UK Labour Market Flows

1. Abstract

The Labour Force Survey (LFS) longitudinal datasets are becoming increasingly scrutinised by users who wish to know more about the underlying movement of the headline figures produced for economic activity in the UK.

These datasets are constructed from cases that are common to each of the consecutive quarterly cross-sectional datasets. The weights are then calibrated and constrained to variables present on the cross-sectional dataset. The primary purpose of this is to ensure additivity, coherence and comparable results across both the net and gross labour market flows. Additionally the datasets account for attrition where methods used seek to compensate for this by scaling the design weights according to housing tenure outcome.

This paper describes the methods used to weight the LFS longitudinal datasets; provides examples of where policy makers in the UK use this data and their expectations going forward; and lastly contrasts the methodology used in the UK with Eurostat statistics on flow estimates.

2. Introduction

The Labour Force Survey (LFS) longitudinal datasets are becoming increasingly scrutinised by users who wish to know more about the underlying movement of the headline figures produced for economic activity in the UK. The longitudinal datasets, which track people over time, continue to have many applications in the field of official statistics. Here they are used to inform analysis of social and economic phenomena. As a result of this it has attracted much research activity in the past and continues to do so currently.

Gross flows are defined as measures of the transitions between states of individuals in a population. In the labour force, the number of people employed in the previous quarter and now unemployed in the current quarter would be classified as a gross flow. Unlike the longitudinal datasets, the quarterly cross-sectional datasets do not measure flows as they only capture one time period. The cross-sectional datasets are used to estimate net change, which is the difference between estimates of the same variable at different time points. For example, subtracting the estimate of employment at t1 from that at t2 gives the net change between t1 and t2; this difference does not say how many have changed their activity status over that time. These datasets are used to calculate stock estimates. In that sense, longitudinal datasets allow analysis at an individual level to produce estimates of gross flows. Stocks differ to flows as the quantities measured here are at a specific time point. The total number of employed people in a given quarter would be classified as a stock estimate.

Analysts use the longitudinal data to understand better gross flows in economic activity as well as change and time dependent relationships. The longitudinal datasets are constructed from the quarterly cross-sectional cases with the weights calibrated and constrained to variables present on the cross-sectional datasets. The primary purpose of this is to ensure additivity, coherence and comparable results across both the net and gross flows. While the high-level economic activity statuses are forced to match the cross-sectional distributions, more detailed breakdowns are not included in the calibration. These create methodological issues as the longitudinal estimates at lower breakdown levels do not coincide with those of the crosssectional estimates. In principle, stocks(t1) + flows(t1 to t2) = stocks(t2). Calibration means this is ensured at high levels (i.e. for variables that form the calibration groups), but this is not guaranteed for lower-level domains. When it comes to analysing stocks across both datasets there appear to be a few inconsistencies, with some movements in the longitudinal data not replicating those in the cross-sectional data.

Labour market flows are of great importance to policy makers in measuring the health of the economy. Section 4 provides some examples of where these datasets have been used to examine changes in trends since the last recession and detail some areas, such as migrant workers entering the UK labour market that will be important as UK leaves the EU.

3. Method

The current methodology used to weight the two-quarter longitudinal datasets, is that proposed by Clarke and Tate (*Clarke, P.S. and Tate, P.F. (1999). Methodological Issues in the Production and Analysis of Longitudinal Data from the Labour Force Survey. GSS, Methodology Series No 17.*). A two-quarter longitudinal dataset is constructed by matching cases of working age (16-64) in both quarters from the cross-sectional datasets. Design weights are calculated and scaled to replicate the distribution of tenure observed in the first quarter cross-sectional dataset. The scaled weights are calibrated to known marginal totals of a set of control variables:

- Age-sex (mid-year population estimates derived from the Census)
- Region (mid-year estimates derived from the Census)
- Economic activity in the previous quarter (estimated from the first quarter cross-sectional dataset)
- Economic activity in the current quarter (estimated from the second quarter cross-sectional dataset)

The sum of the population totals will differ for the economic activity variables in the two quarters because they are measured at different periods. This is managed by adding the difference in totals between the two periods to the inactive category of the first linked quarterly dataset. As the longitudinal datasets are primarily used to analyse flows in economic activity it is important this variable is used in calibration to achieve consistency at this level.

