

LABOUR MOBILITY AND EARNINGS IN THE UK, 1992–2017*

Fabien Postel-Vinay and Alireza Sepahsalari

We combine information from the British Household Panel Study and the United Kingdom Household Longitudinal Study (also known as Understanding Society) to construct consistent time series of aggregate worker stocks, worker flows and earnings in the United Kingdom over the period 1992–2017. We propose a method to harmonise data between the British Household Panel Study and United Kingdom Household Longitudinal Study, which we validate by checking the consistency of some of our headline time series with equivalent series produced from other sources, notably by the Office for National Statistics. In addition to drawing a detailed aggregate picture of the United Kingdom labour market over the past two and a half decades, we use our constructed data set to compare the impact of industry, occupation and employer tenure on wages in the United Kingdom. We find that returns to occupation tenure are substantial. All else equal, five years of occupation tenure are associated with a 3.3% increase in wages. We also find that industry tenure plays a non-negligible part in driving wage growth.

We document aggregate changes in worker stocks, worker flows, and earnings in the UK labour market over the period 1992–2017, drawing information from a combination of the British Household Panel Survey (BHPS) and the UK Household Longitudinal Study (UKHLS, also known as Understanding Society).¹

The BHPS was discontinued in 2008 and replaced by the UKHLS, a larger survey with a slightly different design. We offer a new way of harmonising labour market history data between BHPS and UKHLS, which we validate by benchmarking some of our time series against those produced by the Office for National Statistics (ONS). We thus offer what, to our knowledge, is the first aggregate picture of UK labour market stocks, flows and earnings based on a ‘spliced’ BHPS/UKHLS data set.²

Our new, spliced data set consists of a long panel (over two and a half decades) of monthly individual data covering a wide variety of different variables. We first use this monthly data set to draw a detailed aggregate picture of the UK labour market over the past 25 years. Second, in order to illustrate the usefulness of our new data set, we use it to estimate the returns of industry, occupation and employer tenure on wages. Differences in returns to those various measures

* Corresponding author: Alireza Sepahsalari, University of Bristol, Queens Rd, Bristol BS8 1QU, UK. Email: alireza.sepahsalari@bristol.ac.uk

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The data and codes for this paper are available on the Journal repository. They were checked for their ability to reproduce the results presented in the paper. The replication package for this paper is available at the following address: <https://doi.org/10.5281/zenodo.8067343>.

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² Giannarakis (2017) makes joint use of BHPS and UKHLS in an analysis of the earnings losses of displaced workers in the UK, but only appends observations pertaining to the BHPS subsample of UKHLS to BHPS records. By contrast, we offer a method to harmonise and splice BHPS the whole UKHLS sample (not just the BHPS subsample) to produce a continuous panel from 1991 to 2018.

of tenure have been studied extensively on United States data (starting with Kambourov and Manovskii, 2009). Our data set is uniquely suited to assess those differences in the UK context, as it provides reliable information on wages and the mobility across different occupations, industries and employers of a large number of workers over a long period of time. Our results indicate that, while the exact specification of the estimated wage equation matters, Kambourov's and Manovskii's main result, which is that wages growth is much more responsive to occupation tenure than to employer tenure, is also found in our UK data. However, contrary to the United States data used by Kambourov and Manovskii (2009), our UK data suggests that wage growth is also somewhat responsive, *ceteris paribus*, to industry tenure.

The rest of this paper is organised as follows. In Section 1 we present our data set, the definition of variables, the difficulties we faced constructing our series and our suggested solutions to overcome those. In Section 2, we document the behaviour of worker stocks in the UK labour market over the past 25 years. We turn to worker transition/flow rates in Section 3, then to earnings in Section 4. Finally, in Section 5 we analyse the wage returns of industry, occupation and employer tenure. Section 6 concludes.

1. Data

1.1. Generalities

The British Household Panel Survey (BHPS) is an annual longitudinal study which follows all adult members of around 10,000 households in the UK from 1991 until the end of 2008.³ Because initial BHPS interviews were conducted gradually over the course of 1991, the cross-section sample size of BHPS is initially small and gradually increases until the end of 1991. Then, following the final BHPS interviews at the end of 2008, all remaining respondents were invited to participate in the UK Household Longitudinal Study (UKHLS, also known as *Understanding Society*), a successor to BHPS which follows a larger sample of around 40,000 households and collects data on a broader range of topics.

