On gross worker flows in the United Kingdom: evidence from the Labour Force Survey

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Abstract

Empirical studies of worker flows in the United States and Europe have found that these flows are large when compared with the change in the stocks of employment and non-employment and have a distinct cyclical pattern. In the United Kingdom, studies of this kind have been hampered by limitations in the available data. In this paper we make use of newly released longitudinal data from the Labour Force Survey. We show that on average since 1993, 7.3% of those in the working-age population have changed labour market state in a given three-month period. This compares with a consistently calculated annual figure of 12.5%. In addition, we present an array of evidence to show that UK gross flows appear to follow a similar cyclical pattern to those found in other countries. We also present evidence on the potential problems that previous research may suffer from with their use of recall data to determine prior labour market status. While stocks are similar using recall or recorded labour market state, flows inferred from recall data are severely biased by recall error.

Summary

Empirical studies of worker flows in the United States and Europe have found that these flows are large when compared with the change in the stocks of employment and non-employment and have a distinct cyclical pattern. In the United Kingdom, studies of this kind have been hampered by limitations in the available data. In this paper we make use of newly released longitudinal data from the Labour Force Survey (LFS) to document the size and cyclical patterns of the gross worker flows in the United Kingdom.

The motivation for considering gross worker flows is a simple one: to uncover what lies behind the headline levels of – and changes in – key statistics such as employment and unemployment. In particular, data on gross worker flows allow us to observe two features of these flows: their magnitude and cyclical properties. The magnitude of worker flows may allow us to gauge the flexibility of an economy, as the rate at which workers flow from less efficient plants to more efficient ones will affect how quickly an economy responds to economic shocks. And the cyclical properties of the gross flows allow us to uncover how labour demand is met over the business cycle. In short, the availability of data on gross worker flows allows us to go behind the aggregate stock data to examine the nature of labour market dynamics.

Data on gross flows may be affected by measurement biases to a greater extent than the levels data. In particular, sample attrition and response error may cause errors in estimating the flows. We test this by looking at the number of ‘inconsistent’ transitions. In the LFS, individuals in employment and unemployment are asked not only about their current state, but also how long they have been in that state. If the duration contradicts the transition, then the transition is ‘inconsistent’. We observe a significant level of inconsistent transitions, but suspect that most of the error occurs because individuals are unclear as to their exact duration in any state rather than about their current state. To the extent that these transitions are not genuine, they will lead to overestimation of the gross flows.

Over the past five years, the stock of unemployed fell by an average of 40,000 per quarter. Given an average stock of 1.9 million, this may seem to suggest that the market for labour can be characterised as fairly static. Yet such a conclusion would be wrong. We find that, over the same period, almost three-quarters of a million people entered unemployment in a quarter, with numbers drawn equally from employment and inactivity. Similarly, almost one million people start a new job each quarter after previously being unemployed or inactive.

Theoretical models of labour market flows generate predictions about the cyclical pattern of flows and associated hazard rates (the chances of making a transition from a given labour market state to another). These predictions can be tested using the LFS longitudinal data. In particular, we examine the cyclicality of both the gross flows and the associated hazard rates in the United Kingdom using a variety of data and techniques. We find that:

1. Flows from employment to unemployment are countercyclical, as is the hazard rate. The reverse flow, from unemployment to employment, is also countercyclical – while its associated hazard is strongly procyclical.
2. Flows from employment to inactivity tend to be procyclical and there is no clear pattern to the associated hazard rate. Flows from unemployment to inactivity appear to be countercyclical.
3. Flows and hazards from inactivity are imprecisely measured, and we cannot be confident of any statement on their cyclical characteristics.
4. Flows of workers moving from one job to another, without a recorded period of unemployment or inactivity, are strongly procyclical.

These findings are broadly consistent with similar results for the United States and Europe.

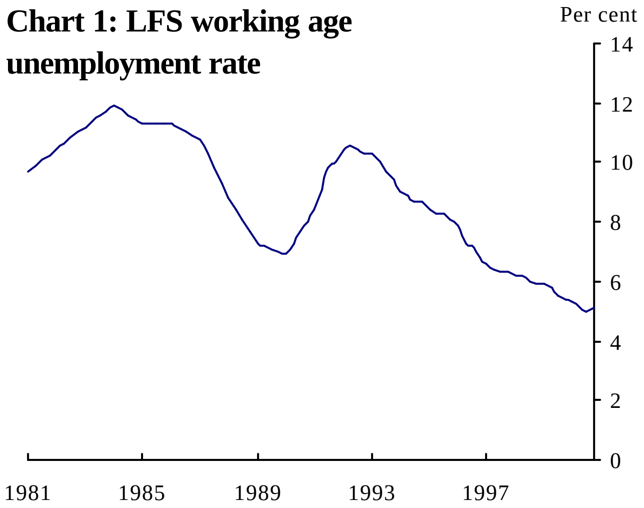
In addition, we are also able to measure the incidence of job-to-job flows. Little is known about these flows in the United Kingdom and previous research has tended to focus on the prevalence of on-the-job search without knowing whether that search was successful. We show that 2.9% of those in employment change employer in an average quarter. This represents a movement of three-quarters of a million workers. Unsurprisingly, the probability of making such a move is much higher for those who are engaged in on-the-job search. Such movements tend to occur much more frequently for workers with short tenure in their initial job. This is consistent with the model of Pissarides (1994) which suggests that individuals search on the job when they are in poor matches. As tenure lengthens and job-specific human capital is acquired, the incentive to move jobs falls.

1. Introduction

The motivation for considering gross worker flows is a simple one: to uncover what lies behind the headline employment, and non-employment rates. In particular, data on gross worker flows allow us to observe two features of these flows: their magnitude and cyclical properties. The magnitude of worker flows may allow us to gauge the flexibility of an economy, as the rate at which workers flow from less efficient plants to more efficient ones will affect how a country responds to economic shocks.[(1)] Disaggregated data on gross worker flows over time help us to understand how the process of worker allocation evolves over the business cycle. For example, does the increase in employment during an upturn come from those not participating in the labour market moving into employment, or from the pool of unemployed workers moving to jobs? These data can also provide evidence on whether the fall in employment during a recession is driven by firms sacking workers (increased job destruction) or by a fall in recruitment (decreased job creation).

In the United Kingdom, unemployment increased considerably in the 1980s before falling back sharply (see Chart 1). It is generally accepted that increases in the UK unemployment rate over this period can be attributed to a fall in the outflow rate from unemployment with the inflow rate remaining stable.[(2)] In this paper we will use longitudinal data to show that, in contrast, the fall in unemployment since 1993 has been caused by a drop in both inflow and outflow rates, with the inflow rate declining more steeply than the outflow rate over the sample period.

Chart 1: LFS working age unemployment rate



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(1) Assuming of course that workers do on average flow from less to more productive plants (see Foster, Haltiwanger and Krizan (1998) for evidence on this).
(2) Layard, Nickell and Jackman (1991), Chapter 5, Table 3. A recent contrarian view is presented by Burgess and Turon (2000).

Data from the LFS longitudinal dataset show that around 7.3% of workers change jobs or labour market state each quarter. And the cyclical pattern of these worker flows is similar to that found in other countries. Flows between employment and unemployment seem to be countercyclical and flows between employment and inactivity appearing to be procyclical. UK gross worker flows are generally larger than those of other European countries but are smaller than those in the United States.

In Section 2 we will give a brief review of some theoretical models of worker flows and highlight the predictions these models have for the cyclicality of flows between different labour market states. Section 3 will, briefly, outline some of the existing empirical evidence on gross worker flows in OECD countries. In Section 4 we outline the dataset that we shall be using and highlight some of the pitfalls that inevitably occur in the use of such data. Section 5 presents the evidence on gross flows and examines the time-series properties of the data. We also compare measures using recall data and discuss the implications. Our conclusions then follow in Section 6.

2. Theoretical perspectives

It is helpful to begin with some perspective on the predictions of theoretical models for gross flows. Our aim in this section is not to provide a thorough review of the theoretical literature, rather to highlight a few simple models and predictions. The most useful way to think of the flows within the labour market are the search models developed principally by Mortensen and Pissarides (eg Pissarides (2000) and Mortensen and Pissarides (1994)). A simple presentation of the flow approach to labour markets is given by Blanchard and Diamond (1992). They have a model with three components: (i) a specification of labour demand in terms of gross flows of job destruction, x, and job creation, y; (ii) a matching function; and (iii) a specification for the determination of wages.

In this bare-bones model, labour demand is simply:

$$x = x(w,q_x)$$
$$y = y(w,q_y)$$

where w is the wage and the q's shift job creation and destruction. In this simple model, all flows come from the process of creation and destruction. Hiring occurs with a standard constant-returns matching function of the form:

$$h = m(u, v)$$

where h is total hires, u is unemployment and v denotes vacancies. Finally, wages can be set by many different methods. If, for example, they are set to deter shirking, then the wage will depend on the probability of finding a job when unemployed, *m/u*. Under constant returns in the matching technology, this depends only on *v/u* so that:

$$w = w(v/u)$$

Putting all this together gives two dynamic equations for unemployment and vacancies:

$$du/dt = x[w(v/u), q_x] - m(u, v)$$
$$dv/dt = y[w(v/u), q_y] - m(u, v)$$

Shocks to aggregate activity lead to opposite shifts in job creation and destruction. Workers will move between labour market states and jobs for a number of reasons unrelated to job destruction and job creation (eg health, education and career advancement). But job reallocation necessitates worker reallocation. Therefore, we expect the number of workers moving from employment to unemployment (and inactivity) to be countercyclical as jobs are destroyed, while the movement from unemployment to employment should be procyclical as job creation falls.