As noted previously, a number of cases are lost on the longitudinal datasets because of attrition. This problem is mainly mitigated by including tenure in the weighting controls. The design weights are scaled prior to calibration using a tenure variable to allow for weights to reproduce the distribution of the first quarter cross-sectional sample according to the tenure categories: owned, rented, partly rented.

Recent research into attrition on the LFS has highlighted a few variables as having a significant impact on the propensity to drop out between waves. These were found to be: region, age, tenure, ethnicity, household type and disability status. The weighting for the longitudinal datasets incorporates some of the variables mentioned and so tries to account for attrition bias. However, it is important to note that the economic activity totals used in calibration of the longitudinal dataset are cross-sectional estimates, and could therefore contain non-response and attrition bias. The longitudinal stock estimates between key statuses of economic activity are reasonably consistent when compared with the cross-sectional estimates. However, assuming that the cross-sectional estimates are unbiased, there is evidence of bias in the longitudinal stock estimates for more detailed groups that are not used in the weighting regime. This bias is seen to have an impact on the estimates for full-time and part-time individuals, affecting part-time estimates more than full-time estimates as the size of the datasets reduces. This is partly because of imputed cases being present on the cross-sectional datasets but not on the longitudinal datasets.

Whilst there is an attempt to control for non-response bias and produce more consistent estimates, the weighting strategy does not account for biases in response errors. This also applies to the cross-sectional datasets. These response errors can be defined as errors introduced into the data through respondents giving incorrect information. There are many sources of response error, such as:

· Proxy respondents - those who provide responses on another respondent's behalf may give incorrect answers.

· Mode of interview - wave 1 of the LFS is typically a face-to-face interview, whilst wave 2-5 is typically a telephone interview for respondents. Respondents may act differently and hence provide different responses when being interviewed at different modes.

· Transition and internal inconsistencies - as the longitudinal datasets collect data on more than one time period; it is possible to get conflicting results. Respondents may say in the current quarter they have been in the state of employment for four months. But the response in the previous quarter (three months earlier) may state they are unemployed. In such cases it is difficult to determine which period has the incorrect response.

In general these will have an impact on longitudinal flows but are very difficult to correct for.

