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Reassessing the ins and outs of unemployment ☆

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ABSTRACT

This paper uses readily accessible aggregate time series to measure the probability that an employed worker becomes unemployed and the probability that an unemployed worker finds a job, the ins and outs of unemployment. Since 1948, the job finding probability has accounted for three-quarters of the fluctuations in the unemployment rate in the United States and the employment exit probability for one-quarter. Fluctuations in the employment exit probability are quantitatively irrelevant during the last two decades. Using the underlying microeconomic data, the paper shows that these results are not due to compositional changes in the pool of searching workers, nor are they due to movements of workers in and out of the labor force. These results contradict the conventional wisdom that has guided the development of macroeconomic models of the labor market since 1990.

1. Introduction

This paper measures the probability that an employed worker becomes unemployed and the probability that an unemployed worker finds a job. Using United States data from 1948 to 2010, I find that there are substantial fluctuations in unemployed workers' job finding probability at business cycle frequencies, while the probability a worker exits employment is comparatively acyclic. This is particularly true in the last two decades, during which period the employment exit probability has secularly declined despite three spikes in the unemployment rate. Ninety percent of the fluctuations in the unemployment rate since 1987 were a consequence of movements in the job finding probability. This suggests that if one wants to understand fluctuations in unemployment, one must understand fluctuations in the transition rate from unemployment to employment, the 'outs of unemployment'. This conclusion is in opposition to the conventional wisdom, built around research by Darby et al. (1985, 1986), Blanchard and Diamond (1990), and Davis and Haltiwanger (1990, 1992), that recessions are periods characterized primarily by a high exit rate from employment.

I base my conclusion on novel but simple measures of the job finding and employment exit probabilities. These measures rely on two strong assumptions: workers neither enter nor exit the labor force but simply transit between employment and unemployment; and all workers are *ex ante* identical, and in particular in any period all unemployed workers have the same job finding probability and all employed workers have the same exit probability. Given these assumptions, I show that the probability that an unemployed worker finds a job during a period is a simple function of the number of unemployed

☆ My title borrows from Darby et al. (1986). I am grateful for comments from Fernando Alvarez, Gadi Barlevy, Francesco Belviso, Tito Boeri, Steven Davis, Jason Faberman, Robert Hall, Andreas Hornstein, David Laibson, Gary Solon, Gianluca Violante, Randall Wright, an anonymous referee, and from seminar participants at the Bank of Italy, Bocconi University, the Chicago Fed, Harvard University, the St. Louis Fed, and the University of Texas–Austin on an earlier version of this paper. This research is supported by grants from the National Science Foundation and the Sloan Foundation.

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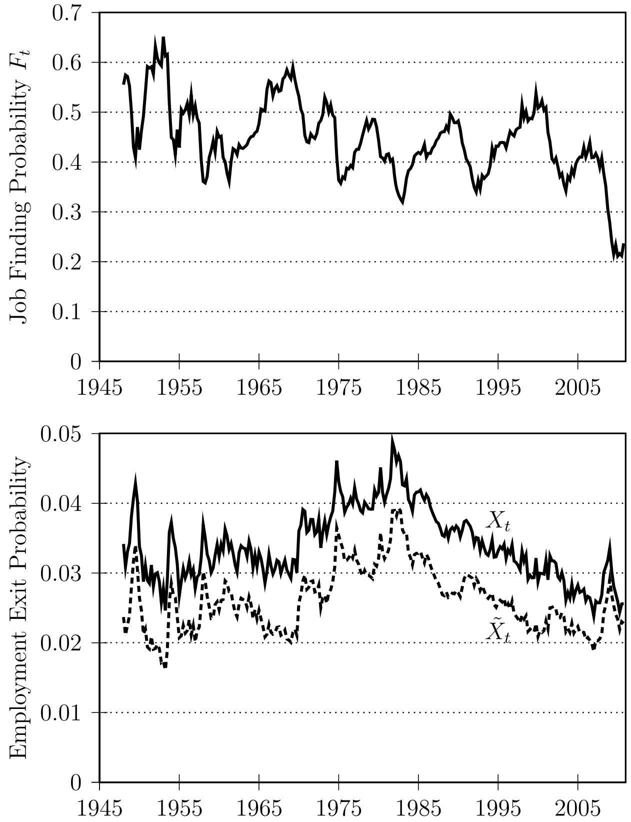

Fig. 1. Job finding and employment exit probabilities, 1948Q1–2010Q4, quarterly average of monthly data. The job finding probability F_t (top figure) is constructed from unemployment and short term unemployment according to Eq. (4). The employment exit probability X_t (bottom figure, solid line) is constructed from employment, unemployment, and the job finding probability according to Eq. (5). $\tilde{X}_t$ (bottom figure, dashed line) is constructed without accounting for time aggregation according to Eq. (6) with $\tilde{F}_t = F_t$. Employment, unemployment, and short term unemployment data are constructed by the BLS from the CPS and seasonally adjusted. Short term unemployment data are adjusted for the 1994 CPS redesign as described in Appendix A.

workers at the start of the period, the number of unemployed workers at the end of the period, and the number of unemployed workers at the end of the period who were employed at some point during the period ('short term unemployment'). The probability that a worker exits employment to become unemployed can be found using the same data and the number of employed workers at the start of the period. Calculations using these data give me my preferred measures of the job finding probability and employment exit probability, shown in Fig. 1. I find that movements in the job finding probability account for 77 percent of fluctuations in the unemployment rate since 1948, rising to 90 percent after 1987.

It is not surprising that strong assumptions deliver strong results, so this paper also explores what happens if I relax these assumptions. Consider first the restriction that workers neither enter nor exit the labor force. Once I relax this assumption, I can no longer use publicly available aggregate data on employment, unemployment, and short term employment to construct the job finding and exit probabilities. Instead, I follow a standard methodology (Marston, 1976; Abowd and Zellner, 1985; Poterba and Summers, 1986; Blanchard and Diamond, 1990) and use microeconomic data on individuals' employment status in consecutive months from 1967 to 2010 to construct time series for the gross flow of workers between employment, unemployment, and inactivity (out of the labor force). I then compute the job finding probability for unemployed workers and the probability of exiting employment for unemployment from these data. Both the theory and the requisite data analysis are far more cumbersome and less transparent than in the approach that ignores entry and exit from the labor force. It is thus reassuring that, although this changes the level of the job finding and exit probabilities, it does not quantitatively affect their fluctuations. Fluctuations in the unemployment-to-employment transition rate are more than twice as important as fluctuations in the employment-to-unemployment transition rate for explaining movements in both the unemployment rate and the employment–population ratio. Moreover, fluctuations in the employment-to-unemployment transition rate are partially offset by opposing movements in the employment-to-inactivity transition rate.[1]

[1] A related assumption, which I do not relax in this paper, is that workers only separate from their employer to become unemployed or exit the labor force. Using United States data from 1994 to 2003, Fallick and Fleischman (2004) find that employer-to-employer transitions are "markedly procyclical". If this is correct, the total separation rate, either out of employment or directly to another employer, may be acyclic or even procyclical. See Hall (2005b) and

I then relax the restriction that all workers are homogeneous. The first question that arises is what exactly *the* job finding probability measures if different workers have a different job finding probability. I show that my methodology measures the probability that the average worker who is unemployed at the start of period t finds a job during period t. Other alternatives would give an identical measure of the job finding probability if workers were homogeneous, but have a predictable bias if workers are heterogeneous. United States data are consistent with the predicted bias.

Another issue that arises when workers are heterogeneous is whether that heterogeneity can explain fluctuations in the job finding probability. Darby et al. (1985, 1986) argue that the job finding probability declines during recessions because workers who are unemployed during recessions are different from those who are unemployed during expansions. According to this theory, recessions are periods when prime-age workers suffer permanent job loss in particularly large numbers. Such workers have a low probability of finding a job, but they would have had a low job finding probability regardless of when they became unemployed. Darby et al. argue that this compositional effect drives down the measured job finding probability during recessions, a possibility that Baker (1992) labeled the "heterogeneity hypothesis". I test this hypothesis by examining the compositional variation of the unemployment pool along several different observable dimensions and find scant evidence in support of it.

Many previous authors have measured the cyclicality of the job finding and employment exit probabilities, but this paper offers several contributions to the existing literature. First, I use data from the last two decades, during which period the employment exit probability has become noticeably less cyclical. Second, I use publicly available data whenever possible, making it easy for others to verify my results, extend them as more data becomes available, and examine their consistency both within the United States and across countries.[2] Third, I emphasize the importance of time aggregation throughout the paper, working explicitly in a continuous time model in which data are available at discrete intervals. I argue that ignoring time aggregation will bias a researcher towards finding a countercyclical employment exit probability, because when the job finding probability falls, a worker who loses her job is more likely to experience a measured spell of unemployment.[3] Fourth, I stress heterogeneity throughout my analysis, arguing that changes in the composition of the unemployed population do not drive my results.

The rest of this paper proceeds as follows. Section 2 proposes new measures of the job finding and employment exit probabilities that use readily accessible data and avoid the time aggregation bias. I then discuss the behavior of the job finding and employment exit probabilities in the United States from 1948 to 2010. Section 3 relaxes the assumption that workers never enter or exit the labor force. I use gross flow data to measure the probability that a worker who is in one employment state at the beginning of the month (employed, unemployed, or inactive) switches to another employment state by the end of the month. Since workers can go through multiple states within a month, I then adjust these measures for time aggregation to get the instantaneous transition rates between employment states. I find strong correlations between this measure of the unemployment–employment transition probability and the job finding probability and between the employment–unemployment transition probability and the employment exit probability.

Section 4 examines the role of heterogeneity. First I show that the job finding probability which I construct in Section 2 measures the mean job finding probability for an unemployed worker. Alternative measures of the job finding probability would be identical if workers were homogeneous, but with heterogeneous workers these correspond to a weighted average of the job finding probability for unemployed workers, over-weighting certain groups of workers, e.g. the long term unemployed. I then address Darby et al.'s (1986) heterogeneity hypothesis. I confirm that the unemployment pool switches towards 'job losers not on temporary layoff' during recessions, and that these workers always have an unusually low job finding probability. Nevertheless, this explains little of the overall fluctuations in the job finding probability. Other dimensions of heterogeneity—age, sex, race, marital status, education, and geographic region—contribute virtually nothing to explaining fluctuations in the job finding probability.

Section 5 discusses the conventional wisdom on the cyclicality of the job finding and employment exit probabilities, especially the evidence presented by Davis and Haltiwanger (1990, 1992). I argue that this evidence has frequently been misinterpreted and may shed little light on the question of interest in this paper. This misinterpretation profoundly influenced the development of macroeconomic models of the labor market during the past 20 years, including such well-known papers as Mortensen and Pissarides (1994) and Caballero and Hammour (1994). Subsequent research has focused on the cause of job loss during recessions rather than the difficulty of finding a job. That section also discusses some recent papers that respond to and extend the analysis in an earlier version of this paper. Section 6 concludes.

Shimer (2005b) for evidence on this point. Previous versions of this paper referred to the 'exit rate' as the 'separation rate'; the change in nomenclature is intended to reduce confusion.

2 The main time series I construct in this paper and the programs I use to construct them are available online at https://sites.google.com/site/robertshimer/research/flows.

3 At least since Perry (1972), authors have recognized the importance of time aggregation for the level of the job finding and employment exit probabilities (see also Kaitz, 1970; Sider, 1985; Darby et al., 1986; Baker, 1992). As I discuss in Section 2, the approach in this paper is slightly different than in those earlier works. Time aggregation has received less attention in the gross flows literature examining movements in and out of the labor force.

2. A new measure of transition probabilities

In this section, I develop novel measures of the job finding probability for unemployed workers F_t and the exit probability for employed workers X_t.[4] I then use publicly available data from the Current Population Survey (CPS) to measure the two transition probabilities in the United States from 1948 to 2010. I find that the job finding probability is strongly procyclical while the employment exit probability explains only one-quarter of the fluctuations in the unemployment rate, and less during the last two decades.

To obtain simple measures of the job finding and employment exit probabilities, it is necessary to make strong assumptions. Throughout this section, I ignore movements in and out of the labor force, so workers simply transition between employment and unemployment. I also assume that all unemployed workers find a job—become employed—with probability F_t and all employed workers lose a job—become unemployed—with probability X_t during period t, ignoring any heterogeneity or duration dependence that makes some unemployed workers more likely to find and some employed workers less likely to lose a job within the period. Sections 3 and 4 argue that these assumptions do not qualitatively affect my conclusions.

