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The Ins and Outs of Involuntary Part-time Employment

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The Ins and Outs of Involuntary Part-time Employment

Daniel Borowczyk-Martins *et* Etienne Lalé

Avril 2019

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The Ins and Outs of Involuntary Part-time Employment*

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Abstract

We develop an adjustment procedure to construct 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 dynamics of involuntary part-time work. Transitions from full-time to involuntary part-time employment dominate this dynamics, spiking up at recessions' onsets and persisting well into recovery periods. Weaknesses in job creation, on the other hand, contribute little to these fluctuations. Our data and findings are relevant to inform a broader assessment of labor market performance and to develop models of cyclical labor adjustment.

JEL codes: E24; E32; J21.

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

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1 Introduction

In this paper we measure transition probabilities across five labor market states (full-time employment, voluntary and involuntary part-time employment, unemployment and nonparticipation) using United States data over the past forty-five years. We use these measurements to uncover the main sources of cyclical labor adjustment on the intensive and extensive margins.[1] Our motivation is to provide macroeconomists with a picture of the cyclical behavior of both margins of labor adjustment and the interactions between them.

The empirical literature on worker flows focuses on the dynamics of unemployment using a three-state model (employment, unemployment and nonparticipation). This focus is justified by the very large contribution of unemployment to the cyclical behavior of the extensive margin (see Hall [2005] and Rogerson and Shimer [2011]). In recent work (Borowczyk-Martins and Lalé [2019]), we showed that cyclical fluctuations on the intensive margin are predominantly driven by changes in flows between part-time and full-time employment, and used a four-state model to describe those dynamics. In this paper we introduce a conceptual distinction between voluntary and involuntary forms of part-time employment, and develop a new method to measure these concepts consistently from 1976 until today. We see this conceptual distinction as being analogous to the one made between unemployment and nonparticipation. Voluntary part-time employment and nonparticipation capture states in which individuals are not actively searching for new opportunities to adjust their labor supply, whereas both involuntary part-time employment and unemployment are predicated on workers willing and being available to increase their labor supply. In introducing this distinction, our main motivation is rooted in search theories of the labor market, in which states of search are notionally distinct from non-search states.[2]

[1] There are two margins of variation in labor input. The intensive margin refers to changes in hours per employed worker, while the extensive margin corresponds to changes in the number of employed workers.

[2] While search theory serves as a motivation, it does not constrain the interpretation of the data. Another important motivation of our analysis is the spectacular response of involuntary part-time employment during the Great Recession: at the recession's trough, it reached 5 percent of the U.S. labor force. A few recent papers (reviewed in Subsection 6.2 of the paper) measured and analyzed flows in and out of part-time

The distinction between voluntary and involuntary part-time employment introduces two measurement challenges that we address in this paper. Our main source of data is the Current Population Survey (CPS), which has informed the majority of studies on worker flows in the U.S. labor market. The monthly CPS underwent a significant redesign in 1994, which, among other things, introduced a tighter concept of involuntary part-time employment.[3] 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 estimate the levels of voluntary and involuntary part-time employment stocks prior to 1994. We combine data from the Annual Social and Economic Supplements with monthly data from the basic CPS to backcast monthly series of part-time employment stocks based on the post-1994 definition. In the second step, we adjust the series of voluntary and involuntary part-time employment flows before 1994.[4] To do so, we combine Markovian assumptions on the dynamics of labor stocks and the series of stocks estimated in the first step of our adjustment protocol.

The first step of our protocol offers an alternative to the standard approach in the literature to deal with the 1994 redesign, which consists of using the factors provided in Polivka and Miller [1998] (henceforth PM98) to adjust pre-1994 series. PM98 estimate adjustment factors for various aggregate measures (including involuntary part-time work) based on data from a parallel survey run by the U.S. Bureau of Labor Statistics (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

employment to understand this phenomenon. For reasons of data availability, these studies focused on the period after 1994. This is quite restrictive both for uncovering systematic patterns of labor adjustment during recessions (there have been only two recessions since 1994) and for tracking secular changes in high-frequency labor-market reallocation.

[3]An individual is considered to be working part-time involuntarily if she cannot find a full-time job or works part-time because of slack work / poor business conditions in her current job. To be classified as an involuntary part-timer in the redesigned CPS, the individual must also be willing and available to work full-time. To the extent that this requirement captures a constraint on desired labor supply, it aligns the notion of involuntary part-time work with that of unemployment.

[4]Since there series of flows are derived from the basic monthly files during that period, they are based on the pre-1994 definitions of involuntary and voluntary part-time employment.

does not depend on the levels of that series during the period spanned by the BLS parallel survey.[5] Another limitation is practical: PM98 estimated adjustment factors only for certain aggregates measures and the BLS survey is confidential. By contrast, 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.[6] Of course, our method is not free of assumptions: it rests on the requirement that the relationship between the annual supplements and the basic monthly CPS remains unchanged across the 1994 redesign. For this reason, we run several tests to check, and confirm, the robustness of our adjustment protocol.

The second measurement challenge arises from the fact that, while conceptually distinct, workers' classification between voluntary and involuntary part-time employment might be 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 very large biases in estimates of worker flows. As we show in the paper, the elevated levels of flows between voluntary and involuntary part-time employment are suggestive of such classification errors. To address this problem, we build on Elsby et al. [2015] and correct suspicious flows using a practical reclassification approach. We argue that this approach delivers the more credible sets of estimates.[7]

Having addressed the two measurement challenges, we use the newly created dataset to study the cyclical dynamics of the involuntary part-time employment rate and the unemployment rate. Fluctuations in these 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

[5] PM98 provide two types of adjustment factors: multiplicative and additive. The multiplicative adjustment factors depend on the levels of a series at the time when the adjustment factors are estimated. The additive adjustment factors avoid this issue, but are valid only under the assumption that the difference between the unadjusted and adjusted series remains the same over time. In practice researchers tend to use multiplicative adjustment factors.

[6] When working with time series for which there exist no adjustment factor from PM98's collection of estimates, researchers typically compute an alternative weight by taking the ratio of the January 1994 to the December 1993 observation of the time series (see Elsby et al. [2009] and Shimer [2012]).

[7] We are making these data publicly available from our personal webpages.

find themselves constrained in their desired labor supply. Because our findings on unemployment fluctuations reinforce the conclusions of the recent literature (Elsby et al. [2009], Fujita and Ramey [2009], Shimer [2012] and Elsby et al. [2015]), our main contribution concerns the analysis of involuntary part-time employment fluctuations and their interactions with unemployment. We establish three main facts. First, involuntary part-time employment is a very transitory labor-market state – an average spell lasts about 30% less than an average unemployment spell. Second, its main source of variation is cyclical and it is predominantly driven by within-employment reallocation – transitions to and from full-time and voluntary part-time employment account for just over three quarters of the short-run variation in involuntary part-time work. Third, 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 (mainly from full-time work) and by a drop in outflows to other employment states. As the recovery gets underway, low outflows to other employment states become a more important driver of involuntary part-time employment dynamics.

The second set of findings pertain to the interaction between involuntary part-time work and unemployment. While the unemployment and involuntary part-time employment rates are strongly correlated, the flows across the two states are low and exhibit no systematic cyclical pattern. Part-time employment flows play a minor role in the dynamics of unemployment, as the unemployment rate is driven mainly by flows in and out of full-time employment and nonparticipation. On the other hand, involuntary part-time employment dynamics are predominantly driven by flows in and out of other employment states.

The final set of findings concerns the changes in the dynamics of involuntary part-time employment and unemployment across different recessions. The long-run perspective afforded by our data brings to light a compositional shift in the cyclical dynamics of involuntary part-time employment. In the two most recent recessions the role of inflows from other employment states is much greater and is accompanied by a substantial increase in workers

who report slack work conditions as their main reason for working part-time involuntarily.

Our analysis brings to light a systematic pattern of cyclical labor adjustment manifest in fluctuations in involuntary part-time flows. We argue that those fluctuations reflect the operation of a distinct labor-adjustment channel compared to job creation and destruction, which drive the behavior of unemployment flows. As a result, and contrary to a common view, we find that the high levels of involuntary part-time work during and after recessions are unlikely to reflect weak job creation (i.e. the lack of new full-time employment opportunities). In contrast, our analysis points to continued fragility of ongoing employment relationships. In the last section of the paper we discuss how our findings relate to, and can be informative for, research in macroeconomics of the labor market.

This paper extends the empirical literature on labor market dynamics focused on the dynamics of unemployment (Elsby et al. [2009], Fujita and Ramey [2009], Shimer [2012] and Elsby et al. [2015]) and involuntary part-time employment (Canon et al. [2014], Warren [2017] and Lariau [2017]).[8] Our approach to deal with the 1994 CPS redesign adds to existing approaches proposed by PM98, Elsby et al. [2009] and Shimer [2012]. As we mentioned above, the present study is in part motivated by observations we made in Borowczyk-Martins and Lalé [2019] (BML19). In that paper, we focused on explaining the cyclical behavior of average hours per worker. We used CPS data from the basic monthly survey and from the Outgoing Rotation Group samples to construct series of *overall* part-time employment flows from 1976 to 2017 and series of the *relative* shares of voluntary and involuntary transitions towards part-time employment based on adjustment factors *à la* PM98 (see Footnote 6).[9] We used them to study the composition (voluntary vs. involuntary) of part-time employment inflows, which served to establish but one of the five facts documented in BML19. In the

[8]The analysis of involuntary part-time employment stocks and flows in this paper differs from earlier ones, not only by using a longer time window, but also in the methods used and analytical choices made. We provide a detailed discussion of these differences in Subsection 6.2. The current work also improves substantially upon the first working paper version of this paper, 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.

[9]The measurement of involuntary part-time work in the CPS Outgoing Rotation Group files suffers from the same discontinuity in 1994, meaning that the *levels* of voluntary and involuntary part-time employment inflows and outflows cannot be recovered from these data only.

present paper we estimate 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.

The paper is organized as follows. Section 2 introduces data and measurement issues. Section 3 sets out the adjustment protocol to address these issues and presents our empirical framework. Section 4 assesses the performance of the adjustment protocol. Sections 5 and 6 describe our main findings and their interpretation. Section 7 concludes.

2 Data and Measurement

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 on about 60,000 households. Its rotational design can be used to measure worker flows across up to four consecutive months. The ASEC files record information on individuals' labor market situation over the past calendar year. Our adjustment procedure (Section 3) relies on the combination of data in the BM and ASEC files.[10]

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.[11] It is worth stressing that the notion 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 (see U.S. Bureau of the Census [2017]):

[10]We use all BM files that are publicly available, i.e. since January 1976. Unfortunately, the BM files prior to this date used to construct the BLS series plotted in Figure 3 are not publicly available.

[11]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.

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?

The first sentence of the question above singles out individuals who are counted as involuntary part-time workers.[12]

The ASEC uses similar concepts of part-time and involuntary part-time employment, but measures 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 at least once 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.[13] First, it 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.[14] Second, the concept of involuntary part-time work was made more precise, by explicitly including the predicate that the individual wants and is available to work full-time.

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,

[12]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.

[13]See Section A of the online appendix for the relevant extracts of the old and revised CPS questionnaires.

[14]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 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 these predictions, 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. To sum up, for the purposes of our analysis some protocol must be devised to make the series derived from the old CPS consistent with those based on the post-1994 definitions.

3 Empirical Approach

Before presenting our adjustment protocol for the 1994 break, we introduce the framework used to study the dynamics of involuntary part-time employment.