Interviews for wave 1 of UKHLS began in 2009, with those BHPS sample members who accepted the invitation to join the UKHLS sample members joining in wave 2. Interviews for each BHPS wave were completed within one calendar year. By contrast, interviews for each wave of UKHLS take place over a period of 24 months, but these 24-month periods overlap to ensure that each individual is interviewed once a year. So, for example, wave 1 interviews took place in 2009 and 2010, wave 2 interviews took place in 2010 and 2011, wave 3 in 2011 and 2012, and so on. Wave 11, which is the most recent release, contains information from interviews conducted in 2019 and 2020. A consequence of the overlapping waves in UKHLS is that data for 2009 and 2020, the first and last years currently covered by the data, relate to only half of the UKHLS sample (as half of the sample did not have their wave 1 interview until 2010, and half of the responses to interviews conducted in 2020 will not be released until wave 12). Data in these years are therefore less reliable than other years of UKHLS.

Those sample size issues (small BHPS sample in 1991, discontinuity between the final BHPS interview in 2008 and the initial UKHLS interview in 2009, and smaller UKHLS samples in 2008 and 2019) will impact the construction of our analysis sample, as explained in Section 1.3.

³ The original BHPS panel consisted of 10,300 individuals from around 5,500 households in Great Britain. The survey was expanded in 1999 to include an extra 1,500 households from each of Scotland and Wales, and again in 2001 to include an extra 2,000 households from Northern Ireland. These additional samples included 3,659 individuals from Scotland, 3,852 individuals from Wales and 4,335 individuals from Northern Ireland.

Cross-sectional weights are supplied by BHPS and UKHLS to ensure that each cross-section of both panels is representative of the UK population at the time. Those weights are designed to adjust for different probabilities that each individual is selected into the sample and different probabilities of sample attrition, including selective attrition of BHPS sample members between BHPS and UKHLS. We consistently use those weights in this paper.

1.2. *Individual Employment Histories*

While each sample member is interviewed at annual intervals, respondents are asked to report job histories since the time of their previous interview in each wave. We use these recalled job histories to construct a data set containing each individual's employment status and any transitions between states (or from one job to another) in each month of the period since their previous interview.⁴

We face two main difficulties in our construction of monthly employment histories: inconsistencies between the reported end date of one employment spell and the start date of the next, and inconsistencies between information reported in different waves. First, in some cases, the date that an individual recalls ending one spell of employment, unemployment or inactivity does not match the date at which they report having started their next spell. This results in either a gap in the individual's employment history or a period where labour market spells overlap. In such cases, we systematically set the start date for all non-left censored spells equal to the end date of the previous spell.

Second, the job histories reported by individuals sometimes contradict information provided in previous waves. For example, an individual may have reported being employed at the time of their wave 1 interview, while reporting a retrospective calendar of activities in wave 2 that implies that they were non-employed at the date of their wave 1 interview. In such cases, we give precedence to information provided in older interviews over information provided subsequently, i.e., we give precedence to information provided about labour market spells provided at interviews closest to those spells. The rules that we apply to rectify inconsistencies in individual responses are thus in the spirit of the 'closest interview method' discussed by Smith (2011).

In Appendix B, we further examine the magnitude and nature of the adjustments that these corrections impose on the raw data. We also investigate the consequences of simply discarding inconsistent observations (rather than attempting to correct them) on some of the main aggregate series that we construct.

1.3. *Sample Selection*

We construct monthly employment histories for all respondents in BHPS and UKHLS aged between 16 and 64 at the time of their interview. (Sample members therefore leave our sample on their 65th birthday and join our sample on their 16th birthday.) This selection is intended to make our analysis comparable with employment aggregates produced by the Office for National Statistics (ONS) based on the UK Labour Force Survey (UKLFS).

⁴ Respondents are also asked about their complete employment history when they are interviewed for the first time. However, for reasons explained in detail in Appendix A (namely, large recall bias and the unavailability of pre-panel weights), we do not include pre-survey employment histories in any of our analysis. Respondents enter our data on the date of their first interview.