2.1. Theory

I model a continuous time environment in which data are available only at discrete dates. For $t \in \{0, 1, 2, \ldots\}$, refer to the interval $[t, t+1)$ as 'period t'. The goal is to recover the job finding probability $F_t \in [0, 1]$ and employment exit probability $X_t \in [0, 1]$ during period t from commonly available data. I assume that during period t, all unemployed workers find a job according to a Poisson process with arrival rate $f_t \equiv -\log(1 - F_t) \geqslant 0$ and all employed workers lose their job according to a Poisson process with arrival rate $x_t \equiv -\log(1 - X_t) \geqslant 0$. Throughout this paper, I refer to f_t and x_t as the job finding and employment exit *rates* and to F_t and X_t as the corresponding *probabilities*, i.e. F_t is the probability that a worker who begins period t unemployed finds at least one job during the period and similarly for X_t.

Fix $t \in \{0, 1, 2, \ldots\}$ and let $\tau \in [0, 1]$ be the time elapsed since the last measurement date. Let $e_{t+\tau}$ denote the number of employed workers at time $t+\tau$, $u_{t+\tau}$ denote the number of unemployed workers at time $t+\tau$, and $u_t^s(\tau)$ denote 'short term unemployment', workers who are unemployed at time $t+\tau$ but were employed at some time $t' \in [t, t+\tau]$. Note that $u_t^s(0) = 0$ for all t. It is convenient to define $u_{t+1}^s \equiv u_t^s(1)$ as the total amount of short term unemployment at the end of period t.

With these definitions, unemployment and short term unemployment evolve according to

$$\dot{u}_{t+\tau} = e_{t+\tau} x_t - u_{t+\tau} f_t, \tag{1}$$

$$\dot{u}_t^s(\tau) = e_{t+\tau} x_t - u_t^s(\tau) f_t. \tag{2}$$

Unemployment increases when workers exit employment, at an instantaneous rate x_t, and decreases when unemployed workers find jobs, at an instantaneous rate f_t. Short term unemployment increases when workers exit employment and decreases when short term unemployed workers find jobs.

To solve for the job finding probability, eliminate $e_{t+\tau} x_t$ between these equations, giving

$$\dot{u}_{t+\tau} = \dot{u}_t^s(\tau) - \big(u_{t+\tau} - u_t^s(\tau)\big) f_t$$

for $\tau \in [0, 1)$. By construction, $u_t^s(0) = 0$, so given an initial condition for u_t, this differential equation can be solved for u_{t+1} and $u_{t+1}^s \equiv u_t^s(1)$:

$$u_{t+1} = (1 - F_t) u_t + u_{t+1}^s. \tag{3}$$

The number of unemployed workers at date $t+1$ is equal to the number of unemployed workers at date t who do not find a job (fraction $1 - F_t = e^{-f_t}$) plus the u_{t+1}^s short term unemployed workers, those who are unemployed at date $t+1$ but held a job at some point during period t. Invert this,

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t}, \tag{4}$$

to express the job finding probability as a function of unemployment and short term unemployment.

One can also solve the differential equations (1) forward to obtain an implicit expression for the employment exit rate:

$$u_{t+1} = \frac{(1 - e^{-f_t - x_t}) x_t}{f_t + x_t} l_t + e^{-f_t - x_t} u_t, \tag{5}$$

where $l_t \equiv u_t + e_t$ is the size of the labor force during period t, which I assume is constant since I do not allow entry or exit from the labor force. Since $l_t > u_t$, the right-hand side of this expression is increasing in x_t. Given the job finding

[4] Shimer (2005b) follows the same approach.

probability from Eq. (4) and data on unemployment and employment, Eq. (5) uniquely defines the employment exit rate x_t and probability X_t.

To understand Eq. (5), note first that if unemployment is constant during period t, the unemployment rate is determined by the ratio of the employment exit rate to the job finding rate, $\frac{u_t}{l_t} = \frac{x_t}{x_t + f_t}$, a standard formula. More generally, it helps to compare Eq. (5) with a discrete time model in which there is no possibility of both finding and losing a job within a period. In this case,

$$u_{t+1} = \tilde{X}_t e_t + (1 - \tilde{F}_t) u_t. \tag{6}$$

A fraction $\tilde{X}_t$ of employed workers lose their job and a fraction $\tilde{F}_t$ of unemployed workers find a job during period t, determining the unemployment rate at the start of period $t+1$. For example, if we assume $\tilde{F}_t = F_t$, Eq. (4) implies $\tilde{X}_t = u^s_{t+1}/e_t$. When the time period is sufficiently short, or equivalently $x_t + f_t$ is sufficiently small, Eq. (5) converges to this simple expression. But with longer time periods, Eq. (5) allows workers to lose a job and find a new one, or vice versa, within the period.

The distinction between Eqs. (5) and (6) may be quantitatively important for measuring both the level of the employment exit probability and its cyclicality. When the job finding rate f_t is high, Eq. (5) captures the fact that a worker who loses her job is more likely to find a new one without experiencing a measured spell of unemployment. These exits are missed in Eq. (6), so the latter formula yields fewer exits and, more importantly for this paper, a bias in the measured cyclicality of the employment exit rate. Because the probability of losing a job during the month that it is found is comparatively small, time aggregation causes relatively little bias in the job finding rate.

It is worth stressing that my approach allows for the possibility that a worker can only find or lose a job during certain portions of the month, e.g. during the regular workday from nine in the morning to five in the afternoon on weekdays. If that were the case, f_t and x_t would measure the job finding rates during the regular workday, while the interpretation of F_t and X_t would be unchanged. Kaitz (1970) and Perry (1972) appear to be the first to observe that measures of the job finding probability F_t may be biased because individuals can lose and find—or find and lose—a job within a month.[5] Starting with those papers, many authors have adjusted for time aggregation by computing a *weekly* probability of finding a job, which implicitly assumes that individuals cannot find and lose a job within a week. While this assumption is consistent with the Bureau of Labor Statistics definition that a worker is employed if she works at all during a particular week, there is neither a theoretical justification nor empirical evidence supporting the notion that a week represents the minimum duration of an employment or unemployment spell. This is why I take the time aggregation adjustment to a logical extreme by computing instantaneous job finding and employment exit rates. In practice, this distinction turns out to have a quantitative small effect on my findings (see Elsby et al., 2009, p. 97).

2.2. Measurement

Since 1948, the Bureau of Labor Statistics (BLS) has published monthly data on employment, unemployment, and unemployment duration based on the CPS, downloadable from the BLS web site.[6] The measures of the number of employed and unemployed workers are standard, and I use these to quantify e_t and u_t. The survey also asks unemployed workers how long they have been searching for a job and the BLS tabulates the number of unemployed workers with zero to four weeks duration.[7] I use this as my measure of short term unemployment u^s_t from January 1948 to December 1993. Unfortunately, the redesign of the CPS instrument in 1994 introduced a significant discontinuity in the short term unemployment series (Polivka and Miller, 1998; Abraham and Shimer, 2001); Appendix A describes how I measure the short term unemployment rate after 1994.

The solid lines in Fig. 1 show the time series for the job finding probability F_t and the employment exit probability X_t constructed according to Eqs. (4) and (5) from January 1948 to December 2010. Several facts stand out. First, the job finding probability is high, averaging 44 percent over the post-war period. Second, it is variable, falling by about forty log points from peak to trough during recent decades. Third, the employment exit probability averaged 3.4 percentage points during the same period and was somewhat less volatile, particularly from the mid-1980s to the mid-2000s. The dashed line in Fig. 1 shows $\tilde{X}_t$ constructed using Eq. (6) with $\tilde{F}_t = F_t$, i.e. not accounting for time aggregation. The effects of time aggregation on both the level and cyclicality of the employment exit probability are readily apparent.[8]

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[5] Perry (1972) does not examine the employment exit probability X_t. Since in practice time aggregation has a larger effect on the cyclical properties of X_t than F_t, he did not emphasize the consequences of time aggregation for his cyclical findings. Darby et al. (1985) compute an expression for the job finding probability similar to Eq. (4)—see their Eq. (14)—but do not recognize that this controls for time aggregation. Perhaps for this reason, they do not adjust the employment exit rate for time aggregation. Their footnote 17 suggests using a continuous time approach to make this correction, but they do not implement their idea and do not discuss how doing so would affect the measured cyclicality of the employment exit rate.

[6] http://www.bls.gov/cps/.

[7] More precisely, the survey asks workers on temporary layoff how long they have been on layoff and it asks other unemployed workers how long they have been looking for work. Elsby et al. (2011) observe that in recent years, a quarter of the workers who are employed in month $t-1$ and unemployed in month t report a job search duration in month t that exceeds six months. I return to the implications of this recent finding when I compare alternative measures of the job finding probability in Fig. 4 below.

[8] Detrend both series using an HP filter with parameter 10^5. The standard deviation of detrended X_t is 0.07 while the corresponding number for $\tilde{X}_t$ is 0.11.

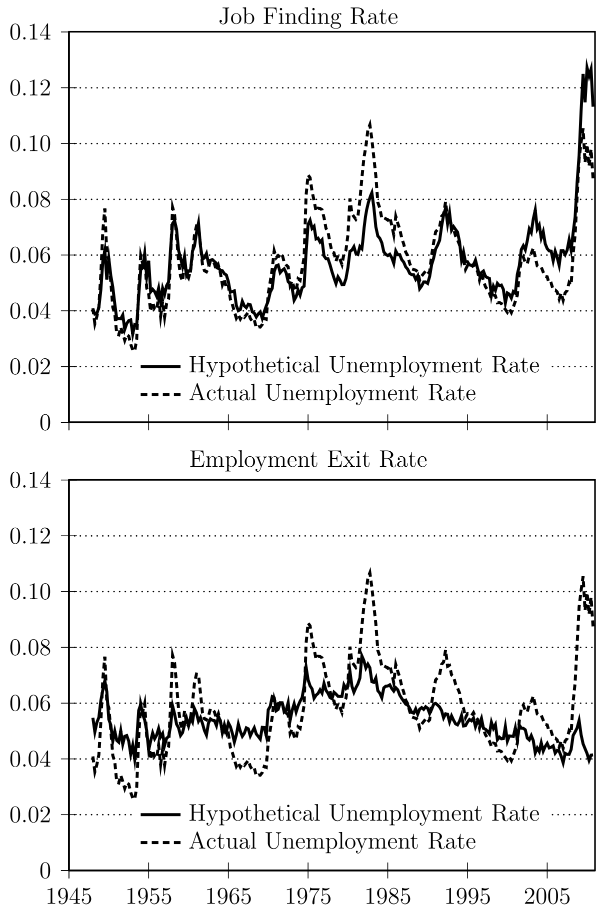

Fig. 2. Contribution of fluctuations in the job finding and employment exit rates to fluctuations in the unemployment rate, 1948Q1–2010Q4, quarterly average of monthly data. The job finding rate f_t is constructed from unemployment and short term unemployment according to Eq. (4). The employment exit rate x_t is constructed from employment, unemployment, and the job finding rate according to Eq. (5). The top panel shows the hypothetical unemployment rate if there were only fluctuations in the job finding rate, $\bar{x}/(\bar{x}+f_t)$, and the bottom panel shows the corresponding unemployment rate with only fluctuations in the employment exit rate, $x_t/(x_t+\bar{f})$. Both panels show the actual unemployment rate for comparison. Employment, unemployment, and short term unemployment data are constructed by the BLS from the CPS and seasonally adjusted. Short term unemployment data are adjusted for the 1994 CPS redesign as described in Appendix A.

To quantify the cyclicality of the job finding and employment exit probabilities, recall that if unemployment were constant, $u_t = u_{t+1}$, Eq. (5) implies that the unemployment rate would be $\frac{u_t}{l_t} = \frac{x_t}{x_t+f_t}$. In fact, $\frac{x_t}{x_t+f_t}$ is a very good approximation to the end-of-month unemployment rate; in monthly data, the correlation between $\frac{u_{t+1}}{l_{t+1}}$ and $\frac{x_t}{x_t+f_t}$ is 0.98. I use this strong relationship to distinguish between the importance of fluctuations in the job finding and employment exit rates for fluctuations in unemployment. Let $\bar{f}$ and $\bar{x}$ denote the average values of f_t and x_t during the sample period and compute the hypothetical unemployment rates $\frac{\bar{x}}{\bar{x}+f_t}$ and $\frac{x_t}{x_t+\bar{f}}$ as measures of the contributions of fluctuations in the job finding and employment exit rates to overall fluctuations in the unemployment rate.[9]

The top panel in Fig. 2 shows that a decline in the job finding rate f_t contributed to every increase in the unemployment rate during the post-war period. The bottom panel shows that from 1948 to 1985, the employment exit rate tended to move with the unemployment rate, although it rarely explained more than half the fluctuation in unemployment. Notwithstanding a spike in 2008, the exit rate more recently has varied little over the business cycle.