3.1 Our 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). As will become clear in Section 5, it is important to distinguish V and F, as their dynamic interactions with involuntary part-time employment are fundamentally different. 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 3, 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 source of bias that affects the measurements of most labor market 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 1 shows alternative series of stocks of voluntary (Plot 1a) and involuntary (Plot 1b) 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 his period.[15] The basic idea of our

[15]It is conceivable, though, that there could be some spillover between the redesigned BM survey and the ASEC, and also that computerizing 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 1.

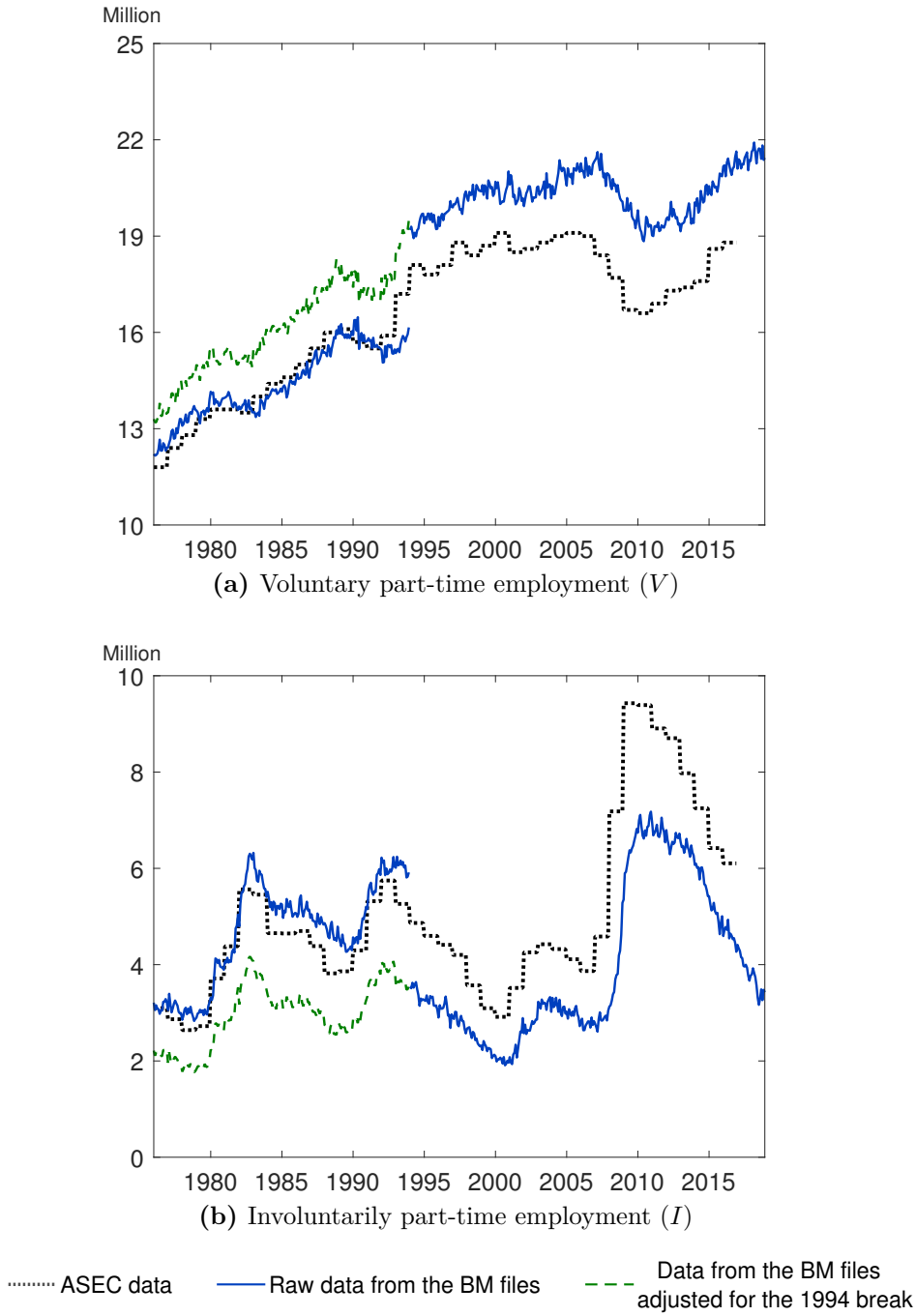
adjustment protocol is to use the information on the ASEC stock of involuntary part-time workers to predict the unobserved annual stocks implied by the monthly CPS prior to 1994. To do so, we assume that the relationship between the ASEC-based and BM-based time series observed post 1994 is the same in the pre-1994 period. This assumption is motivated by the very close covariance between the two series in the post-1994 period. The outcome of implementing this assumption are represented by the dashed lines in Figure 1. The levels of the series are well aligned with the 1994 ones, and mere visual inspection suggests their volatility is also similar.

We now formalize this approach. Let $s_{y,m}^{\text{BM}}$ 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_y^{ASEC} the series calculated from the ASEC. We observe s_y^{ASEC} throughout the whole period, but prior to 1994 we have a biased measurement of $s_{y,m}^{\text{BM}}$, which we denote by a breve superscript $\breve{s}_{y,m}^{\text{BM}}$. To obtain an estimate of $s_{y,m}^{\text{BM}}$ prior to 1994, we first compute the predicted yearly average of $s_{y,m}^{\text{BM}}$ before the CPS redesign, $\widehat{\overline{s}}_y^{\text{BM}}$. We construct it by running a regression of $s_{y,m}^{\text{BM}}$ against s_y^{ASEC} using data from the post-revision period:[16]

$$s_{y,m}^{\text{BM}} = \vartheta_0 + \vartheta_1 s_y^{\text{ASEC}} + \varepsilon_{y,m}, \quad y = 1994, \ldots, 2007, \ m = 1, \ldots, 12. \tag{4}$$

Having estimated ϑ_0 and ϑ_1, we use s_y^{ASEC} pre-1994 to generate $\widehat{\overline{s}}_y^{\text{BM}}$ before 1994. The next step involves using $\widehat{\overline{s}}_y^{\text{BM}}$ to derive $\widehat{s}_{y,m}^{\text{BM}}$, an estimate of $s_{y,m}^{\text{BM}}$ prior to 1994. We focus on linear specifications, i.e. we posit the following relationship: $\widehat{s}_{y,m}^{\text{BM}} = \phi_{0,y} + \phi_{1,y}\breve{s}_{y,m}^{\text{BM}}$. 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

[16] We experimented with different time windows to run this regression. Our favorite specification excludes data after 2007, when the Great Recession hits the labor market and the correlation between the BM-based and ASEC-based time series becomes less stable. Our results are robust to using alternative regression windows, as we show in the online appendix.



(a) Voluntary part-time employment (V)

(b) Involuntarily part-time employment (I)

Figure 1: Labor market stocks derived from the ASEC and the BM files of the CPS

Notes: CPS Annual Social and Economic Supplement (ASEC) data, 1976 – 2017; CPS basic monthly (BM) data, 1976m01 – 2018m12. 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.

of the adjusted time series, i.e. we solve

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

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.[17] Solving the problem above under restriction (i), we get $\phi_{1,y} = \widehat{\bar{s}}_y^{\text{BM}} / \frac{1}{12} \sum_{m=1}^{12} \breve{s}_{y,m}^{\text{BM}}$. The coefficients $\phi_{1,y}$'s used to correct the stocks V_t and I_t are displayed in Table B1 in the appendix.

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.

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 probabilities without any additional data or assumptions. We exploit 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

[17] Multiplicative and additive adjustment factors produce different adjusted series; see Footnote 5. Notice, in addition, that multiplicative adjustment factors rescale, not only the mean, but also the variance of the time series. Another appealing property of multiplicative factors is that, by construction, they cannot predict negative values when a time series is scaled down. The latter is an important advantage in practice, since the stock of involuntary part-time workers is a small number.

flows prior to the CPS redesign.[18]

In practice, we adapt the margin-error correction procedure proposed by Elsby et al. [2015]. Let $\breve{\boldsymbol{p}}_t$ denote the vector of outflow transition probabilities measured using the raw data from the BM files. The procedure involves adjusting $\breve{\boldsymbol{p}}_t$ to make it consistent with the series of changes in stocks obtained in step 1 (denoted $\Delta \boldsymbol{s}_t$, where Δ is the first-difference operator). Starting from equation (3) of the paper, i.e. $\boldsymbol{s}_t = \boldsymbol{M}_t \boldsymbol{s}_{t-1}$, we re-write it as

$$\Delta \boldsymbol{s}_t = \boldsymbol{S}_{t-1} \boldsymbol{p}_t, \tag{6}$$

where $\boldsymbol{S}_{t-1}$ is a conformable matrix of labor market stocks in the previous month and $\boldsymbol{p_t}$ is the 'true' vector of outflow transition probabilities. $\boldsymbol{p_t}$ is recovered by minimizing the weighted sum of squares of the margin-error adjustments:

$$\min_{\boldsymbol{p}_t} \left(\boldsymbol{p}_t - \breve{\boldsymbol{p}}_t\right)' \boldsymbol{W}_t^{-1} \left(\boldsymbol{p}_t - \breve{\boldsymbol{p}}_t\right) \text{ s.t. } \triangle \boldsymbol{s}_t = \boldsymbol{S}_{t-1} \boldsymbol{p}_t, \tag{7}$$

where $\boldsymbol{W}_t$ is a weighing matrix proportional to the covariance matrix of $\breve{\boldsymbol{p}}_t$ (see Appendix A.1 for details about $\boldsymbol{S}_t$ and $\boldsymbol{W}_t$).

3.3 Addressing other measurement issues

In addition to our proposed solution to the 1994 break, we adjust the series of stocks and flows to deal with other measurement problems. We describe these adjustments below. It is important to describe first how we obtain raw estimates of transitions based on CPS micro-data. To measure individual transitions, we longitudinally match CPS respondents across four consecutive months using household and personal identifiers.[19] Our measurements of individual transitions are based on the sequence of individuals' labor market states observed

[18] 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.

[19] 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].

in the second and third months in the sample.[20] To construct the gross flows data, we aggregate individual transitions using the longitudinal weights provided in the CPS files.

Seasonality. We remove potential outliers and seasonal variation from both stocks and flows using the U.S. Census Bureau's X-13ARIMA-SEATS program.

Classification error. Classification error in individual's labor force state is a long-standing issue in the measurement of worker flows based on survey data. Perhaps the most prominent example concerns the distinction between unemployment and nonparticipation: there is a clear conceptual difference between those two labor market states, but in practice it is sometimes difficult for respondents and interviewers to correctly assign an individuals' labor market state to the two categories (see e.g Abowd and Zellner [1985] and Poterba and Summers [1986]). In the context of our measurement framework, the elevated number of measured transitions between voluntary (V) and involuntary (I) part-time employment suggests there is some fuzziness between these two labor market states. This fuzziness will tend to overstate the amount of turnover between the two states. To address this issue, we subject our data to a 'deVIVification' procedure.[21] The deVIVification procedure identifies particular sequences of labor market states in the raw data as suspicious (those displayed in columns 'Observed' in Table 1) and then recodes them to another sequence that is deemed more plausible (those denoted 'Adjusted' in Table 1).

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

[20] In the CPS, respondents are interviewed for 4 consecutive months, rotated out of the survey for 8 months, and then included in the survey again for an additional 4 months. By second and third months, we refer to those from the 4-months 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 4 consecutive CPS interviews.