As explained above, cross-section sample sizes are smaller at the start of BHPS in 1991 (for dates when wave 1 interviews were not yet complete), and become smaller again in the most recent wave of UKHLS in 2019 (for dates in which some respondents had already completed their final interview and so had left our sample). We cut those small-sample dates and restrict our time window to the period January 1992 to January 2018.

Final BHPS interviews were conducted in the third quarter of 2008, and the first UKHLS interviews were not conducted until January 2009. In constructing our monthly series, we switch from using BHPS data to UKHLS data in October 2008. During this ‘changeover’ period between the two surveys, the only information we have is from the 9,230 BHPS sample members who agreed to participate in UKHLS (and were aged between 16 and 64).

Our final sample contains 88,690 individuals (a total of 5.02 million person-months) and 129,395 transitions between employment states. This total is made up of 27,093 individuals (2.03 million person-months) with 61,851 transitions for the period covered by BHPS from January 1992 until October 2008 and 70,863 individuals (2.98 million person-months) with 67,480 transitions for the period from October 2008 until January 2018 covered by UKHLS. As many as 9,345 individuals from the BHPS sample continued into the UKHLS sample.

1.4. *Definition of Labour Market States*

We consider four possible employment states which we label as follows: employed (E), self-employed (S), unemployed (U), and inactive (I). In some of our analysis, we combine employment and self-employment into a single ‘in work’ state $W = E \vee S$. We assign individuals to states in each month based on their self-reported status at the end of the month. The four states are defined as follows.

- (1) *Employment* (E) includes all individuals who report being employed (part-time or full-time), in an apprenticeship, on maternity leave, working as unpaid family workers or participating in a government training scheme. This corresponds with the ONS definition of employment.⁵ Including women on maternity leave in the definition of employment is consistent with Smith (2011).
- (2) *Self-employment* (S) includes all individuals who report being self-employed.
- (3) *Unemployment* (U) includes individuals who satisfy any of the following criteria: (1) report being unemployed, (2) report having searched for work in the four weeks prior to their interview while not being employed, or (3) report having claimed unemployment benefits while not reporting being employed.⁶
- (4) *Inactivity* (I) includes all individuals who are not employed, self-employed or unemployed. This includes people who (1) report being out of work due to long-term sickness, in full-time education, caring for family members, in retirement, or for ‘other reasons’, (2) have

⁵ See, for example, <https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/labourforcesurveyflowsestimatesx02>.

⁶ For example, we classify an individual as being unemployed if they report being out of work due to long-term sickness, but have either searched for work or claimed unemployment benefit in the four weeks prior to their interview. If an individual is out of work due to long-term sickness and has not searched for work or claimed unemployment benefit, we classify them as inactive. The UKLFS defines an individual as being unemployed if they are out of work, have searched for work in the last four weeks, and are available to start work in the next two weeks. We have also used self-reported unemployment status and receipt of unemployment benefit in our definition of unemployment to make efficient use of the survey data, which we expect is subject to measurement error.

not searched for work in the four weeks prior to their interview, and (3) have not claimed unemployment benefits.

1.5. *BHPS/UKHLS Versus UKLFS*

We use a combination of BHPS and UKHLS to document UK labour market indicators. An alternative would have been to use the UKLFS. What are the pros and cons of each data set? The UKLFS has a larger cross-sectional sample size (nearly three times as large as the UKHLS). It was not interrupted at such an unfortunate time as the end of 2008, and so does not require the ‘splicing’ that BHPS and UKHLS do. While those indisputably argue in favour of the UKLFS, we believe that the BHPS/UKHLS combination has five key advantages (which are also emphasised by Smith, 2011). Those are (1) a higher frequency of observations: calendars of activities in BHPS and UKHLS allow the construction of monthly series, whereas it is only possible to construct series at quarterly frequency from the UKLFS. (2) A better tracking of respondents: BHPS and UKHLS sample designs are such that if individuals move their address or households, they will be tracked, whereas the UKLFS is an address-based sample and so does not track respondents if they move. (3) A longer time span: BHPS and UKHLS follow individuals for a much longer period than the UKLFS, with some respondents being present throughout the entire 1992–2016 sample period and are thus observed through most of their working life, while the UKLFS only follows each respondent for five quarters, which allows for a maximum of four labour market transitions. (4) Fewer proxy responses: the frequency of proxy responses is around 1% in BHPS and 8% in UKHLS, compared to almost 30% in the UKLFS. (5) Face-to-face interviews: in BHPS and UKHLS, all individuals are interviewed face-to-face and separately (when possible), whereas in the UKLFS only the first interview is face-to-face and the other four interviews are carried out by telephone.