We must be careful here in distinguishing between flows and hazard rates. The flow is simply the number of people flowing from one state to another, while the hazard rate is the probability of moving from one state to another. During a recession, the hazard rate from U to E should fall. However, since the stock of unemployed is rising, the actual flow from U to E may *increase* since the matching function implies that, *ceteris paribus*, a larger stock of unemployed leads to more hires. Hence the hazard rate of U to E should be procyclical while the flow from U to E can be countercyclical. Blanchard and Diamond suggest quits can be incorporated into the model by allowing for employed workers in bad matches to search. This is the essential feature of Pissarides (1994) discussed below.

Pissarides (2000) discusses the issue of labour force participation (or equivalently inactivity) within the standard search model. Individuals enjoy leisure, l, when out of the labour force, which is greater than leisure during search, because individuals can concentrate on leisure full-time and avoid any search costs. It follows that for an individual to participate, l must be strictly less than the reservation wage, r. If l is drawn from a cumulative density, $H(l)$, then the fraction of the population that participates is $H(r)$. Given the usual specification for the reservation wage, it follows that participation is higher when wages are higher, labour market tightness is greater and the rates of interest and job loss are lower. Hence we might expect flows from inactivity into both employment and unemployment to be procyclical, as labour market tightness rises as the employment rate increases.[3]

Blanchard and Diamond (1990) suggest a mechanism that allows for differential effects from the unemployed and the inactive. In their model, 'primary' workers have high labour force attachment and brief spells of unemployment. In contrast, 'secondary' workers have much weaker labour force attachment and are likely to spend significant time both in unemployment and inactivity. Search behaviour is likely to differ between the two types of workers and firms may perceive these workers differently with a preference for hiring primary workers over secondary workers and firing secondary workers first.

As in the previous model, we have an aggregate matching function, where hires, *h*, are a function of vacancies and the pool of non-employed workers. The matching function is then:

$$h = m[(u+i), v]$$

where *i* are the inactive. Blanchard and Diamond assume that firms *rank* primary workers above secondary workers. This implies that the matching function for primary workers is given by:

$$h_1 = m_1(u, v)$$

where *i* does not appear. Conditional on vacancies, an increase in secondary workers has no effect on the employment prospects of unemployed primary workers. Finally, the hiring function of secondary workers is given by $h_2 = h - h_1$. Note that this structure implies that unemployment has a negative effect on the hires of secondary workers. Since secondary workers are often inactive, this means that flows from inactivity to employment are likely to be greater when unemployment is low, ie procyclical.

(3) This is not quite correct since Pissarides's definition of tightness is a function of the *u/v* ratio rather than the employment rate. However over the period of our data there is a very strong negative correlation between the employment rate and *u/v*.

Finally, we are also able to derive a series for the flow from unemployment to employment. Pissarides (1994) presents a model with on-the-job search. In his model, there are two types of jobs, ‘good’ and ‘bad’. Unemployed job seekers will accept either type while employed job seekers will only accept good jobs. Employed workers only search if they are in bad jobs. However, on-the-job search mainly occurs at short job tenures because the accumulation of job-specific human capital ensures that at some point, t, the wage growth in the bad job offsets all the benefits of switching to a good job with zero tenure. In response to a rise in aggregate activity, t increases because there are more job vacancies and the expected cost of search is lower. However, as workers in bad jobs succeed in finding good jobs, there are fewer workers in bad jobs at all tenures. Hence employment in bad jobs falls but workers in them search longer. This implies an ambiguity in the response of the steady-state number of employed job seekers to a rise in aggregate activity. But, in the adjustment from one state to the other, the number of employed job seekers first increases, then decreases. Therefore, at least in the beginning of the cycle, we expect job-to-job movements to be procyclical.

To summarise: we expect the flows out of employment to be countercyclical, flows between jobs to be procyclical, flows from inactivity to employment to be procyclical and no clear pattern for flows between unemployment and inactivity. The hazard rate from U to E should be procyclical while the flow from U to E may be countercyclical.

3. Previous empirical evidence

Some preliminaries

Before discussing the findings of previous studies on worker flows, it is useful to outline our notation and timing conventions and to spell out the indicators that are useful in analysing cyclical and trend variations in worker flows. We start with the stocks of the three labour market states: employment (*E)*, unemployment (*U*) and inactivity (*I*), which sum to the population, L:

ie, $E + U + I = L$

The levels of those in employment at the end of period *t* equal the number of people in employment at the start of the period *plus* those entering from other states *less* those becoming unemployed or inactive:[(4)]

$$\begin{matrix} \textit{Employment} \\ \textit{at time } t+1 \end{matrix} = \begin{matrix} \textit{Employment} \\ \textit{at } t \end{matrix} + \begin{matrix} \textit{Inflows to employment} \\ \textit{during period } t \end{matrix} - \begin{matrix} \textit{outflows from employment} \\ \textit{during period } t \end{matrix}$$

Using A_t^E to denote the number of people who flow into employment during period *t*, and B_t^E as the outflow from employment during period *t*, we can use the diagram below to illustrate how changes in employment occur over time:

levels:	E_t		E_{t+1}		E_{t+2}
flows:		$A_t^E - B_t^E$		$A_{t+1}^E - B_{t+1}^E$	

Extending the convention above by using A_t^J to denote the number of people flowing into state *J* (*J*=*E, U, I*) during period *t*, and B_t^J to denote the number of people leaving state *J* during period *t*, we can define a simple intertemporal constraint for each labour market state:

$$E_{t+1} = E_t + A_t^E - B_t^E$$
$$U_{t+1} = U_t + A_t^U - B_t^U$$
$$I_{t+1} = I_t + A_t^I - B_t^I$$

Using the notation above, we can define the probability of the non-employed entering employment during *t*, a_t^E as:

$$\frac{\textit{Number of people entering employment from U or I during period t}}{\textit{Total non-employed at the begining of period t}}, \text{ or } \frac{A_t^E}{L - E_t}$$

Similarly, we can define the probability of leaving employment during period *t*, b_t^E :

$$\frac{\textit{Number of people leaving employment during period t}}{\textit{Total employed at the begining of period t}}, \text{ or } \frac{B_t^E}{E_t}$$

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(4) Under the assumption of a steady-state population – ie: $L_{t+1} = L_t = L$.

Using the above expressions (and the equivalent for unemployment and inactivity) and normalising our original constraints using the population, L:

$$e_{t+1} = e_t + a_t^E(1-e_t) - b_t^E e_t \text{, or } e_{t+1} = e_t(1-a_t^E - b_t^E) + a_t^E$$
$$u_{t+1} = u_t + a_t^U(1-u_t) - b_t^U u_t \text{, or } u_{t+1} = u_t(1-a_t^U - b_t^U) + a_t^U$$
$$i_{t+1} = i_t + a_t^I(1-i_t) - b_t^I i_t \text{, or } i_{t+1} = i_t(1-a_t^I - b_t^I) + a_t^I$$

The expressions above link changes in employment and non-employment rates to the gross flows. Taking the example of the employment rate:

$$\Delta e = \alpha_t^E \, (1 - e_t) - ß_t^E \, e_t$$

Change in the emp rate	prob flowing into emp	Non-emp rate	prob of leaving emp	emp rate

Hence, we can decompose any change in the employment rate into the probability of flowing between states (ie the a and b terms) and the number of people in a specific state at the beginning of the period (ie the employment and non-employment rates).

Although there are number of indicators that we could use to examine the properties of the gross flows, there are two that are particularly important in the framework above. First, the rate at which workers move into and out of labour market states, independent of the size of the pool from which they came – the probabilities or hazard rates. Second, in order to evaluate changes in the employment rate caused by inflows and outflows we must look at the flows normalised by the population (ie $a_t^E(1-e_t) = \frac{A_t^E}{L}$ for inflows and $b_t^E e_t = \frac{B_t^E}{L}$ for outflows).

As outlined in Section 2, we are not simply interested in flows in and out of labour market states but also the flows between them. Therefore, we decompose the flows and hazards defined above into their components. For example, A_t^E is made up of flows from I to E and flows from U to E. We use the '$\rightarrow$' symbol to denote a labour market flow between individual labour market states. For example, the $E \rightarrow U$ flow is the movement of a worker from employment to unemployment during period t. For simplicity we also use the '$\rightarrow$' symbol to denote inflows to a particular labour market state, eg '$\rightarrow$E' will denote A_t^E and 'E$\rightarrow$' will denote B_t^E.

Gross worker flows in the United States

We shall concentrate on two studies for the United States. Blanchard and Diamond ((1990), henceforth B&D) consider CPS data from 1968-86 while Bleakley *et al* (1999) use CPS data from 1976-99. Both of these studies report gross worker flows relative to the working-age population and the business cycle properties of these flows.