[21] 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. Therefore, in conjunction with the deVIVification procedure, we also deNUNify the data (as we will study unemployment fluctuations in Section 5). DeNUNification amounts to replacing V by N and U by I in the sequences displayed in Table 1.

Table 1: Description of deVIVification procedure

Observed	Adjusted	Observed	Adjusted
$F \to V \to I \to V$	$F \to V \to \boldsymbol{V} \to V$	$F \to I \to V \to I$	$F \to I \to \boldsymbol{I} \to I$
$V \to V \to I \to V$	$V \to V \to \boldsymbol{V} \to V$	$I \to I \to V \to I$	$I \to I \to \boldsymbol{I} \to I$
$U \to V \to I \to V$	$U \to V \to \boldsymbol{V} \to V$	$U \to I \to V \to I$	$U \to I \to \boldsymbol{I} \to I$
$N \to V \to I \to V$	$N \to V \to \boldsymbol{V} \to V$	$N \to I \to V \to I$	$N \to I \to \boldsymbol{I} \to I$
$V \to I \to V \to F$	$V \to \boldsymbol{V} \to V \to F$	$I \to V \to I \to F$	$I \to \boldsymbol{I} \to I \to F$
$V \to I \to V \to V$	$V \to \boldsymbol{V} \to V \to V$	$I \to V \to I \to I$	$I \to \boldsymbol{I} \to I \to I$
$V \to I \to V \to U$	$V \to \boldsymbol{V} \to V \to U$	$I \to V \to I \to U$	$I \to \boldsymbol{I} \to I \to U$
$V \to I \to V \to N$	$V \to \boldsymbol{V} \to V \to N$	$I \to V \to I \to N$	$I \to \boldsymbol{I} \to I \to N$

Notes: Each cell 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.

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.[22]

Time aggregation. Time aggregation bias is a well-known and well-understood problem that 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, this bias is substantial in what concerns both the levels and cyclicality of worker flows. We address time-aggregation bias by adapting the continuous-time correction proposed in Shimer [2012].

4 Assessment of our Protocol

We have proposed a protocol to address the discontinuity triggered by the CPS redesign. We implemented a number of complementary adjustments to obtain our dataset of stocks and transition probabilities. Before analyzing these data, we summarize the results of several robustness exercises (detailed results are provided in the online appendix) and describe the

[22] While we call it 'deVIVification', it should be clear from Table 1 that we also adjust 'IVI' sequences.

effects of each step of the adjustment protocol. We do so to be transparent about our methodological choices and verify that they are grounded in sensible practical observations.

4.1 Stocks

4.1.1 Comparison to PM98. A natural starting point to assess the plausibility of our approach is to compare its results with those in PM98. In Table 7.7 of their paper, PM98 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.[23] PM98 report adjustment factors of 1.074 for men and 1.125 for women. The corresponding 1993 figures based on our protocol are respectively 1.056 and 1.182. Last, PM98's multiplicative coefficient for involuntary part-time work is 0.806.[24] Our adjustment coefficient in 1993 for that series is 0.749. Overall, our adjustment factors seem to be very consistent with those estimated by PM98.

4.1.2 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 (Figure B1 of the online appendix).

The Survey of Income and Program Participation (SIPP) provides another source of data against which we can check the consistency 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

[23] Table B1 of the appendix presents our multiplicative coefficients used to adjust the series of voluntary and involuntary part-time employment for the whole working-age population and separately by gender.

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

including the period of the break in the CPS.[25] Comparison of the dynamics of the CPS-based adjusted series and their SIPP counterparts around the 1994 break shows they are remarkably similar (Figure B2 of the online appendix). Since our adjustment protocol does not target consistency with the SIPP, these findings give us additional confidence in the reliability of our estimates.

4.1.3 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. Specifically, we run regressions of each series of stocks and flows against a flexible polynomial of time, monthly dummies and a dummy for the CPS redesign. The results of this exercise, reported in the online appendix, show no evidence of a break in any of the adjusted series.

4.1.4 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 in smaller groups partitioned by gender interacted with educational attainment or interacted with marital status (details are provided in the online appendix).

[25] 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.

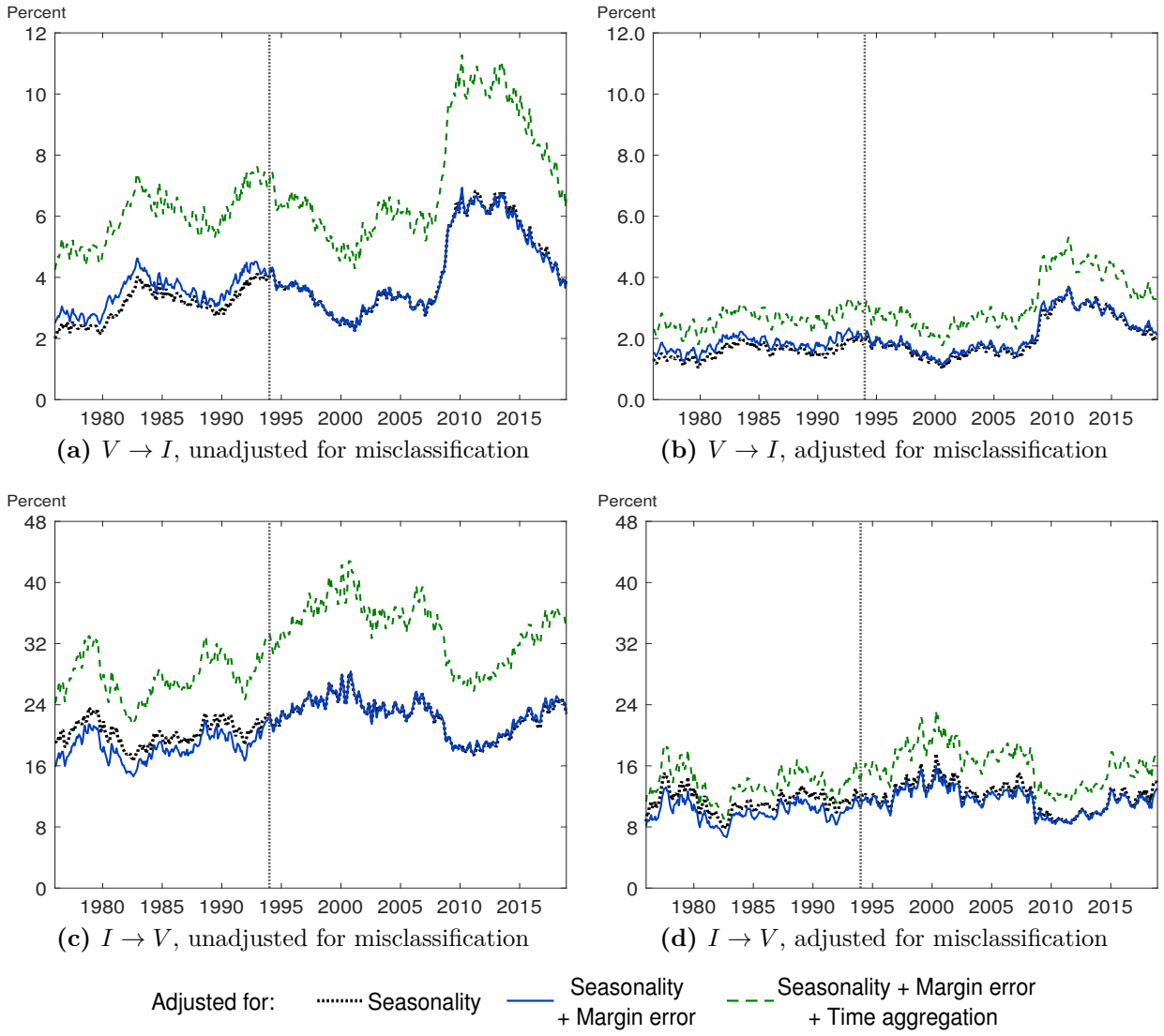
4.2 Flows and other adjustments

Figure 2 shows two sets of time series corresponding to alternative estimates of transition probabilities $p(V \to I)$ and $p(I \to V)$ to gauge the incremental effects of the different steps of the adjustment protocol. The plots on the left-hand side are based on data unadjusted for misclassification, while the plots on the right-hand side are based on the deVIVified data. In each plot, three series are reported: a seasonally adjusted (SA) series, the SA series adjusted for margin error (ME) and the SA+ME series adjusted for time aggregation.[26]

We start by focusing on the effects of margin-error adjustment and time aggregation. Comparing the lines in each plot, two patterns stand out. First, there is a salient difference between the solid and the dotted lines in the pre-1994 period. This highlights the differential effect of the margin-error correction across the 1994 break. Post 1994 there is a very small (almost invisible) difference between the two series, consistent with previous studies that showed that correcting for margin error (mainly bias do to sample attrition) has a limited impact on the levels of transition probabilities estimates. On the other hand, prior to 1994 the impact on the levels of the series is clearly visible, but with no apparent differential impact on the evolution of the series at high or low frequencies across 1994. This indicates that step 2 of our correction procedure for the 1994 break works well in practice. Second, in all plots the dashed line lies well above the solid and dotted lines: correcting for time aggregation has a large effect on the levels of transition probabilities.

Next, to tease out the effect of addressing classification error, we compare each pair of plots on the same row. Once again we emphasize two features. First, deVIVifying the data entails a very substantial reduction in the series levels – most of the affected series are reduced by half. The second feature is that the impact of the time-aggregation correction is

[26] The attentive reader will note that we use only one-period, two-sided MA averaging for the time series displayed in Plots 2a and 2c (footnote to Figure 2), whereas we use two-period, two-sided MA averaging for the plots on the right-hand side and for Figure 4. The reason is the following. When working with data unadjusted for misclassification, we need only match CPS respondents across two consecutive months (instead of four months required to run the deVIVification procedure). As a result, we have less sample variation, meaning that the series are already quite smooth before MA averaging.



(a) $V \to I$, unadjusted for misclassification

(b) $V \to I$, adjusted for misclassification

(c) $I \to V$, unadjusted for misclassification

(d) $I \to V$, adjusted for misclassification

Figure 2: Comparing effects of different steps of adjustment protocol

Notes: CPS data, 1976m01 – 2018m12, monthly transition probabilities. The dotted lines show series adjusted for seasonality; the solid lines show series adjusted for seasonality and margin error; the dashed-dotted lines show series adjusted for seasonality, margin error and time aggregation bias. The series on Plots 2a and 2c (Plots 2b and 2d) show data that have not been corrected (have been corrected) for misclassification, and are smoothed by one-period, two-sided (two-period, two-sided) MA averaging. The vertical line in each plot indicates January 1994.

magnified in the unadjusted data. Not only do the series increase by much more compared to the series adjusted for misclassification (by between 15 to 20 percent depending the transition probability), but also they gain greater cyclical variation. We find the resulting series (the dashed lines on the left-hand side plots) somewhat implausible. Indeed, using estimates of

transition probabilities without correcting for misclassification but controlling for margin error and time aggregation, the overall monthly inflow probability of involuntary part-time employment is close to 1 (Table C1 in the appendix, bottom row).

To further convince ourselves that adjusting for misclassification is a sensible procedure, we compute the shares of transitions discarded by deVIVification. On average, deVIVification turns down 44.2 percent of the raw $V \to I$ transitions and 48.2 percent of $I \to V$ transitions.[27] 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 6.77 and 31.3 percent, respectively.[28] The shares of discarded transitions exhibit no clear cyclical patterns, and remain stable around their sample means. These two results suggest a stable pattern of measurement error. Of course, we cannot be sure that this procedure discards all, and only those, spurious transitions. For transparency, we report our main findings based on series unadjusted for misclassification in Appendix C.

