathbb{1}\{y(t) < 1994\}$ is a dummy for the CPS redesign, $\sum_n \gamma_n t^n$ is a flexible polynomial of time, the $\mathbb{1}\{m(t) = m\}$'s are monthly dummies, and v_t is the residual. Typically, we set $n = 7$ and use a window of 25 years of monthly data centered on January 1994. The results (available upon request) unanimously show that the coefficient α in these regressions is not statistically significant.

B.1.3 Adjusting data at finer levels. In this paper we present results concerning the whole working-age population. Increasingly, macro- and labor economists are interested in studying stocks and flows among more disaggregated segments of the labor market (e.g. by gender, age groups, etc.). Therefore, the usefulness of our adjustment protocol depends, at least partially, on its performance in the estimation of stocks and flows at a finer level. In the dataset that accompanies the paper, in addition to the aggregate data, we provide data (namely, estimates of stocks and transition probabilities for F_t, V_t, I_t, U_t, N_t, and also for I_t disaggregated by reason) separately for men and women. These data show a great deal of consistency over the whole sample period.

Our adjustment protocol also works well at even finer levels of aggregation. We are able to obtain consistent time series of stocks and flows for the following 20 subgroups of the population aged 15 to 75 years old: Men aged 15 to 24; Men aged 25 to 39; Men aged 40 to 54; Men aged 55 to 75; Women aged 15 to 24; Women aged 25 to 39; Women aged 40 to 54; Women aged 55 to 75; Men with less than high school education; Men with high school education; Men with some college education; Men with college or higher education; Women with less than high school education; Women with high school education; Women with some college education; Women with college or higher education; Unmarried men; Married men; Unmarried women; Married women.

B.2 Adjustment for potentially spurious transitions

In Section 5, we studied the consequences of potentially spurious transitions within part-time employment. To complement this study, In Figure B2 we report the shares of transitions between V and I discarded by deVIVification. As we highlighted in the main text, the levels of these series are similar. On average: 44.2 percent for $V \to I$, 48.2 percent for $I \to V$, despite very large differences between the transition probabilities in the raw data. Figure B3, which compares our baseline transition probabilities (solid lines) with those obtained after adjusting for potentially spurious transitions (dashed lines), further shows the effect of deVIVification on all involuntary part-time employment inflows and outflows.

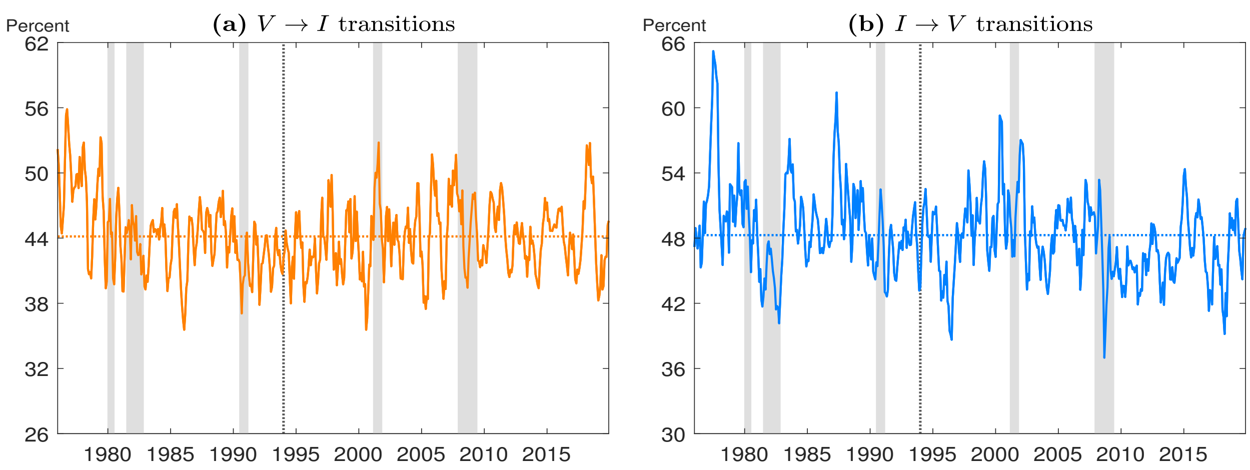

Figure B2: Fraction of discarded transitions between V and I

Notes: CPS data, 1976m01 – 2019m12. The plots show the fraction of transitions from V to I (Plot B2a) and from I to V (Plot B2b), where V (I) denotes voluntary (involuntary) part-time employment, discarded by the correction procedure. All series are expressed in percent. The vertical line in each plot indicates January 1994. Gray-shaded areas indicate NBER recession periods.