(i) Size of monthly gross flows

Table A provides evidence from the two papers on US flows. Three facts emerge quite strongly from this. First, during the recent expansion in the United States, gross worker flows have stayed close to their long-run averages.[(5)] Second, flows from *I* to *E* are as large, if not larger than those from *U* to *E*. This confirms the view that the inactive category is an important source of labour supply. Finally, according to the measure presented by Bleakley *et al*, 6.4% of the US working-age population change labour market status every *month.*

Table A: Average monthly gross flows in the United States
(% of working-age population)

	E®U	*E®I*	*U®E*	*U®I*	*I®E*	*I®U*
B&D (1968-86)	0.8	1.0	1.0	0.5	1.0	0.6
Bleakley *et al* (1994-98)	0.8	1.7	1.0	0.8	1.5	0.6

While the US data are well established, they are not comprehensive. As a result, B&D and Bleakley *et al* have little information on flows of workers between jobs (job-to-job flows). While these flows are unimportant in accounting for changes in the levels of *E*, *U* and *I,* they are important in analysing overall labour market activity. Fallick and Fleischman (2001) take advantage of CPS 'dependent interviewing'[(6)] to construct a measure of job-to-job flows. They find that job-to-job flows are significant: on average 2.7% of those employed change employer in

[(5)] The exception to this is the flows between $E \rightarrow I$ and $I \rightarrow E$. The increase in these gross flows is consistent with their cyclical properties discussed below.
[(6)] Rather than re-asking questions, CPS interviewers refer to answers given at the last interview. So rather than asking industry etc of employer, they only ask more detailed questions if the employer has changed.

a given month. In addition to the large size of the flows, they find no evidence that the flows are procyclical for their sample period (flows since 1994).

(ii) Cyclicality and other properties of gross flows

There are a number of findings that are common to both papers focusing on the United States. First, the amplitude (volatility) of time series fluctuations in $E\rightarrow$ is much greater than for $\rightarrow E$. This is surprising if one considers that we would intuitively expect cyclical fluctuations in $\rightarrow E$ to exceed $E\rightarrow$, if the process of job creation and job destruction is symmetrical. This is because the properties of $E\rightarrow$ should be self-nullifying to some extent (in a downturn higher job destruction will be offset by lower quits), whereas the business cycle properties of $\rightarrow E$ are likely to be self-reinforcing (in a downturn less jobs will be created and those who quit are less likely to be replaced). The conclusion from this is that job destruction is more important in driving the business cycle properties of worker flows than job creation.[7]

The second interesting finding from these studies is the differing behaviour of $I\rightarrow E$ and $U\rightarrow E$ flows. B&D observe that half of the flow into E comes from I, but the cyclical properties of these flows are quite different. Flows between I and E are procyclical whereas flows between U and E are countercyclical. B&D suggest that their model of 'primary' and 'secondary' workers discussed in Section 2 can explain this.

Gross labour market flows in Europe

As in the US case, we are interested in the size and pattern of gross flows in Europe. However, data availability for European worker gross flows is scarce, prompting researchers to come up with a number of ways of estimating gross flows. In particular, Burda and Wyplosz (1994) build a series of stylised facts for gross worker flows in Europe. There are also a number of studies that focus on individual countries. For example, Blanchard and Portugal (2001) focus on Portugal, Balakrishnan (2001) on Spain and Schmidt (1999) on Germany. In this section we focus on the data survey by Burda and Wyplosz (1994) and only cite the other studies when their evidence is contradictory.

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[7] Darby, Haltiwanger and Plant (1986) examine the net worker flows into and out of unemployment for the United States and find that changes in inflows typically lead changes in outflows.

(i) The size of gross worker flows

Due to data limitations, the studies listed above do not provide data directly comparable to those in Table A. As an alternative, we have reworked Table A from Burda and Wyplosz, which provides evidence on the relative size of *annual* European worker flows. These figures are given in Table B.

Table B: Annual gross labour market flows in 1987 (percentage)

Country	®*U*(a)	*U*®(a)	®*E*(b)	*E*®(b)
France	151	151	29	31
Germany	149	146	22	21
Spain	221	212	-	-
United Kingdom (manufacturing)	112	129	7	7
United States	238	243	25	27
Japan	118	116	9	9

(a) These data are given as a percentage of the stock of *U*.

(b) These data are given as a percentage of the stock of *E*.

There are a number of issues regarding the comparability of the data in the Table B. First, the data for the United States and Japan are from household surveys and are therefore not directly comparable to the European data which, for the most part, are derived from administrative sources.[8] Second, the data in Table B are annual. It is not possible to interpolate monthly or quarterly data from annual data because annual data miss a number of short-term transitions. For example, a worker who moves from inactivity to employment via unemployment in a short space of time will be registered as an $I \rightarrow E$ transition rather than making an initial $I \rightarrow U$ transition followed by a $U \rightarrow E$ transition. Blanchard and Portugal (2001), comparing the United States to Portugal, find that on an annual basis the two economies have relatively similar gross worker flows. However, when they construct a quarterly series they find that Portugal has flows only one-quarter the size of those in the United States. This is due to the high number of short-term transitions in the United States that are missed in annual data. Therefore, it is not possible to make an adequate comparison of European and US labour markets based on annual data. This emphasises the need to take into account the frequency of data when making cross-country comparisons.

[8] The data for the United Kingdom are taken from the *Employment Gazette* and are for the manufacturing sector only.

(ii) Cyclicality and other properties of gross worker flows

Due to data limitations, Burda and Wyplosz have a definition of employment inflows and outflows such that they include job-to-job moves. Their finding that $\rightarrow E$ and $E\rightarrow$ are procyclical is a result of the countercyclical flows between E and U being more than offset by procyclical flows from inactivity or between jobs. We prefer to separate job-to-job flows from employment inflows and outflows from other labour market states. Other findings in Burda and Wyplosz are that $\rightarrow U$ and $U\rightarrow$ are found to be countercyclical and highly coherent (ie there is a high correlation between the two series and they have the same trend) while quits (or voluntary separations) only play a minor role on $\rightarrow U$. Finally, overall $\rightarrow I$ and $I\rightarrow$ are found to exhibit no particular pattern – this suggests, that since flows between I and E are procyclical, the flows between I and U are countercyclical. Contradictory evidence can be found in Balakrishnan (2001) for Spain. He finds that E flows are coherent but U flows are not and that $U\rightarrow$ are pro rather than countercyclical.

The findings on the pattern of European worker flows are similar to those found in the United States. However, the inclusion of job-to-job flows means that $\rightarrow E$ and $E\rightarrow$ are found to be procyclical, as job-to-job flows are large and procyclical. In addition, the studies outlined above show that *annual* worker flows in Europe are very similar to those in the United States but when measured at higher frequencies, a substantial difference emerges.

4. New data on UK gross worker flows

This section describes the new longitudinal LFS data in detail and discusses some of the practical issues associated with the use of these data. When used in other countries these data have been found to have significant measurement problems (see, for example, Abowd and Zellner (1985) for a discussion of this issue with respect to CPS data). This section discusses the implications of these measurement issues for our analysis. In addition, we will briefly describe the seasonal properties of these data.

In December 2000, the ONS made available quarterly longitudinal data from the LFS. These data match LFS respondents between quarters - showing changes in labour market states. This means that we have data on gross worker flows, which are measured on the same basis as economy-wide unemployment. Previous studies of the empirical significance of UK worker flows have relied upon a number of data sources; none of which were consistent with aggregate statistics on employment and unemployment.[9] The LFS panel, introduced in the spring of 1992, allows us to follow individual survey respondents for up to five successive quarters. The design involves sampling around 60,000 households every quarter with each household staying in the sample for one year (five successive quarters). The sample is comprised of subgroups or waves which are rotated, so that one wave joins the sample each quarter and one wave leaves. So, for any two successive quarters, four waves are common to both. By matching respondents in two successive quarters we are able to observe changes in labour market status and therefore derive gross flows for LFS respondents.

Biases in the longitudinal data

In addition to the usual sampling variability, the ONS has identified two further issues in their published methodology documentation[10] that will impact upon the quality of estimates from LFS longitudinal data: non-response bias and response-error bias. Non-response bias is caused by the fact that those refusing to take part in the LFS (or who cannot be contacted during the sampling window) are atypical of the population. In particular, non-response is related to age, marital status and region. Response-error bias occurs when an LFS respondent provides erroneous information in response to the survey questions. In the cross-sectional data, the ONS has undertaken a census-based analysis to ensure that it has corrected for non-response bias and cites OECD research[11] as justification for ignoring response-error bias. In the longitudinal data, non-response bias is exacerbated by the patterns of non-response over the waves of the LFS survey, and response-error bias is thought to bias positively the gross flows.[12]

Patterns of non-response differ over successive waves of the survey. Clarke and Tate (2000) detail the work done by the ONS to develop a procedure for weighting the two-quarter longitudinal data. The outcome of the ONS's research is the identification of factors associated with non-response over successive waves of the longitudinal data. The result is an augmented weighting procedure that uses housing tenure and the distribution of employment, unemployment and inactivity as additional control totals in the weighting procedure.

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[9] See Pissarides (1994) for a discussion on the available data on employment inflows.
[10] A comprehensive account of their methodology work is given in Clarke and Tate (2000), though a useful summary is published in *Labour Market Trends* (July 1999).
[11] Lemaitre (1994) concludes that the aggregate effect of response errors will be negligible.
[12] The ONS believes that response errors will *net* to zero, but cause spurious flows that will affect the gross data.

It is plausible that response-error bias will not affect the cross-sectional data, but there are good reasons for thinking that this will not be the case in the longitudinal data. In the cross-sectional data, the effects of response-error bias are thought to cancel out—that is, as many individuals say they are unemployed when they are inactive as the other way around. In the longitudinal data, a response error is likely to lead to a spurious transition. For example, if individuals state that they are unemployed, when they are actually inactive, this may well cause a spurious $I \rightarrow U$ transition (if the person has given the correct answer in the previous questionnaire and, as is likely, has not changed state in the meantime). In the longitudinal data, if someone makes the opposite error, rather than cancelling out the original error, it is likely to cause another spurious transition. Hence, random response errors will not cancel out. This problem is exacerbated because the number of state changes (between *E*, *U* and *I*) is relatively small compared to the numbers that stay in the same state. As a result it is much more likely that response errors will significantly affect gross flows between labour market states than the numbers in a particular state.