5 Main Findings

To set the stage for the empirical analysis of work flows, Figure 3 displays the series of unemployment and involuntary part-time employment stocks since 1955 until today. From 1955 to 1975, the reported series come from data published by the BLS, which we align to post-1976 CPS data using a multiplicative factor (the ratio of the mean-1975 to the mean-1976 values). Involuntary part-time employment exhibits a stable pattern of large countercyclical variation around recessions. While nothing indicates that these fluctuations have limited information, they still play a minor role in our understanding of labor market

[27] Elsby et al. [2015]'s deNUNification procedure turns down 43.2 percent of the raw $N \to U$ transitions and 44.3 percent of $U \to N$ transitions for the sample period that we analyze (online appendix). While these figures might seem elevated, they are consistent with estimates of classification noise in labor force status, which is known to have a large impact on measured transitions. Poterba and Summers [1986] find that the probability that unemployed workers are misclassified as non-participants is 11.5 percent. Veracierto [2015] infers that this probability can be as high as 27.3 percent.

[28] By unadjusted data, we mean data that has not been subjected to the 'deVIVification' procedure, but that has been cleared from seasonal variations, margin error problems and time-aggregation bias.

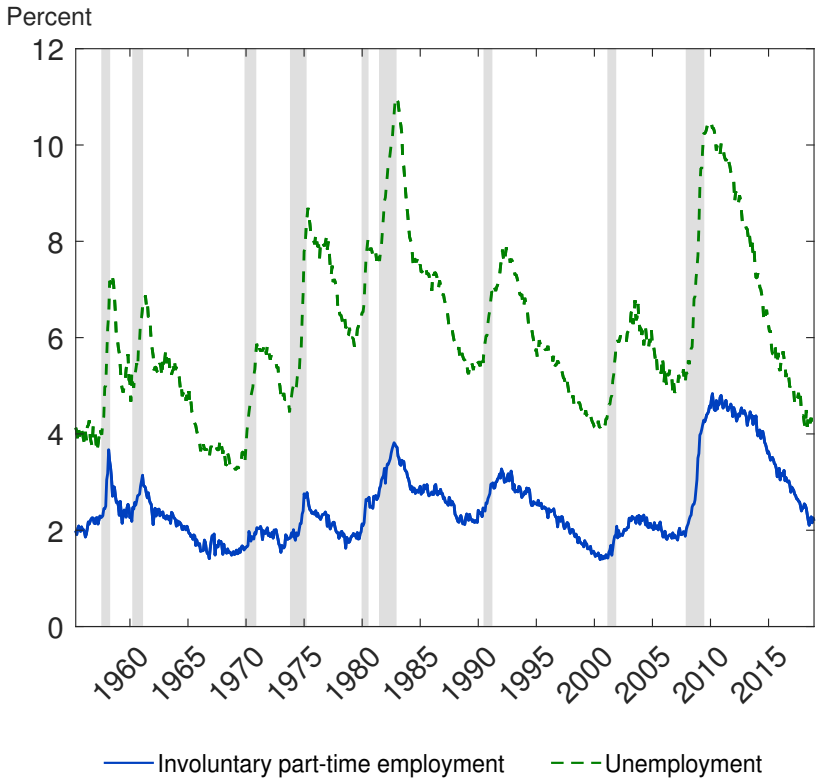


Figure 3: The involuntary part-time employment and unemployment rates

Notes: BLS data, 1955m05 – 1975m12 and CPS data, 1976m01 – 2018m12. The series show the percentage of involuntary part-time and unemployed workers divided by the civilian labor force. Data coming from the BLS are the series ID LNS11000000 (Civilian Labor Force Level), LNS12032194 (Employment Level - Part-Time for Economic Reasons) and LNS13000000 (Unemployment Level). The BLS data are aligned to post-1976 CPS data using a multiplicative adjustment factor. The post-1976 CPS data on involuntary part-time work are corrected for the 1994 break. All series are adjusted for seasonality and smoothed by one-period, two-sided MA averaging. The gray-shaded areas indicate NBER recession periods.

dynamics. Indeed, most of our knowledge in this area remains based on the behavior of the unemployment rate (Rogerson and Shimer [2011]), which is also the headline statistic to assess the strengths and weaknesses of the labor market. One explanation for this state of affairs is the very strong co-movement between involuntary part-time employment and unemployment (contemporaneous correlation in levels of 79%), which could suggest there is little additional data in involuntary part-time work fluctuations. In the current and following sections, we argue that this conclusion is premature. We find that the ins and outs of involuntary part-time employment carry information that is complementary – and not redundant – to the one offered by unemployment flows.

5.1 Fact 1: A transitory state

To get a first sense of the dynamics of involuntary part-time employment, we describe the average behavior of its underlying transition probabilities and compare it to those of unemployment. Inspection of Table 2 shows that, with two-thirds of the stock entering in the previous month (66.1 percent) and an almost similarly large share leaving in the following one (59.5 percent), involuntary part-time employment exhibits much faster dynamics compared to unemployment (cf. bottom row, 3rd and 4th columns). Put differently, spells of involuntary part-time employment are, on average, about 30 percent shorter than those of unemployment.[29] Analyzing the various rows of Table 2, the very close interaction between involuntary part-time work and full-time employment stands out. On average, 28.6 percent of all involuntary part-timers were employed full-time in the previous month, and a similar fraction (28.8 percent) will enter full-time employment next month. Transition probabilities between involuntary and voluntary part-time work are smaller (though still more than half as large as those with full-time employment) followed by slightly lower levels of turnover with unemployment.[30] Flows between involuntary part-time work and nonparticipation are very small. By comparison, unemployment displays a smaller but nonetheless strong interaction with full-time employment, and the flows to and from nonparticipation are much greater (about as high as those with full-time employment, whereas for involuntary part-time work the nonparticipation flows are six times lower than those with full-time employment). Last, the interaction between unemployment and both forms of part-time employment is limited.

5.2 Fact 2: Variation driven by within-employment reallocation

Figure 4 complements this static portrait by displaying the evolution of selected transition probabilities. In each plot the same transition is shown both for involuntary part-time work

[29] We calculate this as the ratio of the outflow probability of U over that of I, i.e. 42.1/59.5=29.2 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.

[30] Recall that the numbers reported in Table 2 have been adjusted to remove potentially spurious transitions between involuntary and voluntary part-time employment.

Table 2: Inflow and outflow transition probabilities: Sample averages

Involuntary part-time work				Unemployment			
Inflows		Outflows		Inflows		Outflows	
$q(F \to I)$	28.6	$p(I \to F)$	28.8	$q(F \to U)$	17.5	$p(U \to F)$	15.7
$q(V \to I)$	16.2	$p(I \to V)$	15.1	$q(V \to U)$	6.67	$p(U \to V)$	7.70
$q(U \to I)$	16.0	$p(I \to U)$	11.1	$q(I \to U)$	4.39	$p(U \to I)$	6.28
$q(N \to I)$	5.27	$p(I \to N)$	4.40	$q(N \to U)$	15.7	$p(U \to N)$	12.4
$\sum_{i \neq I} q(i \to I)$	66.1	$\sum_{j \neq I} p(I \to j)$	59.5	$\sum_{i \neq U} q(i \to U)$	44.2	$\sum_{j \neq U} p(U \to j)$	42.1

Notes: CPS data, 1976m01 – 2019m12. Transition probabilities are corrected for the 1994 break, and adjusted for misclassification, seasonality, margin error, and time aggregation. The table reports the averages of monthly transition probabilities over the sample period. The inflow transition 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 transition probabilities are the elements of the Markov transition matrix. All table entries are expressed in percent.

(solid line) and unemployment (dashed line). The most salient feature in the six plots is a very clear pattern of sizable cyclical variation of (most) transition probabilities.[31]

We first focus on the behavior of inflows, starting with the series of inflow transitions from full-time employment (Plot 4a). Similar to its unemployment counterpart, the inflow probability to involuntary part-time employment spikes at recessions' onsets and returns to pre-crisis level during their aftermaths. However, its recovery is much slower. In the typical recession, a year after the trough the unemployment inflow is already recovering, while the involuntary part-time employment inflow is still well above its peak level. Inflows from voluntary part-time employment and nonparticipation bring to light differences in the cyclical dynamics across the two states (Plot 4c). While $p(V \to U)$ is surprisingly acyclical, the behavior of $p(V \to I)$ is very similar to that of $p(F \to I)$. This picture is reversed for nonparticipation inflows displayed in Plot 4e. Though less pronounced, $p(N \to U)$ is

[31] In the interest of space, we do not report series of transition probabilities between voluntary part-time employment and full-time employment. Consistent with the statistical definition of voluntary part-time employment, its series are either acyclical ($p(V \to F)$), or exhibit a very mild procyclical pattern ($p(F \to V)$). Both series are available in the dataset that accompanies the paper.

clearly countercyclical, while $p\,(N \to I)$ is at best mildly countercyclical and only in the two most recent recessions. Next, we turn our attention to the evolution of outflows. The three plots on the right-hand side column of Figure 4 show a much more consistent picture of the dynamics of involuntary part-time employment and unemployment. With some differences in the magnitude of variation, all six transitions move in the same direction over the business cycle. They rise steadily in normal times and fall around the beginning of each recession, lasting over several years after the recession's trough.

So far we have identified the states with which involuntary part-time employment interacts the most on average, as well as very large cyclical variation in the ins and outs of involuntary part-time employment. We now quantify their relative importance for the cyclical dynamics of the labor market, by computing their contributions to the short-run variation of involuntary part-time employment and unemployment. Specifically, for involuntary part-time employment we calculate the following coefficients:

