Labour Economics 80 (2023) 102304

Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

Job-to-job transitions, job finding and the ins of unemployment☆

Michael Simmons

Samhällsvetarhuset, Biblioteksgränd 6, Umeå University, 901 87 Umeå

ARTICLE INFO

JEL classification:
E24
E32
J6

Keywords:
Unemployment dynamics
Heterogeneity
Separations
Job-to-job
Worker flows

ABSTRACT

Increases in the ins of unemployment during recessions are the result of two major forces: increased separations, or a fall in job finding of potential job-to-job transitions. This paper quantifies the contribution of these two channels using the flows approach to the labour market in the UK and US over a period of two decades including the Great Recession. First, the paper documents large variation in outcomes by reason for separation. Second, the paper shows that abstracting from this variation can significantly bias the importance of separations and job finding in driving changes in the ins of unemployment and the unemployment rate. Finally, the paper shows that fluctuations in layoffs and job finding conditional on separation are both important drivers of fluctuations in the ins of unemployment.

1. Introduction

Why does the unemployment rate rise during recessions? A large body of literature has decomposed unemployment variations into components attributed to the inflows into and outflows from unemployment. The main conclusions being that the ins and outs of unemployment are both important to varying degrees.[1] Understanding which of these forces drives unemployment variation is thought to be fundamental to our understanding of how recessions impact labour markets, in particular whether there is predominantly either a spike in separations or a decline in hiring.

The rise in employment to unemployment transitions during recessions does, however, not have to be due to an increase in separations. Instead, the rise could be due to a decline in job finding conditional on separation.[2] Attributing changes in employment to unemployment transitions as due to changes in separations may be inaccurate. In this paper I quantify the importance of the separation and job finding channels, where I importantly allow for the large heterogeneity in the reason workers separate from jobs. My results outline the role of changes in overall layoffs and quits, and illustrate how ignoring heterogeneity in the reason for separation can create considerable bias in the importance of the job separation and job finding channels.

This is not the first paper to acknowledge that employment to unemployment transitions can be split into job separation and job finding components. Bachmann (2005) and Nagypal (2008) both show that the proportion of workers who move to new employment following a separation drops in recessions, and that separations remain stable. This observation may lead one to conclude that separations are unimportant. As I discuss in Section 2, and is acknowledged by Bachmann (2005) and Nagypal (2008), this conclusion may be premature. The reason being because all separations are not identical. Some separations occur when a worker enjoys their job but has received a superior offer and almost certainly will transition to the new job; others occur because a worker has begun to find their job unsatisfactory and may quit to unemployment if

☆ Many thanks to the editor, and three anonymous referees who have helped greatly improve the quality of this work. I also would like to thank Jesper Bagger, Bjoern Bruegemann, Mike Elsby, Giulio Fella, Manolis Galenianos, Pedro Gomes, Gregor Jolivet, Jacob Short, Carl Singleton, Ija Trapeznikova, Ludo Visschers and Jonathan Wadsworth and many others from different conferences and seminars for valuable comments. A previous version of this paper was titled "Job-to-job transitions and unemployment dynamics". Replication files and the data used can be found through the following link https://sites.google.com/view/michael-simmons/research. The research was funded by Handelsbankens forskningsstiftelser through a Browaldh-scholarship.

E-mail address: michael.simmons@umu.se

[1] The influential work of Shimer (2012) and Hall (2005) conclude that outflows are far more important than inflows. This result was contrary to conventional wisdom (Darby et al. (1985), Darby et al. (1986) and Davis and Haltiwanger (1992)) and was challenged by Fujita and Ramey (2009) and Elsby et al. (2009) who conclude that the role of inflows was understated by Shimer and Hall.

[2] This point was originally made by Perry (1972b) and reemphasized by Hall (2005), Bachmann (2005) and Nagypal (2008). Perry (1972b) discussing the inflows: *It consists of persons about to enter the labour force, and of workers about to leave one job to look for another, either at their own initiative (quitting) or at their employer's (layoff or firing). These additional job seekers can be conceived of as holding lottery tickets just as the unemployed do. These tickets define the probability that, when they make the transition into the labour force or out of their present jobs, their numbers come up and they have new jobs. If their numbers do not come up, they become this week's newly unemployed.*

https://doi.org/10.1016/j.labeco.2022.102304
Received 14 September 2021; Received in revised form 22 November 2022; Accepted 23 November 2022
Available online 28 November 2022

a job offer does not arise; and some separations are employer initiated and are plausibly likely to result in unemployment. These differences in the reason for separation not only likely result in different outcomes, but also change in different directions during recessions.[3] Ignoring these compositional changes may result in inaccurate conclusions.

This paper offers three main contributions in relation to previous work. First, in Section 3, I document large variation in outcomes by reason for separation in the US and UK, both between layoffs and quits, but also by heterogeneity in the reason for quitting. Some reasons for separation almost never result in unemployment, whilst others very often do. I show that this heterogeneity in the reason for separation varies differently over the business cycle. As is well known, layoffs rise and quits decline during recessions. The decline in quits is, however, driven by the subset of quits that almost never result in a transition to unemployment.

Second, in Section 4, I incorporate a decomposition of the ins of unemployment following Nagypal (2008) into a non-steady state decomposition of unemployment dynamics as in Elsby et al. (2015). The decomposition from Nagypal (2008) splits the employment to unemployment rate into three components: (i) separating, (ii) remaining in the labour force following the separation, and (iii) subsequently not finding a job. I allow these individual components to depend on the underlying reason for separation, and detail analytically how this can impact the results.

Third, I estimate the contribution of fluctuations of overall separations, layoffs, quits and job finding to the dynamics of the unemployment rate over a period of two decades which includes the Great Recession. If separations are treated as uniform, changes in the separation rate drive close to none of unemployment variation. Allowing for heterogeneity in the reason for separation increases the contribution to a quarter in the US. Despite this, I find that job finding conditional on separation is also an important driver of the dynamics of the ins of unemployment in both countries. I show that these results are not driven by fluctuations in observable characteristics such as changes in on-the-job search; robust to adjustments for time aggregation and classification error; and discuss other caveats with worker flow analyses.

The remainder of this paper proceeds as follows. Section 2 discusses the decomposition of the ins of unemployment and outlines two conceptual issues with this decomposition. Section 3 discusses the data, presents cross sectional heterogeneity in outcomes by reason for separation, and documents how these reasons for separation change over the business cycle. Section 4 shows how it is possible to assess the fluctuations of the decomposed ins of unemployment in a three-state system, presents the results, studies the Great Recession, and presents further results and robustness. Section 5 provides further discussion relating this paper to existing empirical and theoretical work, and Section 6 concludes.

2. Conceptual framework

We begin with the basic decomposition of the employment to unemployment transition probability described by Nagypal (2008),[4]

$$p^{eu} = p_t^{sep} p_t^{lf|sep} (1 - p_t^{jj|lfsep}).^4 \quad (1)$$

The probability is split into three components, (i) the probability of separating from ones job, (ii) the probability of remaining in the labour force upon separation, and (iii) the probability of subsequently not having a replacement job lined up.[5] With this decomposition, instead of analysing overall changes in the employment to unemployment transition rate, I am able to study the dynamics of each underlying component separately. Importantly, the employment to unemployment transition rate varies because of changes in job separations, component (i), but also through changes in the rate at which workers line up jobs following a separation that remains in the labour force, component (iii). While this is a natural extension to the standard analysis of overall worker flows, there are concerns with working with this decomposition. I outline two main issues, which are connected, next.

Issue 1: Workers separate from jobs for different reasons

Workers sometimes lose jobs and sometimes quit jobs. Both of these types of separation sometimes end in inactivity, unemployment and employment, but the proportions likely differ significantly. Workers who quit plausibly are more likely to remain employed, and workers who lose their job are more likely to become unemployed.[6] If layoffs rise in recessions, aggregating separations will mask this heterogeneity in the reason for separation, and potentially lead to inaccurate conclusions. Moreover, treating separations as uniform does not allow us to understand the individual roles of layoffs and quits.

We should, therefore, disaggregate (1) by quits and layoffs. This, however, is still likely not at an appropriate level of disaggregation. The reason being because there is of course heterogeneity in the reason for quitting a job, and there may be important differences in employment outcomes by reason for the quit. More generally, we can split the decomposition into N_r distinct reasons,

$$p_t^{eu} = \sum_{r \in \mathbf{R}} p_t^{sep^r} p_t^{lf|sep^r} (1 - p_t^{jj|lfsep^r})^7, \quad (2)$$

[7] where $N_r = |\mathbf{R}|$. Now all three components are dependent on reason r, leaving us with $3 * N_r$ probabilities, which is each allowed to contribute to the overall changes in the employment to unemployment probability.

Issue 2: Many quits are unrelated to unemployment.

Included in the overall separation rate are workers who enjoy their job and only move because they have received a superior offer, the traditional way job to job transitions are motivated.[8] In this accounting exercise, through the lens of (1), these quits do not directly impact the employment to unemployment transition rate since the relevant $p^{jj|lfsep} \approx 1$. By incorporating (1) into the analysis of unemployment dynamics, these transitions can distort the importance of each probability. The decomposition shown in (2), disaggregated by reason, can account for this if we are able to identify which quits have $p^{jj|lfsep^r} \approx 1$. If quits of this type change over time, they will not contribute to changes in the employment to unemployment transition probability, since the importance of such changes depends on the relevant value of $1 - p^{jj|lfsep}$, which in this case is approximately 0. Fortunately, the data I will use for the US provides a useful proxy for such transitions where we will see that the $p^{jj|lfsep} \approx 1$.[9] Of which I will come to in the next section.