By their nature, response errors are difficult to observe. As there are no re-interview data,[13] it is not easy to observe when such errors have taken place. One way of testing this is to look at the number of 'inconsistent' transitions. In the LFS, individuals in employment and unemployment are asked how long they have been in that state. If the duration contradicts the transition (eg an individual had been in employment for more than three months but was reported to have made the transition $U \rightarrow E$) then the transition is 'inconsistent'. Table C shows the number of inconsistent transitions for the Summer/Autumn 2000 longitudinal data:

Table C: Inconsistent transitions in LFS longitudinal data

Transition type: state1 ® state2	*Percentage inconsistent*	*Percentage in state2 at t-4 months*[14]
$U \rightarrow E$	8.3	5.7
$I \rightarrow E$	24.5	22.9
$E \rightarrow U$	17.4	8.3
$I \rightarrow U$	40.0	24.3

[13] This kind of data identifies the rate of response error and is used as the basis for adjustments to worker flows from the CPS data.
[14] These data attempt to investigate whether it is simply the case that LFS respondents have had trouble remembering when they moved from state1→state2. Unfortunately unemployment duration is reported in three-month buckets so we cannot see how many state changes were consistent in *t*-4 months. As a result, the data in the third column above are calculated by adding in the 4-6 month unemployed bucket.

These results are broadly consistent with those outlined in Clarke and Tate (2000) and show a high incidence of inconsistent data. However, it should be borne in mind that this depends upon the LFS respondents' recollection of their own labour market state three months ago. We suspect that most of the error occurs because individuals are unclear as to their exact duration in any state. This would imply that the transitions are correct and the duration data are wrong. However, to the extent that these inconsistencies are genuine they will lead to overestimation of the gross flows. We shall have more to say on recall bias later in this paper.

Seasonality of worker flows

The worker flows that we estimate show distinct seasonal patterns. The table below shows the results of regressing each of the different worker flows on a set of seasonal dummies.

Table D: Seasonality of gross flows in LFS longitudinal data since Spring 1993 (figures in small italics exclude those in full-time education)

000's	*Coefficient on dummy for:*				
Transition	Spring	Summer	Autumn	Winter	R^2
$E \rightarrow U$	389	377	399	427	0.2
	365	*335*	*356*	*396*	*0.2*
$E \rightarrow I$	439	412	621	484	0.9
	335	*345*	*362*	*357*	*0.3*
$U \rightarrow E$	517	513	567	467	0.5
	474	*459*	*499*	*414*	*0.3*
$U \rightarrow I$	313	303	362	357	0.4
	249	*269*	*241*	*281*	*0.2*
$I \rightarrow E$	408	566	469	376	0.9
	252	*239*	*298*	*220*	*0.8*
$I \rightarrow U$	354	488	384	312	0.8
	269	*251*	*296*	*237*	*0.4*

As shown by the value of R^2, seasonality is most important for flows between E and I. For $I \rightarrow E$ the largest flow is in summer (surveys done between June and August) with the largest $E \rightarrow I$ flows coming in the autumn (September to November), indicating that the academic calendar is important in driving seasonal patterns.

In order to investigate this, we repeated the exercise excluding students from the calculation. The exclusion of students generally reduces the explanatory power of the seasonal dummies in terms of R^2. However, the explanatory power of the seasonal dummies on the $I \rightarrow E$ flow has barely been reduced by the exclusion of students – although the seasonal pattern has changed. We repeated this exercise, excluding temporary workers, those under 24 and those who cited family responsibilities as the initial reason for being inactive, with similar results.

Bleakley *et al* use a set of dummies to seasonally adjust the CPS data. However, in what follows, we shall seasonally adjust all the data using Census Bureau X-11 (CB X-11). We use this procedure for several reasons. First, it is a standard package and is readily available. Second, it has similar properties to the package used by the ONS.(15) Finally, it is the same as that used by B&D. It should be noted however that we have experimented with alternative seasonal adjustment procedures and found that the choice of seasonal adjustment method made little difference to the resulting series and made no change to our conclusions.

5. UK gross flows

The aim of this section is to ascertain the basic facts of gross flows since 1993, ie how the flows have evolved as the UK economy has expanded. We shall concentrate on a macro analysis of the flows, only looking at the micro characteristics of those who make individual transitions when they are of particular interest.

Before presenting the flows data, it is worth making a few comments on the data used in this section. First, all data are seasonally adjusted. Second, in order to concentrate on worker flows between different labour market states, we exclude new labour market entrants (ie those who have moved into the 16 and over population in the second quarter of the two-quarter datasets) and those who have reached the official retirement age by the second quarter. Finally, we report the flows as a percentage of the working-age population.

(15) The ONS use X-11 ARIMA to adjust LFS data (see *Labour Market Trends*, February 2000).

Chart 2: Average quarterly flows since Spring 1996

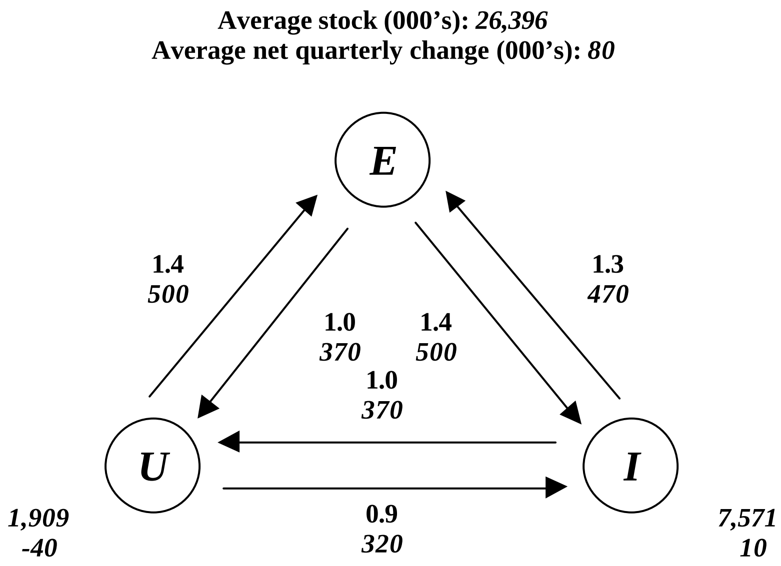


Chart 2 illustrates the average size of the gross worker flows from Spring 1996 to Winter 2000/01. The most noticeable feature of the data is the size of the gross flows compared to the net flows. For example, over our sample period employment has increased by an average of 80,000 per quarter. However, employment inflows have averaged around 970,000 and outflows around 870,000 (with the residual accounted for by changes in the working-age population). This is a very important observation as only relatively small changes in gross flows are required to shift the path of employment. The data in Chart 2 show that around 7% of those in the working-age population at two successive quarters will change labour market state in a three-month period. This compares with around 6% of Americans who change state every *month.*

The averages in Chart 2 say very little about the pattern of worker flows movement since 1993. Hence we will now set out the pattern of gross worker flows, concentrating on their cyclical properties.

i) Employment flows

Over the period for which LFS longitudinal data are available, the employment rate has increased steadily (see Chart 3) as the inflow rate has fallen less steeply than the outflow rate. If we assume that the flows were initially in steady state, then in an accounting sense, an increase in employment must be the result of inflows rising relative to outflows. Chart 4 shows that inflows and outflows have both fallen, but, over the sample period, inflows have generally been higher than outflows.

Chart 3: Employment rate

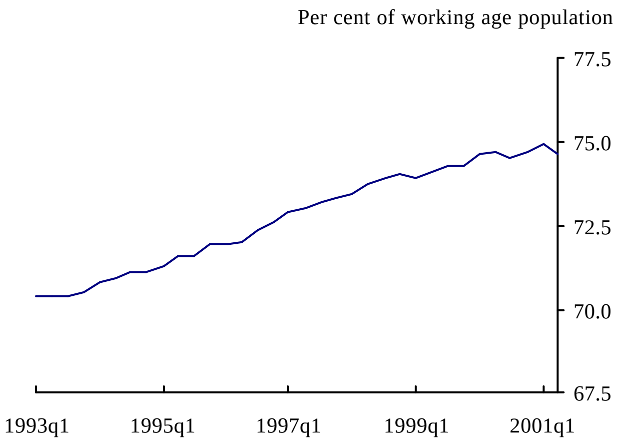
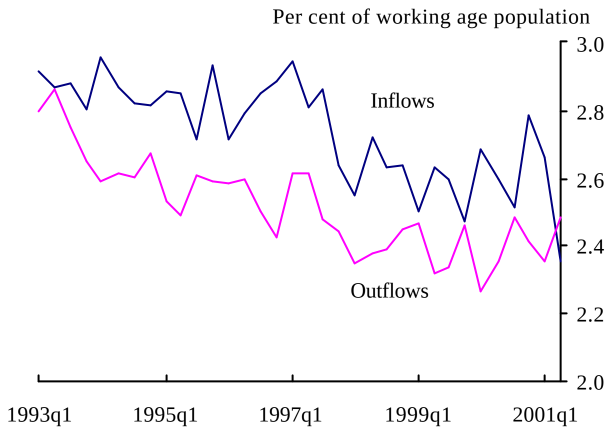


Chart 4: Employment inflow and outflow rates



Inflows and outflows from employment appear to be coherent. They follow the same trend and are positively correlated (*corr* (→*E*, *E*→) = 0.6). In the United States, fluctuations in →*E* have been found to be smaller than those in *E*→ – suggesting job destruction is more important in explaining cyclical fluctuations in employment. Superficially, this does not seem to be true for the UK data. The ratio of standard deviations of the two series is very close to 1, with the standard deviation of →*E* slightly the larger of the two. However, the US result is driven by large increases in *E*→ during recessions. As the data for the United Kingdom only cover one period of expansion in the UK economy, it is not possible to be confident as to whether a similar result holds here.