One way to quantify this is to look at the comovement of detrended data.[10] Over the entire post-war period, the covariance of the cyclical components of $\frac{u_{t+1}}{l_{t+1}}$ and $\frac{\bar{x}}{\bar{x}+f_t}$ accounts for about three-quarters of the variance of the cyclical component

[9] Pissarides (1986) constructs similar objects using UK data on inflows and outflows from registered unemployment. He finds that most of the secular increase in the unemployment rate during the 1970s was due to a decrease in the job finding rate.

[10] I time-aggregate the underlying monthly data to get quarterly averages, removing substantial high-frequency fluctuations that likely reflect measurement error in the CPS. I then detrend the quarterly data using an HP filter with smoothing parameter 10^5. This is a much lower-frequency filter than is commonly used in business cycle analyses of quarterly data. A standard filter seems to remove much of the cyclical volatility in the variable of interest. I use this same filter throughout the paper.

Table 1
Decomposition: Job finding and employment exit rates. The first row shows the covariance of $\frac{u_{t+1}}{l_{t+1}}$ and $\frac{\bar{x}}{\bar{x}+f_t}$ divided by the variance of $\frac{u_{t+1}}{l_{t+1}}$, i.e. the coefficient in a regression of $\frac{\bar{x}}{\bar{x}+f_t}$ on $\frac{u_{t+1}}{l_{t+1}}$. The second row shows the covariance of $\frac{u_{t+1}}{l_{t+1}}$ and $\frac{x_t}{x_t+\bar{f}}$ divided by the variance of $\frac{u_{t+1}}{l_{t+1}}$. All series are quarterly averages of monthly data and detrended using an HP filter with smoothing parameter 10^5.

	1	2	3	4	5
	all workers 1948–2010	all workers 1967–2010	all workers 1976–2010	all workers 1987–2010	men 25–54 1976–2010
$\frac{\bar{x}}{\bar{x}+f_t}$	0.77	0.83	0.85	0.90	0.69
$\frac{x_t}{x_t+\bar{f}}$	0.24	0.17	0.15	0.10	0.32

of $\frac{u_{t+1}}{l_{t+1}}$, while the covariance of $\frac{u_{t+1}}{l_{t+1}}$ and $\frac{x_t}{x_t+\bar{f}}$ accounts for the remaining quarter (Table 1, column 1).[11] The next three columns of Table 1 show that the relative importance of the job finding rate has increased steadily over time; since 1987, including the recessions in 1990–1991 and 2001, and 2008–2009, the job finding rate accounted for virtually all fluctuations in the unemployment rate.

Although not the main topic of this paper, it seems worth commenting on the secular decline in the employment exit probability since the early 1980s (Fig. 1). This finding would appear to contradict a sizable literature that finds evidence for a constant or even increasing separation rate during the 1980s and early 1990s. For example, Gottschalk and Moffitt (1999) write, "Almost all studies based on the various Current Population Surveys (CPS) supplements …show little change in the overall separation rates through the early 1990s." Part of the difference has to do with the fact that Gottschalk and Moffitt (1999) measure the total separation rate, including separations directly to another employer. Much is due to differences in samples; Gottschalk and Moffitt study married men age 20–62, while I examine the entire population. During the last two decades, the labor force has aged; since younger workers have the highest employment exit rates, this has reduced the exit rate. In addition, women have become increasingly attached to the labor force, further reducing turnover. Consistent with that view, Fig. 3 indicates almost no trend in the employment exit probability for 25 to 54 year old men since 1976.[12] Table 1 shows that fluctuations in the job finding rate are more than twice as important as fluctuations in the employment exit rate for prime-age men. This is particularly interesting since entry and exit from the labor force are likely to be less important for this group of workers, a topic I turn to next.

3. Entry and exit from the labor force

This section relaxes the restriction that all workers are either unemployed or employed by examining the gross flow of workers between three labor market states, employment (E), unemployment (U), and inactivity (I). Compared to the previous section, the theory here is more cumbersome, the data limitations are more serious, and the data analysis is more involved. For each of these reasons, the simpler analysis in Section 2 remains a useful benchmark, but it is reassuring that the quantitative findings of the two sections are consistent.

3.1. Theory

As with the job finding and employment exit probabilities, I account for time aggregation bias by modeling a continuous time environment in which data are available only at discrete dates $t \in \{0, 1, 2, \ldots\}$. Let λ_t^{AB} denote the Poisson arrival rate of a shock that moves a worker from state $A \in \{E, U, I\}$ to state $B \neq A$ at any point during the time interval $[t, t+1)$. Also let λ_t be the associated 3×3 continuous time Markov transition matrix, i.e. a matrix with nonnegative off-diagonal entries and columns that sum to 0. Then if the state of the system is $x(t+\tau)$ at some time $t+\tau \in [t, t+1)$, it evolves according to $\dot{x}(t+\tau) = \lambda_t x(t+\tau)$.

Unfortunately I do not have data on λ_t. Instead, I use the CPS to measure directly the full month transition probabilities n_t, where n_t is a 3×3 discrete time Markov transition matrix, with nonnegative entries n_t^{AB} and columns that sum to 1. I am interested in the relationship between the matrices λ_t and n_t. In particular, given an arbitrary discrete time Markov matrix n_t, can I construct a continuous time Markov matrix λ_t and can I do so uniquely?

To answer this, first consider a related question. Suppose period t is divided into $1/\Delta$ subperiods of length Δ. The transition matrix during each subperiod is some constant $n_{t,\Delta}$, while the transition matrix during the entire period is still n_t. Obviously given a matrix $n_{t,\Delta}$, it is possible to compute n_t through matrix multiplication: let $\mu_{t,\Delta}$ denote a diagonal matrix of eigenvalues of $n_{t,\Delta}$. Let $p_{t,\Delta}$ denote the associated matrix with eigenvectors in the columns. If the eigenvalues are distinct, we can diagonalize the matrix as $n_{t,\Delta} = p_{t,\Delta}\mu_{t,\Delta}p_{t,\Delta}^{-1}$. Then matrix multiplication implies that $n_t = p_{t,\Delta}\mu_{t,\Delta}^{1/\Delta}p_{t,\Delta}^{-1}$.

[11] I obtain these numbers by regressing detrended $\frac{\bar{x}}{\bar{x}+f_t}$ or $\frac{x_t}{x_t+\bar{f}}$ on detrended $\frac{u_{t+1}}{l_{t+1}}$. Since this is not an exact decomposition, the columns do not sum to 1. For this exercise, however, the sum of the contributions of the job finding and employment exit rates in each column of Table 1 lies between 0.99 and 1.01. See Fujita and Ramey (2009) for a similar exercise.

[12] See Abraham and Shimer (2001) for a further discussion of the impact of demographic change on unemployment duration.

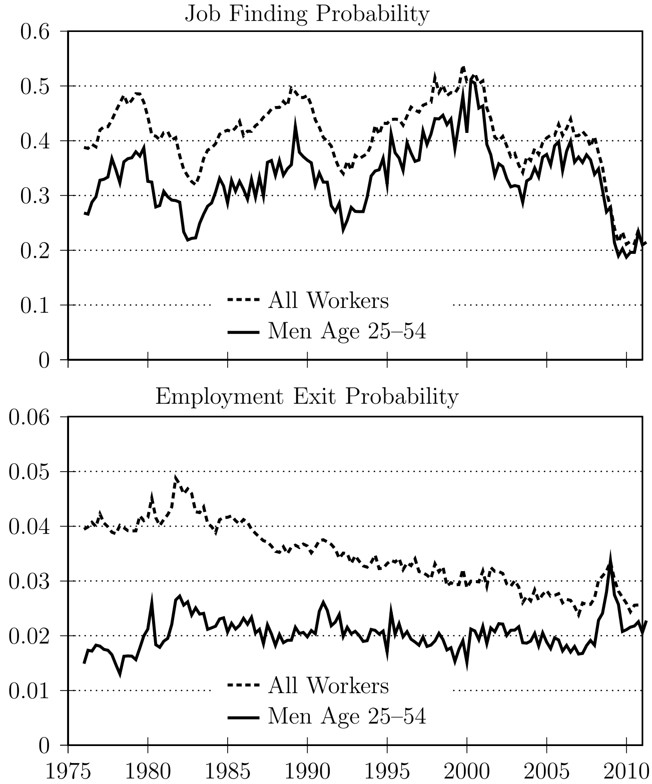

Fig. 3. Job finding and employment exit probabilities, prime-age men, 1976Q1–2010Q4, quarterly average of monthly data. The job finding probability is constructed from unemployment and short term unemployment according to Eq. (4). The employment exit probability is constructed from employment, unemployment, and the job finding probability according to Eq. (5). Employment, unemployment, and short term unemployment data are constructed by the BLS from the CPS and seasonally adjusted. Short term unemployment data are adjusted for the 1994 CPS redesign as described in Appendix A.

It follows that the eigenvalues of n_t are simply the eigenvalues of $n_{t,\Delta}$ raised to the $(1/\Delta)$th power, while the eigenvectors of the two matrices are the same.

Is it possible to reverse this logic, i.e. to construct a $n_{t,\Delta}$ from n_t? I claim that the answer is "yes" if the eigenvalues of n_t are all distinct, real, and nonnegative, which fortunately is the case in my dataset.[13] To do this, simply let $n_{t,\Delta} \equiv p_t \mu_t^{\Delta} p_t^{-1}$, where μ_t^{Δ} is the diagonal matrix of eigenvalues of n_t raised to the Δth power and p_t is the eigenvector matrix. Moreover, if we also insist that the eigenvalues of $n_{t,\Delta}$ are distinct, real, and nonnegative, then there is a unique such transformation.[14]

On the other hand, if the eigenvalues of n_t are all distinct and real but at least one is negative, then the answer is "no" for any even value of $1/\Delta$. If it were possible to do this transformation, then the matrix $n_{t,\Delta}$ would have an imaginary eigenvalue corresponding to the negative eigenvalue of n_t; but complex eigenvalues of real matrices must appear in conjugate pairs, a contradiction. Combining these two claims, if the eigenvalues of n_t are all distinct, real, and nonnegative, there is a unique $n_{t,\Delta}$ that can be constructed as the square of some real matrix $n_{t,\Delta/2}$.[15]

Now return to the continuous time Markov transition matrix λ_t, which is simply the limit of $(n_{t,\Delta} - I)/\Delta$ as Δ converges to 0, where I is the identity matrix. The fact that $\lim_{\Delta \to 0}(\varepsilon^{\Delta} - 1)/\Delta = \log \varepsilon$ leads to the main result: if n_t has distinct, real, and positive eigenvalues, $\lambda_t = p_t \tilde{\mu}_t p_t^{-1}$, where $\tilde{\mu}_t$ is a diagonal matrix with diagonal elements equal to the natural logarithm of the eigenvalues of n_t and p_t is the matrix of eigenvalues of n_t, and thus necessarily also of λ_t. This gives both conditions under which the matrix λ_t is uniquely defined and a recipe for constructing it.

[13] Generically n_t constructed from gross flows data will not have repeated eigenvalues and so I am not concerned about this case. Moreover, the eigenvalues of any Markov matrix lie within the unit circle. The empirical question is whether the eigenvalues are real and nonnegative.

[14] The 2×2 Markov matrix with off-diagonal elements 3/8 has eigenvalues 1 and 1/4. It is the square of two different Markov matrices, one with off-diagonal elements 1/4 and another with off-diagonal elements 3/4. Only the first has positive eigenvalues.

[15] If n_t has distinct complex eigenvalues, it is in general possible to construct many $n_{t,\Delta}$. Matrices with complex eigenvalues have cyclical dynamics and the multiple solutions correspond to cycles of different periodicity.

3.2. Measurement

To measure a time series for the full month transition probability between states A and B, I follow an approach adopted by many previous authors, most prominently by Blanchard and Diamond (1990).[16] The CPS is a rotating panel, with each address in the survey for four consecutive months. After the attrition of households that move or otherwise leave the survey—unfortunately, not a representative sample of the population—it is in principle feasible to match nearly three-quarters of the survey records in the microdata files across months. Using these matched records, one can construct the gross flows of workers between labor market states, i.e. the number of workers who switch from state A to state B in month t.