Finally, those who enter the labour market are at risk of becoming unemployed. This risk potentially depends on whether an individual enters during a recession or an expansion. In the main analysis, I will decompose the inactivity to unemployment probability in a similar manner

[3] See Slichter (1919), Akerlof et al. (1988), Anderson and Meyer (1994) and Davis et al. (2012), who show that layoffs are countercyclical and quits are procyclical

[4] The components of Eq. (1) are calculated by: $p_t^{sep} = \frac{Sep_t}{E_{t-1}}$, $p_t^{lf|sep} = \frac{LFSep_t}{Sep_t}$ and $p_t^{jj|lfsep} = \frac{JJLFSep_t}{LFSep_t}$. Sep_t constitutes the stock of all those who separate from their employer between $t-1$ and t. $LFSep_t$ constitutes the stock of all those who separate from their employer between $t-1$ and t and are in the labour force at t. $JJLFSep_t$ constitutes the stock of all those who separate from their employer between $t-1$ and t and are in employment at t. A flow diagram is available in the Online Appendix.

[5] See a flow diagram of the decomposition in the Online Appendix.

[6] Steven Davis made this point is response to Hall (2005) in the ensuing comments.

[7] The components of Eq. (2) are calculated by: $p_t^{sep^r} = \frac{Sep_t^r}{E_{t-1}}$, $p_t^{lf|sep^r} = \frac{LFSep_t^r}{Sep_t^r}$ and $p_t^{jj|lfsep^r} = \frac{JJLFSep_t^r}{LFSep_t^r}$. Sep_t^r constitutes the stock of all those who separate from their employer between $t-1$ and t for reason r. $LFSep_t$ constitutes the stock of all those who separate from their employer between $t-1$ and t for reason r and are in the labour force at t. $JJLFSep_t^r$ constitutes the stock of all those who separate from their employer between $t-1$ and t for reason r and are in employment at t.

[8] See Burdett and Mortensen (1998), Postel-Vinay and Robin (2002b) and Cahuc et al. (2006) for three prominent examples.

[9] Even for such transitions, we can imagine that there is still some small probability of ending up unemployed, if, for example, the agreement is suddenly terminated and the worker is unable to be recalled.

to the employment to unemployment probability. The decomposition is as follows,[10]

$$p^{nu} = p_t^{entry}(1 - p_t^{e|entry}).^{10} \quad (3)$$

The probability is split into two components, (i) the probability of entering the labour force, and (ii) the probability of subsequently not having a job lined up. This allows us to understand whether labour market entry drives changes in the inactivity to unemployment rate or whether job finding conditional on entry is of most importance.

3. Separations and outcomes in the data

3.1. Data description

In this section I will briefly describe and present important features of the data from the Survey of Income and Program Participation (SIPP) for the US, and the Labour Force Survey (LFS) for the UK.

The Survey of Income and Program Participation

The SIPP is a longitudinal survey of US households. The survey is split into panels. Each panel features a nationally representative sample interviewed over a multi-year period lasting approximately four years. I analyse the 1996, 2001, 2003 and the most recently completed panel in 2008 at the time of writing. During the first month of a panel, a quarter of the entire sample, described as a rotation group, give detailed information regarding their exploits in the last four months.[11] This is the beginning of the first wave. A month later the second rotation group give detailed information regarding their exploits in the last four months. This then continues for a further two rotation groups. In the fifth month, the second wave begins and rotation group one is interviewed again, and so on. The rolling nature of the survey allows for the calculation of monthly labour market transitions in the US, which I weight using the longitudinal calendar year weights provided by the US Census Bureau.

During each interview, individuals give information on as many as two jobs and as many as two businesses they have held during the preceding four months. Each job or business is given a unique identifier that remains the same for the entire panel. Attached to each job or business is information on when the individual started working for the employer or started the business, and, if the relationship ended during the preceding four months, information on when the individual finished working for their employer or ended the business. Using this information it is possible to construct monthly job-to-job transitions using the SIPP.

Unlike the Current Population Survey, the SIPP provides the reason for separation from a workers previous employer independent of the destination. I categorise the reason for separating, r, in the following way.

- **Involuntary (I)**
  - On layoff, discharged/fired, employer bankrupt, employer sold business, job was temporary and ended.
- **Voluntary (V)**
  - **Traditional (T)**: Quit to take another job.
  - **Unsatisfied (U)**: Slack work or business conditions, unsatisfactory work conditions.
  - **Personal (P)**: Retirement or old age, childcare problems, other family/personal obligations, own illness, own injury, school/training.
  - **Other (O)**: Left work for some other reason.

The reason "Quit to take another job" is conceptually analogous to how job-to-job transitions are motivated in theory.[12] A worker is in a job that they enjoy, and only separate because they have received a superior offer. We will see that almost none of the workers who report to separate because of this reason will transitions to unemployment, and so is a useful proxy for job-to-job transitions that are unrelated to unemployment.

The UK Labour Force Survey

The LFS is a household-based survey that is used as the backbone for UK government labour force statistics. While the survey was originally used for cross-sectional analysis, in 1992 the survey introduced a longitudinal component.[13] Following this reform, survey participants are sampled for five consecutive quarters. This reform allows for the estimation of quarterly labour market flows. I use the period between 1996q1 and 2016q4.[14]

I follow Gomes (2012) and assign job-to-job transitions using a job tenure approach. A job-to-job transition occurs when an individual is employed at time $t-1$ and, since the survey is quarterly, has less than three months job tenure at time t.

Like the SIPP, the LFS provides the reason why the worker has separated from their previous employer for both currently employed and non-employed workers. I categorise the reasons for separating, r, in the following way.

- **Involuntary (I)**
  - Dismissed, made redundant, temporary job finished.
- **Voluntary (V)**
  - **Traditional (T)** + **Unsatisfied (U)**: Resigned, took voluntary redundancy.
  - **Personal (P)**: Took early retirement, retired, gave up work for health reasons, gave up work for family or personal reasons.
  - **Other (O)**: Left work for some other reason.

I take the view that workers who resign or take voluntary redundancy encompass both "Traditional" and "Unsatisfied" quits, as I have defined with the US data. I will test whether this distinction is important by combining these two reasons with the US data in Section 4.

3.2. Worker flows

The worker flows for the SIPP and LFS with different adjustments for error (described in Section 4) can be found in Appendix A. The flow of workers switching jobs is large as has been abundantly documented, reflecting the pervasiveness of on the job search (see Faberman et al., 2022). Interestingly, the job-to-job rate estimated from the SIPP displays similarities to the adjusted series estimated from the CPS in Fujita et al. (2020). The authors adjust for a sharp rise in missing answers to the question used to assign whether a worker transitioned from job to job in 2007. In particular the SIPP job-to-job rate calculated in the present paper and the adjusted CPS job-to-job transition rate calculated in Fujita et al. (2020) display a much smaller drop during the Great Recession than the unadjusted job-to-job rate from the CPS.

3.3. Key descriptives

Table 1 shows the proportion of separations, job switches, and employment to unemployment transitions by reason; and the underlying components of the employment to unemployment probability split by

[10] The components of Eq. (3) are calculated by: $p_t^{entry} = \frac{Entry_t}{N_{t-1}}$, and $p_t^{e|entry} = \frac{EEntry_t}{Entry_t}$. $Entry_t$ constitutes the stock of all those who enter the labour market between $t-1$ and t. $EEntry_t$ constitutes the stock of all those who enter the labour market between $t-1$ and t and are employed at t.

[11] Perry (1972a) shows that recall over short periods like those used here are unlikely to significantly impact the flows.

[12] See Burdett and Mortensen (1998), Postel-Vinay and Robin (2002b) and Cahuc et al. (2006), for prominent examples.

[13] A longitudinal component, at a lower frequency, implicitly exists preceding this period by the use of retrospective data, see Elsby et al. (2016). The retrospective technique used in that paper cannot be used to estimate each separation type by reason or the job-to-job probability.

[14] I begin in 1996q1 because this is the period where the reason for separation was introduced.

Table 1
Heterogeneity in the components of the decomposed employment to unemployment probability.

	(1)	(2)	(3)	(4)	(5)	(6)
US						
	% of seps	% of JJ	% of EU	p^{sep}	$p^{l\,f\,|sep}$	$p^{jj|l\,f\,sep}$
Overall	100	100	100	4.23	73.2	69.6
Reason for separation						
Involuntary	28.6	21.7	53.7	1.21	79.4	49.4
Traditional quit	24.6	39.9	6.7	1.04	88.1	92.7
Unsatisfied quit	13.3	12.5	18.3	0.56	78.3	60.4
Personal quit	18.3	12.7	6.6	0.77	43.9	81.4
Other quit	15.1	13.2	14.8	0.64	65.8	67.2
UK						
	% of seps	% of JJ	% of EU	p^{sep}	$p^{l\,f\,|sep}$	$p^{jj|l\,f\,sep}$
Overall	100	100	100	5.30	66.0	61.7
Reason for separation						
Involuntary	27.7	20.9	49.3	1.47	75.2	41.4
Traditional or Unsatisfied quit	31.6	44.3	26.1	1.67	78.1	72.6
Personal quit	19.6	6.0	10.3	1.04	25.6	48.2
Other quit	21.1	28.8	14.3	1.12	73.9	76.2

Note: Probabilities are measured at a monthly frequency for the US and a quarterly frequency for the UK, and are based on measures unadjusted for margin error and seasonality. The sum of individual reasons may not exactly sum to the overall because of rounding. Source: Author calculations using data from the SIPP and LFS. Ages 16–64/59. The data spans 1996q1-2016q4 for the LFS and 1996m4-2013m5 for the SIPP.

reason. In the SIPP data, on the first row, we can see that 4.23% of workers separate from their jobs each month. Of these separators, 73.2% remain in the labour force. Conditional on remaining in the labour force upon separation, 69.6% move to new employment. In the LFS data, 5.3% of workers separate from their jobs each quarter. Of these separators, 66% remain in the labour force. Conditional on remaining in the labour force upon separation, 61.7% move to new employment.