Charts 5 and 6 break down employment inflows and outflows by labour market state. The charts suggest the same empirical results as for the United States and Europe. Flows between *E* and *U* (ie *E*→*U* and *U*→*E*) have decreased, suggesting a countercyclical pattern to these flows. Flows between *E* and *I* seem to have risen slightly over the sample period indicating procyclicality. In terms of the trends in →*E* and *E*→, the flows between *E* and *U* have dominated. This is because the fall in flows between *E* and *U* is greater than the rise in flows between *E* and *I*. Chart 7 shows the net contribution of flows between *E* and *I* and those between *E* and *U* to the aggregate employment rate.(16) In terms of their net contribution to employment growth over the sample period, net inflows from *U* to *E* have more than offset the net flows between *E* and *I*.

(16) Calculated from longitudinal data.

Chart 5: Employment inflow rates

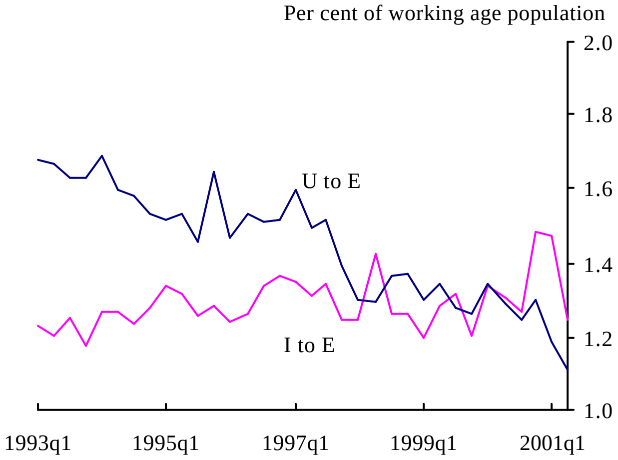


Chart 6: Employment outflow rates

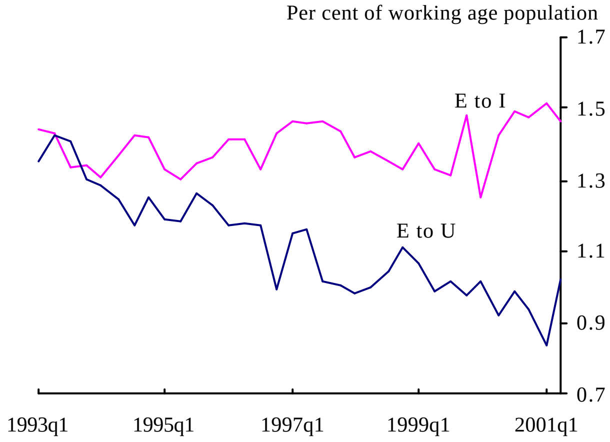
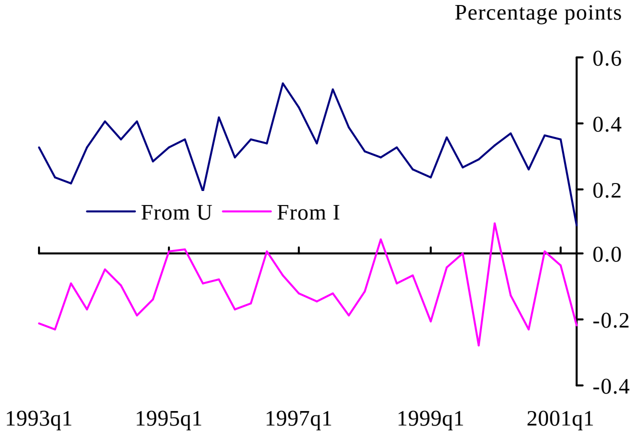


Chart 7: Changes in the employment rate

Contributions from U and I flows



Charts 8 and 9 show the *probability* of moving into and out of employment by previous labour market state, ie the hazard rate. In particular, the probability of moving from *U* to *E* has risen, even though the flow from *U* to *E* has fallen. So as the employment rate has risen, the probability of leaving unemployment for employment has increased. At the same time, the probability of transitioning into unemployment from employment has fallen. The probability of moving from *I* to *E* has marginally increased whereas the probability of moving from *E* to *I* has fallen (in contrast to the *E*→*I* flow). These charts demonstrate how the aggregate flows are driven partly by changes in the *probability* of making a given transition and partly by changes in the *stock* available to make a transition. Flows from *U* to *E* have fallen, but the probability of finding a job if you are unemployed has increased. In other words, the increase in the probability has come from a fall in the denominator.

Chart 8: Probability of moving from U to E

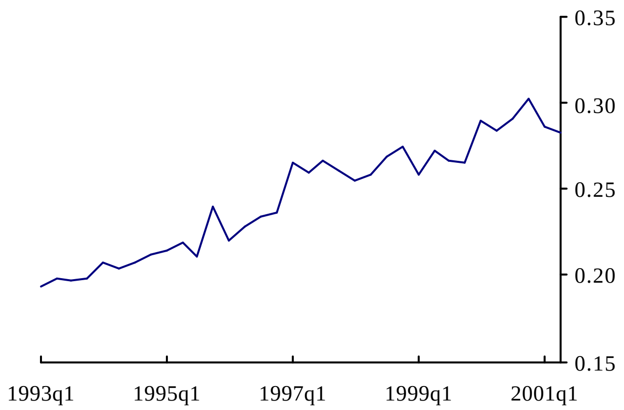


Chart 9: Probablility of moving from I to E

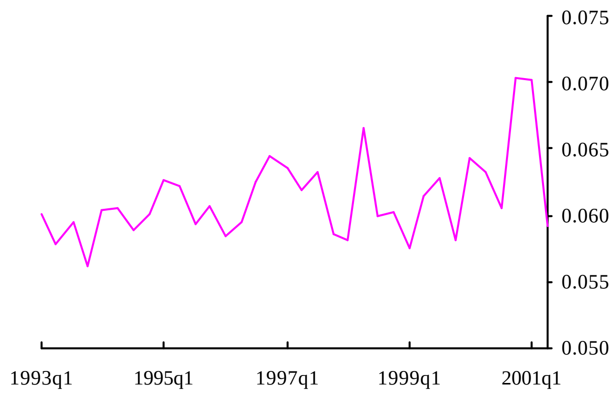
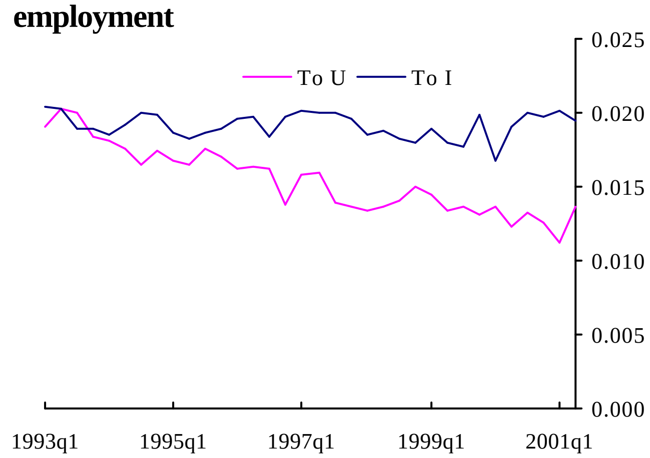


Chart 10: Probability of moving out of employment



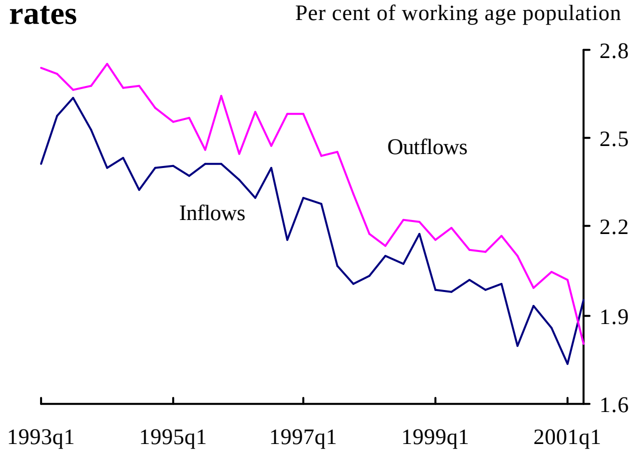
Breaking down the hazard rate from unemployment by demographic and personal characteristics reveals that the probability is greater for the young, women and those who have been unemployed for a short duration.

The probability of moving from *E* to *U* is, again, higher for the young and for females. However, breaking down the probability of moving from *E* to *U* by industry shows that construction has been the industry in which workers are most likely to transition to unemployment. But there is little difference in the hazard rates between the manufacturing and service sectors.

ii) Unemployment and inactivity flows

The LFS longitudinal data also allow us to build up a picture of how workers flow into and out of unemployment and inactivity. In looking at employment inflows and outflows we looked at four of the six possible flows between *E*, *U* and *I*. We will now look at flows into and out of unemployment, explaining the role of the flows that have not yet been considered, ie flows between U and I. We will then turn to flows into and out of inactivity – before concluding this section with a summary of the results.