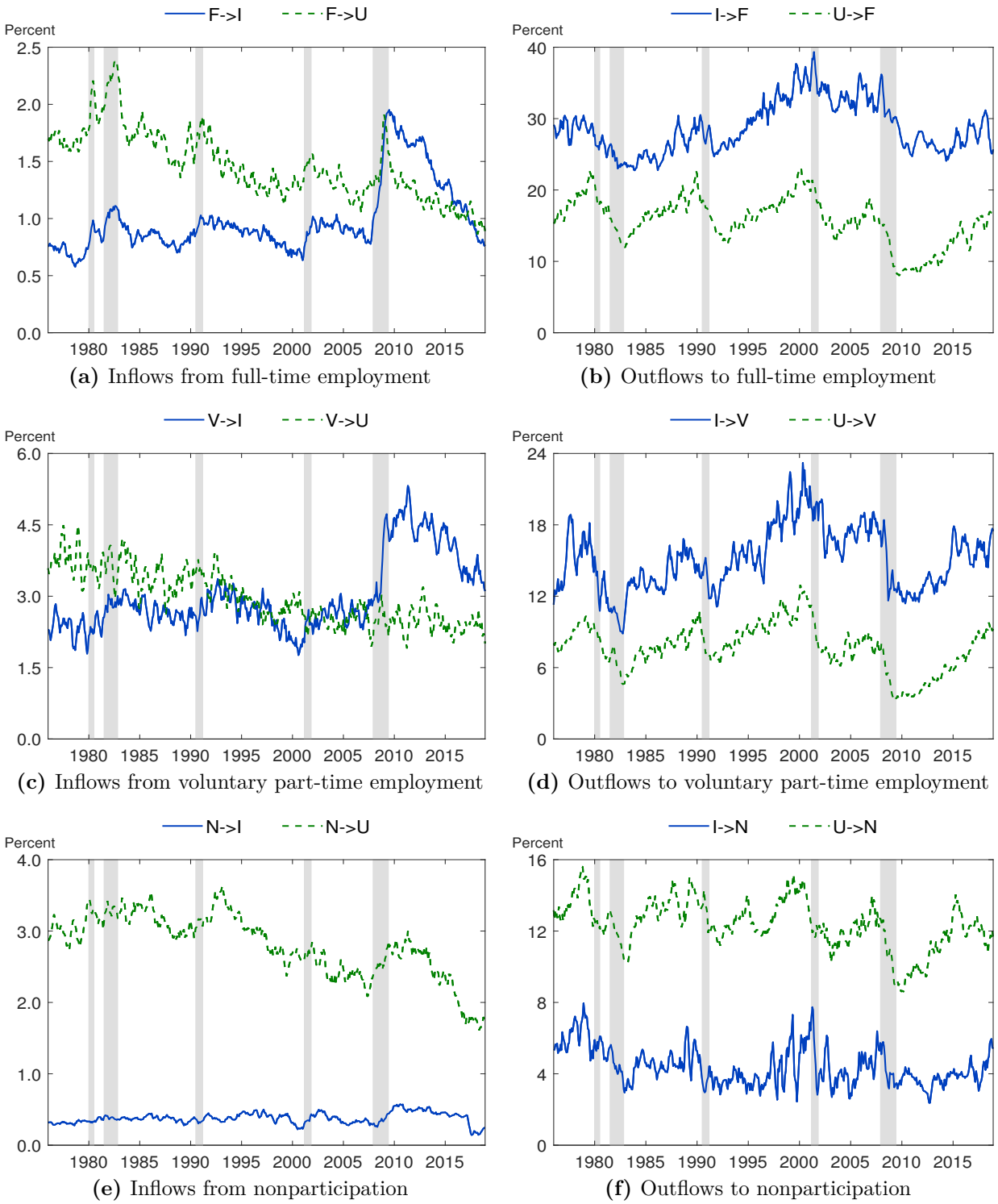
$$\beta\,(j \to k) = \frac{\mathbb{C}\text{ov}\left(\Delta i_t, \Delta \widetilde{i}_t^{jk}\right)}{\mathbb{V}\text{ar}(\Delta i_t)}. \tag{8}$$

$\Delta \widetilde{i}_t^{jk}$ 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}.[32] The results are reported in Table 3.

The beta coefficients offer a precise and distinctive picture of involuntary part-time employment and unemployment dynamics.[33] The ins and outs of full-time employment are quantitatively very important for both states. Adding up their contributions, flows to and from F explain $28.2 + 23.6 = 51.8$ percent of fluctuations in involuntary part-time employment. The corresponding figure for unemployment is 49.3 percent. When we add contribu-

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

[33]The bottom row displays the sum of beta coefficients. In both instances the sum is very close to 100 percent, meaning that each $\beta\,(j \to k)$ can be interpreted as the relative contribution of flow hazard λ^{jk} to the cyclical variations under study.



(a) Inflows from full-time employment

(b) Outflows to full-time employment

(c) Inflows from voluntary part-time employment

(d) Outflows to voluntary part-time employment

(e) Inflows from nonparticipation

(f) Outflows to nonparticipation

Figure 4: Evolution of transition probabilities

Notes: CPS data, 1976m01 – 2018m12. Transition probabilities are corrected for the 1994 break, and adjusted for misclassification, seasonality, margin error, and time aggregation. All series are smoothed by two-period, two-sided MA averaging. Gray-shaded areas indicate NBER recession periods.

tions from flows in and out of voluntary part-time employment, transitions from employment states explain 78.5 (66.4) percent of the variation in i_t (u_t).[34] On the other hand, nonparticipation plays an important role in explaining unemployment fluctuations (26.2 percent), in line with Elsby et al. [2015]'s analysis, but are largely irrelevant for the dynamics of involuntary part-time employment. This suggests that involuntary part-timers and unemployed workers are quite different in terms of their distance to the other employment states. Consistent with this notion, turnover between involuntary part-time work and unemployment is low and its cyclical behavior plays a small role in the dynamics of involuntary part-time work and unemployment. In fact, changes in $p(U \to I)$ explain less than 5 percent of the cyclical variation in the unemployment rate, and about 10 percent of fluctuations in involuntary part-time employment.

In what concerns the relative importance of inflows and outflows from other employment states (V and F) to the dynamics of the two rates, we also find some differences. Consistent with findings in the previous literature (see e.g Shimer [2012]), the outs account for 44.7 percent of unemployment variation, against 20.7 percent accounted for by the ins. By contrast, the ins and outs play a similar quantitative role in the dynamics of involuntary part-time employment (the ins vs. outs split is 43.5:35.1, so that the ins actually have a larger impact). This observation dovetails well with some of the qualitative evidence in the two plots in the top row of Figure 4. The differences between the cyclical behavior of flows between full-time employment and unemployment seem much greater compared to the flows between full-time and involuntary part-time employment. In particular, the spike in $p(F \to U)$ at the onset of recessions is sharper and more short-lived compared to the jump in $p(F \to I)$, which then remains elevated well into the recovery. Similarly, the recessionary drop in $p(U \to F)$ is more pronounced and more persistent than that in $p(I \to F)$. In other words, the dynamics of

[34] Workers who move from voluntary to involuntary part-time employment ($p(V \to I)$) have their weekly working hours reduced by about 1 hour, on average, whereas transitions in the reverse direction ($p(I \to V)$) entail an average increase of 1 working hour per week. Therefore, though quantitatively smaller, these transitions seem to be result of labor adjustment on the intensive margin. This is why we sometimes aggregate them with their full-time employment counterparts (i.e. $p(F \to I)$ and $p(I \to F)$).

Table 3: Inflow and outflow transition probabilities: Variance contributions

Involuntary part-time work rate				Unemployment rate			
Inflows		Outflows		Inflows		Outflows	
$\beta(F \to I)$	28.2	$\beta(I \to F)$	23.6	$\beta(F \to U)$	16.4	$\beta(U \to F)$	32.9
$\beta(V \to I)$	15.3	$\beta(I \to V)$	11.4	$\beta(V \to U)$	5.33	$\beta(U \to V)$	11.8
$\beta(U \to I)$	10.3	$\beta(I \to U)$	4.23	$\beta(I \to U)$	2.34	$\beta(U \to I)$	3.79
$\beta(N \to I)$	3.53	$\beta(I \to N)$	3.16	$\beta(N \to U)$	11.4	$\beta(U \to N)$	14.8
$\sum_{i \neq I} \beta(i \to I)$	57.3	$\sum_{j \neq I} \beta(I \to j)$	42.4	$\sum_{i \neq U} \beta(i \to U)$	35.5	$\sum_{j \neq U} \beta(U \to j)$	63.2
$\sum_{i \neq I} \beta(i \to I) + \sum_{j \neq I} \beta(I \to j) = 99.8$				$\sum_{i \neq U} \beta(i \to U) + \sum_{j \neq U} \beta(U \to j) = 98.8$			

Notes: CPS data, 1976m01 – 2018m12. Transition probabilities are corrected for the 1994 break, and adjusted for misclassification, seasonality, margin error, and time aggregation. The table reports the variance contributions of flows hazard λ^{jk} to the dynamics of involuntary part-time employment and unemployment rates (see equation (8)). All table entries are expressed in percent.

involuntary part-time employment inflows and outflows to full-time employment seem more closely aligned compared to their unemployment counterparts. This is consistent with the notion that fluctuations in involuntary part-time flows with other employment states (i.e. V and F) reflect a distinct labor adjustment channel compared to unemployment flows with other employment states.

5.3 Fact 3: In recessions the ins go up and the outs drop

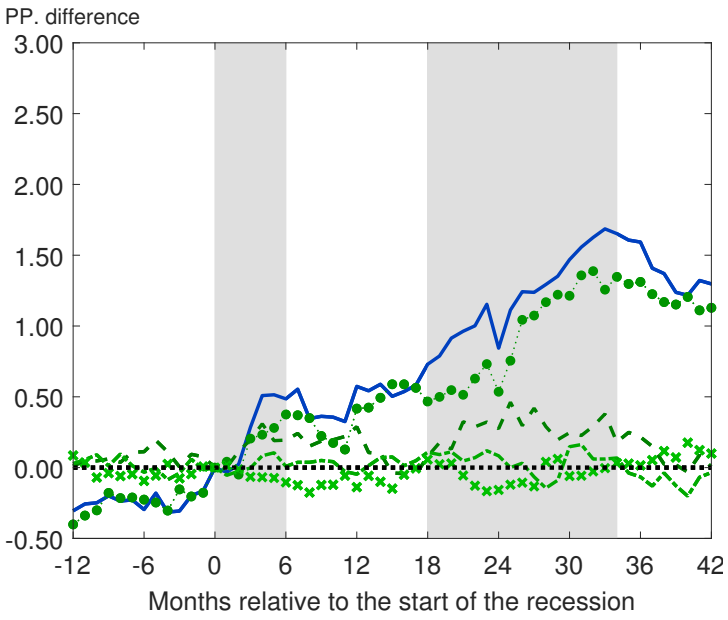
While useful to summarize variation over a long time period, the beta coefficients ignore potential differences across recessions. To better understand which flows dominate the dynamics of involuntary part-time work during recessions, Plots 5a–5d display the contributions of the most relevant flows for changes (in levels) in i_t around each recession. We first focus on the recessions in the pre-1994 period (Plots 5a and 5b). In all three recessions, the drop in the probability to move from involuntary part-time employment to other employment states ($I \to F + V$) is the main source of the rise in the involuntary part-time employment rate

(see Footnote 34). The reverse transition probability ($F + V \rightarrow I$) contributes in similar ways during the early stages of the recessions, but its effect vanishes as the recovery gets underway. Next, we consider the role of unemployment. On the one hand, variation in $p(I \rightarrow U)$ plays no role in the rise of i_t. On the other, $p(U \rightarrow I)$ is countercyclical in the pre-1994 period (albeit by small magnitude) suggesting that some workers take part-time jobs to escape unemployment during recessions. This plays a small role in the initial rise of i_t in all three recessions. $p(U \rightarrow I)$ then reverts quickly to its pre-recession levels and this pushes the involuntary part-time employment rate downwards. This is especially apparent in the 1990s recession's aftermath.

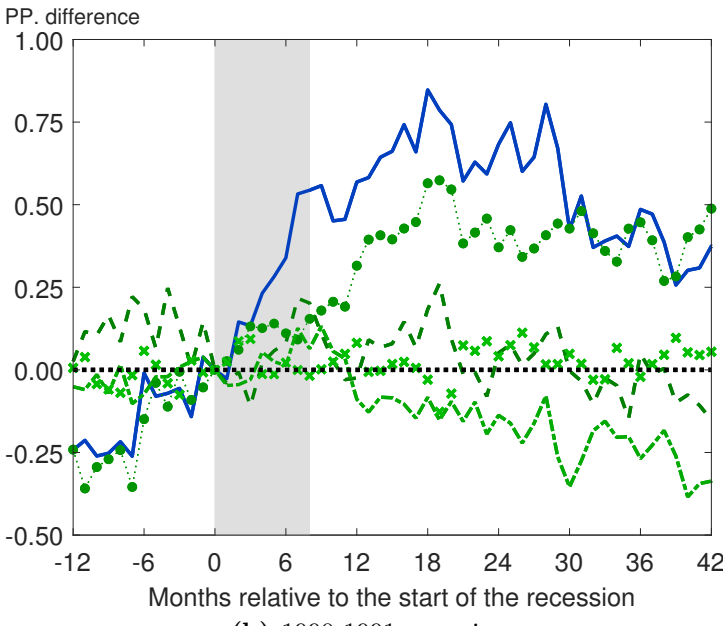
We pursue a similar analysis in Plots 5c–5d. Several patterns stand out. First, contrary to the earlier recessions, now the initial spike in i_t is driven by the jump upwards in other employment inflows ($F + V \rightarrow I$), and their high levels are the main contributors to the elevated involuntary part-time employment until 6 to 12 months after the recessions' trough. Consistent with earlier recessions, ($I \rightarrow F + V$) is the main source of the elevated levels of involuntary part-time employment during the recovery. Second, the role of unemployment is slightly different compared to the pre-1994 period. The contribution of $p(I \rightarrow U)$ to the recessionnary increase of i_t is, if anything, positive. In what regards $p(U \rightarrow I)$, it is more clearly procyclical in the post-1994 period and contributes to dampening involuntary part-time work during the recessions' recoveries.