Before 1976, I do not have access to the microdata and so I use Joe Ritter's tabulation of the gross flows from June 1967 to December 1975.[17] For the later period, the monthly CPS public-use microdata are available from the NBER website.[18] Starting with about 42 gigabytes of raw CPS data files, I match individual records from consecutive months using rotation groups, household identifiers, individual line numbers, race, sex, and age. I obtain 31 million matched records during the sample period, 75,000 in an average month. Using these, I compute the sample-weighted transition probabilities between employment states during the relevant month and seasonally adjust the time series using a ratio-to-moving average technique. This gives me a series for the discrete time transition matrix n_t.[19] I then adjust for time aggregation bias by constructing the instantaneous transition rates λ_t using the diagonalization developed in the previous subsection. In every month, the eigenvalues of the discrete time matrix are real, positive, and distinct. Finally, I construct the full month transition probability between states A and B as $\Lambda_t^{AB} = 1 - \exp(-\lambda_t^{AB})$. This should be interpreted as the probability that a worker who starts the period in state A transitions to state B during the month conditional on not experiencing a transition to state C.

The top panel in Fig. 4 compares the job finding probability F_t, computed according to Eq. (4) from publicly available data on unemployment and short term unemployment, with the UE transition probability Λ_t^{UE}, computed using the procedure described here. Although the two series are constructed from different data, their behavior is remarkably similar. They are equally volatile and their correlation is 0.96 in quarterly-averaged data. On the other hand, the job finding probability is consistently about 31 log points higher than the UE transition probability. This is probably because the former measure presumes that all workers exiting unemployment do so in order to take a job while the latter measure recognizes that some unemployment spells end when a worker exits the labor force. In any case, the level difference between the two probabilities is inconsequential for the cyclical behavior of the job finding probability. Gross worker flow data from the CPS confirm this paper's thesis that the job finding probability is strongly procyclical.

The bottom panel in Fig. 4 shows the analogous comparison between the employment exit probability X_t and the EU transition probability Λ_t^{EU}. The correlation between the two series is 0.83 in quarterly-averaged data, with X_t averaging 56 log points higher than Λ_t^{EU}. Moreover, the amplitude of the fluctuations in both series at low frequencies is similar, although the EU transition probability tends to fluctuate a bit more at business cycle frequencies. A curious and notable difference between the two series arises during the last two years of the sample, when the employment exit probability fell back to its pre-recession level, while the EU transition probability remained significantly elevated. This may reflect a growing bias in my measure of the incidence of short term unemployment in recent years (Elsby et al., 2011), which would drive down my measures of the job finding and employment exit probabilities.

I next quantify the importance of changes in the six transition rates for fluctuations in the unemployment rate. In steady state, the flows in and out of employment are equal, as are the flows in and out of unemployment:

$$\left(\lambda^{EU} + \lambda^{EI}\right)e = \lambda^{UE}u + \lambda^{IE}i \quad \text{and} \quad \left(\lambda^{UE} + \lambda^{UI}\right)u = \lambda^{EU}e + \lambda^{IU}i,$$

where e, u, and i are the number of employed, unemployed, and inactive individuals. Manipulate these equations to get

$$\begin{aligned} e &= k\left(\lambda^{UI}\lambda^{IE} + \lambda^{IU}\lambda^{UE} + \lambda^{IE}\lambda^{UE}\right), \\ u &= k\left(\lambda^{EI}\lambda^{IU} + \lambda^{IE}\lambda^{EU} + \lambda^{IU}\lambda^{EU}\right), \\ i &= k\left(\lambda^{EU}\lambda^{UI} + \lambda^{UE}\lambda^{EI} + \lambda^{UI}\lambda^{EI}\right), \end{aligned}$$

where k is a constant set so that e, u, and i sum to the relevant population.

In Section 2 I argued that $\frac{x_t}{f_t + x_t}$ is almost identical to the unemployment rate. Analogously, if the economy were in steady state at some date t, the unemployment rate in a three-state system would equal

[16] See Abowd and Zellner (1985) and Poterba and Summers (1986) for discussions of measurement problems in gross flows data. Data limitations prevent me from addressing these issues.

[17] I am grateful to Hoyt Bleakley for providing me with that data.

[18] http://www.nber.org/data/cps_basic.html. There are a few gaps in the series due to changes in the household identifiers in the public-use files. It is impossible to match data for Dec. 1975/Jan. 1976, Dec. 1977/Jan. 1978, Jun. 1985/Jul. 1985, Sep. 1985/Oct. 1985, Dec. 1993/Jan. 1994, and May 1995/Jun. 1995 to Aug. 1995/Sep. 1995.

[19] Hoyt Bleakley also provided me with his independent estimates of gross flows from January 1976 to May 1993. During the overlapping period, the two series are virtually identical; the standard deviation of the log of the ratio of the two sets of series is less than 1 percent.

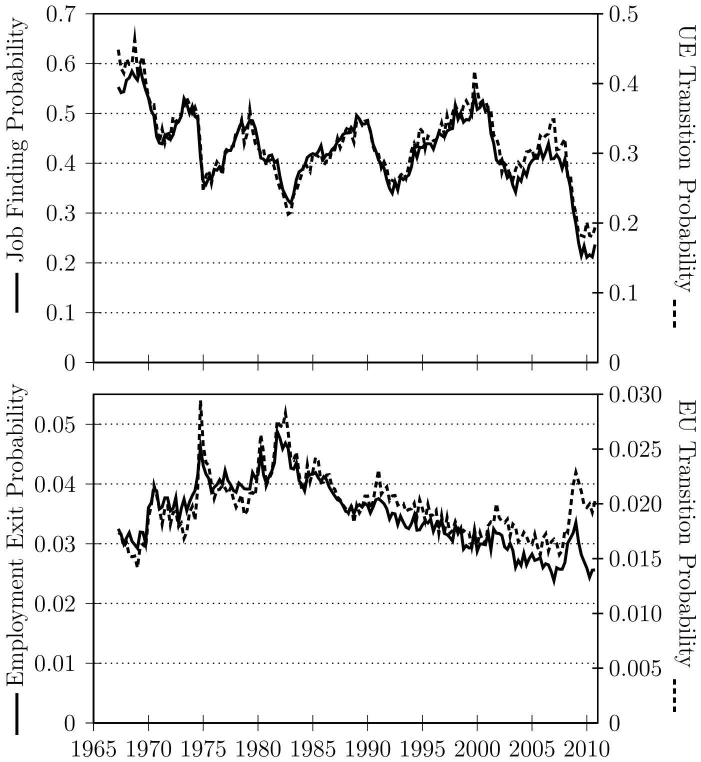

Fig. 4. Alternative measures of the job finding and employment exit probabilities, 1967Q2–2010Q4, quarterly average of monthly data. The job finding probability is constructed from unemployment and short term unemployment according to Eq. (4). The employment exit probability is constructed from employment, unemployment, and the job finding probability according to Eq. (5). Employment, unemployment, and short term unemployment data are constructed by the BLS from the CPS and seasonally adjusted. The gross flows are computed from matched CPS microdata files by Joe Ritter (1967Q2–1975Q4) and by the author (1976Q1–2010Q4), seasonally adjusted using a ratio to moving average, and then used to infer the transition probabilities following the procedure described in Section 3.1. Short term unemployment data are adjusted for the 1994 CPS redesign as described in Appendix A.

$$\frac{\lambda_t^{EI}\lambda_t^{IU} + \lambda_t^{IE}\lambda_t^{EU} + \lambda_t^{IU}\lambda_t^{EU}}{(\lambda_t^{EI}\lambda_t^{IU} + \lambda_t^{IE}\lambda_t^{EU} + \lambda_t^{IU}\lambda_t^{EU}) + (\lambda_t^{UI}\lambda_t^{IE} + \lambda_t^{IU}\lambda_t^{UE} + \lambda_t^{IE}\lambda_t^{UE})}.$$

This is also a good approximation. In quarterly-averaged data, the correlation between this steady state measure and next month's unemployment rate is 0.99.

This suggests a method for calculating the contribution of changes in each of the six transition rates to fluctuations in the unemployment rate. To be concrete, focus on the UI transition rate. Define

$$\begin{aligned} e_t^{UI} &= \lambda_t^{UI}\bar{\lambda}^{IE} + \bar{\lambda}^{IU}\bar{\lambda}^{UE} + \bar{\lambda}^{IE}\bar{\lambda}^{UE}, \\ u_t^{UI} &= \bar{\lambda}^{EI}\bar{\lambda}^{IU} + \bar{\lambda}^{IE}\bar{\lambda}^{EU} + \bar{\lambda}^{IU}\bar{\lambda}^{EU}, \\ i_t^{UI} &= \bar{\lambda}^{EU}\lambda_t^{UI} + \bar{\lambda}^{UE}\bar{\lambda}^{EI} + \lambda_t^{UI}\bar{\lambda}^{EI}, \end{aligned} \tag{7}$$

where $\bar{\lambda}^{AB}$ is the average AB transition rate from 1967 to 2010. That is, only λ_t^{UI} is permitted to vary over time, with the other five transition rates fixed at their average values. Then the contribution of fluctuations in the unemployment-inactivity transition rate to changes in the unemployment rate is $\frac{u_t^{UI}}{u_t^{UI}+e_t^{UI}}$, the hypothetical unemployment rate if there were only fluctuations in the unemployment-inactivity transition rate. Calculate the contribution of the other five transition rates in a similar fashion.

Fig. 5 shows the resulting time series, with the actual unemployment rate plotted for comparison. The first column of Table 2 decomposes the contribution of each of the transition rates by reporting the coefficient from a regression of each detrended hypothetical unemployment rate on the detrended actual unemployment rate.[20] Fluctuations in the UE transition rate (middle left panel of Fig. 5) account for about half of the movement in the unemployment rate, while the EU transition rate accounts for less than a quarter. The third most important factor is a decrease in the UI transition rate, which tends to raise the unemployment rate during downturns. This suggests that unemployed workers are more attached to the labor force

[20] This is again not an exact decomposition but turns out to be quantitatively close. The sum of the entries in each column range from 1.01 to 1.03.

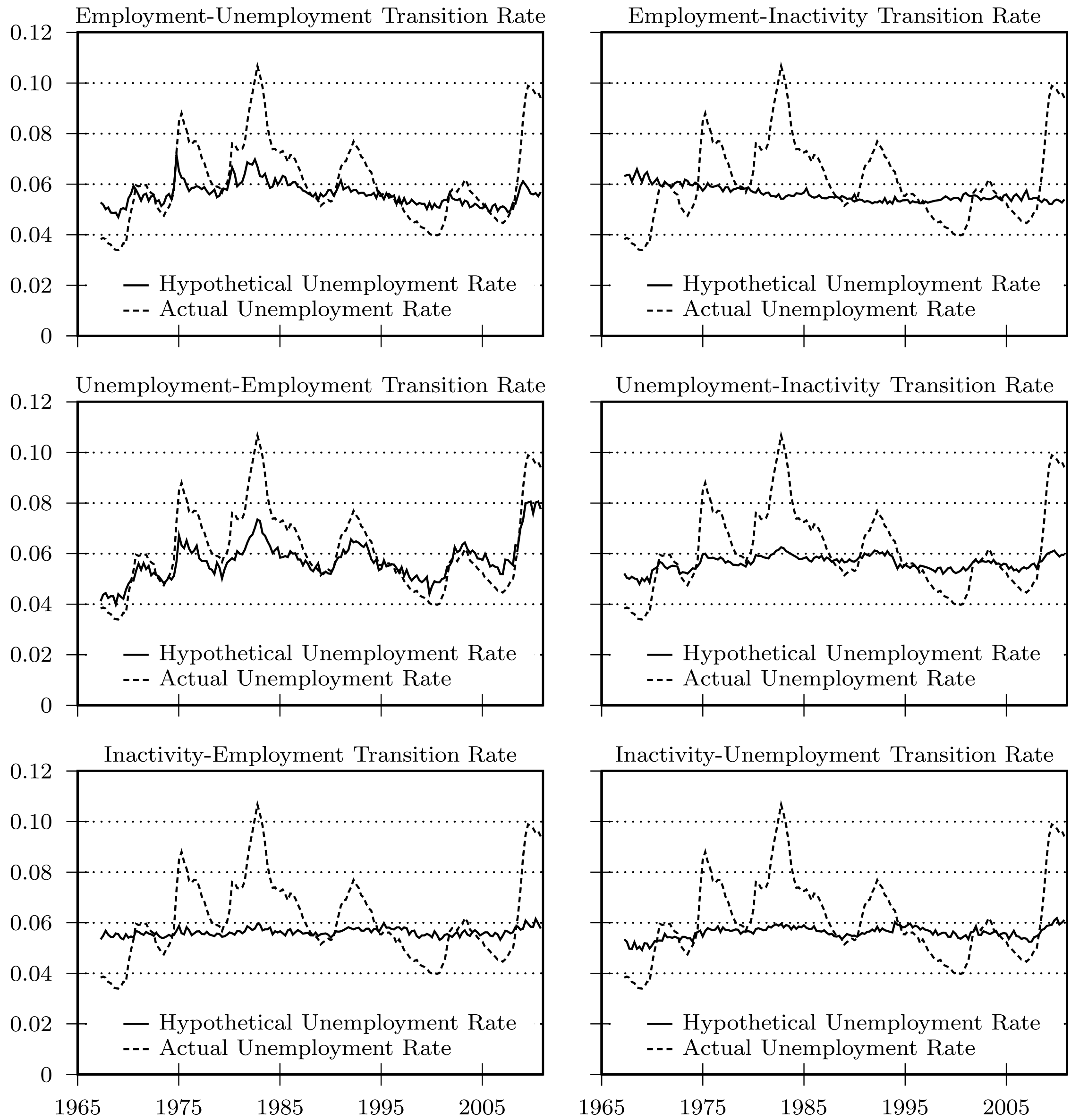

Fig. 5. Contributions of fluctuations in the instantaneous transition rates to fluctuations in the unemployment rate, 1967Q2–2010Q4, quarterly average of monthly data. The gross flows are computed from matched CPS microdata files by Joe Ritter (1967Q3–1975Q4) and by the author (1976Q1–2010Q4), seasonally adjusted using a ratio to moving average, and then used to infer the transition rates following the procedure described in Section 3.1. The contributions to the unemployment rate are inferred as in Eq. (7). Each panel shows the actual unemployment rate for comparison.

during downturns than they are during expansions, a possibility I return to in Section 4 when I examine cyclical changes in the composition of the unemployed population. The remaining three transition rates have a quantitatively minor effect on fluctuations in the unemployment rate. The second column in Table 2 shows that the relative importance of fluctuations in the UE transition rate has grown and the importance of fluctuations in the EU transition rate has shrunk during the last two decades. Although less overwhelming than the comparable numbers in column 4 of Table 1, the UE transition rate is now three times as volatile as the opposing flow.