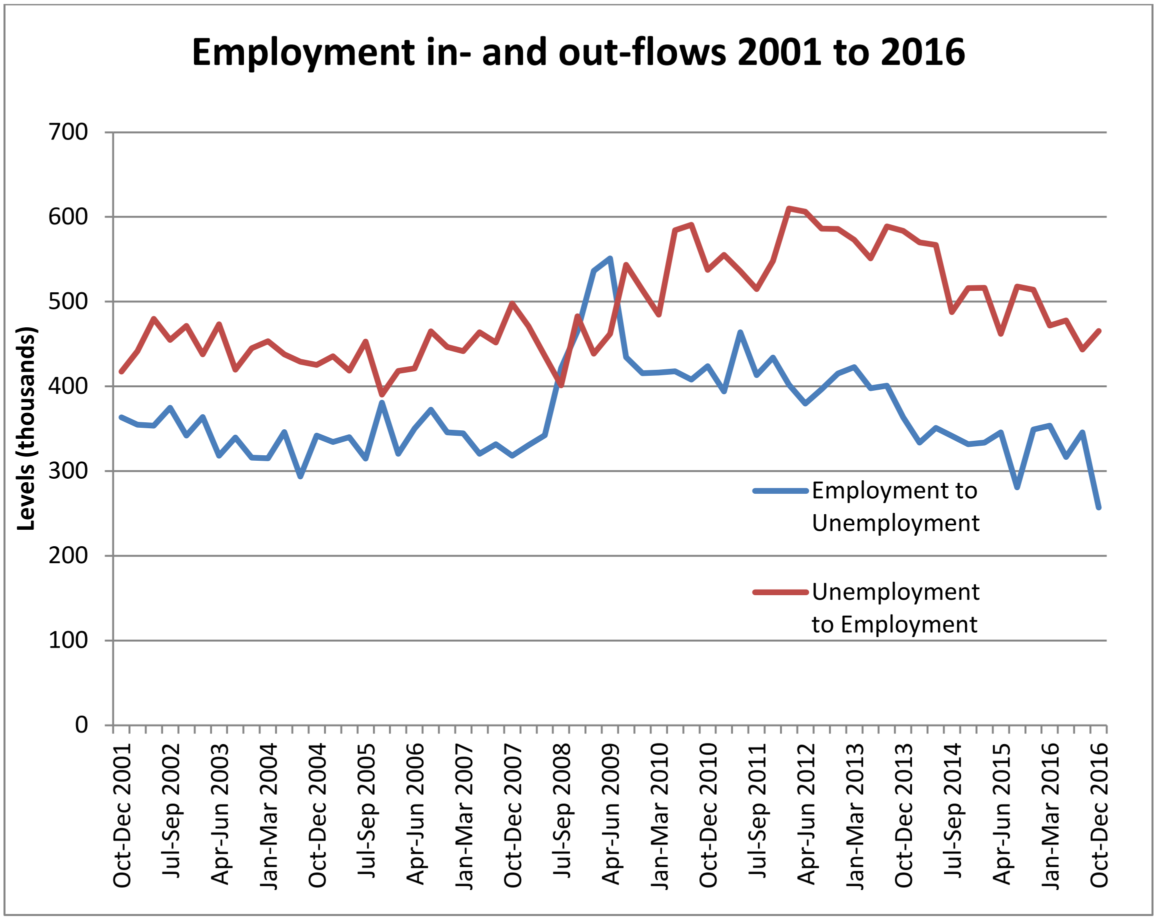
4. Examples of analysis

Labour market flows are of great importance to policy makers in measuring the health of the economy.

We investigated the magnitude of the changes in the statuses (employed, unemployed, and economically inactive) since the financial recession that began in the UK circa 2007-8. In the UK the employment stocks declined between the years 2007-10 and recovered since then, eventually passing the pre-recession peak, while the reverse occurred for the unemployment stocks. We observed this in both our cross-sectional LFS quarterly data (net changes in the levels) and our two-quarter longitudinal flow data (net flows). However, the flows data showed that the areas of employment growth since 2010 came from different sources to what was experienced prior to the recession.

Most unexpectedly was the fact that the unemployment to employment flows were not as largely affected by the recession for as long as policy makers expected. This chart shows that in early 2008 UK witnessed a sharp increase in moves from employment to unemployment, but the unemployment to employment flows continue to increase. In recent years they have followed similar patterns.

Chart 1:



In analysis of the flows we observed that female participation (that is, women who are active in the labour market) strongly increased since the downturn. There are a number of policy reasons for this, some of the key ones include:

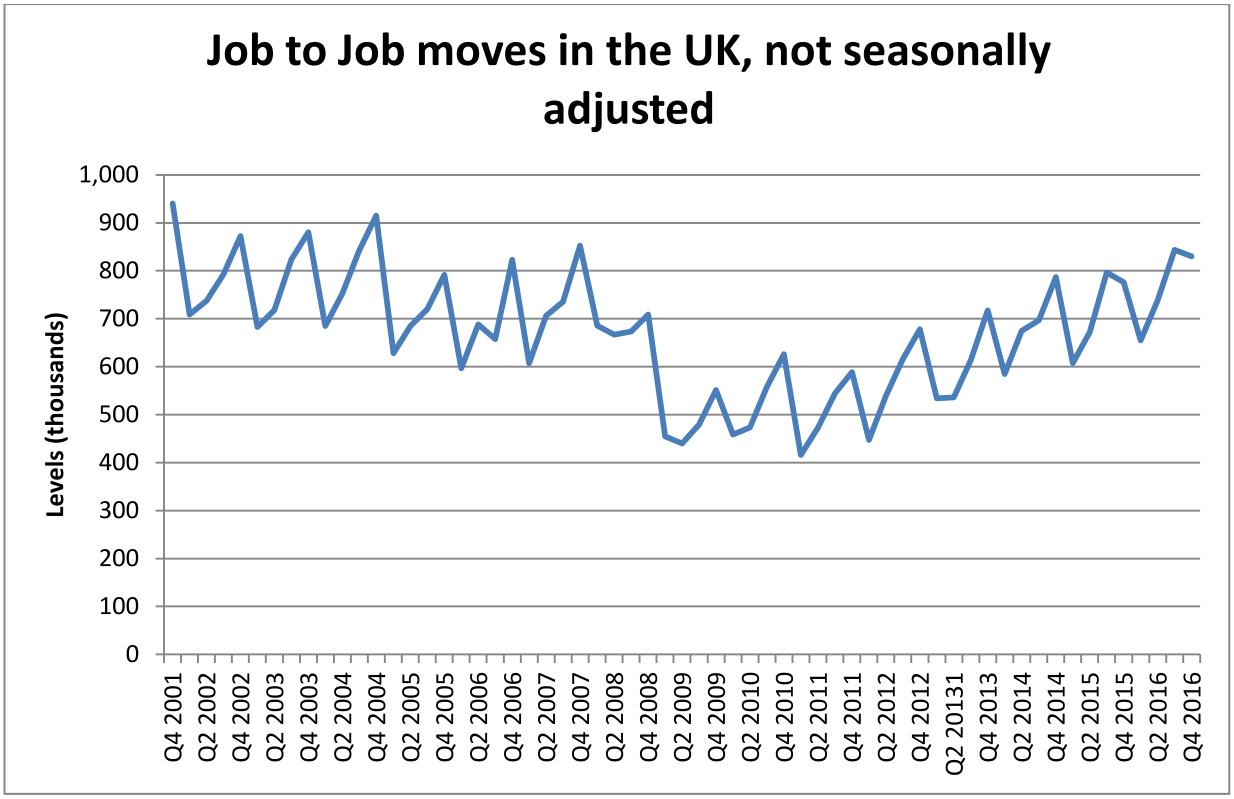
- Gradual increase in State Pension Age for women.
- Lone Parents Conditionality introduction
- Policy changes on Incapacity Benefit

All of the above policies were put in place with a view to getting more women into work; they had varying degrees of success, and the real effects can be observed in the longitudinal flow data with increases in the inactivity to unemployment cohort post-recession. This drive to get more women into the labour market (‘economically active’) was a major reason why unemployment inflows increased and then flows to employment from unemployment (chart 1) grew.

<u>Changes in job to job flow over time (chart 2):</u> One of the examples of the increased granularity that the flow analysis gives us is the ability to indicate or measure confidence in the labour market. This can be seen directly in the job to job flows. This is people staying

within the employment stocks (employment to employment) but their job changes. If many people are changing jobs it indicates an increase in employment churn in the labour market.

Chart 2:



We observe a downward level shift over the recession period. The employment levels have since recovered past the pre-recession peak, but the job to job move levels have yet to do the same. This indicates that while the number employed in the labour market is back on trend, labour market churn in the labour market has yet to reach this level.

Moreover, we can also look at reasoning behind a switch in jobs to go into slightly further detail. One of the possible reasons is resignation, so those who resigned at their previous job in order to move to a new job. This is perhaps the strongest of the reasons as an indicator of confidence in the labour market. The story is similar to the overall job to job levels; the levels have yet to fully recover from the downturn after the recession.