To characterize further involuntary part-time employment across different recessions, Figure 6 plots the dynamics of the involuntary part-time employment rate along with the rates implied by workers' stated reasons for working part-time hours (namely, whether it is due to 'slack work conditions' or because the worker 'cannot find a full-time job').[35]

[35]Recall that, according to the structure of the revised CPS, the sum of the number of involuntary part-time workers by each of those two reasons adds up to the total count of involuntary part-time workers. In the ASEC, workers report whether the main reason for working part-time involuntarily during the previous calendar year was because of slack work conditions or because they could not find a full-time job. This matches the categories of involuntary part-time employment available in the monthly revised CPS. As a result, we can also apply our protocol to construct time series of involuntary part-time work by reasons that remain consistent over the whole sample period.



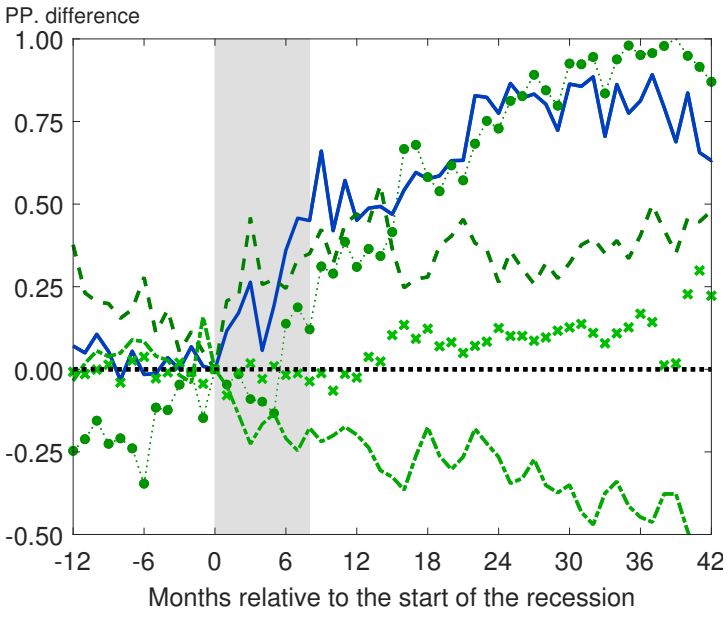
(a) Twin recessions of the 1980s



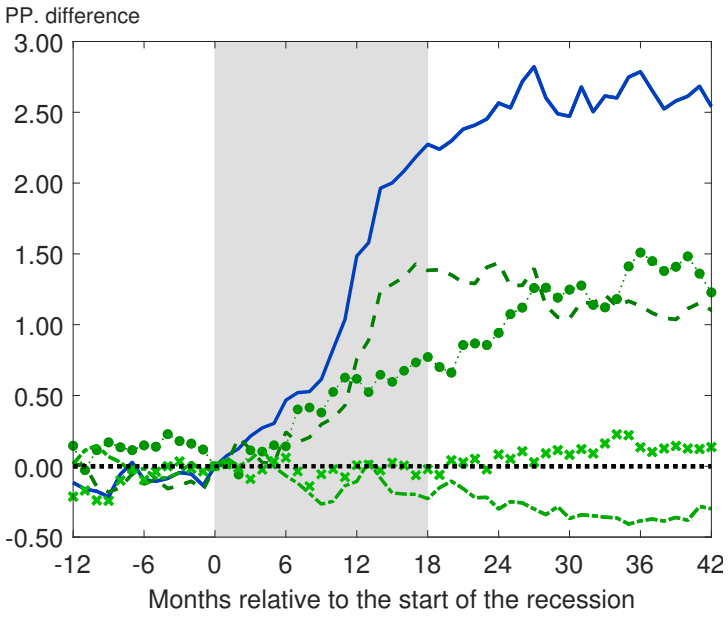
(b) 1990-1991 recession

Figure 5: Sources of 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 reports 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 (8). The scale on the vertical axis is different for the large 1980s recessions (Plot 5a) and the milder 1990-1991 recession (Plot 5b). Gray-shaded areas indicate NBER recession periods.



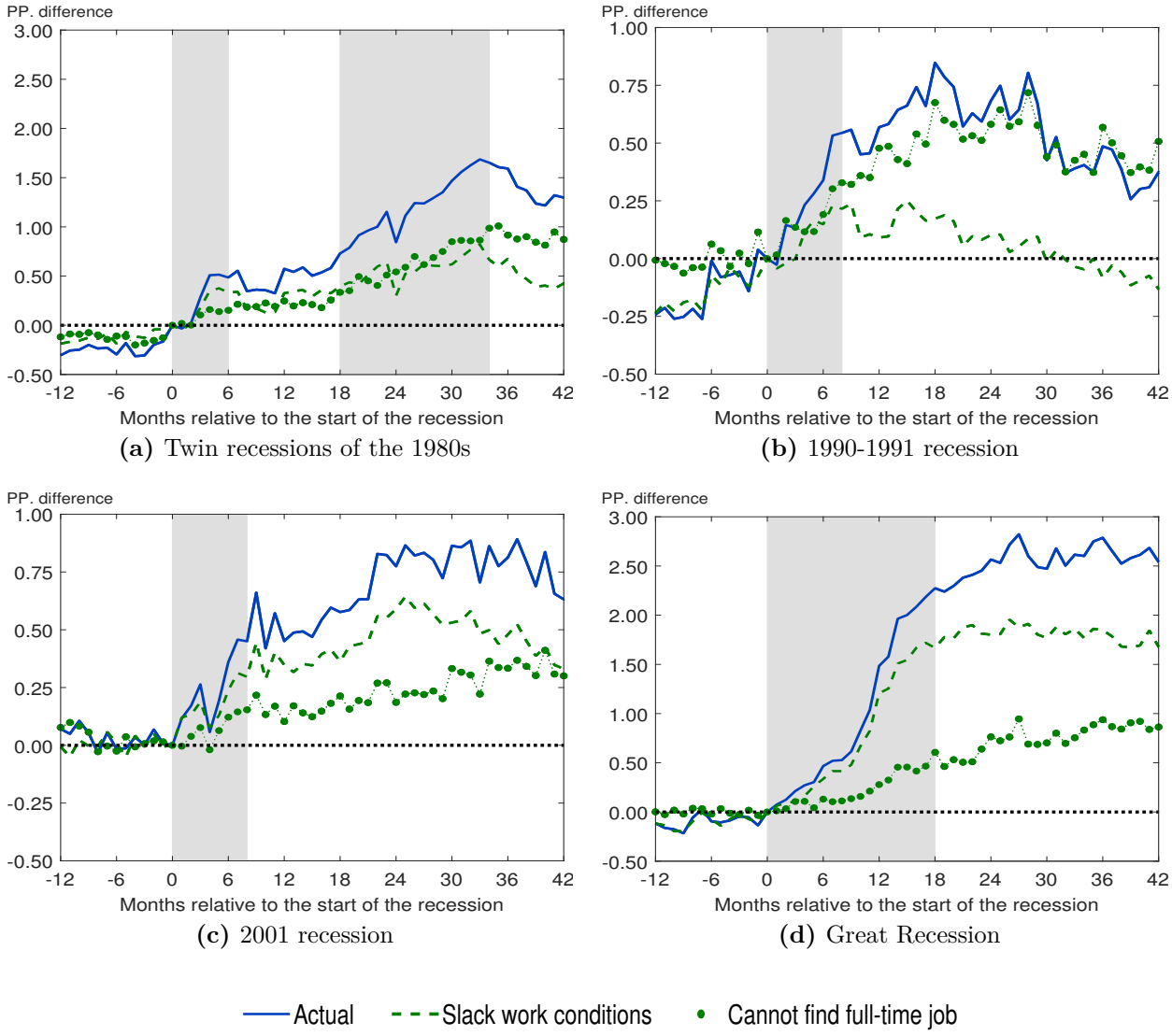
(c) 2001 recession



(d) Great Recession

Figure 5: Sources of 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 reports 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 (8). The scale on the vertical axis is different for the milder 2001 recession (Plot 5c) and the Great Recession (Plot 5d). Gray-shaded areas indicate NBER recession periods.



(a) Twin recessions of the 1980s

(b) 1990-1991 recession

(c) 2001 recession

(d) Great Recession

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 reports 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). The scale on the vertical axis is different for the milder recessions (Plots 6b and 6c) and the large recessions (Plots 6a and 6d). Gray-shaded areas indicate NBER recession periods.

Across all recessionary episodes, the change driven by slack work conditions (dashed lines) in Figure 6 tracks very closely that implied by the behavior of inflows from other employment ($F+V \rightarrow I$) in Plots 5a–5d. Changes driven by workers who cannot find a full-time job (the dots in Figure 6), on the other hand, evolves similarly to the rate implied by the dynamics

of outflows to other employment ($I \to F + V$) in Plots 5a–5d. 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 part-time employment changed in the two most recent recessions.

5.4 A look at the behavior of $p(F \to I)$ and $p(I \to F)$

The variance contributions reported in Table 3 suggest focusing on the behavior of $p(F \to I)$ and $p(I \to F)$ to understand what drives the dynamics of involuntary part-time employment. We do so in Table 4. The first row shows that roughly 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 might seem unexpectedly elevated, it is consistent with the patterns of within-employment transitions documented in BML19.[36] This finding is based on time series starting in 1994 for reasons of data availability, but we have no reason to believe that this pattern is only a recent phenomenon.[37,38] Overall, this provides strong evidence in favor of a characterization of involuntary part-time employment reallocation as operating mainly within employment – what we have called 'Fact 2'.

The second and third rows of Table 4 focus on workers' stated reasons for working part-time involuntarily. Respectively 67.8 and 63.1 percent (66.9 and 65.7 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

[36] 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.

[37] Information on job-to-job transitions is available only in the revised 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?*".

[38] Shimer [2005] devises an ingenious way to measure job-to-job transitions based on the ASEC (which asks respondents if they have had one, two, or three or more employers in the previous year). Unfortunately we cannot extend his approach to measure transitions between full-time and part-time employment at the same employer before 1994. The reason is that we can use the ASEC to infer the number of workers in the cross section who change employers from month to month, but we cannot determine whether these workers also make a transition between full-time and part-time employment.