An advantage to looking at a system in which workers move in and out of the labor force is that I can distinguish between fluctuations in the unemployment rate $\frac{u_t}{e_t+u_t}$ and fluctuations in the employment–population ratio $\frac{e_t}{e_t+u_t+i_t}$. Following the same methodology, Fig. 6 graphs the contribution of each of the six transition rates to fluctuations in the employment–population ratio. This picture is more muddled than Fig. 5. For example, the low frequency trend in the employment–population ratio is driven primarily by a decline in the EI transition rate, which reflects an increase in women's labor force attachment (Abraham and Shimer, 2001). At business cycle frequencies, the third column in Table 2 shows that a 1 percentage point cyclical increase in the employment–population ratio is associated with a 1.05 percentage point

Table 2
Decomposition: entry and exit from the labor force. The first row, first and second columns are the covariance of $\frac{u_{t+1}}{u_{t+1}+e_{t+1}}$ and $\frac{u_t^{EU}}{u_t^{EU}+e_t^{EU}}$ divided by the variance of $\frac{u_{t+1}}{u_{t+1}+e_{t+1}}$ for different time periods. The first row, third and fourth columns are the covariance of $\frac{e_{t+1}}{u_{t+1}+e_{t+1}+i_{t+1}}$ and $\frac{e_{t+1}^{EU}}{u_{t+1}^{EU}+e_{t+1}^{EU}+i_{t+1}^{EU}}$ divided by the variance of $\frac{e_{t+1}}{u_{t+1}+e_{t+1}+i_{t+1}}$ for different time periods. The remaining rows show decompositions from fluctuations in the other five transition rates. All series are quarterly averages of monthly data and detrended using an HP filter with smoothing parameter 10^5.

	1	2	3	4
	unemployment rate		employment–population ratio	
	1967–2010	1987–2010	1967–2010	1987–2010
λ_t^{EU}	0.22	0.17	0.37	0.30
λ_t^{EI}	−0.05	−0.05	−0.36	−0.40
λ_t^{UE}	0.49	0.51	1.05	1.16
λ_t^{UI}	0.17	0.16	−0.48	−0.50
λ_t^{IE}	0.08	0.09	0.69	0.73
λ_t^{IU}	0.12	0.13	−0.36	−0.42

increase in $\frac{e_t^{UE}}{e_t^{UE}+u_t^{UE}+i_t^{UE}}$, so UE fluctuations are critical for changes in the employment–population ratio. The second most important determinant is the IE transition rate (regression coefficient 0.69), which reflects the lower likelihood that an inactive worker finds a job during a downturn. Turning to measures of the employment exit rate, the EU transition rate tends to rise when the employment–population ratio falls (0.37), but this is mostly offset by a decline in the EI transition rate (−0.36). In net, the probability of leaving employment scarcely affects the employment–population ratio at business cycle frequencies, while fluctuations in the probability of finding a job drive both the unemployment rate and the employment–population ratio. The final column in Table 2 shows that all of these associations have become more pronounced in the last two decades, so fluctuations in the UE transition rate explain significantly more than one hundred percent of the fluctuations in the employment–population ratio, while fluctuations in the two exit rates from employment actually in net *reduce* the volatility of the employment–population ratio.

4. Heterogeneity

This section relaxes the assumption that all workers are homogeneous. I first show that if some workers are more likely to find a job than others, F_t measures the mean job finding probability among unemployed workers. Using other moments of the unemployment duration distribution, one can construct other weighted averages of the job finding probability for unemployed workers, all of which co-move with the job finding probability. I then ask why the job finding probability declines during recessions. Is it because all unemployed workers are less likely to find a job or because the type of workers who becomes unemployed during a recession is somehow different, less likely to find a job regardless of the stage of the business cycle, as Darby et al. (1985, 1986) suggest? I find no evidence to support the latter 'heterogeneity hypothesis' (Baker, 1992).

4.1. Accounting for heterogeneity

Suppose unemployed workers are heterogeneous. For example, long term unemployment may diminish a worker's prospect of finding a job. Alternatively, some time-invariant characteristic may affect the job finding probability, so a dynamic selection process makes it appear that the long term unemployed are less likely to find a job. In its most general form, one can model heterogeneity in the job finding probability by indexing the u_t unemployed workers at time t by $i \in \{1, \ldots, u_t\}$ and letting F_t^i denote the probability that worker i finds a job during month t. Eq. (3) generalizes to the case where F_t^i varies with i:

$$u_{t+1} = \sum_{i=1}^{u_t} \left(1 - F_t^i\right) + u_{t+1}^s,$$

where I assume that the randomness in the outcome of the job finding process cancels out in the aggregate so u_{t+1} is not a random variable. End-of-month unemployment is equal to the number of unemployed workers who fail to obtain a job within the month, $\sum_{i=1}^{u_t}(1 - F_t^i)$, plus the number of workers who are unemployed at the end of the month but held a job at some time during the month, u_{t+1}^s. Rearrange to get

$$\frac{\sum_{i=1}^{u_t} F_t^i}{u_t} = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t}.$$

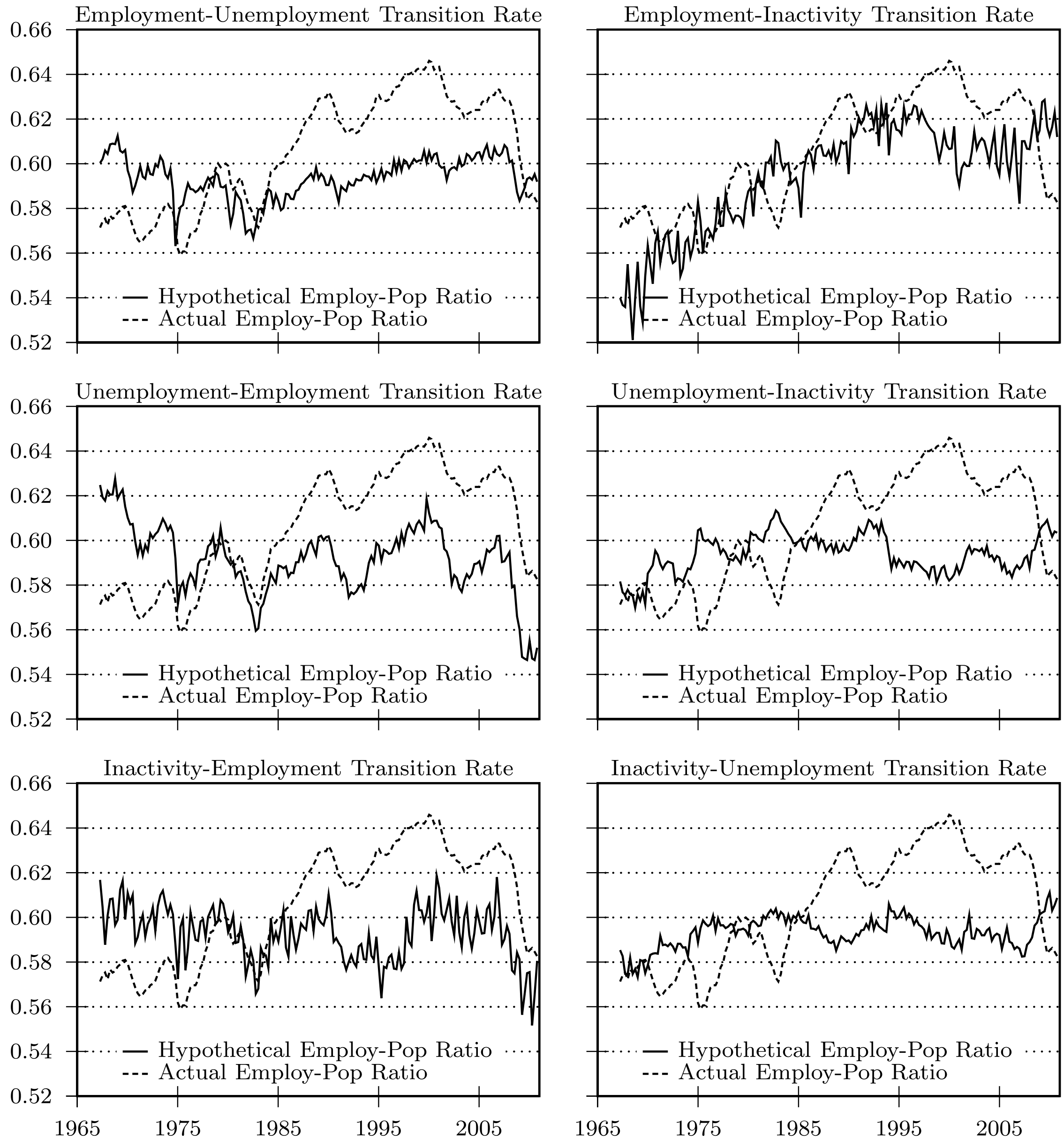

Fig. 6. Contributions of fluctuations in the instantaneous transition rates to fluctuations in the employment–population ratio, 1967Q2–2010Q4, quarterly average of monthly data. The gross flows are computed from matched CPS microdata files by Joe Ritter (1967Q3–1975Q4) and by the author (1976Q1–2010Q4), seasonally adjusted using a ratio to moving average, and then used to infer the transition rates following the procedure described in Section 3.1. The contributions to the employment–population ratio are inferred as in Eq. (7). Each panel shows the actual employment–population ratio for comparison.

Comparing this with Eq. (4) gives

$$F_t = \frac{\sum_{i=1}^{u_t} F_t^i}{u_t},$$

so F_t is the mean job finding probability among workers who are unemployed at date t.