<u>Migrant worker flows</u>

In June 2016 there was a referendum on whether the UK would stay in the EU. The topic of immigration became a large part of the debate. The cross-sectionals stocks showed a record high year on year increase in the employment levels of the non-UK born in the immediate quarter post-referendum.

This has led to misreporting in the UK press over a greater proportion of the 'share of new jobs' going to non-UK born. This has been reported despite best efforts to state that numbers are net changes of employment levels and not a measure of new jobs in the UK economy.

This can be explained from the flow statistics. With the aid of the two quarter and five quarter longitudinal flows we can effectively look at flows into employment (from unemployment and inactivity) for those born in the UK and those born outside the UK separately. Taking inflows as a proxy for new jobs, we would expect to see a much higher flow into employment for UK born than for non-UK born but also a much higher outflow. This is because the UK born stocks are much higher to begin with. This has been helpful in explaining to users the difference between net changes and shares of a stock.

We have also looked at the specific countries of birth where the biggest flows into employment exist, although this has been difficult to draw firm conclusions from because of a low sample size at that level of breakdown. Some reconciliation issues are also apparent between low level analyses of flows on comparison with the stocks from the cross-sectional; these are explained in section 3 and are an unfortunate limitation of the UK method.

The UK is scheduled to leave the EU in 2019 and migration remains one of, if not the, most important concern to the UK labour market. We expect to see a huge demand for analysis in this area.

24th April 2017

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Annex. Eurostat comparisons

Main findings

As a result of the task force Eurostat have announced the production and distribution of quarter-on-quarter flow estimates by sex for individual countries in Europe and have released some test statistics. The initial approach currently involves a raking procedure to weight the longitudinal dataset constraining to marginal totals by sex and economic activity. This section outlines the major differences in methodological techniques compared to how flow estimates are currently produced in the UK and the impact these could have on estimates. In general no major concerns were identified but a few points are discussed in turn:

- The method suggested by Eurostat does not use age in their final marginal totals hence age is not used in calibration. This is of concern as not calibrating to age can skew the age distribution within the final estimates.
- The linking procedures used to create the longitudinal dataset may not be unique and it might be worth investigating certain variables on the cross-sectional dataset which are of better use.
- Eurostat used a raking method to produce the final weights for the longitudinal dataset. The method currently used in ONS is generalized regression estimation. It can be assumed that the changes in method alone will not have an impact on the estimates.
- The methods described by the Eurostat task force do not appear to take account of attrition whereas the methods used in the ONS seek to compensate for this by scaling the design weights according to tenure outcome. It would appear that adjusting for tenure does not make a great deal of difference to the final estimates.

It is recommended to consider adding an age variable to the final calibration constraints as not including age may have an impact on some of the estimates. In this review, the change when scaling the design weights to tenure is not major but nonetheless, ways to compensate for attrition should still be investigated. These may produce better results and one should always seek to take account of the effects of attrition.

Age

The target population for the Eurostat flow estimates is 15 - 74 compared to 16 - 64 used currently in the UK. Eurostat use 10 year age breakdowns whilst 5 year breakdowns are used in the UK. The former is unlikely to have any great differences in terms of the direction of flow estimates as the additional cases on the Eurostat dataset will probably fall into inactive category.

It is not very clear whether age breakdowns are used as marginal totals to be calibrated to at the end of the weighting process. From the documentation it would appear that breakdowns of age are used in intermediate steps but then aggregated prior to ranking in order to avoid empty or poorly populated cells. The resulting calibration constraints used are then just sex and economic activity and as a result when comparing to UK methods different calibration totals are used for weighting. This may be of concern as not compensating for the effect of age can skew the age distribution within the final estimates. Research shows age can be linked to attrition, particularly those in the 24-35 age band. Hence the removal of age bands at the calibration stage may have an impact results.

It can also be noted from the report that Eurostat do not seek to capture those respondents who may enter into the target population between successive quarters as the techniques used restrict cases to the 15 - 74 age band in both quarters used to create the longitudinal dataset. In this case you might have a respondent aged 14 in the initial quarter yet 15 in the second quarter. With the techniques identified, this respondent would not be captured in the analysis and so the resulting estimates are not as representative.