We can see in column (1) that over a quarter of separations occur because a worker lost their job involuntarily, and, for the US, just under a quarter because of "Traditional quits". The remaining half is approximately evenly split between "Unsatisfied quits", "Personal quits", and other reasons for separation. From column (2), two fifths of job-to-job transitions occur because a worker quit to take a new job. Over a fifth occur because a worker lost their job. The remaining two fifths occur because of other reasons. The numbers are very similar for the UK. Less than half of job to job transitions occur when a worker made a "Traditional" or "Unsatisfied" quit. From column (3) around a half of employment to unemployment transitions occur due to a layoff, for both the US and UK. These numbers suggest that job switching does not only occur when a worker enjoys their job but has received a superior offer, and employment to unemployment transitions are not all layoffs. A sizeable proportion of job switches occur because the worker was pushed out from the firm, and many workers quit to unemployment.[15]

This variation in the reason for separation results in large differences in outcomes as can be seen in columns (4) to (6). If a worker involuntarily separates from their employer and subsequently remains in the labour force, just under a half will move to new employment in both the US and UK. Crucially, this is 93% for those who report to separate because they quit to take another job.[16] This suggests that this reason for separation is a useful proxy for how job-to-job transitions are typically motivated in theory.[17] Given these large difference in outcomes by reason for separation, if the composition of separations changes over the business cycle, aggregating reasons will mask the important heterogeneity shown in Table 1.

Figure 1 shows the monthly and quarterly probability of separating from your job by reason for the US and UK, respectively. For the US, we see a dramatic fall in "Traditional" quits, and little change in "Unsatisfied" quits during the Great Recession. This is accompanied by a large rise in involuntary separations. We see the same dynamics for the UK, but the increase in layoffs is less stark. The US results show that it is not that all quits fall in recessions. Instead, it is those quits that almost never result in unemployment that fall. We will see the importance of this in Section 4.

4. Decomposition of unemployment variation

In this section I explain how it is possible to assess the impact of the fluctuations of the decomposed ins of unemployment on overall labour market state rate dynamics. To do this, I utilise a non-steady state variance decomposition developed by Elsby et al. (2015). Later I will present the results.

4.1. Methodology

The following first-order Markov process describes the evolution of the three state variables where: e is the employment-to-population rate, u is the unemployment-to-population rate and n is the inactivity-to-population rate. $p_t^{ij} = \frac{IJ_t}{I_{t-1}}$ describes the probability of moving from state i to j during period t, where IJ_t is the number of individuals moving from state i to j during period t, and I_{t-1} is the stock of individuals in state i at time $t-1$.

$$\begin{bmatrix} e \\ u \\ n \end{bmatrix}_t = \begin{bmatrix} 1-p^{eu}-p^{en} & p^{ue} & p^{ne} \\ p^{eu} & 1-p^{ue}-p^{un} & p^{nu} \\ p^{en} & p^{un} & 1-p^{ne}-p^{nu} \end{bmatrix}_t \begin{bmatrix} e \\ u \\ n \end{bmatrix}_{t-1} \tag{4}$$

Substituting in for the decomposed ins of unemployment described in Section 2, and exploiting the fact that $e_t + u_t + n_t = 1$, results in the following reduced dynamic system

$$\underbrace{\begin{bmatrix} e \\ u \end{bmatrix}_t}_{\mathbf{s}_t} = \underbrace{\begin{bmatrix} 1-\sum_r \left[p^{sep^r}(1-p^{sep^r}p^{l\,f\,|sep^r}p^{jj|l\,f\,sep^r})\right] - p^{entry}p^{e|entry} & p^{ue}-p^{entry}p^{e|entry} \\ \sum_r \left[p^{sep^r}p^{l\,f\,|sep^r}(1-p^{jj|l\,f\,sep^r})\right] - p^{entry}(1-p^{e|entry}) & 1-p^{ue}-p^{un}-p^{entry}(1-p^{e|entry}) \end{bmatrix}_t}_{\mathbf{P}_t} \underbrace{\begin{bmatrix} e \\ u \end{bmatrix}_{t-1}}_{\mathbf{s}_{t-1}} + \underbrace{\begin{bmatrix} p^{entry}p^{e|entry} \\ p^{entry}(1-p^{e|entry}) \end{bmatrix}_t}_{\mathbf{q}_t}. \tag{5}$$

The limiting distribution, or steady state, of the Markov process is then given as

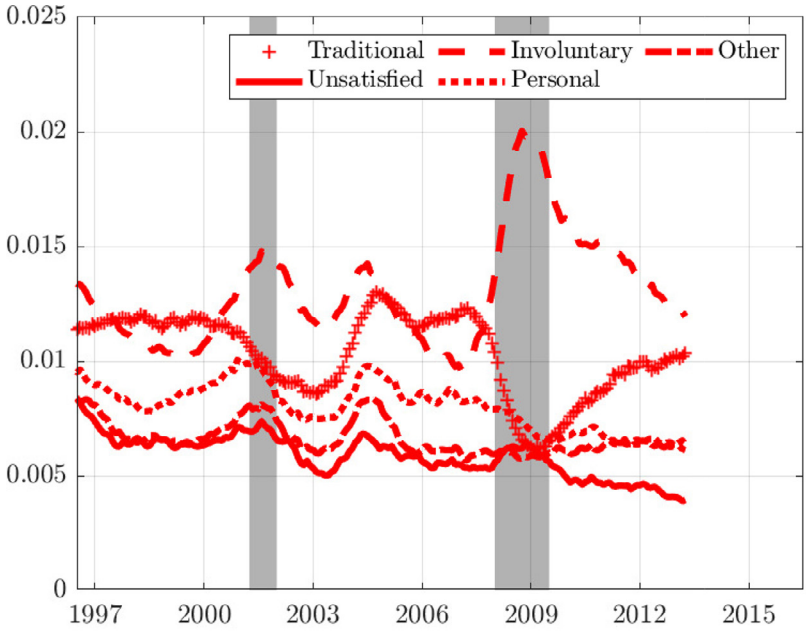
$$\bar{\mathbf{s}}_t = (\mathbf{I} - \mathbf{P}_t)^{-1}\mathbf{q}_t. \tag{6}$$

The steady state rates are a function of the underlying flow probabilities and the decomposed ins of unemployment. Given this functional form,

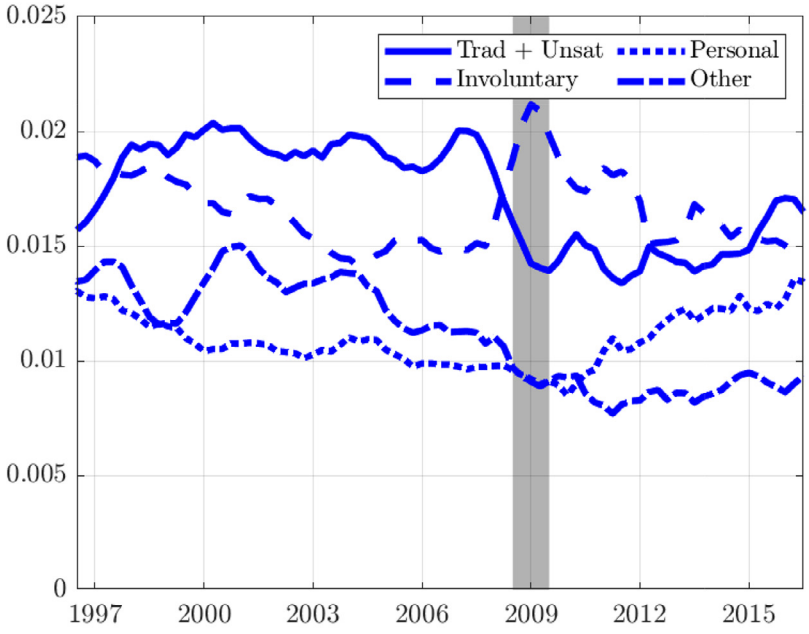
[15] Some job switches may in fact be employment-unemployment-employment transitions. In the main analysis I will make an adjustment for this time aggregation bias.

[16] We can imagine that those who quit to move to a new employer still have some small probability of ending up unemployed a month later, if, for example, the poaching firm rescinds the offer, and the incumbent firm cannot recall the workers.

[17] See Burdett and Mortensen (1998), Postel-Vinay and Robin (2002b) and Cahuc et al. (2006), for prominent examples. Of course, some separations do have zero probability of becoming unemployed, but the numbers in Table 1 associated with "Traditional quits" suggests that this reason for separation is a useful proxy for these types of transitions.



(A) US



(B) UK

Fig. 1. Heterogeneity in the reason for separation over time. *Note:* Probabilities are measured at a monthly frequency for the US and a quarterly frequency for the UK, and are based on measures unadjusted for margin error and seasonality. Source: Author calculations using data from the SIPP and LFS. Ages 16–64/59. The data spans 1996q1-2016q4 for the LFS and 1996m4-2013m5 for the SIPP.

it is straightforward to decompose changes in the steady state rates into those that are due to the underlying probabilities using a first order approximation

$$\bar{\mathbf{s}}_t \approx \bar{\mathbf{s}}_{t-1} + \sum_{y \in \mathbf{Y}} \frac{\partial \bar{\mathbf{s}}_t}{\partial p_t^y}(p_t^y - p_{t-1}^y), \tag{7}$$

where $\mathbf{Y}$ is the set of all probabilities seen in (5). One could raise the expansion to some higher order n but it turns out that a first order expansion is quantitatively sufficient in my data. Elsby et al. (2015) show how to map this decomposition of steady state unemployment variation to actual unemployment variation. I relegate the description to the Online Appendix. This decomposition allows us to understand how the changes in the underlying flows, and more important for this study, changes in the underlying components of the employment to unemployment transition probability split by reason, contribute to the changes in the actual unemployment rate over time.

The potential importance of differing reasons for separation

The importance of fluctuations in the underlying components of the ins of unemployment is largely determined by the first-order expansion of the steady-state unemployment rate. If we consider separations as uniform (left) or allow for differing reasons for separation (right), the

Table 2
Decomposition results - not allowing for differences in the reason for separation.