Chart 11: Unemployment inflow and outflow rates



As suggested by the data for other countries, Chart 11 shows that $\rightarrow U$ and $U\rightarrow$ are coherent and have decreased over the sample period. It is clear that inflows and outflows follow the same trend and are positively correlated ($corr$ ($\rightarrow U$, $U\rightarrow$) = 0.9). The standard deviations of the two series are, again, very similar with the standard deviation of $U\rightarrow$ slightly exceeding that of $\rightarrow U$. Again, this implies that job destruction has not dominated the rise in employment (fall in unemployment).

Chart 12: Transition rates between U and I

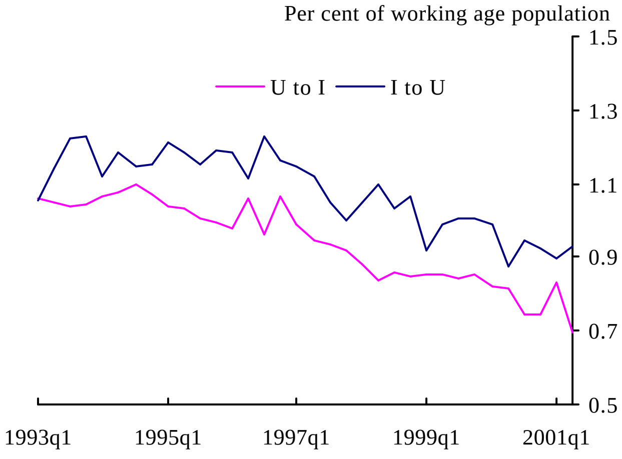
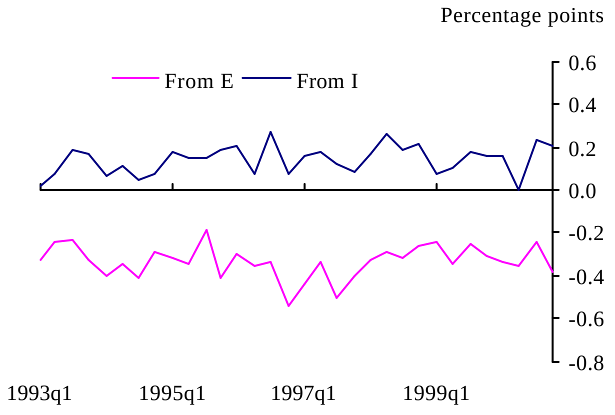


Chart 13: Changes in the unemployment rate

Contributions from E and I flows



As one might expect the components of $\rightarrow U$ and $U\rightarrow$ (ie flows between U and E and U and I) have trended downwards over the sample period. Charts 5 and 6 have already shown that the flows between E and U appear to have a marked countercyclical pattern. Chart 12 shows that flows between U and I also seem to be countercyclical. In net terms, Chart 13 shows the flows between U and E have more than offset the positive net flows from inactivity to unemployment, and hence have been instrumental in driving the fall in the unemployment rate.

Chart 14 shows there is no obvious trend in inactivity over the sample period. However, inactivity inflow and outflow rates have decreased somewhat over the period. As with the other labour market states, inactivity inflows and outflows follow a similar trend. However, they are not highly correlated ($corr\ (\rightarrow I, I\rightarrow) = 0.4$).

Chart 14: Inactivity rate

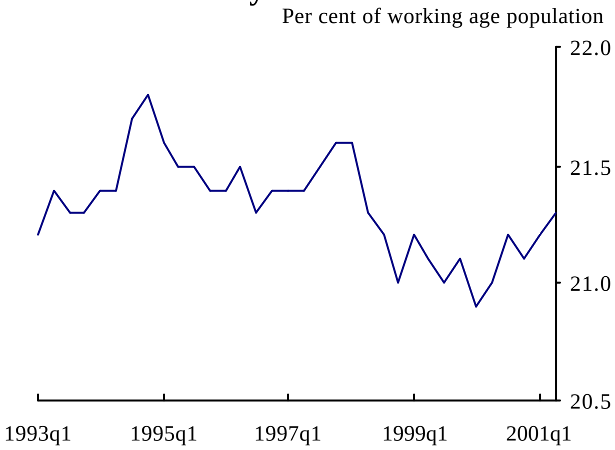
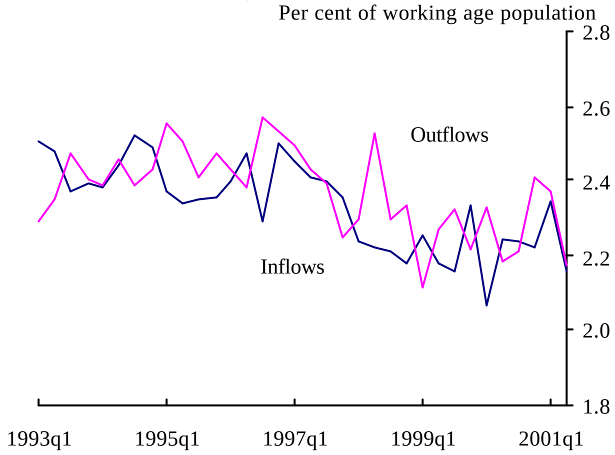


Chart 15: Inactivity inflow and outflow rates



As shown above, the components of $\rightarrow I$ and $I\rightarrow$ (flows between I and E and I and U) are quite different. Flows between E and I seem to be procyclical with flows between U and I appearing to be countercyclical. These findings are similar to Burda and Wyplosz (1994) but they find $\rightarrow I$ and $I\rightarrow$ are acyclical, whereas Chart 15 suggests they are countercyclical in the United Kingdom. The reason for the countercyclical pattern displayed in Chart 15 is that flows between E and I seem to be more weakly procyclical than found by Burda and Wyplosz, and therefore do not offset the countercyclical flows between I and U.

Chart 16: Changes in the inactivity rate

Contributions from E and U flows

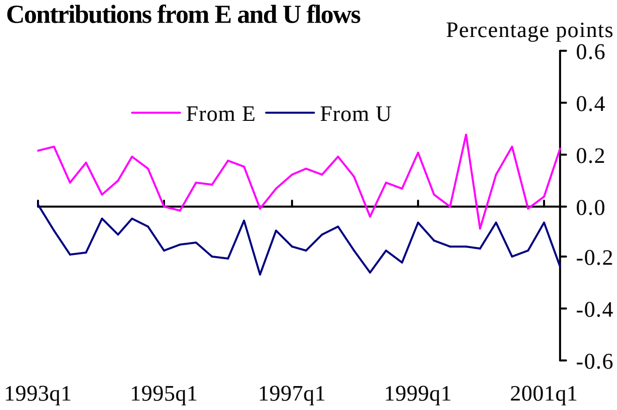
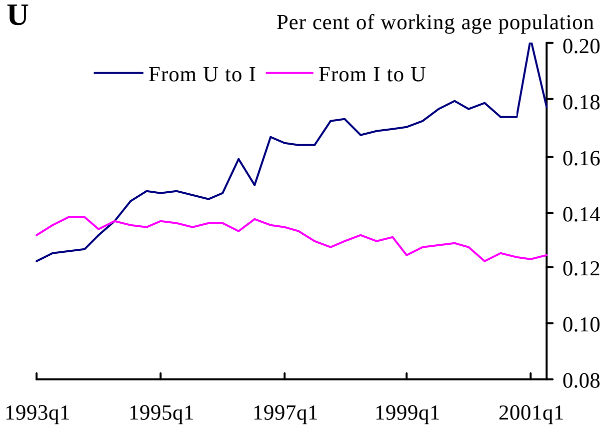


Chart 17: Probability of moving between I and U



Neither flows from *E* nor flows from *U* seem to dominate the changes in the overall inactivity rate. Chart 16 shows that the net contribution of flows from *E* and *U* to changes in the inactivity rate have been roughly equal and offsetting – with flows from *E* tending to increase the inactivity rate, but flows from *U* tending to reduce it.

Finally, Chart 17 shows the properties of the probabilities of moving between *U* and *I* are slightly different from the properties of the flows between these two states. The probability of moving from *I* to *U* has decreased over the period, but the probability of moving from *U* to *I* has increased. This implies that, in a similar way to flows from *U* to *E*, the effect of the reduction in the levels of those unemployed dominates the effect on the (increasing) probability of making the transition.

iii) Job-to-job flows

Flows of workers between jobs are important but until now there have been little available data on their significance. The extent to which both employees and their employers are free to separate given match-specific problems (ie the employee no longer wants the job or the employer no longer needs the employee) will clearly impact on their welfare. In addition, as previously noted, the observation of procyclical flows into employment, as reported in Burda and Wyplosz, suggests that job-to-job flows are large and procyclical (to counteract the countercyclical flows between unemployment and employment). However, problems with the measurement of these flows have meant only an opaque picture of their significance has emerged. The longitudinal data allow us to obtain a measure of the job-to-job flows[17] and hence complete our picture of worker flows in the UK labour market.