Table 4: Further decomposition of within-employment flows

Inflow $F \to I$			Outflow $I \to F$		
	1976-2018	1994-2018		1976-2018	1994-2018
β (SAME)		92.8	β (SAME)		89.3
$\beta\,(F \to S)$	67.8	66.9	$\beta\,(S \to F)$	63.1	65.7
$\beta\,(F \to C)$	32.2	33.1	$\beta\,(C \to F)$	37.6	34.6
			β (SHARE)	-0.72	-0.30
$\beta\,(F \to S$, SAME)		62.8	$\beta\,(S \to F$, SAME)		61.3
$\beta\,(F \to C$, SAME)		29.8	$\beta\,(C \to F$, SAME)		27.6
			β (SHARE, SAME)		-0.36

Notes: CPS data, 1976m01 – 2018m12. 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 2018m12); '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.5) in Appendix A). Transition probabilities are corrected for the 1994 break, and adjusted for misclassification, seasonality, margin error, and time aggregation. All table entries are expressed in percent.

by slack work conditions. This dovetails with the finding that turnover between involuntary part-time work and non-employment states plays a limited role in the variation of i_t. The next set of rows of Table 4 shows the interaction between within-employer transitions and involuntary part-time work by reason.[39] This shows a strong overlap between changes at the same employer and transitions reflecting slack work conditions: over 60 percent of the variation of $p\,(F \to I)$ and $p\,(I \to F)$ is explained by the conjunction of these two factors. When we combine the numbers with results from Table 3, we find that 32.2 percent ($= 62.8 \times 28.2\% + 61.3 \times 23.6\%$) of the variation of i_t is driven solely by within-employer fluctuations between full-time and involuntary part-time work due to slack work conditions.

[39]The results reported here present two important refinements of findings available in the existing literature. First, to our knowledge, within-employer transitions and workers' stated reasons for working part-time involuntarily have only been studied in isolation from one another. Second, to date we only had information about the composition of the inflows of overall part-time employment (for instance, this is the information underlying Fact 5 in BML19). In the present work on the other hand, we analyze the specific dynamics of inflow and outflow transition probabilities of involuntary part-time work by reason.

6 Discussion

6.1 Implications of our main findings

We established that involuntary part-time work is a highly transitory state (Fact 1), and that its cyclical variation is predominantly driven by fluctuations in transitions to and from other forms of employment (Fact 2). Moreover, we documented specific time patterns of the behavior of involuntary part-time flows around recessions: the ins go up and the outs drop, with the latter being more persistent and explaining the slow recovery of the involuntary part-time employment rate (Fact 3). We have also shown that flows to and from unemployment play a very small role in the dynamics of involuntary part-time work, and vice versa. We now discuss the implications of these findings for macroeconomic analysis of labor markets.

The main conclusion of our analysis is that the dynamics of involuntary part-time employment flows are driven by a different labor adjustment channel compared to job creation and job destruction. Specifically, following a negative shock, some employed workers are "turned down" by their employers into lower hours (which results in F/V to I transitions) with the understanding that they will be brought back to higher working hours when business conditions improve (I to F/V transitions). Consistent with this interpretation, the main source of cyclical variation in flows between involuntary part-time work and other employment states is accounted for by changes within employment. While direct evidence on the importance of transitions at the same employer only exists post 1994, the strong procyclicality of job-to-job transitions in the pre-1994 period (Shimer [2005], Mukoyama [2014]) suggests that employer-to-employer transitions are unlikely to play a major role in the dynamics of those flows in earlier recessions. For workers undergoing these 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.[40] To paraphrase Bell and Blanchflower [2018], involuntary part-time employment is personal in a way that unemployment is not.

More broadly, our analysis points to a form of job heterogeneity that determines whether the adjustment in response to a given adverse economic shock occurs through involuntary part-time work 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 recent 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 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 employment and other employment states are as large and as cyclical as their unemployment counterparts (in fact, transitions between unemployment and voluntary part-time employment are acyclical and much lower than their involuntary part-time employment counterparts). This indicates that involuntary part-time reallocation is used more intensively in bad times and, therefore, it constitutes an important element

[40] 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 $p(I \to F)$.

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 work 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 work during recessions and their aftermaths (Figure 4a). 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. 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 (Plot 5d). 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). Figure 5 shows that high rates of involuntary part-time employment during recessions are not fueled by large inflows of unemployed workers.[41] The composition of involuntary part-time work inflows by reason (Table 4), which is dominated

[41] In fact, we see that $p(U \to I)$ exerts a negative drag on the involuntary part-time employment rate during recessions. $p(U \to I)$ exhibits no clear cyclical pattern that could easily explain this result. To understand it, we analyzed the composition of involuntary part-time employment inflows. The share of workers entering involuntary part-time work for lack of full-time jobs has fallen secularly over time. Its main cyclical component is the inflow of unemployed workers. While this inflow rose sharply during the twin recessions of 1980-1982, it was only mildly countercyclical in the last two decades.

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.[42] The evolution of the U.S. labor market after 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).[43] 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 [2018] 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 [2018] 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.[44]

6.2 Relation to the previous literature on involuntary part-time employment

In this section we draw on the facts established in the previous sections to put findings from the recent literature on involuntary part-time work into perspective. Before doing so, we

[42] 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.

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

[44] 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 [2018] show that its impact on wage growth (and the lack thereof) has become more important than the impact of the unemployment rate.

should make clear that our measurement protocol differs quite significantly from previous papers. Some of the adjustments included in our protocol are necessitated by the break created by the 1994 CPS redesign, but others are not. Specifically, different from papers in that literature, our measurement approach sequentially adjusts transition probabilities for potential misclassification between involuntary and voluntary part-time employment, margin error and time aggregation. As we have argued in Section 4.2, addressing time aggregation without correcting for misclassification produces estimates of involuntary part-time inflows and outflows that seem implausible. Second, adjusting for margin error is necessary to guarantee that a dynamic decomposition of the short-run variation of involuntary part-time employment into the contributions of each transition sums up to a 100 percent. In the quantification exercise of Subsection 5.2 this property enables us to interpret the beta coefficients as *relative* contributions to the dynamics of involuntary part-time work.

Canon et al. [2014], Lariau [2017] and Warren [2017] all present empirical analyses of involuntary part-time employment flows based on post-1994 data. The paper closest to ours is Canon et al. [2014]. They use a measurement framework similar to our own, but do not address misclassification, margin error or time aggregation. In addition, they employ a different method to decompose the variation in involuntary part-time employment.[45] Canon et al. [2014] reach the conclusion that flows within employment are the main driver of the dynamics of involuntary part-time in the aftermath of the Great Recession. This is consistent with Fact 2 which, as we have shown, holds more generally over the period from 1976 until today. Like us, Lariau [2017] and Warren [2017] emphasize that involuntary part-time work is a highly transitory state (Fact 1). They highlight the high levels and strong cyclicality of transition probabilities to and from other employment states, suggesting that these are likely to contribute most of the short-run variation of involuntary part-time employment (Fact 2). They do not, however, quantify these contributions through a formal variance

[45]They use a steady-state decomposition method similar to the one proposed by Shimer [2012]. The dynamic decomposition we use, which was developed by Elsby et al. [2015], accounts for the out-of-steady-state dynamics of involuntary part-time employment.

decomposition.[46,47] Lariau [2017] and Warren [2017] also note the importance of transitions at the same employer underlying transitions between involuntary part-time employment and full-time work (Table 4). Differently from them, we emphasize contributions to the short-run variation of transition probabilities, which is relevant to substantiate further Facts 2 and 3.[48]

An important motivation underlying the recent empirical literature on involuntary part-time employment was the latter's extraordinary increase during the Great Recession. A key question addressed in this literature concerns whether that behavior reflects, in addition to cyclical factors, contemporaneous changes in the structure and policies of the U.S. labor market. Valletta et al. [2018] use a regression-based decomposition of state-level involuntary part-time work rates and find evidence that changes in the industry composition of state-level employment can explain about a 1 percentage point elevation of the involuntary part-time rate during the Great Recession's aftermath. A competing hypothesis, studied among others by Even and Macpherson [2018], argues that elevated part-time employment is partly the result of the anticipated effects of the Affordable Care Act (ACA), which imposes penalties on firms with more than 50 full-time equivalent employees that do not provide health insurance to all full-time workers. They show that involuntary part-time work increased the most for employees more directly affected by the ACA mandate (i.e. those employed in large firms and with no employer-provided health insurance).[49] While these papers provide evidence that elevated involuntary part-time work during the Great Recession and its aftermath is related to policy or structural changes in the U.S. economy, they also highlight that the

[46] Lariau [2017] does not address misclassification and margin error, but she adjusts transitions probabilities to account for time aggregation bias. Warren [2017] seems to follow the same approach (since he refers to Shimer [2012]'s adjustment protocol to measure transition probabilities).

[47] The quantification exercise (viz. Tables 3 and 4) serves the purpose of offering precise figures to establish our facts. These figures could in turn be useful to inform future analyses, for instance to discipline the calibration of quantitative models.

[48] Lariau [2017] and Warren [2017] highlight that the vast majority of transitions between involuntary part-time employment and full-time work occur at the same employer. However, given that the monthly job-to-job mobility rate is 2.21 percent on average over the period considered, this finding is not unexpected. In our view, it remains important to verify that the cyclical component of transitions between involuntary part-time employment and full-time work is also driven by changes occurring at the same employer.

[49] Previous work by Buchmueller et al. [2011] and Dillender et al. [2016] use differences-in-differences designs and find that similar employer-mandated health insurance legislation adopted respectively in Hawaii and Massachusetts increased part-time employment among low-skill workers.

largest portion of the variation is driven by the business cycle. In fact, Valletta et al. [2018] show that the large countercyclicality of involuntary part-time employment holds when the data is sliced at the state level.

Our findings are consistent and complementary to this research. First, we uncovered a stable pattern of the behavior of involuntary part-time employment flows across the five recessions covered in our dataset and summarized in Facts 1 to 3. In other words, looking at recent U.S. business-cycle history, large changes in involuntary part-time employment flows are an important element of how cyclical shocks are reflected in the labor market. This conclusion is not affected by the fact that part of the spectacular response during the Great Recession is attributable to non-cyclical factors. In some respects, every recession is different from the other – the source of shocks at their origin is usually distinct, the institutional context and the structure of the labor market at the moment they occur is also changing. Second, and perhaps more importantly, the patterns of within-employment reallocation that are the crux of involuntary part-time dynamics are helpful to understand how changes in the industry composition of employment and/or policy changes can produce such a large response in the number of workers employed part-time involuntarily. It is precisely because, like argued in BML19, labor utilization in the U.S. economy can adjust by so much over the business cycle that, in a period of large labor market slack like the Great Recession, firms can adjust to shocks (e.g. the announced adoption of the ACA) by moving workers from full-time to part-time employment.

7 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. By splitting employment into finer categories (full-time, voluntary and involuntary part-time work), we uncover important movements in cyclical labor adjustment that occur without an

intervening spell of non-employment. The dataset created in this paper can be useful to calibrate and assess quantitatively models of cyclical labor adjustment.

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. Our analysis provides a clear and consistent characterization of how the flows characterizing these margins respond to the different phases of the business cycle. We think we have made important strides forwards, but are also keenly aware that our analysis raises several 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 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 Section 5.

A.1 Margin-error adjustment

Written in explicit form, Equation (6) used in the margin-error adjustment procedure is

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

where the transition probabilities $p\left(j \to k\right)$ across states j and k at time t have been written as p_t^{jk} in order to lighten the notation.