	(1) sep	(2) $lf\|sep$	(3) $jj\|lfsep$	(4) ue	(5) un	(6) $entry$	(7) $e\|entry$
US	4.2	1.6	39.5	26.8	11.7	-0.6	17.5
UK	-8.5	2.3	38.2	30.6	17.3	-3.4	23.2

Note: The interpretation of the top left cell is: the past and present fluctuations in the separation probability contributes to 4.2% of the dynamics of the unemployment rate in the US. The numbers do not exactly sum to 100 because of approximation error and rounding. Source: Author calculations using data from the SIPP and LFS. Ages 16–64/59. US 1996m4-2013m5. UK 1996q1-2016q4.

contribution of fluctuations in separations are written as

$$\frac{\partial \bar{u}_t}{\partial p_t^{eu}} p_t^{lf|sep}(1-p_t^{jj|lfsep})(p_t^{sep}-p_{t-1}^{sep}) \text{ and}$$

$$\frac{\partial \bar{u}_t}{\partial p_t^{eu}} \sum_{r\in\mathbf{R}} p_t^{lf|sep^r}(1-p_t^{jj|lfsep^r})(p_t^{sep^r}-p_{t-1}^{sep^r}). \quad (8)$$

On the left, changes in separations are weighted by the aggregate probability of subsequently becoming unemployed, $(1-p_t^{jj|lfsep})$, whilst on the right, changes in separations for each reason are weighted by the relevant probability of subsequently becoming unemployed, $(1-p_t^{jj|lfsep^r})$. As we have seen for the US, the subset of quits that fall during the Great Recession is predominantly those that are very unlikely to result in unemployment, and will not significantly impact the employment to unemployment rate. Moreover, the increase in layoffs will be weighted highly since the probability of becoming unemployed following the layoff is large. Aggregation ignores these compositional changes, incorrectly weighting the fluctuations in the underlying reasons for separation.

Next, the relationship between changes in the aggregate probability of finding a job conditional on separation, and the same probability conditional on separation for reason r is

$$p_t^{jj|lfsep}-p_{t-1}^{jj|lfsep}=\sum_{r\in\mathbf{R}} w_t^r p_t^{jj|lfsep^r}-\sum_{r\in\mathbf{R}} w_{t-1}^r p_{t-1}^{jj|lfsep^r}, \quad (9)$$

where w_t^r is the proportion of separations that remain in the labour force for reason r. Changes in the aggregate probability on the left do not imply changes in the probabilities by reason. Instead, these changes could be due to overall changes in the composition of separations. Again, aggregation ignores potentially important compositional fluctuations in the reason for separation.

4.2. Results

In this subsection I will present decomposition results in the following order.

1. A decomposition where I do not allow for heterogeneity in the reason for separation in Table 2.
2. A decomposition where I disaggregate the underlying components into different reasons for separation, but where I group "Traditional quits" and "Unsatisfied quits" in the US data in Table 3. I do this since such a distinction is not available in the UK data, and so will provide a better comparison across countries.
3. Finally, a decomposition where I disaggregate across all reasons in the US data in Table 4.

Moving from 1) to 2) to 3) highlights the bias created by ignoring the heterogeneity in the reason for separation, both between quits and layoffs (decomposition 1) to 2)) but also the heterogeneity in the reason for quitting (decomposition 2) to 3)).

I provide a comparison of the results from a standard decomposition of the six worker flows using SIPP and CPS data in Table B1. In general the results are very similar, but that the SIPP data ascribe a greater importance for the employment to unemployment rate.

Table 3
Decomposition results - allowing for differences in the reason for separation but grouping "Traditional quits" and "Unsatisfied quits" in the US data before conducting the decomposition.

	(1) sep^I	(2) $\sum_{r\in V} sep^r$	(3) $lf\|sep^I$	(4) $\sum_{r\in V} lf\|sep^r$	(5) $jj\|lfsep^I$	(6) $\sum_{r\in V} jj\|lfsep^r$
US	25.4	-7.3	3.5	-0.2	8.0	15.9
	(1)+(2)=18.0		(3)+(4)=3.2		(5)+(6)=23.9	
UK	12.4	-14.4	1.4	2.1	8.5	21.9
	(1)+(2)=-2.0		(3)+(4)=3.4		(5)+(6)=30.4	

Note: The set $V=\{Traditional+Unsatisfied, Personal, Other\}$. The numbers beneath each row sum the relevant columns. (1)+(2)=18.0, for example, is the sum of 25.4 and -7.3 with rounding. The ue, un, $entry$ and $e|entry$ probabilities are omitted since they are exactly the same as in Table 2. The interpretation of the top left cell is: the past and present fluctuations in the involuntary separation probability contributes to 25.4% of the variations in the unemployment rate in the US. Source: Author calculations using data from the SIPP and LFS. Ages 16–64/59. US 1996m4-2013m5. UK 1996q1-2016q4.

Table 4
Decomposition results - allowing for all differences in the reason for separation.

	(1) sep^I	(2) $\sum_{r\in V} sep^r$	(3) $lf\|sep^I$	(4) $\sum_{r\in V} lf\|sep^r$	(5) $jj\|lfsep^I$	(6) $\sum_{r\in V} jj\|lfsep^r$
US	25.4	-1.5	3.5	-0.2	8.0	10.0
	(1)+(2)=23.8		(3)+(4)=3.3		(5)+(6)=18.1	

Note: The set $V=\{Traditional, Unsatisfied, Personal, Other\}$. The numbers beneath each row sum the relevant columns. (1)+(2)=23.8, for example, is the sum of 25.4 and -1.5 with rounding. The ue, un, $entry$ and $e|entry$ probabilities are omitted since they are exactly the same as in Table 2. The interpretation of the top left cell is: the past and present fluctuations in the involuntary separation probability contributes to 24.3% of the variations in the unemployment rate in the US. Source: Author calculations using data from the SIPP and LFS. Ages 16–64/59. US 1996m4-2013m5. UK 1996q1-2016q4.

Uniform separations

Table 2 shows the results of a decomposition with the incorporated decomposed ins of unemployment, but not allowing for differences in the reason for separation. The results are very similar for the US and UK. From column (1) and (2) we see that changes in separations, and changes in the proportion of separations that remain in the labour force, are estimated to drive very little of unemployment variation. From column (3), changes in the probability that workers move to new employment following separation is estimated to drive over a third of unemployment variation. This suggests that fluctuations in job finding drives all the countercyclicality of the employment to unemployment rate. The final two columns show that entry in the labour force is relatively stable during recessions, but that job finding conditional on entry drives all the variation originally attributed to changes in the inactivity to unemployment transition rate.

Heterogeneity in the reason for separation

Table 3 shows the results from a decomposition where I allow for heterogeneity in the reason for separation, but where I group "Traditional quits" and "Unsatisfied quits" in the US data. The results are quantitatively different to in Table 2. Fluctuations in separations are more important, and fluctuations in job finding conditional on separations are less important. From columns (1) and (2), in the US, layoffs drive around a quarter of unemployment variation, and overall separations just under a fifth. Whilst, from columns (5) and (6), job finding conditional on separation contributes around a quarter. Layoffs drive around an eighth of unemployment variation in the UK, but this is mitigated by procyclical quits. Job finding conditional on separation is, again, less important in

the UK when allowing for heterogeneity in the reason for separation but the difference is smaller than for the US.

The explanation for separations rising in importance is because layoffs are more likely to result in an employment to unemployment transition. The rise in layoffs during the Great Recession is, therefore, weighted more than the decline in quits, which results in the contribution of overall separations being larger than if separations are not disaggregated by reason. This changing direction of quits and layoffs also results in the reduction in the contribution of fluctuations in job finding conditional on separation.

The US data provides a proxy for particular reasons for separation where the worker is very unlikely to experience a spell of unemployment, "quit to take a new job" which I coin as "Traditional quits". The UK does not. Since there is a large decline in such separations during the Great Recession, not disaggregating quits into those that are very unlikely to become unemployed with those who quit because they are dissatisfied with their job, will impact the contribution of the underlying probabilities associated with quits. I finally separate quits into "Traditional quits" and "Unsatisfied quits" in the US, and show the results in Table 4. There are two takeaways. First, the contribution of fluctuations in quits increases by 6 percentage points, and, second, the contribution of fluctuations in job finding conditional on separation falls by 6 percentage points. Again, this is due to the large decline in "quits to take a new job" during the Great Recession, which is not correctly weighted when we do not allow for heterogeneity in the reason for quitting. Overall separations drive around a quarter of unemployment variation. This suggests that the contribution of changes in separations are biased down for the UK in Table 3.

To close this subsection, for the US especially, the contributions of changes in separations and changes in job finding conditional on separation have, respectively, increased and decreased dramatically when moving from Tables 2 to 3 to 4. This exercise has shown how important it can be to allow for the large heterogeneity in the reason for separation when studying why the employment to unemployment transition probability and unemployment rate change over the business cycle.

Focusing on the Great Recession

Figure 2 shows the underlying contributions of the employment to unemployment transition probability, and split into the constituent components, during the Great Recession.[18] We can see that the involuntary separation probability and job finding conditional on separation both were important in driving increases in employment to unemployment transitions during the Great Recession. In line with the results in Tables 3 and 4, involuntary separations were particularly important in the US.[19] The reduction in the number of workers lining up jobs following separation is more important than layoffs in the UK. Since we are unable to distinguish between "Traditional" and "Unsatisfied" separations in the UK, however, the contribution of job finding conditional on separation is likely biased upwards.

4.3. Potential caveats to the analysis

Heterogeneity

As suggested by Darby et al. (1985), reductions in the job finding probability during a recession may be contributed to by compositional shifts in the pool of individuals looking for employment - from individuals who are more effective at finding work, to individuals who are less effective at finding work. In Appendix C I assess the role of compositional changes in worker type including: age, sex, education, relationship to head of household, whether searching on the job, the reason for searching on the job, and whether the job was temporary. I find no evidence that compositional shifts in observable characteristics are driving fluctuations in the job finding components of the ins of unemployment.[20]

Time aggregation

Part of the contribution that comes through the job finding probabilities conditional on separation or labour market entry would be attributed to fluctuations in the unemployment to employment probability if we could observe each individuals' labour market status every day. This is because some of those who I categorise as making a job to job or inactivity to employment transition may have experienced a spell of unemployment in between. This would result in an upward bias in the job finding components of the ins of unemployment. I adjust the probabilities for time aggregation following Shimer (2012) and Mukoyama (2014). Tables B2 and B3 show the continuous time analog of Table 3 for the US and Table 4. The differences in the contributions in the continuous time environment compared to the discrete time environment are small.