Chart 18: Matching rate

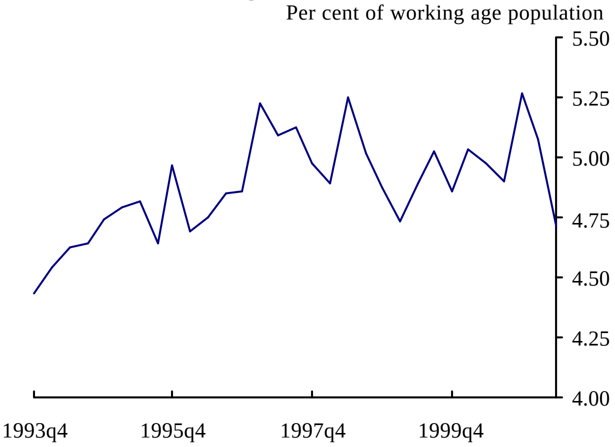
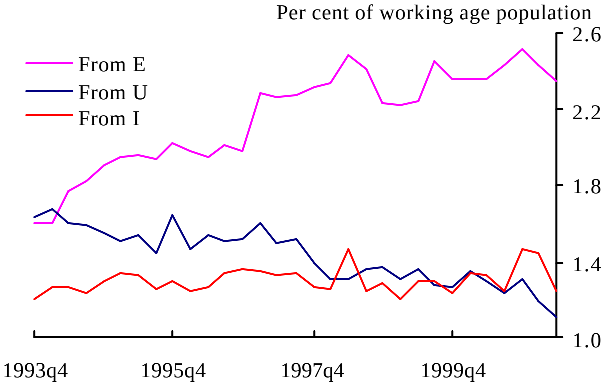


Chart 19: Breakdown of the matching rate by previous labour market state



The charts above show that total matches (ie new hires from *E*, *U* and *I*) have risen strongly over the period. Chart 19 shows that total matches have been driven by job-to-job flows which are procyclical. This is consistent with findings from the data in other countries.[18] While possibly unsurprising, this result is significant as we have been able to observe job-to-job flows directly using LFS longitudinal data – rather than using indirect data and making untestable assumptions about the behaviour of labour market participants. We estimate that 2.9% of employed workers make a job-to-job move each quarter.

The charts below show how the incidence of on-the-job search and short job tenure are associated with a higher probability of moving from one job to another. Individuals who engage in on-the-job search are on average six times more likely to make such a transition within three months. Furthermore, we find that job-to-job moves are predominantly amongst those with low job tenure. This finding is consistent with the Pissarides (1994) model discussed in Section 2.

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(17) In reality the LFS does not measure this perfectly (even on a quarterly basis). This is because a 'job-to-job' move is registered when an individual is observed as being in employment at successive quarters and has current job tenure of *less* than three months. As the variable measuring job tenure in months is discrete, job moves that take place between two and three months will be missed.
(18) With the exception of the findings of Fallick and Fleischman (2001) who find no evidence that job-to-job flows are procyclical in the United States.

Chart 20: Probability of making an E to E transition by whether searching on the job

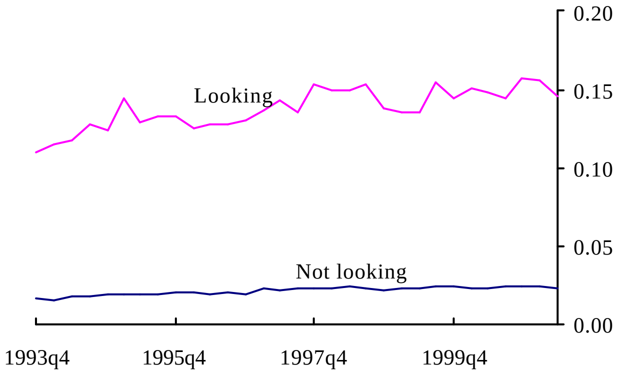
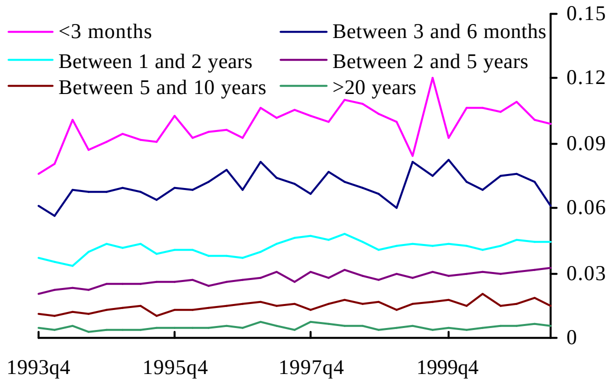


Chart 21: Probability of making an E to E transition by job tenure



The frequency of data is critical in correctly identifying the number of job-to-job transitions (and indeed all other gross flows). The *quarterly* data presented above will only count individuals who make more than one job-to-job transition in a given three-month period as having made a single transition. This is particularly important given that, at short tenures, individuals are more likely to transition between jobs. Similarly, it will not record those who have spent a short period of time in non-employment between surveys as having made more than one transition. As a result caution is required when comparing UK data to US (monthly) data and European (largely annual) data. Monthly data multiplied by three[19] are likely to be significantly larger than quarterly data.

(iv) Summarising the cyclical properties of the flows

To summarise this section, we estimate the correlation between the various flows and hazard rates and the aggregate employment rate.[20] Table E reports the results of this exercise. The first point to note is that, on average, 7.3% of the working-age population moved to another labour market state in a given three-month period.

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[19] This is the approach taken by Blanchard and Portugal (2001) to convert US CPS data to a quarterly frequency.
[20] Other measures of the cycle, including GDP growth and capacity utilisation, give similar results.

Table E: Summary of findings on the cyclicality and size of gross worker flows from the longitudinal data, 1993-2000

	Correlation coefficient of employment rate series with:		*Size of quarterly gross worker flow as percentage of pop.*
Flow	*Flow*	*Hazard rate*	
E→ *U*	-0.91*	-0.93*	1.12
E→ *I*	0.16	-0.23	1.39
U→ *E*	-0.90*	0.97*	1.46
I→ *E*	0.37	0.46	1.29
U→ *I*	-0.92*	0.95*	0.95
I→ *U*	-0.84*	-0.86*	1.09
Job-to-job	0.90*	0.70*	2.93†
→*E*	-0.73*	0.38*	2.75
E→	-0.84*	-0.91*	2.51
→*U*	-0.93*	-0.95*	2.22
U→	-0.93*	0.99*	2.40
→*I*	-0.75*	-0.84*	2.33
I→	-0.54*	-0.58*	2.38

* Denotes coefficients that are significantly different from zero at the 5% level.

† Job-to-job flows are as a percentage of total employment.

Table E provides confirmation of the cyclical pattern of the gross worker flows described in the text. All the flows between individual states are countercyclical with the exception of flows between *E* and *I*, which are procyclical (but less significantly so). In contrast, the probability of moving between states has a slightly different cyclical pattern. Movements from *U* (to *E* and *I*) have procyclical probabilities but countercyclical flows. This shows that when calculating the size of the overall flows out of unemployment, the effect of the fall in the numbers of the unemployed outweighs the increase in the probability of moving out of unemployment. There is a similar effect on flows from *E* to *I*. In this case, the increase in the number of people in employment outweighs the fall in the probability of moving from *E* to *I*, making the overall *E*→ *I* flow procyclical.

(v) Cyclicality tests using regional data

Given the short time span of the longitudinal data and the fact that the UK employment rate rose consistently over the period, it may be argued that it is difficult to make convincing claims as to the cyclical properties of the various flows and hazards. An alternative is to make use of the regional variation in the data to test these cyclical properties.(21) There is naturally much greater

(21) Fallick and Fleischman (2001) use the state variation in gross flows in the United States to examine the cyclical properties of the data over the period 1994-2000.

variation in the time series of employment rates by region than for the national figure. In this section we estimate fixed-effect panel models of the form:

$$flow_{it} = a_i + b_t + g emprate_{it} + u_{it}$$

where $flow_{it}$ is either the flow or the hazard rate in region i at time t, a_i is a region fixed effect, b_t is a set of time dummies and $emprate_{it}$ is the employment rate in region i at time t.

Note that we have time dummies for each quarter. This implies that not only do we remove all aggregate macro effects, but also remove seasonality. Seasonality can be of a completely unrestricted form, but must be the same across regions (at least to an additive constant). It is important to recognise that the variation in the data that identifies the parameter of interest, g, is completely unrelated to the source of the variation in the data that previously identified this parameter in the macro data. This follows directly from the inclusion of a full set of time dummies. Hence we believe these models provide an important and independent test of the previously reported macro results.

Of course we are hoping that there is reasonable variation in the evolution of employment growth across regions over our sample period. To assess this, we simply report the change in the employment rate over the sample period (and two subperiods) for the nation as a whole and for the largest and smallest regional change. The results are given in Table F. As can be seen, over the period as a whole the fastest-growing region increased its employment rate at almost three times the rate of the slowest-growing region.

Table F: Changes in employment rates, 1992-2000

	National (GB)	*Max. region*	*Min. region*
Dec. 92 to Dec. 00	4.1%	5.7% (South West)	2.0% (London)
Dec. 92 to Dec. 96	1.8%	3.4% (South East)	-0.6% (Yorks.)
Dec. 96 to Dec. 00	2.3%	3.7% (East Anglia)	0.6% (East Mids.)

Table G below reports the results. In unreported results we find that the raw correlations between the flows and hazards and the employment rate at the regional level replicate the correlations reported in Table E for the national data.[22] When we control for region and time dummies some important differences emerge. Most importantly, flows and hazards from inactivity to either employment or unemployment show no significant cyclicality. Other than that, the previous results stand up remarkably well and appear to be statistically significant. Since our results are driven by different variation in the data, this gives us added confidence in these conclusions.