To set up the adjustment procedure, we also need to define the weighing matrix $\boldsymbol{W}_t$. $\boldsymbol{W}_t$ is proportional to the covariance matrix of $\breve{\boldsymbol{p}}_t$. 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 Appendix B of 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

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

(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.2).[50] By looking at the diagonal elements of the matrices on both side of equation (A.2), 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:

$$\triangle i_t \approx \frac{\triangle\tilde{I}_t\left(1-i_{t-1}\right) - \left(\triangle\tilde{F}_t + \triangle\tilde{V}_t + \triangle\tilde{U}_t\right) i_{t-1}}{\tilde{F}_{t-1} + \tilde{V}_{t-1} + \tilde{I}_{t-1} + \tilde{U}_{t-1}} \tag{A.3}$$

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

[50] 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).

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 4, 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:

$$\underbrace{p_t^{FI} - p_{t-1}^{FI}}_{F\to I} = \underbrace{p_t^{FS} - p_{t-1}^{FS}}_{F\to S} + \underbrace{p_t^{FC} - p_{t-1}^{FC}}_{F\to C}. \tag{A.4}$$

For instance, $\beta\left(F \to S\right)$ in Table 4 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:

$$\begin{aligned}\underbrace{p_t^{IF} - p_{t-1}^{IF}}_{I\to F} = &\underbrace{\frac{\frac{i_t^S}{i_t} + \frac{i_{t-1}^S}{i_{t-1}}}{2}\left(p_t^{SF} - p_{t-1}^{SF}\right)}_{S\to F} + \underbrace{\frac{\frac{i_t^C}{i_t} + \frac{i_{t-1}^C}{i_{t-1}}}{2}\left(p_t^{CF} - p_{t-1}^{CF}\right)}_{C\to F} \\ &+ \underbrace{\frac{p_t^{SF} + p_{t-1}^{SF}}{2}\left(\frac{i_t^S}{i_t} - \frac{i_{t-1}^S}{i_{t-1}}\right) + \frac{p_t^{CF} + p_{t-1}^{CF}}{2}\left(\frac{i_t^C}{i_t} - \frac{i_{t-1}^C}{i_{t-1}}\right)}_{\text{SHARE}}.\end{aligned} \tag{A.5}$$

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} (Table 4).

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, IS, IC) 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 Adjustment Coefficients

Table B1 reports the multiplicative adjustment coefficients (the $\phi_{1,y}$'s reported in Section 3) delivered by our adjustment protocol. These are the coefficients 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.

Table B1: 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.

C Robustness Checks

Our analysis relies on data adjusted for misclassification between voluntary and involuntary part-time employment (and between nonparticipation and unemployment). To be transparent about our results, in this appendix we report: average inflows and outflows (Table C1), beta coefficients (Table C2) and the dynamics of the involuntary part-time employment rate during recessions (Figure C1) in data that has not been adjusted for misclassification. We reach the following conclusions:

- When we do not control for misclassification, the dynamics of involuntary part-time employment is implausibly fast. Indeed, Table C1 indicates that 91.0 percent of involuntary part-time workers were in a different labor market state in the previous month in the unadjusted data.

- The importance of flows between full-time employment and involuntary part-time work is not a fabrication of our adjustment. In the unadjusted data, $q\left(F \rightarrow I\right)$ and $p\left(I \rightarrow F\right)$ are at 32.3 and 31.1 percent vs. around 29 percent in the adjusted data.

- *Mutatis mutandis*, similar conclusions apply for unemployment. Its dynamics in the unadjusted data is very fast because of the high levels of flows coming from and going

towards nonparticipation. The average interaction with other labor market states changes little after correcting these data for misclassification.

- The analysis of beta coefficients is quite robust to the adjustments we make for misclassification (Table C2). Not surprisingly, the variance contribution of voluntary part-time employment is larger in the unadjusted data because of the higher levels of transition probabilities. In the adjusted data, part of this contribution is transferred to flows in and out of full-time employment. The ins vs. outs split of the dynamics of involuntary part-time employment (last row of Table C2) is the same in the unadjusted and adjusted data.

- Similarly, the analysis of individual recessions is not substantially altered by the misclassification adjustment. As can be seen in Figure C1, if we focus on $F + V \rightarrow I$, $I \rightarrow F + V$, $U \rightarrow I$ and $I \rightarrow U$ and use the unadjusted data, we explain a lower share of the dynamics of the involuntary part-time employment rate during recessions. However, the dynamics of the different lines, and the differences in behavior across recession episodes, is essentially the same as that revealed by Figure 5.

Table C1: Inflow and outflow transition probabilities in data unadjusted for misclassification: Sample averages

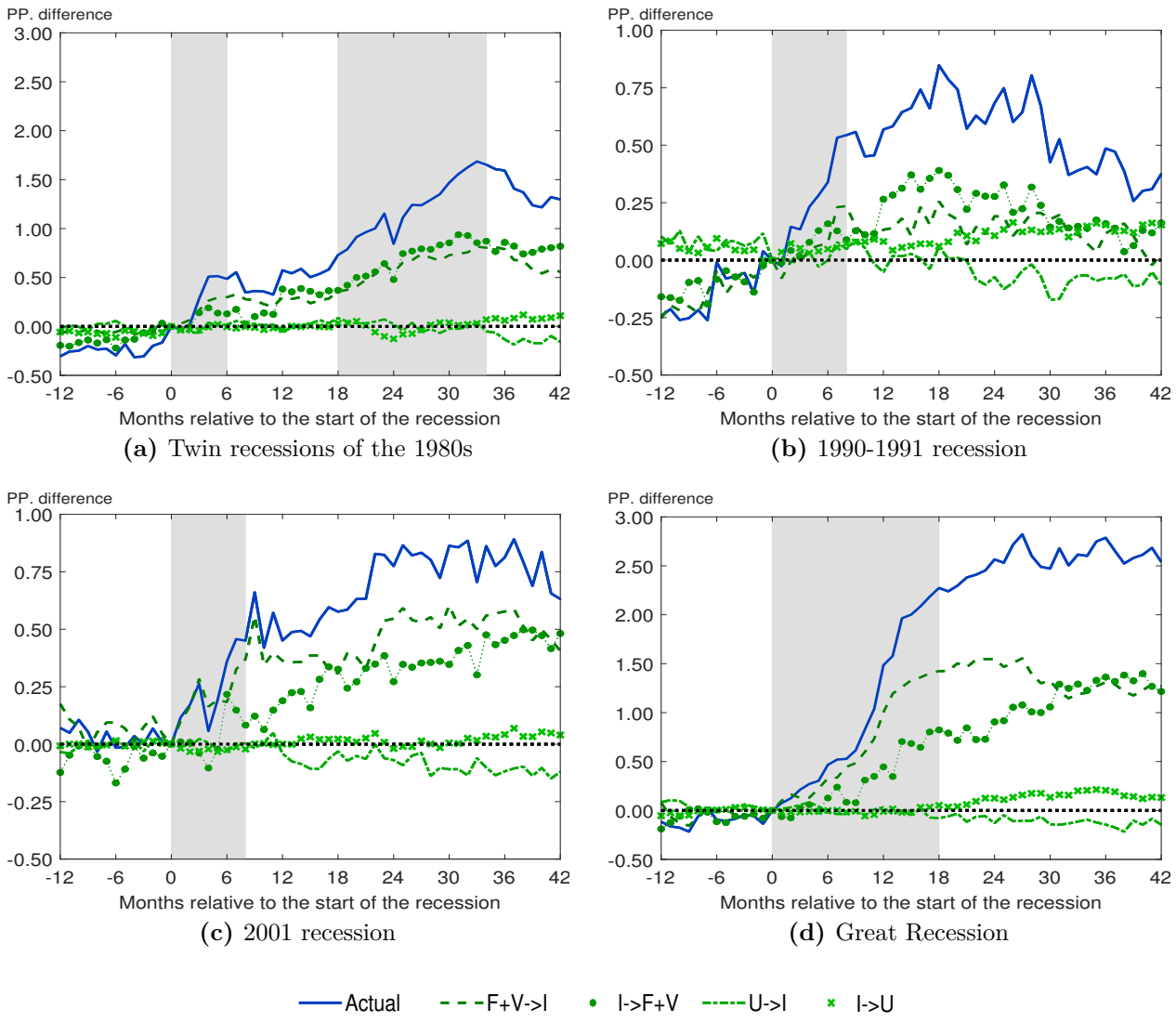
Involuntary part-time work				Unemployment			
Inflows		Outflows		Inflows		Outflows	
$q(F \to I)$	32.3	$p(I \to F)$	31.1	$q(F \to U)$	19.0	$p(U \to F)$	17.8
$q(V \to I)$	36.6	$p(I \to V)$	31.3	$q(V \to U)$	6.18	$p(U \to V)$	7.84
$q(U \to I)$	19.4	$p(I \to U)$	14.1	$q(I \to U)$	5.54	$p(U \to I)$	7.65
$q(N \to I)$	2.74	$p(I \to N)$	2.89	$q(N \to U)$	36.1	$p(U \to N)$	28.0
$\sum_{i \neq I} q(i \to I)$	91.0	$\sum_{j \neq I} p(I \to j)$	79.3	$\sum_{i \neq U} q(i \to U)$	66.8	$\sum_{j \neq U} p(U \to j)$	61.2

Notes: CPS data, 1976m01 – 2018m12. Transition probabilities are corrected for the 1994 break, and adjusted for seasonality, margin error, and time aggregation. The table reports the averages of monthly transition probabilities over the sample period. The inflow transition 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 transition probabilities are the elements of the Markov transition matrix. All table entries are expressed in percent.

Table C2: Inflow and outflow transition probabilities in data unadjusted for misclassification: Variance contributions

Involuntary part-time work rate				Unemployment rate			
Inflows		Outflows		Inflows		Outflows	
$\beta(F \to I)$	18.4	$\beta(I \to F)$	20.2	$\beta(F \to U)$	13.5	$\beta(U \to F)$	25.0
$\beta(V \to I)$	25.8	$\beta(I \to V)$	21.0	$\beta(V \to U)$	2.91	$\beta(U \to V)$	9.22
$\beta(U \to I)$	7.32	$\beta(I \to U)$	3.44	$\beta(I \to U)$	0.21	$\beta(U \to I)$	4.52
$\beta(N \to I)$	3.42	$\beta(I \to N)$	0.72	$\beta(N \to U)$	12.9	$\beta(U \to N)$	28.2
$\sum_{i \neq I} \beta(i \to I)$	54.9	$\sum_{j \neq I} \beta(I \to j)$	45.3	$\sum_{i \neq U} \beta(i \to U)$	29.6	$\sum_{j \neq U} \beta(U \to j)$	66.9
$\sum_{i \neq I} \beta(i \to I) + \sum_{j \neq I} \beta(I \to j) = 100.2$				$\sum_{i \neq U} \beta(i \to U) + \sum_{j \neq U} \beta(U \to j) = 96.5$			

Notes: CPS data, 1976m01 – 2018m12. Transition probabilities are corrected for the 1994 break, and adjusted for seasonality, margin error, and time aggregation. The table reports the variance contributions of flows hazard λ^{jk} to the dynamics of involuntary part-time employment and unemployment rates. All table entries are expressed in percent.



(a) Twin recessions of the 1980s

(b) 1990-1991 recession

(c) 2001 recession

(d) Great Recession

Figure C1: Sources of the recessionary increase in involuntary part-time employment in data unadjusted for misclassification

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 reports 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 as defined in equation (8). The scale on the vertical axis is different for the milder recessions (Plots C1b and C1c) and the large recessions (Plots C1a and C1d). Gray-shaded areas indicate NBER recession periods.