Classification error

Abowd and Zellner (1985) and Poterba and Summers (1986) found that some individuals incorrectly report their labour market status.[21] It is possible to use estimates from Table 6 in Abowd and Zellner (1985), for example, to adjust the flows for misclassification. However, the data estimates are time invariant and come from the Current Population Survey. Instead Elsby et al. (2015) devise a method to adjust for this misclassification that is not time invariant, and can be implemented on data sets that can be matched over at least four periods - a possibility with the SIPP and LFS. The authors coin it a "deNUNification" procedure. The idea is to recode observed transitions such as NNUN (inactivity to inactivity to unemployment to inactivity) to NNNN - to omit spurious transitions in and out of the labour market. Despite the focus of this work being on the separation margin, for completeness I apply this adjustment for classification error, and show the results in the Tables B2 and B3.[22] The results are quantitatively very similar.[23]

Accounting

Finally, it is tempting to interpret changes in the flow probabilities as "causing" changes in the unemployment rate. It is possible, however, to construct stories that would negate a causal interpretation. Prominent examples are: increased separations may cause congestion in the unemployment pool (Pissarides, 2000); individuals who lose their job in recessions may be *unobservably* different than those who lose their job in expansions, or may be less likely to have a recall option (Ahn and Shao, 2021); layoffs may be less likely to be foreseen by the worker in recessions (Garibaldi, 2004); finally, search effort of the unemployed and employed may change in recessions which can impact the job finding probabilities and also cause congestion (Mukoyama et al., 2017 and Ahn and Shao, 2021). This is not to say that accounting exercises are not useful. Worker flow analyses provide the outcomes that labour market models should attempt to replicate, with the model then illuminating the underlying causes of changes in the labour market variable of interest.

[18] I use the most exhaustive decomposition for both countries. That shown in Table 3 for the UK, and Table 4 for the US.

[19] In the Online Appendix, I split the sample into two periods, before 2006 and after 2006. Layoffs were particularly important in the after 2006 sample in the US.

[20] This does not rule out the role of compositional shifts in unobserved characteristics (see Ahn and Shao, 2021). Moreover, Bachmann and Sinning (2016) shows that fluctuations in the duration of unemployment play a role in the dynamics of unemployment to employment rate that I do not entertain here. Consistent with my results, however, they find that, if anything, composition reduces the cyclicality of the employment to unemployment transition rate.

[21] Jones and Riddell (2019) argue that the marginally attached lie between the unemployed and non-attached, highlighting the potential issue with the unemployment-inactivity distinction.

[22] See the Online Appendix for more details of the adjustment procedure.

[23] A recent paper by Kudlyak and Lange (2018) has suggested, however, that transitions in and out of the labour market should perhaps not be seen as spurious. The reason for this is because workers who make NNUN transitions are far more likely to be employed in the near future than those who make NNNN transitions.

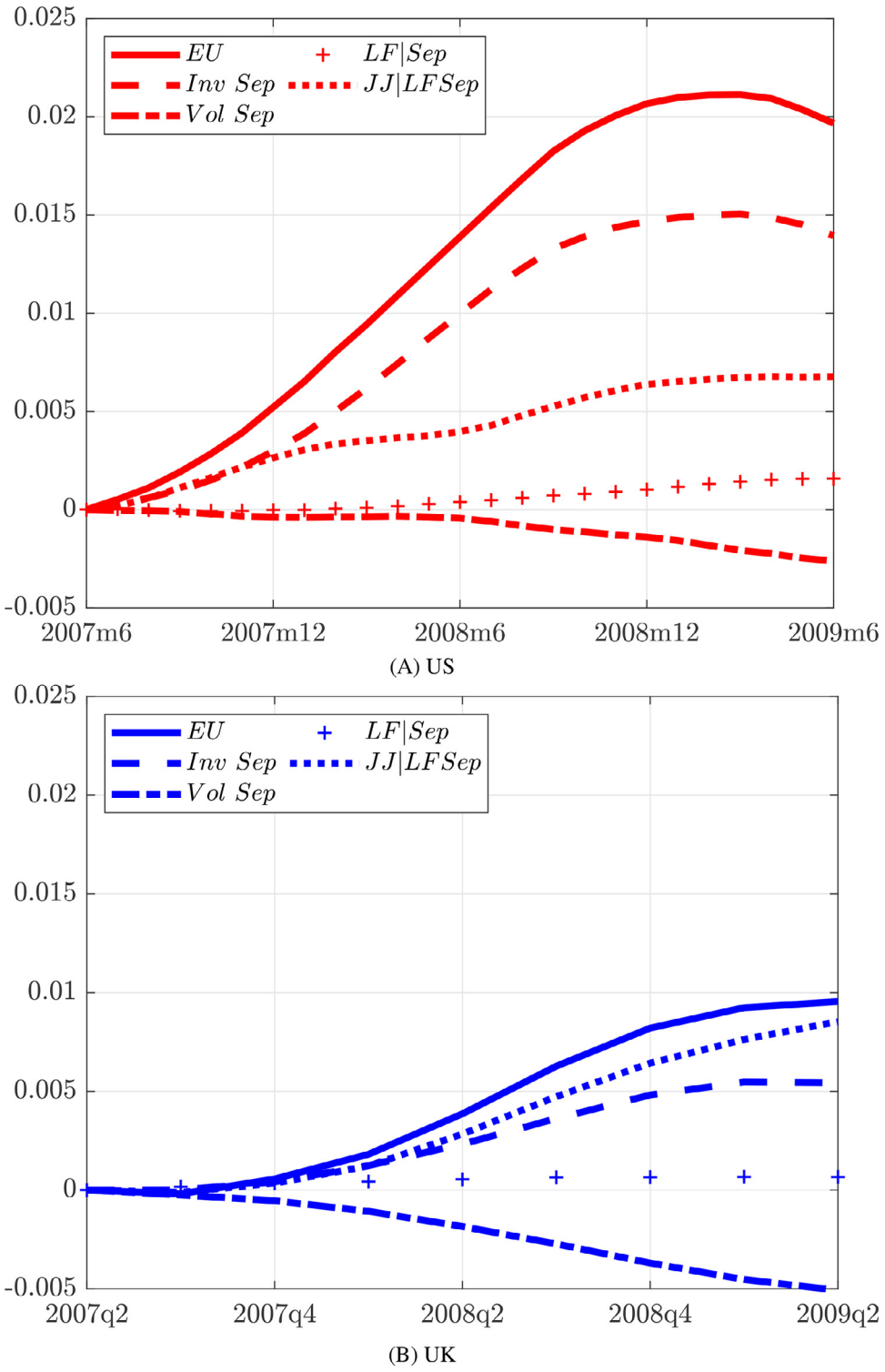


Fig. 2. Contributions of the employment to unemployment transition to the increase in unemployment during the Great Recession, and split into the constituent components. *Note:* The $LF|Sep$ and $JJ|LFSep$ time series represent the sum of contributions over all reasons. The cumulative contributions are calculated based on the most exhaustive estimation - over all reasons for separations - and then adjusted to represent contributions to changes in the unemployment rate as opposed to the unemployment to population ratio.

5. Implications for future work and policy

5.1. Empirical

A now widely used method for estimating the ins and outs of unemployment is developed in Shimer (2012). In a two state world, the evolution of unemployment is written as

$$u_t = (1 - F_{t-1})u_{t-1} + u_t^s, \tag{10}$$

where F is the probability of finding a job and u^s is the percentage of the labour force who are in short term unemployment.[24] The short term unemployed proxy the ins of unemployment. Elsby et al. (2013) study unemployment dynamics across 13 OECD countries by adapting Shimer's framework. They show that fluctuations in the ins are more important

[24] There is a vast number of studies that attempt to understand the dynamics of unemployment in a two state framework. These include Petrongolo and Pissarides (2008), Elsby et al. (2009), Elsby et al. (2010, 2013), Smith (2012), and Lydon and Simmons (2020).

than the outs for many countries. The results of this paper suggest that fluctuations in the short term unemployed are contributed to by fluctuations in the probability by which workers find jobs. Attributing the estimated fluctuations in separations using this framework as due to fluctuations in layoffs, is natural and intuitive, but not necessarily accurate.

Two natural critiques of studying the overall separation rate, that I outlined in Section 2, are that separations can be split into quits and layoffs, and that some quits occur when a worker has very little chance of becoming unemployed. I present evidence in this work that, indeed, these critiques are quantitatively important. Moreover, assuming separations are constant over the business cycle is true but ignores quantitatively important variation in the composition of separations. Future work must allow for the large variation in the reason for separation when studying the importance of overall separations, and the job finding rate.

5.2. Policy and related theory

My results suggest that: firstly, job separations are important drivers of changes in the unemployment rate despite the overall separation rate remaining unchanged over recessions; second, fluctuations in job finding contribute to some of the fluctuations in the employment to unemployment rate. This has important implications for stabilisation policies. Determining whether unemployment rises predominantly because of separations or because of job finding may help policy makers decide which policy tool is most appropriate. If separations are the prominent force, policies that reduce job destruction are potentially key. Whereas, if job finding is the prominent force, policies that encourage vacancy creation are potentially key. While worker flow analyses are important first steps to understanding which policy tools should be targeted to stabilise unemployment, combining these results with structural models is key. To this end, I discuss related theory next.

The prominent model of job-to-job transitions is the job ladder model (Burdett and Mortensen, 1998).[25] Workers receive offers both on and off the job and, when employed, accept offers if the poaching firm has offered a higher wage than the incumbent firm. Job ladder models have been incredibly successful in aiding our understanding of how the labour market functions. For example, and related to this paper, these models have yielded important insights into how a procyclical job to job transition rate can contribute to fluctuations in the unemployment rate. In recent work, the notion of vacancy chains (chains of replacement hiring) has lead to important insights into the importance of procyclical job switching (see Elsby et al., 2022 and Carrillo-Tudela et al., 2022 where the study of vacancy chains extends at least as far back as Akerlof et al., 1988). The presence of replacement hiring exacerbates fluctuations in unemployment since a decline in job switching during recessions induced by a decline in vacancy posting subsequently reduces the need to replacement hire and vacancies fall even further. The present paper dovetails with this literature on the importance of job switching over the business cycle in equilibrium search models, showing that job switching can also play a prominent role in contributing to unemployment variation in non-structural worker flow analyses.