If unemployed workers were homogeneous, there would be other valid methods of constructing the job finding probability. Mean unemployment duration in month $t+1$, d_{t+1}, would be a weighted average of the mean unemployment duration of previously-unemployed workers who failed to get a job in month t and the unemployment duration of newly-unemployed workers,

$$d_{t+1} = \frac{(d_t + 1)(1 - D_t)u_t + (u_{t+1} - (1 - D_t)u_t)}{u_{t+1}}, \tag{8}$$

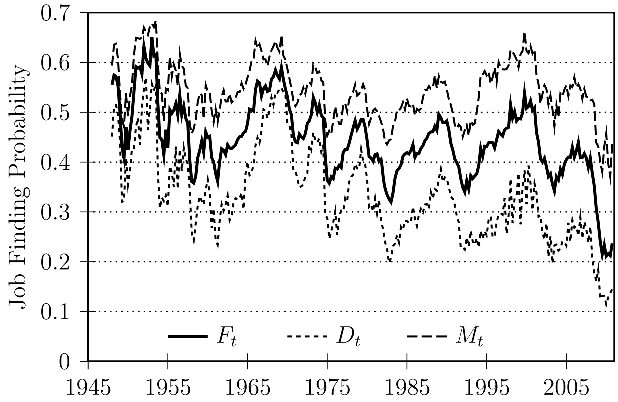

Fig. 7. Three measures of the job finding probability, United States, 1948Q1–2010Q4, quarterly average of monthly data. The job finding probability F_t is constructed from unemployment and short term unemployment according to Eq. (4). The alternative measures D_t and M_t are constructed from mean unemployment duration data (Eq. (9)) and short and medium term unemployment data (Eq. (10)), respectively. All data are constructed by the BLS and seasonally adjusted. Mean unemployment duration and short and medium term unemployment data are adjusted for the 1994 CPS redesign as described in Appendix A.

where D_t is the job finding probability for a worker who is unemployed in month t, a mnemonic device for the fact that it is constructed using mean unemployment *duration* data. There are $(1 - D_t)u_t$ unemployed workers, with mean unemployment duration d_t, who fail to get a job in month t. The mean unemployment duration for these workers increases by one month to $d_t + 1$. In addition, there are $u_{t+1} - (1 - D_t)u_t$ newly-unemployed workers in month $t + 1$, each of whom has an unemployment duration of one month. This equation can be solved for the job finding probability as a function of the current and future mean unemployment duration and the number of unemployed workers,

$$D_t = 1 - \frac{(d_{t+1} - 1)u_{t+1}}{d_t u_t}. \tag{9}$$

In steady state, $u_t = u_{t+1}$ and $d_t = d_{t+1}$, so Eq. (9) reduces to $D = 1/d$, a familiar relationship for a variable with a constant arrival rate.

Heterogeneity throws this calculation off. Again index the u_t unemployed workers in month t by $i \in \{1, \ldots, u_t\}$. Suppose worker i has unemployment duration d_t^i and finds a job with probability F_t^i. By definition, mean unemployment duration in month t is $d_t \equiv \frac{1}{u_t}\sum_{i=1}^{u_t} d_t^i$. Generalizing Eq. (8) to allow for heterogeneous workers, we find that mean unemployment duration in month $t + 1$ will be

$$d_{t+1} = \frac{\sum_{i=1}^{u_t}(d_t^i + 1)(1 - F_t^i) + (u_{t+1} - \sum_{i=1}^{u_t}(1 - F_t^i))}{u_{t+1}}$$

or equivalently,

$$\frac{\sum_{i=1}^{u_t} d_t^i F_t^i}{\sum_{i=1}^{u_t} d_t^i} = 1 - \frac{(d_{t+1} - 1)u_{t+1}}{d_t u_t}.$$

Comparing this with Eq. (9) yields $D_t = \frac{\sum_{i=1}^{u_t} d_t^i F_t^i}{\sum_{i=1}^{u_t} d_t^i}$, a weighted average of the individual job finding probabilities F_t^i, where the weight accorded to individual i is her unemployment duration d_t^i. Compared to the mean job finding probability F_t, this measure over-weights the long term unemployed. Since in practice the job finding probability falls with unemployment duration, one would expect that D_t to be smaller than F_t.

Hall (2005a) proposes a third measure of the job finding probability. Let u_t^m denote the number of medium term unemployed workers, defined because of data limitations as workers who have experienced 5 to 14 weeks (1 to 2 months) of unemployment. This is equal to the number of short term unemployed in previous months who have failed to find a job:

$$u_{t+1}^m = \big(u_t^s + u_{t-1}^s(1 - M_{t-1})\big)(1 - M_t). \tag{10}$$

This is a first order difference equation for M, where 'M' is a mnemonic for *medium* term unemployment. With a reasonable initial guess, e.g. that M_t, u_t^s, and u_t^m were constant before 1948, one can solve this equation forward for M. If all unemployed workers have the same job finding probability at every point in time, this will uncover that probability. But if workers are heterogeneous, this measure captures only the job finding probability of the short term unemployed and hence is likely to yield an estimate that exceeds the mean job finding probability F_t.

Fig. 7 examines these predictions empirically using publicly available BLS time series constructed from the CPS. I use standard time series for the number of employed and unemployed workers; multiply mean unemployment duration, published in terms of weeks, by $\frac{12}{52}$ to convert it to months; and adjust short and medium term unemployment for the effects of the CPS redesign, as discussed in Appendix A. Even though each series is constructed from different moments of the unemployment duration distribution, their cyclical behavior is similar and their levels line up as predicted. The mean value from 1948 to 2010 of F_t is 44 percent, in between the corresponding means for M_t (54 percent) and D_t (33 percent). I conclude that while heterogeneity complicates the definition of 'the' job finding rate, it does not alter the conclusion that the job finding rate is procyclical.

4.2. The heterogeneity hypothesis

There are two distinct explanations for why the job finding probability is procyclical: either the job finding probability declines for each worker or the unemployment pool shifts disproportionately towards workers with a low job finding probability. Darby et al. (1985, 1986) advance the second possibility in their exploration of the cyclical behavior of unemployment duration. They argue that there are two types of workers. The first type experiences frequent short spells of unemployment. The second type, including prime-aged workers and those on layoff, experiences unemployment infrequently and takes a long time to find a new job. If recessions are periods when disproportionately many of the second type of worker lose their job, then the measured job finding probability will fall even if F_t^i does not change for any particular worker. Following Baker (1992), I refer to this as the 'heterogeneity hypothesis'.[21]

To assess whether this argument is quantitatively important, I assume that workers can be divided into J different groups, indexed by $j \in \{1, \ldots, J\}$. For example, the groups may correspond to different reasons for unemployment: job losers, job leavers, re-entrants, or new entrants. I assume that all workers within a group are identical. More precisely, let $u_{t,j}$ be the number of unemployed workers with characteristic j in month t and $F_{t,j}$ be the job finding probability of those workers, computed using a type-dependent analog of Eq. (4). If Darby et al.'s heterogeneity hypothesis is correct, fluctuations in the job finding probability, $F_t = \frac{\sum_j u_{t,j} F_{t,j}}{\sum_j u_{t,j}}$, are due primarily to changes in the shares $u_{t,j}$ rather than in the type-specific job finding probability $F_{t,j}$.

To quantify this, one can construct two hypothetical measures. Let F_t^{comp} denote the change in the job finding probability due to changes in the composition of the work force and F_t^{real} denote the "real" changes due to changes in the job finding probability for each type of worker:

$$F_t^{\text{comp}} \equiv \frac{\sum_j u_{t,j} \bar{F}_j}{\sum_j u_{t,j}} \quad \text{and} \quad F_t^{\text{real}} \equiv \frac{\sum_j \bar{u}_j F_{t,j}}{\sum_j \bar{u}_j},$$

where $\bar{F}_j \equiv \frac{1}{T}\sum_{t=1}^{T} F_{t,j}$ is the time-averaged job finding probability for type j workers and $\bar{u}_j \equiv \frac{1}{T}\sum_{t=1}^{T} u_{t,j}$ is the time-averaged number of unemployed type j workers. If the heterogeneity hypothesis is correct, F_t^{comp} should be strongly procyclical and F_t^{real} should be acyclical. Note that in order to generate large fluctuations in F_t^{comp}, there must be large differences in the average job finding probability of groups with substantially different cyclical fluctuations in their unemployment rates. If average job finding probabilities are too similar, composition effects will not generate substantial fluctuations in the aggregate job finding probability. If the composition of the unemployed population is not sufficiently cyclical, the weights will not change.

I construct measures of the number of short term unemployed workers and total unemployed workers in different demographic groups from the public-use monthly CPS microdata from January 1976 to December 2010.[22] I use these to measure the type-specific job finding probabilities $F_{t,j}$. I consider seven different dimensions of heterogeneity: seven age groups (16–19, 20–24, 25–34, 35–44, 45–54, 55–64, and 65 and over), sex, race (white or nonwhite), four marital status categories (spouse present, spouse absent or separated, widowed or divorced, never married), five reasons for unemployment (job loser on layoff, other job loser, job leaver, re-entrant, and new-entrant), nine census regions, and five education categories (high school dropouts, high school diploma, some college, bachelor's degree, some postgraduate education, only for workers age 25 and over). I analyze each dimension of heterogeneity in isolation.

The best case for the heterogeneity hypothesis is made by looking at changes in the fraction of workers reporting different reasons for unemployment, the focus of Fig. 8. The top panel shows that in an average month between 1976 and 2010, a job loser not on layoff found a job with 30.7 percent probability, much lower than the probability for all other unemployed workers, which averaged 46.9 percent. The bottom panel shows the share of job losers not on temporary layoff

[21] Dynarski and Sheffrin (1990) and Baker (1992) show that unemployment duration is strongly countercyclical, and so the job finding probability is strongly procyclical, for all workers conditional on a broad set of characteristics, including the reason for unemployment, census region, sex, race, education, and previous industry. This leads Baker (1992, p. 320) to conclude that "the heterogeneity explanation of aggregate variation sheds little light on the nature of unemployment dynamics." Based on this type of evidence and on the fact that there is simply not enough measurable variation in the composition of the unemployed population to generate large movements in unemployment duration, van den Berg and van der Klaauw (2001) and Abbring et al. (2002) reach a similar conclusion in their detailed analyses of French data. On the other hand, a recent paper by Hornstein (2011) argues that the persistent increase in unemployment duration during 2008–2010 was due to an increase in the share of newly-unemployed workers with unobserved characteristics that cause them to have a low job finding probability. My analysis here does not account for variation in the unobserved characteristics of the unemployed.

[22] Following Appendix A, I use only the incoming rotation groups after 1994.

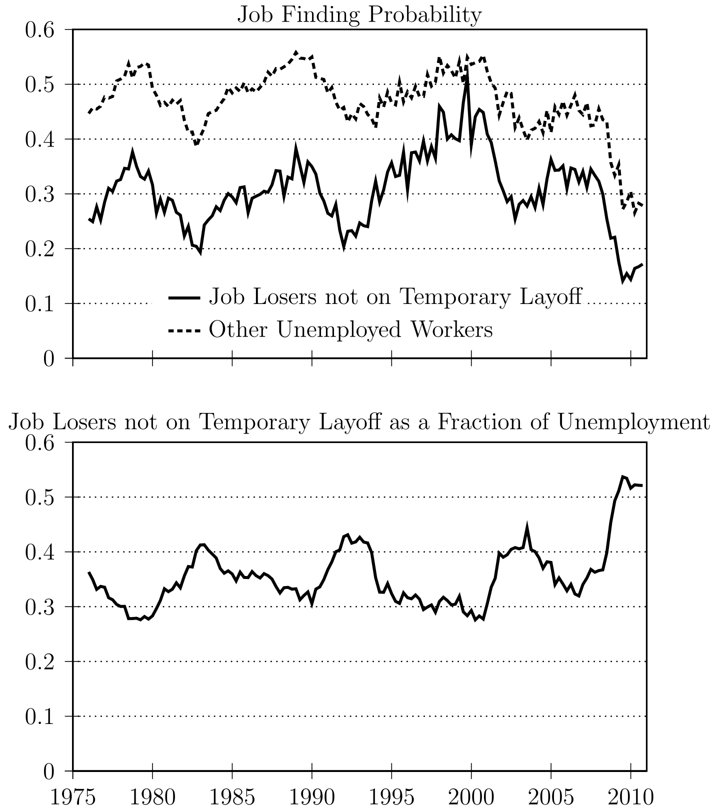

Fig. 8. Fluctuations in the job finding probability and unemployment share of job losers not on temporary layoff, United States, 1976Q1–2010Q4, quarterly average of monthly data. The underlying data are constructed from the monthly CPS, seasonally adjusted and adjusted for the 1994 CPS redesign as described in Appendix A, and averaged within quarters.

in the unemployed population. The correlation between this share and the job finding rate for this group is −0.79. This pattern has the potential to generate fluctuations in the composition component of the job finding probability. For example, this measure of F_t^{comp} averaged 40.1 percent in 1992, rose to 42.2 percent in 2000, and then fell back to 40.1 percent in 2003. But although these changes are noticeable and systematic, they explain little of the overall change in the job finding probability. By comparison, F_t^{real} rose from 36.1 percent in 1992 to 49.7 percent in 2000 and fell to 36.8 percent in 2003.

Fig. 9 shows my measure of the real (F_t^{real}, solid lines) and compositional (F_t^{comp}, dashed lines) changes in the unemployment rate for the seven different dimensions. Each figure shows that virtually all of the change in the job finding probability is "real". I conclude that observable changes in the composition of the unemployed population explain little of the overall fluctuations in the job finding probability.[23] While this analysis does not preclude the possibility that heterogeneity along unobserved dimensions is important, the finding that observable differences explains little of the cyclicality of the job finding probability reduces the plausibility of that (as yet untested) hypothesis.[24]

5. The conventional wisdom

This section serves three purposes: first, it describes the conventional wisdom on the cyclicality of the job finding and the employment exit probabilities; second, it explains the consequences of the conventional wisdom for the development of macroeconomic models of the labor market; and third it discusses some important recent papers that extend or respond to an early draft of this paper.