Creating the longitudinal dataset

The report discussed the linking procedures used to create unique identifiers. These are different to the ones used to create the variable PERSID on the UK longitudinal datasets. It is understandable that not all variables are provided to Eurostat and so there will be some inconsistencies when creating unique identifiers. Currently the variables HHNUM, HHSEQNUM, SEX, YEARBIR, are used by Eurostat to create unique identifiers but one cannot say whether these are really unique. The variable HHSEQNUM is derived and it is not clear how. A question to ask might be, how does the identifier differentiate between students, all of the same sex, of a similar age living in a student household? Is there the possibility of using something like Dob as oppose to YEARBIR as this is more distinctive? The feasibility of creating a more unique identifier would depend on what variables Eurostat have access to.

Raking Vs GREG

A raking method is used by Eurostat to produce the flow estimates whilst regression estimation is the calibration method used to produce estimates in the UK. Although the two method are different and use different approaches, it is difficult to tell what the impact would be without performing the raking adjustments on the current longitudinal datasets. Raking methods have been used in the past within ONS and the results would imply that there is not much difference between raking and GREG. An advantage of using GREG (generalized regression) estimation is that you obtain weighted estimates which agree with given ‘benchmarks’.

Tenure

The approach taken by Eurostat to produce the flow estimates does not seek to take account of attrition. The methods applied in the UK seek to take account of attrition by scaling the design weights using the tenure variable prior to calibration. The impact of not scaling to tenure are displayed in the tables below. Here the first estimate is produced by running the current method whilst the second estimate is produced by running the current method without scaling the design weights to tenure. As the tables show, the difference is minuscule and it is expected that whether or not tenure is considered in the weighting process by Eurostat, the estimates will not differ greatly. Although, as the methodology is currently different we cannot be sure.

Employees:

Period	Total with tenure adjustment	Total without tenure adjustment	Percentage Change
AJ10	24607230.93	24605788.8	-0.00586
JS10	24892800.58	24897515.4	0.01894

OD10	24813337.44	24814283.89	0.003814
JM11	24730384.89	24739112.29	0.03529
OD11	24661729.5	24663201.28	0.005968
AJ13	24989486.63	25023899.74	0.13771

Self Employed:

Period	Total with tenure adjustment	Total without tenure adjustment	Percentage Change
AJ10	3469547.62	3486214.21	0.480368
JS10	3551559.82	3563816.24	0.3451
OD10	3508470.32	3521648.68	0.375616
JM11	3508078.8	3514613.15	0.186266
OD11	3688721.21	3698972.35	0.277905
AJ13	3705491.32	3688940.19	-0.44666

Unemployed:

Period	Total with tenure adjustment	Total without tenure adjustment	Percentage Change
AJ10	2415958.42	2416330.23	0.01539
JS10	2517751.84	2517944.34	0.007646
OD10	2418824.3	2419240.04	0.017188
JM11	2429979.74	2430386.18	0.016726
OD11	2558672.77	2554456.9	-0.16477
AJ13	2438577.8	2438388.29	-0.00777

Inactive:

Period	Total with tenure adjustment	Total without tenure adjustment	Percentage Change
AJ10	9468931.03	9453334.76	-0.16471
JS10	9048959.75	9031796.01	-0.18968
OD10	9317108.94	9302568.39	-0.15606
JM11	9435910.57	9420242.38	-0.16605
OD11	9266230.52	9258723.47	-0.08102
AJ13	9114499.25	9096826.78	-0.19389

Recommendations

It is recommended to consider adding an age variable to the final calibration constraints as not including age may have an impact on some of the estimates. In this review, the change when scaling the design weights to tenure is not major but nonetheless, ways to compensate for attrition should still be investigated. These may produce better results and one should always seek to take account of the effects of attrition.