The canonical job ladder model yields a notable counterfactual result that all job switches result in positive wage growth. Jolivet et al. (2006) and Tjaden and Wellschmied (2014), for example, show that a significant minority of job switches result in negative wage growth.[26] The results in Section 3 show that a large proportion of job to job transitions occur for non-standard reasons: following layoff, being unsatisfied and personal reasons such as health. These non-standard reasons for making job to job transitions may result in important differences in wage dynamics, and help explain the total observed negative wage growth found in previous work.

Nagypal (2005) builds a model where search effort is also a mechanism to avoid unemployment. Matches are categorised by an idiosyncratic productivity level, and workers lose their job when the match hits a lower threshold. Before this threshold is reached workers search much harder to avoid unemployment spells. She argues that, unlike the standard job ladder model, her model is able to capture different stylised facts of job-to-job transitions, and in particular that on the job search is undertaken by those who have a relatively higher risk of becoming unemployed. Relatedly, Simmons (2021) shows that workers increase search effort before they lose their job. I build this behaviour into a job ladder model by allowing workers to experience a change in job insecurity before job loss. Workers mitigate this increased unemployment risk by reducing their reservation wage, increasing search effort, and reducing consumption. I show that the model can replicate, among other things, the differing earnings consequences of job loss by whether the worker moves to unemployment or directly to a new job. I find that the realised changes in job insecurity result in large welfare gains.[27]

This paper and related work pushes for a bigger emphasis in modelling job-to-job transitions as not just a mechanism to climb the waged job ladder, but because of non-standard reasons, with the perhaps most salient reason being to avoid unemployment spells.

6. Conclusion

In this paper I study why the employment to unemployment transition rate is countercyclical in the US and UK. The rise during recessions could be due to increased separations or a lack of job finding conditional on separation. My results indicate that allowing for the large heterogeneity in the reason for separation can have important implications for the analysis. This is especially true for the US during the Great Recession. The explanation is two fold. 1) The reason a worker separates from their job greatly impacts their outcomes. Some reasons for separation rarely result in unemployment, those who “quit to take a new job”, whilst others very often do, layoffs. 2) During the Great Recession, not all quits decline, but the subset that do are those that are very unlikely to result in a transition to unemployment, and layoffs rise substantially. Aggregating separations ignores this cross sectional and dynamic heterogeneity.

If separations are treated as uniform, in the US, separations drive almost none of the variations in the unemployment rate. Allowing for heterogeneity in the reason for separation, however, raises the contribution to a quarter in the US. Job finding conditional on separation is reduced in importance significantly after allowing for this heterogeneity, but still remains an important driver of fluctuations in the employment to unemployment rate in both the US and UK.

My results show that a large proportion of job-to-job transitions occur for non-standard reasons, such as, being fired, being unsatisfied, and personal reasons such as health. These different reasons for switching jobs are in part driving the findings in this work. Studying these different reasons for moving from job to job at the individual level may uncover new and interesting features of wage dynamics associated with job mobility and seems like an interesting direction for future work.

[25] Other prominent work with on the job search includes Postel-Vinay and Robin (2002a) and Cahuc et al. (2006).

[26] A common method to replicate this negative wage growth in search models is to invoke Godfather shocks, “take it or leave it”. Workers are forced to accept new offers or become unemployed.

[27] Further related work is seen in Jarosch (2021) and Krusell et al. (2017). Jarosch (2021) builds a model with a distribution of job productivity and unemployment risk. Job to job transitions, therefore, typically result in an increase in job security. He shows that the model is able to replicate the earnings consequences of job loss estimated in the data. Krusell et al. (2017) build a model of the labour market that includes transitions across the three labour market states. Their model predicts countercyclical inactivity to unemployment transitions. The reason is precisely because of procyclical job finding: *During good times the increase in job opportunity arrival rates implies that marginal N workers are more likely to receive offers that take them into E, thus decreasing the flow of these workers into U.* In this paper, I have decomposed inactivity to unemployment flows, to capture this feature.

Declaration of Competing Interest

None.

Data Availability

Data links and code are available on the title page.

Appendix A. Additional figures

Figures A1–A4

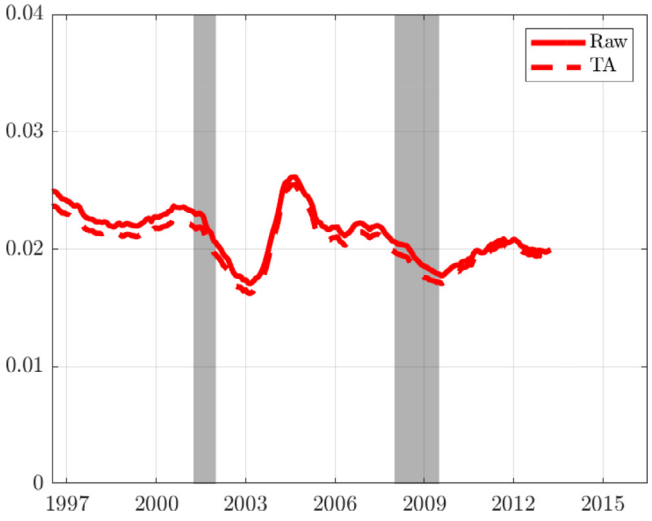


Fig. A1. The SIPP US monthly job-to-job transition probability. *Note:* Probabilities adjusted for seasonality and the dotted line also for time aggregation. Shaded areas denote officially defined US recessions. Source: Author calculations using the SIPP, ages 16–64/59, 1996m4-2013m5.

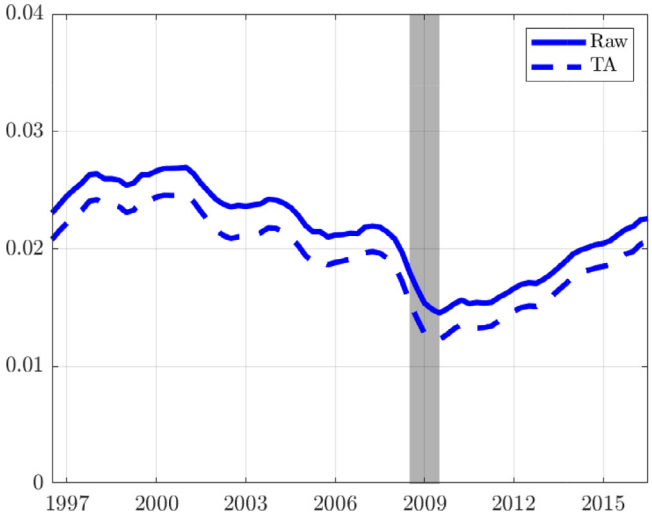


Fig. A2. The UK quarterly job-to-job transition probability. *Note:* Probability adjusted for seasonality and the dotted line also for time aggregation. The shaded area denotes the officially defined UK Great Recession. Source: Author calculations using Two Quarter LFS, ages 16–64/59, 1996q1-2016q4.

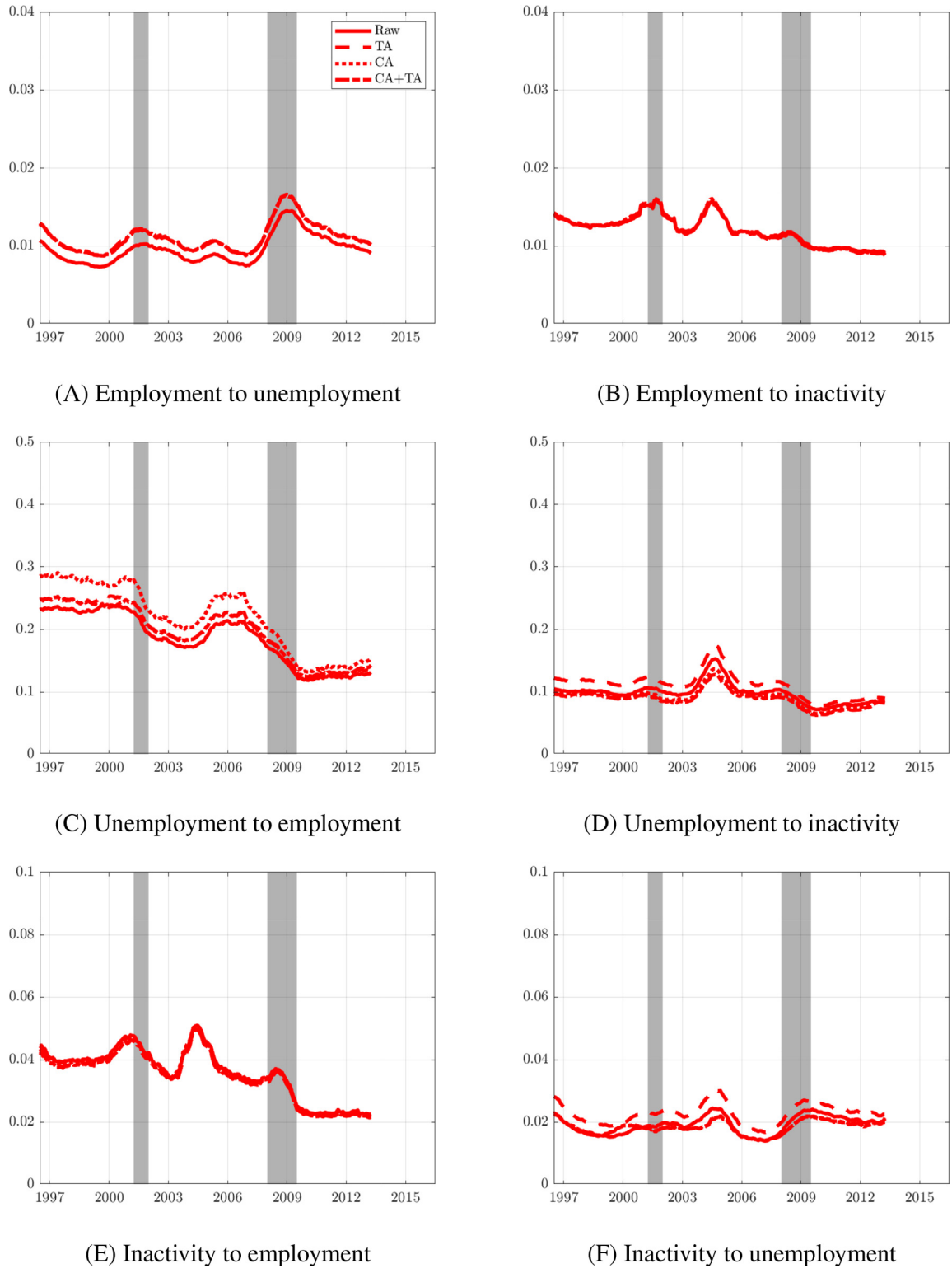


Fig. A3. The SIPP US monthly worker flows over different adjustments. *Note:* All probabilities adjusted for margin error and seasonality. TA refers to time aggregation adjusted, and CA refers to classification error adjusted. Shaded areas denote officially defined US recessions. Source: Author calculations using the SIPP, ages 16–64/59, 1996m4-2013m5.