[23] Changes in the age distribution also lead to some variation in the job finding probability, particularly at low frequencies. This appears to be because older workers are more likely to be 'other job losers', a fact that is already picked up in the panel on 'Reason for Unemployment'.

[24] For the difficulties of testing this hypothesis, see Heckman and Singer (1984). Using a long panel data set, one could in principle test for the importance of time-invariant unobserved heterogeneity by examining how the duration of unemployment for individuals who experience multiple spells varies with business cycle conditions. In practice, the size of existing data sets is likely to limit the power of such tests.

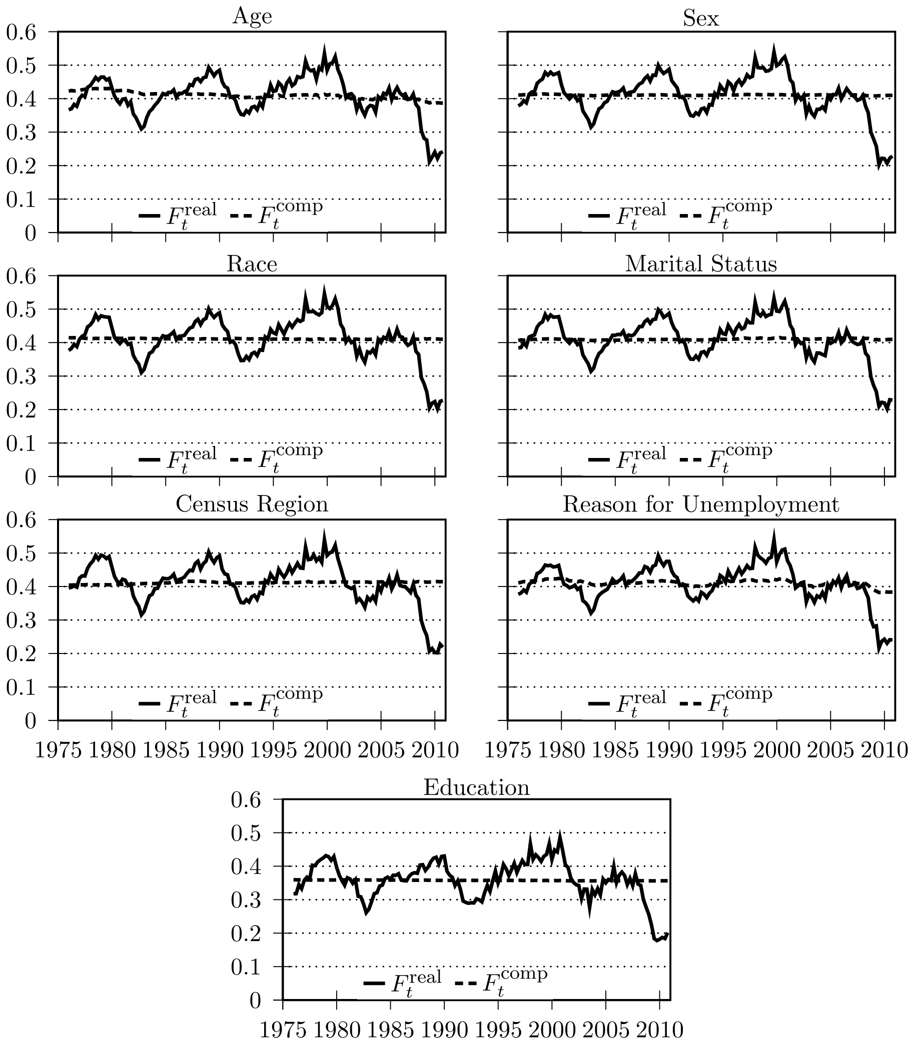

Fig. 9. Seven measures of the 'compositional' and 'real' component of changes in the job finding probability, F_t^{comp} and F_t^{real}, respectively, United States, 1976Q1–2010Q4, quarterly average of monthly data. Each figure uses different characteristics: age (7 groups), sex, race (white or nonwhite), marital status (married spouse present, spouse absent or separated, divorced or widowed, never married), census region (9 regions), reason for unemployment (job loser on layoff, other job loser, job leaver, re-entrant, or new entrant), and education (5 groups, age 25 and over). The underlying data are constructed from the monthly CPS, seasonally adjusted and adjusted for the 1994 CPS redesign as described in Appendix A, and averaged within quarters.

5.1. Review of the existing evidence

The facts that I describe in this paper may appear to contradict the conventional wisdom.[25] From their analysis of gross worker and job flows, Blanchard and Diamond (1990, p. 87) conclude that "The amplitude of fluctuations in the flow out of employment is larger than that of the flow into employment. This, in turn, implies a much larger amplitude of the underlying fluctuations in job destruction than of job creation." While they recognize that the hazard rate of moving from unemployment to employment falls during a recession, many subsequent papers seem to have missed this point. In their 1996 book, Davis et al., building on research by Davis and Haltiwanger (1990, 1992), conclude that evidence from the United States manufacturing sector indicates that "job destruction rises dramatically during recessions, whereas job creation initially declines by a relatively modest amount." (Davis et al., 1996, p. 31) The conventional wisdom based on this type of evidence is eloquently summarized by the title of Darby et al. (1986): "The Ins and Outs of Unemployment: The Ins Win."

[25] Sider (1985) studies the cyclicality of unemployment incidence and duration. If workers are homogeneous and the economy is in steady state, unemployment incidence is equivalent to the employment exit probability and unemployment duration is the inverse of the job finding probability. He concludes that "changes in duration play a very important role in explaining ... fluctuations and trends in total unemployment." (Sider, 1985, p. 461) This paper therefore argues for a return to this older wisdom.

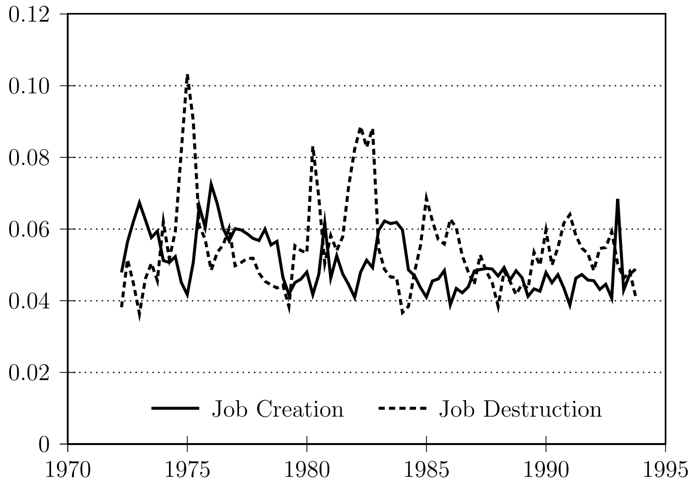

Fig. 10. Job creation and job destruction in manufacturing, United States, 1972Q2–1993Q4. The raw data are constructed by Davis et al. and are available from http://www.econ.umd.edu/~haltiwan/download/8993/RZTM.DAT. They are seasonally adjusted using the Census X-12-ARIMA algorithm with an additive seasonal factor.

Fig. 10 shows Davis and Haltiwanger's quarterly data from 1972 to 1993, with job creation defined as the net increase in employment at expanding business establishments and job destruction as the net decrease in employment at contracting business establishments. Clearly job destruction is more volatile than job creation in this data set, rising during each of the major recessions in the 1970s and 1980s.[26] But while this finding is interesting, it does not say much about the cyclicality of the job finding and employment exit rates.

To understand why, recall that there are important differences between job flows and worker flows. Using the two-state model in Section 2, I found that the monthly employment exit probability averages 3.4 percentage points. In the three-state model in Section 3, the sum of monthly employment–unemployment and employment-inactive flows averages 5.0 percentage points. Accounting for employer-to-employer transitions adds another 2.6 percentage points to these numbers (Fallick and Fleischman, 2004). The quarterly job destruction rate, which one might expect to be three time as large as the monthly worker flows, is instead just 5.5 percent. This reflects the fact that many worker flows are not matched by a corresponding job flow. For example, when a worker quits her job to look for or accept another job or to drop out of the labor force, a firm may hire a replacement within the quarter and hence record neither job creation nor job destruction.

An important implication of this is that firms can destroy jobs either by firing workers or by not hiring to replace workers who leave for other reasons. The former represents an increase in employment exits while the latter leads to a decrease in the job finding probability. One way to distinguish these alternatives is to look at establishments that shut down, when it is clear that firms have fired workers. Davis et al. (1996, p. 34) conclude that "shutdowns do not account for an unusually large fraction of job destruction during recessions." This means that spikes in job destruction are consistent with the view advanced in this paper that there are only small increases in the employment exit probability during downturns. Many contractions in employment are achieved by firms choosing to hire fewer workers, which reduces workers' job finding probability.

In addition, Davis and Haltiwanger focus exclusively on manufacturing establishments, a shrinking portion of aggregate employment. Foote (1998) uses Michigan data to show that job destruction is more volatile than job creation only in the manufacturing sector and argues that Davis and Haltiwanger's measures are biased by underlying trend employment growth. A new BLS survey, Business Employment Dynamics (BED), extends the Davis–Haltiwanger methodology to cover the entire labor market and provides some confirmation for Foote's theory. Fig. 11 indicates that there was a brief spike in job destruction during the 2001 recession and a larger spike during the 2008–2009 recession, but both were quickly reversed. In both cases, job creation fell as well during the recession and recovered in a similar fashion.[27]

There are also shortcomings in the existing literature on gross worker flows, starting with its failure to address time aggregation. To my knowledge, none of the previous research using matched CPS data to measure gross worker flows between employment, unemployment, and inactivity has accounted for the fact that a decrease in the job finding probability indirectly raises the measured transition rate from employment to unemployment.[28]

[26] In a recent working paper, Davis et al. (2006) construct a measure of job creation and job destruction back to 1947 (see their Fig. 5). Although job destruction is more volatile than job creation in the 1960s, curiously they find that job creation and destruction were equally volatile in the 1950s.

[27] On the other hand, Faberman (2004) extends the BED survey back to 1990 and argues that job destruction was more volatile than job creation in the 1991 recession.

[28] See Yashiv (2007) for a reconciliation of recent studies using gross worker flow data.

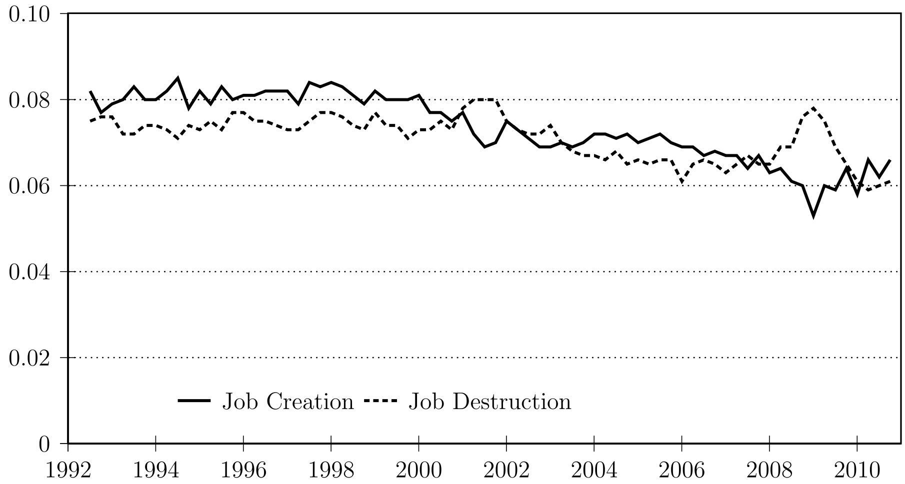

Fig. 11. Job destruction and job creation, United States, 1992Q3–2010Q4. The data are constructed by the BLS as part of the BED and are seasonally adjusted.

Another distinction between this paper and much of the gross flows literature is that while I measure the *probability* that an unemployed worker finds a job or a worker exits employment, e.g. Λ_t^{EU}, Abowd and Zellner (1985), Poterba and Summers (1986), Blanchard and Diamond (1990), and much subsequent research has measured the *number* of workers who switch employment status in a given month. In fact, even after accounting for time aggregation, the decline in the job finding probability almost exactly offsets the increase in the number of unemployed workers at business cycle frequencies, so the number of unemployed workers who find a job in a month shows little cyclicality.