Finally, one contribution of this paper is to provide an algorithm for data imputation and cleaning to produce reliable aggregate series based on the combination of BHPS and UKHLS. As explained below, one of our measures of reliability is closeness to the corresponding series published by the ONS based on UKLFS data. Given that BHPS and UKHLS cover a much wider range of variables than the UKLFS, we think it is useful to produce reliable aggregate time series based on those two data sets, which can be used in conjunction with other variables in any economic analysis based on those same data sets.

2. Stocks

2.1. *Preliminary Remarks*

We denote labour market stocks consistently with the way we label labour market states. For example, we denote the total number of employed workers in a given month t by E_t , the total number of self-employed by S_t , etc. Following this notation, the total number of people who are in work in month t is $W_t = E_t + S_t$. From those aggregate stocks, we derive the corresponding rates. The employment rate is defined as $\frac{E_t}{W_t + U_t + I_t}$. The rates of self-employment and inactivity are defined analogously. So is the total employment rate (including the self-employed), $\frac{W_t}{W_t + U_t + I_t}$. The unemployment rate equals $\frac{U_t}{W_t + U_t + I_t}$.

All the series plotted in this paper are smoothed using a 24-month moving average filter centred in the current month. Moreover, as discussed above the data are particularly noisy at the end of



Fig. 1. Aggregate Monthly Rates: BHPS/UKHLS Versus ONS.

2008 and through 2009, the period covered by the first wave of UKHLS. In all the charts below, we highlight this period using two vertical lines. Finally, in Appendix D, we replicate all the charts showing our aggregate series with added 95% confidence bands.

2.2. Employment, Unemployment, Self-Employment and Inactivity

Figure 1 shows our estimates of the monthly rates of total employment, unemployment, self-employment and inactivity. The ONS publishes series of those four rates based on the UKLFS. Figure 1 also shows those ONS series, for comparison.⁷

Our estimates of the rates of total employment and unemployment are, reassuringly, very close to the ONS series, even during the changeover period 2008 to 2010. The only noticeable discrepancy is that the BHPS/UKHLS-based employment rate dips a little lower than the ONS one in the immediate aftermath of the Great Recession. Our unemployment rate series mirrors that and peaks a little higher than the ONS series. There are small discrepancies between the two inactivity rate series, with the BHPS/UKLHS-based series being more volatile than the ONS one in the period where the quality of our data is low. Yet the two series of inactivity rates follow the same downward trend.

⁷ The ONS series we use are the aggregate employment, unemployment and inactivity rates among people aged 16–64 from ONS Labour Force Survey, Table A02: Labour Force Survey Summary.

The self-employment rate series constructed using BHPS/UKHLS follows a similar trend to its ONS counterpart, however, the latter is around half a percentage point higher between 1995 and 2003, and almost two percentage points higher in the rest of the sample period (Figure 1c). Contrary to the ONS total employment, unemployment and inactivity rate series, which represent individuals aged 16–64, the ONS uses all individuals aged 16 and above to construct the self-employment rate. By contrast, all our BHPS/UKHLS series, including the self-employment rate, are consistently based on individuals aged 16–64. Moreover, in our self-employment category, we only consider individuals who report themselves as self-employed, some of which could also hold a second, salaried job. These may explain some of the discrepancy between our self-employment series and the ONS one. In Appendix C we investigate this further and show the extent to which different ways of counting self-employment can affect the aggregate rate.