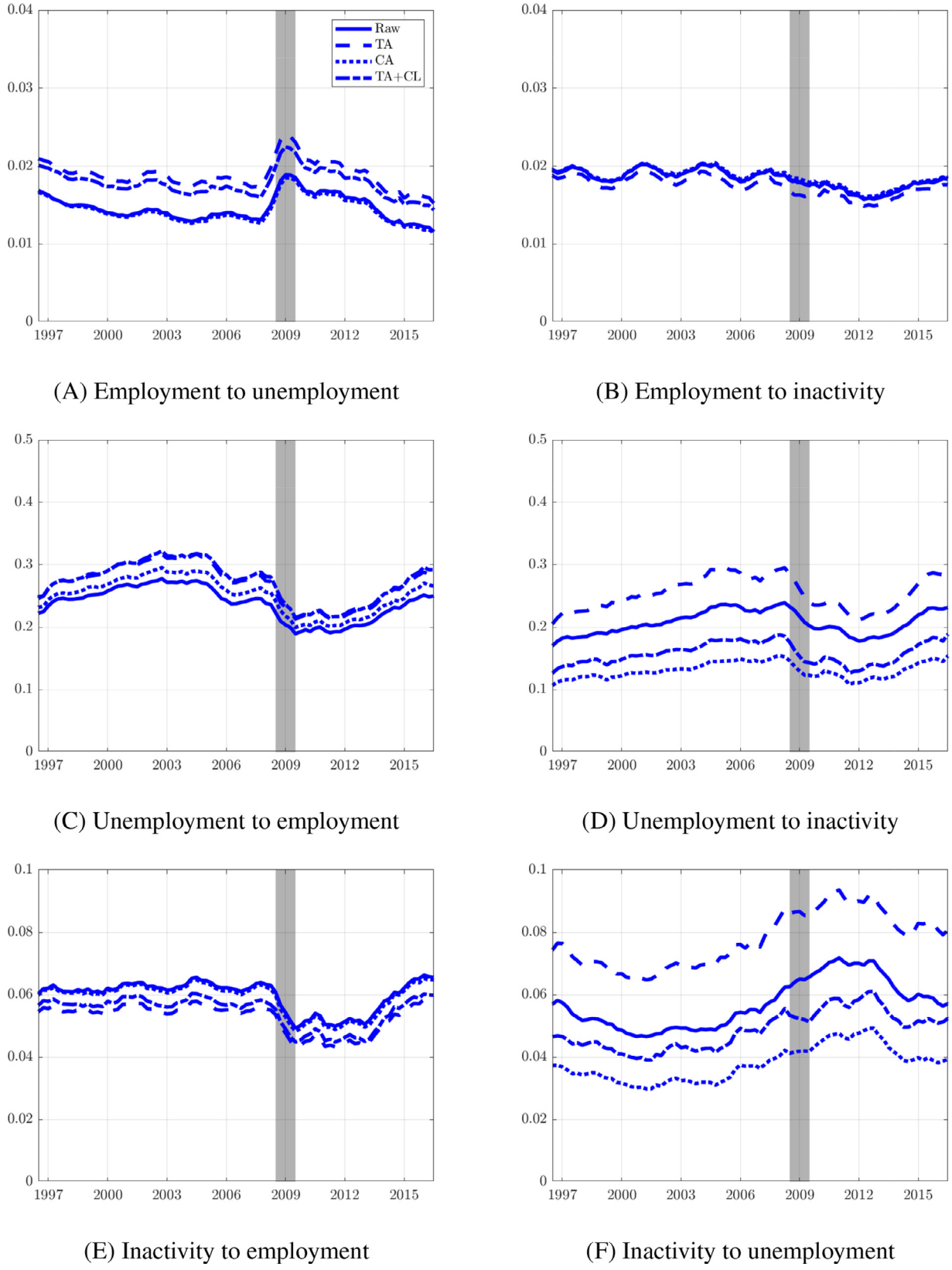


Fig. A4. The UK quarterly worker flows over different adjustments. *Note:* All probabilities adjusted for margin error and seasonality. TA refers to time aggregation adjusted, and CA refers to classification error adjusted. The shaded area denotes the officially defined UK Great Recession. Source: Author calculations using the LFS, ages 16–64/59, 1996q1-2016q4.

Appendix B. Additional tables

Table B1 shows the results from a decomposition of unemployment variation into the contributions that are due to changes in the six worker flows. I also conduct the analysis on CPS data over the same period for comparison. The results are similar between the CPS and SIPP.

Table B1
Standard decomposition - worker flows.

	(1) *eu*	(2) *en*	(3) *ue*	(4) *un*	(5) *ne*	(6) *nu*
US SIPP	44.0	1.08	26.8	11.7	-1.47	18.4
US CPS	29.4	-2.40	35.2	12.5	5.80	20.6
UK	23.3	-1.26	30.6	17.3	4.76	15.2

Note: The interpretation of the top left cell is: the past and present fluctuations in the employment to unemployment probability contributes to 44.0% of the dynamics of the unemployment rate. Source: Author calculations using the SIPP, CPS and LFS. Ages 16–64/59. US SIPP and CPS 1996m4-2013m5. UK 1996q1-2016q4.

Table B2
Allowing for all reasons for separation and across different data adjustments for the US.

	(1) *Raw*	(2) *TA*	(3) *CA*	(4) *TA + CA*
sep^I	25.4	24.7	25.6	24.7
sep^T	-3.58	-3.68	-3.56	-3.66
sep^U	2.74	2.43	2.67	2.34
sep^P	-1.05	-1.25	-1.13	-1.31
sep^O	0.36	0.19	0.23	0.06
$lf|sep^I$	3.52	3.21	4.02	3.76
$lf|sep^T$	0.33	0.33	0.27	0.28
$lf|sep^U$	-0.30	-0.29	-0.29	-0.29
$lf|sep^P$	-0.03	-0.03	-0.05	-0.06
$lf|sep^O$	-0.17	-0.18	-0.15	-0.16
$jj|lfsep^I$	8.05	6.86	8.63	7.43
$jj|lfsep^T$	2.84	2.73	2.99	2.88
$jj|lfsep^U$	2.92	2.61	3.23	2.92
$jj|lfsep^P$	1.70	1.54	1.58	1.43
$jj|lfsep^O$	2.60	2.3	2.74	2.45
ue	26.8	31.7	28.6	33.7
un	11.7	14.50	12.0	14.4
entry	-0.64	-1.36	-1.90	-2.60
e|entry	17.5	16.2	15.2	14.2
resid	-0.71	-2.50	-0.61	-2.50

Note: The interpretation of the top left cell is, the past and present fluctuations in the involuntary separation probability contributes to 25.4% of the dynamics of the unemployment rate. All probabilities adjusted for margin error and seasonality. TA refers to time aggregation adjusted, and CA refers to classification error adjusted. Details of all adjustments can be found in the Online Appendix. Source: Author calculations using the SIPP. Ages 16–64/59. US 1996m4-2013m5.

Table B3
Allowing for all reasons for separation and across different data adjustments for the UK.

	(1) *Raw*	(2) *TA*	(3) *CA*	(4) *TA + CA*
sep^I	12.4	11.3	12.9	11.7
sep^{T+U}	-8.88	-8.88	-9.14	-9.23
sep^P	-2.53	-2.98	-2.18	-2.45
sep^O	-3.03	-3.35	-2.96	-3.26
$lf|sep^I$	1.36	0.73	1.63	1.11
$lf|sep^{T+U}$	1.14	1.14	0.86	1.02
$lf|sep^P$	-0.04	0.03	-0.10	-0.14
$lf|sep^O$	0.98	0.83	0.90	0.87
$jj|lfsep^I$	8.46	6.44	9.23	7.29
$jj|lfsep^{T+U}$	14.6	12.9	15.4	13.9
$jj|lfsep^P$	1.62	1.27	1.63	1.31
$jj|lfsep^O$	5.69	5.05	6.06	5.49
ue	30.6	41.7	34.7	46.2
un	17.3	27.1	15.6	22.0
entry	-3.38	-5.96	-4.73	-6.44
e|entry	23.2	17.2	19.9	16.1
resid	0.48	-4.58	0.25	-5.54

Note: The interpretation of the top left cell is, the past and present fluctuations in the involuntary separation probability contributes to 12.4% of the dynamics of the unemployment rate. All probabilities adjusted for margin error and seasonality. TA refers to time aggregation adjusted, and CA refers to classification error adjusted. Details of all adjustments can be found in the Online Appendix. Source: Author calculations using the Two-Quarter LFS. Ages 16–64/59. UK 1996q1-2016q4.