Without the guide of a model, it is impossible to say which of these measures is more interesting. I focus on the job finding probability because the notion of how difficult it is for an unemployed worker to find a job is a key input into models of job search such as those described in Pissarides (2000). According to these models, the job finding probability should depend directly on the vacancy–unemployment ratio via the matching function. The vacancy–unemployment ratio, in turn, depends only on exogenous variables. I am unaware of any coherent theory which predicts that the number of workers finding a job should be so closely linked to exogenous variables. In that sense, the link between the theory and data for the job finding probability is particularly tight and hence this measure is particularly interesting. Still, it is most important point to recognize the differential behavior of the job finding probability and the number of workers finding jobs; a good model of the labor market should be consistent with both observations.

5.2. Implications for theoretical models

The belief that employment exits drive unemployment fluctuations dominated the development of macroeconomic models of the labor market during the 1990s and early 2000s.[29] Mortensen and Pissarides (1994) extend Pissarides's (1985) model of an endogenous job finding probability to allow for idiosyncratic productivity shocks. Under reasonable conditions, an adverse aggregate shock raises the idiosyncratic threshold for maintaining an employment relationship, leading to the termination of many job matches. As a result, the model predicts that the time series of employment exits should be significantly more volatile than that of the number of workers finding jobs. Nevertheless, Mortensen and Pissarides (1994, pp. 412–413) are cautious, noting that "although empirical evidence on the cyclical issue is inconclusive, these results are consistent with Davis and Haltiwanger's (1990, 199[2]) findings." Over time, this caution has been lost. For example, Cole and Rogerson (1999) accept Davis and Haltiwanger's job creation and job destruction facts at face value in their reduced-form analysis of the implications of the Mortensen and Pissarides (1994) model.

Caballero and Hammour's (1994) model of creative destruction shows that if firms face a linear adjustment cost in hiring, fluctuations in the job finding probability will account for all of employment fluctuations. But because this contradicts the Davis–Haltiwanger and Blanchard–Diamond evidence, Caballero and Hammour (1994, p. 1352) argue that there must be strong convexities in hiring costs, and so conclude that recessions are "times of 'cleansing', when outdated or relatively unprofitable techniques and products are pruned out of the productive system...."[30] Koenders and Rogerson (2005) reason similarly in their analysis of 'jobless recoveries' that employment reductions during recessions are due to firms postponing organizational restructuring until the end of an expansion. The longer the expansion, the more jobs that must be destroyed

[29] Since the dissemination of the first draft of this paper and the publication of Shimer (2005a), the pendulum has swung back in the other direction, with models often focusing exclusively on the determinants of the job finding probability and treating the employment exit probability as exogenous.

[30] More recently, Caballero and Hammour (2005) have argued that job destruction falls after a recession so that "*cumulatively*, recessions result in *reduced* rather than *increased* restructuring."

during the subsequent reorganization, resulting in a jobless recovery after prolonged expansions. In particularly, their model counterfactually predicts a surge of employment exits during 1991 and 2001 recessions.

Hall (1995) builds on the Davis–Haltiwanger and Blanchard–Diamond evidence to argue that spikes in employment exits can generate persistent employment fluctuations: "Brief, sharp episodes of primary job loss are followed by long periods of slowly rebuilding employment relationships over the business cycle. Although the case is far from complete, I believe that these events in the labor market play an important part in the persistence of high unemployment and low output long after the initial shock that triggers a recession." (Hall, 1995, p. 221)[31] Following this logic, Pries (2004) develops a model in which workers go through numerous short term jobs before returning to a long term employment relationship. This results in a persistent rise in the employment exit probability and gradual decline in the unemployment rate after a recession. Ramey and Watson (1997) propose a model of the business cycle with two-sided asymmetric information in which a transitory adverse shock induces a persistent rise in exits. Den Haan et al. (2000) examine how fluctuations in the employment exit probability can propagate and amplify shocks in a real business cycle model augmented with search frictions in the style of Mortensen and Pissarides (1994).

5.3. Recent research

Since I first circulated a draft of this paper in 2005, a number of authors have examined and extended its conclusions. This section addresses some of the more prominent studies but is by no means exhaustive. Hall (2005b) looks at a variety of measures of the total separation rate from employment, including a measure from the monthly CPS that accounts for movements to another job and measures from the March job tenure supplement to the CPS, from the Job Openings and Labor Turnover Survey, and from the Survey on Income and Program Participation. He concludes that this paper, if anything, overstates the importance of separations at business cycle frequencies: "The new view is that separations are not an important part of the story of rising unemployment in recessions. Unemployment is high in a recession because jobs are hard to find, not because more job-seekers have been dumped into the labor market by elevated separation rates."

Elsby et al. (2009) examine the robustness of my findings by considering an alternative adjustment for time aggregation (see the discussion at the end of Section 2.1 in this paper) and by exploring an adjustment for the 1994 CPS redesign based on footnote 38. They conclude that "the results based on the refined aggregation correction methods are broadly similar to those obtained" (p. 16) using my approach and suggest that about two-thirds of the increase in unemployment during a cyclical downturn is explained by the decline in the job finding rate.

Elsby et al. (2009) also reexamine the data on the reason for unemployment. They note that during recessions, the exit rate from employment for job leavers falls while the exit rate from employment for job losers rises. This suggests some changes in the cyclical composition of unemployment, consistent with my findings in Fig. 8. Although they do not question my conclusion that cyclical changes in the composition of unemployment have a small effect on the job finding rate, they argue for a more nuanced view of unemployment. In my view, a more nuanced interpretation of the CPS questions on the reason for unemployment may be appropriate. Following Barro (1977), employment relationships may simply end when the gains from trade disappear, in which case the distinction between layoffs and quits is economically irrelevant. One way to test this is to look at whether there are observable biases in how people answer questions about quits and layoffs. I can do this by taking advantage of the fact that, prior to the CPS redesign in 1994, households with unemployed members were asked their reason for unemployment in each month. From 1976 to 1993, on average 26 percent of individuals who report being a quitter in month t and remain unemployed in month $t+1$ subsequently report being laid off; only 6 percent of those on layoff switch their answer in the opposite direction. Moreover, the "layoff–loser transition rate" rises strongly in recessions. Since most of these reported transitions are spurious, at a minimum one needs to adjust the data to account for this bias. Caution in interpreting any findings based on the distinction between quits and layoffs seems appropriate.

Fujita and Ramey (2009) explore this paper's conclusions along other dimensions. First, they reconstruct the gross flow data in Section 3 but control carefully for margin error (Abowd and Zellner, 1985). They then construct a measure of the impact of fluctuations in the EU and UE transition rates that sidesteps movements in and out of the labor force. The numbers in the first column of their Table 1 suggest that controlling for margin error has little effect on their results, although the importance of the adjustment is more pronounced in the period after 1985. On the other hand, when they look at the data in first differences rather than in deviation from an HP trend,[32] they find a more important role for fluctuations in the employment exit rate. To my eye, however, the series in first differences is dominated by measurement error (see their Figs. 1 and 7), limiting what can be learned from that approach. Fujita and Ramey (2009) also point out that the employment exit rate leads the job finding rate and the unemployment rate by about one-quarter. While this pattern merits further exploration, their conclusion that "this result suggests the possibility that some of the variability of the job finding rate is actually driven by the movements in the [employment exit] rate occurring in previous quarters" (p. 5) seems

[31] But Hall has since recanted, writing more recently, "...in the modern U.S. economy, recessions are not times of unusual job loss. New data on separations show them to be remarkably constant from peak to trough. Bursts of job loss had some role in earlier recessions, but are still mostly a side issue for the reason just mentioned—a burst is quickly reabsorbed because of high job-finding rates." (Hall, 2004).

[32] Fujita and Ramey (2009) use an HP filter with smoothing parameter 1600 on quarterly data, a standard value. See footnote 10 in this paper for discussion of my choice of the HP filter.

to confuse temporal precedence with causality. Models like Mortensen and Pissarides (1994) predict the temporal pattern uncovered by Fujita and Ramey (2009) but not with their proposed causal mechanism.

6. Conclusion

This paper measures the job finding and employment exit probabilities in the United States from 1948 to 2010. Throughout the time period, fluctuations in the job finding probability explains three-quarters of the volatility in the unemployment rate. This finding contradicts the conventional wisdom that fluctuations in the employment exit probability (or in job destruction) are the key to understanding the business cycle.

The goal of this paper was to develop simple but robust measures of important moments in aggregate labor market data. While the observation that the job finding rate is more cyclical than the employment exit rate suggests that papers seeking to understand the cyclicality of the unemployment rate should focus primarily on the job finding rate, I have not sought to establish causality; to do so without a theoretical framework seems futile. Moreover, the observed fluctuations in the employment exit rate may be important for reasons that I do not capture in this paper, e.g. because of the substantial costs of displacement (Jacobson et al., 1993). With these caveats, these measures of the job finding and employment exit rates should provide a target for research that seeks to explain the causes and consequences of cyclical fluctuations in unemployment.

Appendix A. Measurement of short term unemployment

To measure short term unemployment, I rely on workers' self-reported duration of an in-progress unemployment spell. Unfortunately, the CPS instrument was redesigned in January 1994, changing how the unemployment duration question was asked (Abraham and Shimer, 2001).[33] Recall that the CPS is a rotating panel. Each household is in the CPS for four consecutive months (rotation groups 1 to 4), out for eight months, and then in again for four more months (rotation groups 5 to 8). This means that in any month, approximately three-quarters of the households in the survey were also interviewed in the previous month.

Prior to 1994, unemployed workers in all eight rotation groups were asked how long they had been unemployed. But since then, the CPS has not asked a worker who is unemployed in consecutive months the duration of her unemployment spell in the second month. Instead, the BLS calculates unemployment duration in the second month as the sum of unemployment duration in the first month plus the intervening number of weeks. Thus prior to 1994, the CPS measure of short term unemployment should capture the total number of unemployed workers who were employed at any point during the preceding month, while after the redesign, short term unemployment only captures workers who transition from employment at one survey date to unemployment at the next survey date.[34]

There is no theoretical reason to prefer one measure to the other; however, the method I use to measure the job finding and employment exit probability in Section 2 relies on the pre-1994 measure of short term unemployment. In any case, the goal of this paper is to obtain a consistent time series for the job finding probability. To do this, note that one would expect that the redesign of the CPS instrument would not affect measured unemployment duration in rotation groups 1 and 5, the 'incoming rotation groups', since these workers are always asked their unemployment duration, but would reduce the measured short term unemployment rate in the remaining six rotation groups.

To see this empirically, I measure short term unemployment using CPS microdata from January 1976 to December 2010.[35] From 1976 to 1993, short term unemployment accounted for 41.7 percent of total unemployment both in the full CPS and in the incoming rotation groups. From 1994 to 2010, however, short term unemployment accounted for just 37.3 percent of unemployment in the full sample but 43.2 percent in the incoming rotation groups, an economically and statistically significant difference. Put differently, the short term unemployment rate in the full CPS fell discontinuously in January 1994, while it remained roughly constant in the incoming rotation groups.

In this paper I use short term unemployment from the full sample from 1948 to 1993 and then use only the incoming rotation groups in the later period.[36] More precisely, I first use the CPS microdata to compute the fraction of short term unemployed workers among all unemployed workers in the incoming rotation groups in each month from 1976 to 2010. I seasonally adjust this series using the Census's X-12-ARIMA algorithm with an additive seasonal factor. I then replace the standard measure of short term unemployment with the product of the number of unemployed workers in the full CPS sample and the short term unemployment share from 1994 to 2010.[37] This eliminates the discontinuity associated with the redesign of the CPS.[38]

[33] See Polivka and Miller (1998) for a thorough analysis of the redesign of the CPS instrument.

[34] The post-1994 methodology also prevents respondents from erroneously reporting short unemployment duration month after month.

[35] http://www.nber.org/data/cps_basic.html.

[36] In January 1994, all unemployed workers were asked their unemployment duration, the last month in which this occurred. I start my adjustment a month earlier than necessary, using only the incoming rotation groups on and after January 1994, to coincide with the date of the CPS redesign.

[37] I multiply the number of unemployed workers from the full sample by the unemployment share from the incoming rotation groups to avoid another issue with the CPS. From 1976 to 2010, the unemployment rate in the first rotation group averaged 0.4 percentage points more than in the full sample. See Solon (1986) for a detailed discussion of rotation group biases in the CPS.

[38] I have also tried multiplying the standard series for short term unemployment by a constant, 1.1, after 1994. This delivers very similar results.

I use a similar method to construct medium term unemployment and mean unemployment duration in Section 4. The only drawback to these procedures is that the reduced sample makes these measures noisier than those using the full sample, an issue that is discernible in many of the figures in this paper.

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