Table G: Summary of findings on the cyclicality of gross worker flows across regions from the longitudinal data, 1993-2000

	Estimated coefficient on employment rate series with:	
Flow	*Flow*	*Hazard rate*
E®U	-0.032*	-0.059*
E®I	0.049*	0.044
U®E	-0.036*	1.126*
I®E	-0.022	0.066
U®I	-0.033*	0.447*
I®U	0.003	0.116*
®E	-0.058*	0.321*
E®	0.017	-0.016
®U	-0.029	-0.049*
U®	-0.069*	1.573*
®I	0.016	0.121
I®	-0.019	0.182*

***** Denotes coefficients that are significantly different from zero at the 5% level.

(vi) Recall flows 1975-2000

Prior to the availability of longitudinal data, analysis of labour market transitions in the United Kingdom required use of a recall question in the LFS to derive data. Data from the 1975 LFS onwards contained a question that seeks to ascertain the economic activity of the individual twelve months prior to the survey date. Though the precise nature of the question has changed over time, it is possible to generate a variable that shows whether the individual claims they were employed, unemployed or inactive twelve months ago. Comparing this variable with their economic activity in the survey week allows us to derive annual gross flow series. We are interested here in two questions. First, are such recall data a reliable guide to prior economic activity, ie do people correctly recall their economic activity twelve months prior? And second,

[22] This confirms that the seasonal corrections made to the aggregate data are not driving any of the reported correlations as the data in this section are not seasonally adjusted.

does this longer run of data exhibit the same cyclical patterns as reported using the quarterly longitudinal data?

To assess the first issue, we make use of the five-quarter longitudinal data available since 1992. Individuals are followed for five quarters in the LFS. The twelve-month retrospective question has been asked in each spring quarter since 1992. Hence an individual entering in the spring quarter of a given year will exit after the spring quarter of the succeeding year. In their final quarter they are therefore asked what their labour market status was twelve months ago. With no recall bias this should correspond to the labour market status that was actually recorded for them in the first quarter in which they enter the LFS. It is this proposition that we shall test in this section.[23]

We combine all the five-quarter files that begin in the spring quarter. Individuals are included who were over 16 and under 65 at both the beginning and end of their period in the LFS. Table H below gives the results, with percentages expressed in terms of the recall labour market state. It is clear there are significant differences between the recall labour market status and the reported status. While the errors are quite small for those in employment, there appear to be significant discrepancies for those who recall being unemployed or inactive. It is particularly noteworthy that only 65% of those who recall being unemployed actually have this labour market state recorded for them twelve months prior.

Table H: Comparison of recall and reported labour market states, 1993-2000

	Recall *E*	Recall *U*	Recall *I*	Total
Reported *E*	64,868 (97.6%)	515 (12.1%)	1,681 (8.5%)	67,064
Reported *U*	612 (0.9%)	2,771 (64.9%)	1,007 (5.1%)	4,390
Reported *I*	976 (1.5%)	986 (23.1%)	16,987 (86.3%)	18,949
Total	66,456	4,272	19,675	90,403

In more disaggregated analysis, we find that inactivity-reporting discrepancies are smallest for those types of inactivity that may be regarded as most permanent. So while 86% of inactivity reporting coincides, this rises to 93% for long-term sick and 94% for retirement. In contrast, only 76% of those reporting themselves as full-time students twelve months prior where actually

[23] Actually, this claim is not entirely correct. First, there can be coding errors on both the recall question and the labour market status recorded in the first quarter. Second, there is not a perfect match between twelve months ago and the date of the first-quarter interview, though the proximity is very close.

recorded as out of the labour force at the time. Though we suspect that the recall measure is more likely to be at fault than the contemporaneous measure, we have no way of proving this.

An alternative way of examining this issue is to compare the correlation over time between flows measured by the recall question and those using the longitudinal element. We find that the correlation between the alternative measures is reassuringly high for flows between E and U (E ® U = 0.86 and U ® E = 0.84). However, flows involving inactivity show much lower correlation across the two measures, reaching a nadir of only 0.10 for the I ® U flow. We suggest that individuals with lower labour market attachment are likely to be less clear about their labour market status and this makes us sceptical about the reliability of flows that involve inactivity. In contrast, we think that flows between employment and unemployment are likely to be quite robust. Finally, it is important to note that the stocks are not affected by these errors. Using either the recall or reported status gives almost identical levels for the stocks of E, U and I at each point in time. This implies that recall errors tend to cancel out at the cross-section level but generate significant error at the longitudinal level. It is interesting to note that the longitudinal data suggest that the annual gross flow is 12.5% of the working-age population compared to 7.3% for the quarterly flow.

In Table I we report the results of cyclicality tests using the recall-flow data. This has the obvious advantage of covering all stages of the business cycle but suffers from the recall errors identified above. We suggest that focus should be directed at the employment and unemployment flows with a healthy degree of scepticism apportioned to the inactivity flows. Once again, the results are broadly in line with Table E.

Table I: Summary of findings on the cyclicality and size of gross worker flows from the recall data, 1975-2000

	Correlation coefficient of employment rate series with:		*Size of annual gross worker flow as percentage of pop.*
Flow	*Flow*	*Hazard rate*	
E®U	-0.53*	-0.64*	2.26
E®I	0.46*	-0.70*	2.38
U®E	-0.26	0.80*	1.87
I®E	0.59*	0.79*	4.03
U®I	-0.48*	-0.04	0.86
I®U	-0.65*	-0.50*	1.46
Job-to-job	0.93*	0.93*	11.61†
®E	0.07	0.64*	5.90
E®	-0.59*	-0.75*	4.64
®U	-0.63*	-0.66*	3.72
U®	-0.35	0.81*	2.75
®I	-0.61*	-0.71*	3.24
I®	0.06*	0.43*	5.49

* Denotes correlation coefficients that are significantly different from zero at the 5% level.
† Job-to-job flows are as a percentage of total employment.

6. Conclusions

Hiding behind an unemployment rate is a complex pattern of labour market flows. Over the past five years, the stock of unemployed fell by an average of 40,000 per quarter. Given an average stock of 1.9 million, this may suggest that the market for labour can be characterised as a fairly static one. Yet such a conclusion would be wholly wrong. Using data from the LFS, we find that over the same period, almost three-quarters of a million people entered unemployment in a quarter, with equal numbers coming from employment and inactivity. Similarly, almost one million people start a new job each quarter after previously being unemployed or inactive.

While gross flows data have potentially serious measurement biases, their availability allows us to go behind the aggregate stock data to examine the nature of labour market dynamics. For example, they allow us to see whether falls in employment are driven primarily by the destruction of current employment matches or by a fall in the creation of new matches. Blanchard and Diamond (1990) present convincing evidence that job destruction is the primary driving force behind employment falls in the United States. We find no such evidence in the United Kingdom since the volatility of employment inflow and outflow rates is equal, though our sample period is much shorter.

Theoretical models of labour market flows generate predictions concerning the cyclical pattern of flows and hazards. These models were discussed in Section 2. Much of the empirical literature on gross flows has concentrated on the cyclical properties of the data. We have examined the cyclicality of both the gross flows and the associated hazard rates in the United Kingdom using a variety of data and techniques. We find that:

1. Flows from *E* to *U* are countercyclical and the hazard rate is also countercyclical. The reverse flow from *U* to *E* is also countercyclical while the hazard from *U* to *E* is strongly procyclical.
2. Flows from *E* to *I* tend to be procyclical while there is no clear direction for the associated hazard rate. Flows from *U* to *I* appear to be countercyclical.
3. Flows and hazards out of inactivity are all imprecisely measured and we are not confident of any reliable statement on their cyclicality.
4. Job-to-job flows are strongly procyclical.

These findings are broadly consistent with the results for the United States reported by Blanchard and Diamond (1990) and with a collection of European countries summarised by Burda and Wyplosz (1994).

We are also able to produce a measure of the incidence of job-to-job flows. Little is known about these flows in the United Kingdom and previous research has tended to focus on the prevalence of on-the-job search without knowing whether that search was successful. We show that 2.9% of those in employment change employer in an average quarter. This represents a movement of three-quarters of a million workers. Unsurprisingly, the probability of making such a move is much higher for those who are engaged in on-the-job search. Such movements tend to occur much more frequently for workers with short tenure in their initial job. This is consistent with the model of Pissarides (1994), which argues that individuals search on the job when they are in poor matches. As job-specific human capital is acquired, the incentive to move jobs falls.

Information on the labour market is often obtained from survey data of individuals. While much of these data requires individuals merely to report their current activity, there is also a potentially rich amount of information that is obtained by asking individuals about prior activity. However, this type of information is inevitably susceptible to recall bias since individuals may inaccurately recall their activity at previous time horizons (see, for example, Morgenstern and Barrett (1974)). The LFS contains a retrospective activity question which seeks to establish the labour force status of the individual twelve months prior to the survey. Using the longitudinal data, we find that there is significant discrepancy between the retrospective question and the recorded labour market state. This is particularly striking for the inactive category, where we show that the time series of the flow from inactivity to unemployment recorded by the retrospective question is hardly correlated with the same flow measured using the longitudinal data. It seems likely that recall data are not best suited to analyse labour market transitions, particularly between states that are not clearly distinguished in the mind of the respondent.

Throughout this paper we have referred to the data as measuring gross flows. This is a common feature of this literature but it is not correct. We are actually measuring labour market states at two points in time. We miss all flows that are of a higher frequency than the frequency of our observations. Hence, we do not have a clear picture as to the extent to which worker flows occur at shorter horizons, ie are there large daily and weekly flows? In future work, we intend to explore the extent to which the frequency of observation hides the dynamics of worker flows. Our dataset enables us to measure annual gross flows, but also to examine the transition paths that individuals take during the year to make up that annual flow. We can explore the extent to which an annual transition is simply a single transition that occurs at some point during the year or whether it hides multiple transitions throughout the year.

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