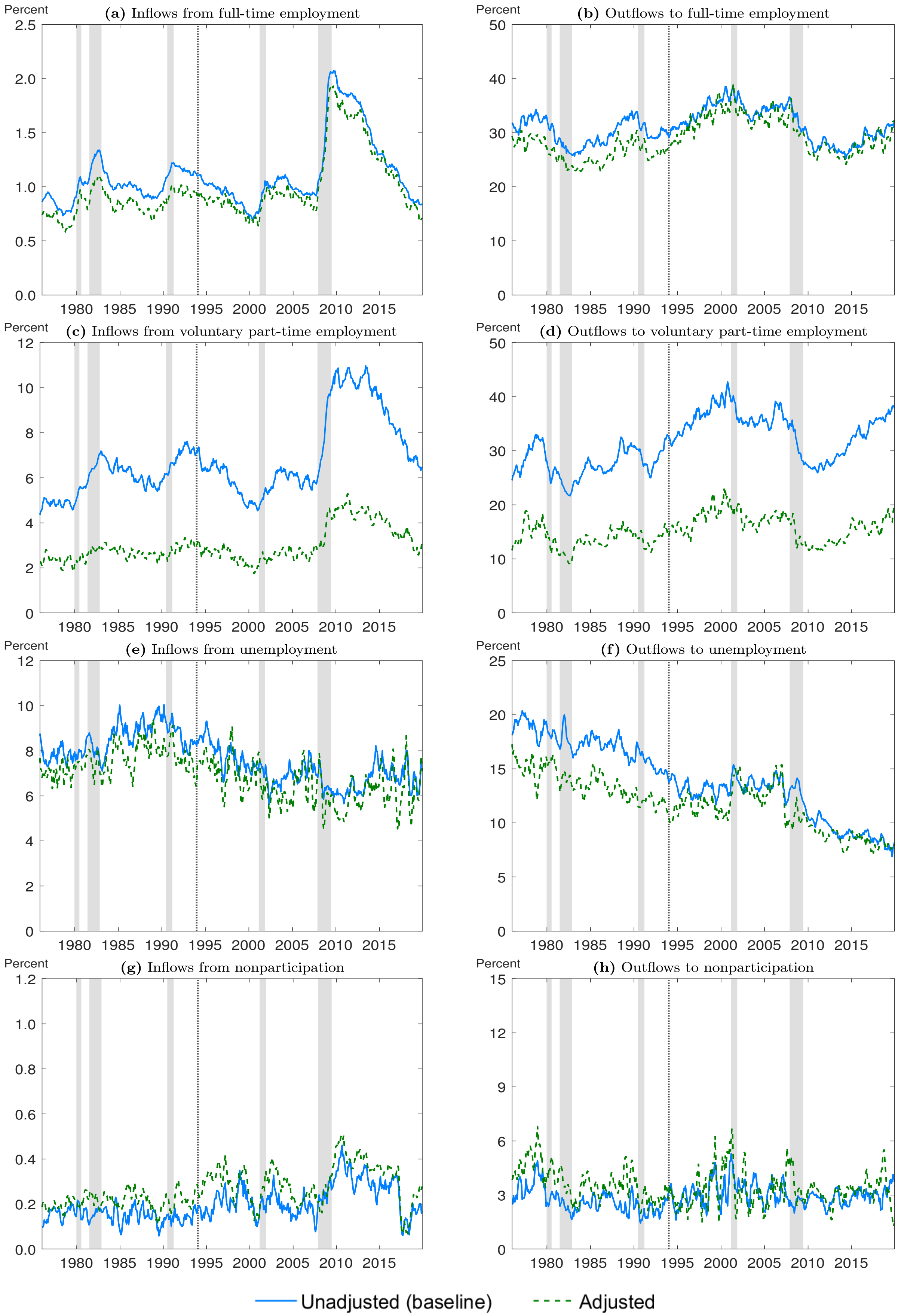

Figure B3: Transition probabilities adjusted for potentially spurious transitions

Notes: CPS data, 1976m01 – 2019m12. The solid lines denote baseline transition probabilities adjusted sequentially for seasonality, margin error and time aggregation. The dashed lines denote transition probabilities adjusted in addition for potentially spurious transitions between I and V. All series are smoothed using a one-period, two-sided moving-average. All series are expressed in percent. The vertical line in each plot indicates January 1994. Gray-shaded areas indicate NBER recession periods.