Appendix C. Heterogeneity

To assess the changing composition effect, I follow the same method as Shimer (2012) and decompose probability $d \in \{jj|lfsep, e|entry\}$ as

$$p_t^d = \sum_g w_{g,t}^d p_{g,t}^d, \tag{11}$$

where g corresponds to the type of the individual and $w_{g,t}^d$ corresponds to the percentage of those type g individuals who separated and remained in the labour force, entered the labour force, or are in the unemployment pool at time t. I estimate the composition effect by keeping $p_{g,t}^d$ fixed at the average and allow $w_{g,t}^d$ to vary. The composition effect is given as

$$C_{type}^d = \frac{cov(\sum_g \overline{p}_{g,t}^d \; w_{g,t}^d, \; p_t^d)}{var(p_t^d)}. \tag{12}$$

Table C1 shows the three probabilities disaggregated by potential salient types: age, sex, education, relationship to head of household, reason for separation from last job, reason for on-the-job search and tenure, and also shows the magnitude of the composition effect for each type. The interpretation of the US $C_{age}^{jj|lfsep}$, for example, is: compositional shifts in the age of those who separate and remain in the labour force contribute to 2.8% of the fluctuations in the $JJ|LFSep$ probability. The Online Appendix provides further discussion of the results.

Table C1
Heterogeneity in the job finding probabilities.

	US		UK	
Type	$p_g^{jj\|lfsep}$	$p_g^{e\|entry}$	$p_g^{jj\|lfsep}$	$p_g^{e\|entry}$
AGE				
16 – 20	71.5	64.9	59.9	57.0
21 – 30	71.9	63.8	68.3	52.8
31 – 40	69.8	61.5	69.8	49.0
41 – 50	66.4	61.9	64.0	50.1
51 – 64/59	65.7	65.2	55.3	54.6
C_{age}^d	2.8	1.0	0.4	-1.7
SEX				
Male	68.4	62.9	62.1	50.9
Female	71.3	64.4	68.8	55.9
C_{sex}^d	0.8	0.3	0.8	0.6
EDUCATION				
Degree or more	76.7	72.8	71.5	62.0
More than school	71.4	67.5	68.4	62.1
School or less	65.0	59.0	60.1	48.5
C_{ed}^d	-3.0	-2.9	-6.5	-5.6
RELATIONSHIP TO HEAD OF HOUSEHOLD				
Head			64.6	45.1
Partner			71.6	58.8
Child			61.0	57.2
C_{hhd}^d			0.1	0.4
REASON FOR ON – THE – JOB SEARCH				
Worried			62.2	
Unsatisfactory			69.1	
Other			72.2	
Not searching			63.2	
C_{ojs}^d			-0.6	
TENURE (months)				
Less than 3			57.8	
3 – 12			61.3	
Greater than 12			67.6	
C_{ten}^d			-3.0	
TEMP JOB				
Yes			59.1	
No			66.4	
C_{temp}^d			0.4	

Note: Probabilities based on measures unadjusted for margin error and seasonality. The interpretation of $C_{age}^{jj|lfsep}$ for the UK is: changes in the composition of the age of separators contribute to 0.4% of the fluctuations in the $JJ|LFSep$ probability. Source: Author calculations using SIPP and LFS. Ages 16–64/59. The data spans 1996q1-2016q4 for the LFS and 1996m4-2013m5 for the SIPP.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.labeco.2022.102304.

References

Abowd, J.M., Zellner, A., 1985. Estimating gross labor-force flows. J. Bus. Econ. Stat. 3 (3), 254–283.
Ahn, H.J., Shao, L., 2021. The cyclicality of on-the-job search effort. B.E. J. Macroecon. 21 (1), 185–220.
Akerlof, A.G., Rose, A.K., Yellen, J.L., 1988. Job switching and job satisfaction in the U.S. labor market. Brookings Pap. Econ. Act. 2, 495–594.
Anderson, P.M., Meyer, B.D., 1994. The extent and consequences of job turnover. Brookings Pap. Econ. Act. 177–236.
Bachmann, R., 2005. Labour Market Dynamics in Germany: Hirings, Separations and Job–to-job Transitions Over the Business Cycle. SFB Discussion Paper 45. Humboldt University.
Bachmann, R., Sinning, M., 2016. Decomposing the ins and outs of cyclical unemployment. Oxf. Bull. Econ. Stat. 78 (6), 853–876.
Burdett, K., Mortensen, D.T., 1998. Wage differentials, employer size, and unemployment. Int. Econ. Rev. 39 (2), 257–273.
Cahuc, P., Postel-Vinay, F., Robin, J.-M., 2006. Wage bargaining with on-the-job search: theory and evidence. Econometrica 74 (2), 323–364.
Carrillo-Tudela, C., Clymo, A., Coles, M., 2022. Wage Bargaining with On-the-job Search: Theory and Evidence. IZA Discussion Paper 14869.
Darby, M., Haltiwanger, J., Plant, M., 1985. Unemployment rate dynamics and persistent unemployment under rational expectations. Am. Econ. Rev. 75 (4), 614–637.
Darby, M., Haltiwanger, J., Plant, M., 1986. The Ins and Outs of Unemployment: The Ins Win. National Bureau of Economic Research Working Paper.
Davis, S., Faberman, J., Haltiwanger, J., 2012. Labor market flows in the cross section and over time. J. Monet. Econ. 59 (1), 1–18.
Davis, S., Haltiwanger, J., 1992. Gross job creation, gross job destruction, and employment reallocation. Q. J. Econ. 107 (3), 818–863.
Elsby, M., Gottfries, A., Michaels, R., Ratner, D., 2022. Vacancy Chains. mimeo.
Elsby, M., Hobijn, B., Sahin, A., 2010. The labor market in the Great Recession. Brookings Pap. Econ. Act. 2, 1–48.
Elsby, M., Hobijn, B., Sahin, A., 2013. Unemployment dynamics in the OECD. Rev. Econ. Stat. 95 (2), 530–548.
Elsby, M., Hobijn, B., Sahin, A., 2015. On the importance of the participation margin for labor market fluctuations. J. Monet. Econ. 72, 64–82.
Elsby, M., Michaels, R., Solon, G., 2009. The ins and outs of cyclical unemployment. Am. Econ. J. Macroecon. 72, 64–82.
Elsby, M., Smith, J.C., Wadsworth, J., 2016. Population Growth, Immigration, and Labour Market Dynamics. mimeo.
Faberman, J.R., Mueller, A.I., Şahin, A., Topa, G., 2022. Job search behavior among the employed and non-employed. Econometrica 90 (4), 1743–1779.
Fujita, S., Moscarini, G., Postel-Vinay, F., 2020. Measuring Employer-to-Employer Reallocation. mimeo.
Fujita, S., Ramey, G., 2009. The cyclicality of separation and job finding rates. Int. Econ. Rev. 50 (2), 414–430.
Garibaldi, P., 2004. Search unemployment with advance notice. Macroecon. Dyn. 8 (1), 51–75.
Gomes, P., 2012. Labour market flows: facts from the United Kingdom. Labour Econ. 19 (2), 165–175.
Hall, R., 2005. Job loss, job finding, and unemployment in the U.S. economy over the past fifty years. Natl. Bureau Econ. Res. Macroecon.Annu. 20, 101–137.
Jarosch, G., 2021. Searching for Job Security and the Consequences of Job Loss. National Bureau of Economic Research Working Paper 28481.
Jolivet, G., Postel-Vinay, F., Robin, J.-M., 2006. The empirical content of the job search model: labor mobility and wage distributions in Europe and the US. Eur. Econ. Rev. 50, 877–907.
Jones, S.R.G., Riddell, W.C., 2019. Unemployment, marginal attachment, and labor force participation in Canada and the United States. J. Labor Econ. 37 (S2), 399–441.
Krusell, P., Mukoyama, T., Rogerson, R., Şahin, A., 2017. Gross worker flows over the business cycle. Am. Econ. Rev. 107 (11), 3447–3476.
Kudlyak, M., Lange, F., 2018. Measuring Heterogeneity in the Job Finding Rates Among the Non-employed Using Labor Force Status Histories. Federal Reserve Bank of San Francisco Working Paper 2017-20.
Lydon, R., Simmons, M., 2020. The ins and outs of the gender unemployment gap in the OECD. Cent. Bank Ireland Res. Tech. Pap. 2020 (8), 1–55.
Mukoyama, T., 2014. The cyclicality of job-to-job transitions and its implications for aggregate productivity. J. Econ. Dyn. Control 39, 1–17.
Mukoyama, T., Patterson, C., Şahin, A., 2017. Job search behaviour over the business cycle. Am. Econ. J. Macroecon. 10, 190–215.
Nagypal, E., 2005. On the Extent of Job-to-Job Transitions. mimeo.
Nagypal, E., 2008. Worker Reallocation Over the Business Cycle: The Importance of Employer-Employer Transitions. mimeo.
Perry, G.L., 1972. Biases in the Reporting of Labour Market Dynamics. Institute for Fiscal Studies Working Paper 02/10.
Perry, G.L., 1972. Unemployment flows in the U.S. labour market. Brookings Pap. Econ. Act. 2, 245–278.
Petrongolo, B., Pissarides, C., 2008. The ins and outs of european unemployment. Am. Econ. Rev. Pap. Proc. 98 (2), 256–262.
Pissarides, C., 2000. Equilibrium Unemployment Theory, second ed. MIT Press.
Postel-Vinay, F., Robin, J.-M., 2002. Equilibrium wage dispersion with worker and employer heterogeneity. Econometrica 70 (6), 2295–2350.
Postel-Vinay, F., Robin, J.-M., 2002. The distribution of earnings in an equilibrium search model with state-dependent offers and counteroffers. Int. Econ. Rev. 43 (4), 989–1016.
Poterba, J.M., Summers, L.H., 1986. Reporting errors and labor market dynamics. Econometrica 54 (6), 1319–1338.
Shimer, R., 2012. Reassessing the ins and outs of unemployment. Rev. Econ. Dyn. 15 (2), 127–148.
Simmons, M., 2021. Pre-Layoff Search. mimeo.
Slichter, S.H., 1919. The Turnover of Factory Labor. D. Appleton and Company, New York.
Smith, J.C., 2012. The ins and outs of UK unemployment. Econ. J. 121 (552), 402–444.
Tjaden, V., Wellschmied, F., 2014. Quantifying the contribution of search to wage inequality. Am. Econ. J. Macroecon. 6 (1), 134–161.