3. Transition Rates

3.1. Preliminary Remarks

In this section we document the labour market flows into and out of employment, self-employment, unemployment and inactivity. The first step in calculating transition rates is identifying and classifying all transitions. For example, we record the occurrence of a transition from unemployment to employment if (1) the respondent was unemployed in $t - 1$ and employed at t , and (2) the respondent reports that they started a new employment spell in month t . We then calculate the weighted sum of each transition type in each month, using the cross-sectional weights supplied with BHPS and UKHLS.

We label all transitions in accordance with our notation for the stocks: for example, the aggregate number of transitions from unemployment to employment transition in month t is denoted as UE_t . Transitions from unemployment to work, irrespective of self- versus salaried employment, will be denoted as UW_t . Note that workers often change jobs without experiencing any interim period of non-employment, giving rise to employment-to-employment (EE_t) and self-employment-to-self-employment transitions (SS_t). Job-to-job transitions, irrespective of self- versus salaried employment, will be denoted as WW_t .

Finally, we construct the transition rate in each month t following the method suggested by Shimer (2012). For example, we calculate the UW transition rate as $\lambda_t^{UW} = -\ln\left(1 - \frac{UW_t}{U_{t-1}}\right)$. Other transition rates are defined similarly.

3.2. Transitions In and Out of Work

We begin by focusing attention on transitions between work, unemployment and inactivity.⁸ Our comparison benchmark series in this case are based on the X02: Labour Force Survey Flows Estimates data set published and updated every quarter by the ONS.⁹ Those ONS series are

⁸ For brevity, we do not distinguish between paid employment and self-employment in this section of the paper. A more detailed description of transition rates between paid and self-employment is available in Appendix I.

⁹ The current version of this data set can be downloaded from <https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/labourforcesurveyflowssestimatesx02>. Other existing series of UK labour market transition rates that we could use as benchmark include the BHPS-based series of Smith (2011) which covers the period 1991–2008 (available from <https://sites.google.com/view/jennifer-smith/data?authuser=0>) and the UKLFS-based series of Gomes (2012) which runs from 1993 to 2010 (sites.google.com/view/pedromaiagomes). Comparisons with both of those series are available on request.

available from 2001:Q4 and, as the name suggests, they are based on data from the UKLFS. Because of the difference in frequencies between the (quarterly) UKLFS and our (monthly) BHPS/UKHLS data set, the ONS set of flow rate series are not directly comparable with ours. Specifically, the time aggregation bias (caused by the fact that both data sets miss all sequences of more than one transition, such as a job loss followed by a new job accession, occurring within their respective unit time period) is likely to be much more severe at quarterly than at monthly frequency.

The impact of time aggregation on the level and cyclicity of estimated labour market flow rates has been studied in a number of contributions based on a variety of different data sets (Petrongolo and Pissarides, 2008; Elsby *et al.*, 2009; Fujita and Ramey, 2009; Nekarda, 2009). While all those authors conclude that the time aggregation bias affects the levels of estimated turnover rates, they also concur in saying that the impact of time aggregation on the cyclicity of said turnover rates is quantitatively small.

Based on that conclusion, for each transition rate, we attempt to make the UKLFS-based ONS series comparable to ours by rescaling the former such that its mean and standard deviation coincide with those of our series over the period where both series overlap. In other words, we adjust the levels of the ONS series, and compare the cyclical behaviour of those adjusted series with that of our own BHPS/UKHLS series.¹⁰

Figure 2 shows the six series of transition rates between work, unemployment and inactivity. Overall, the trends of our transition rate series are very similar to those constructed by the ONS over the period covered by both. The behaviour of our various transition rates over the observation window is in line with what was documented elsewhere in the literature. The UW rate (Figure 2b) increased from the end of the 1992 recession to a peak of almost 10% at the beginning of 2,000. It then started a gradual decline, followed by a sharp drop towards the end of 2008, from which it has yet to recover. The IW rate (Figure 2d) follows a qualitatively similar cyclical pattern, albeit at a much lower level.

The WU job separation rate peaked at 0.65% in the 1992 recession, after which it declined steadily until 2008. It then increased sharply and suddenly during the Great Recession, but quickly resumed its trend decline after 2010, down to a low of around 0.25% since 2014. By contrast, the WI rate (Figure 2c) was hump-shaped over the period 1992–2008, reaching its peak around 2001. But during and after the Great Recession, the WI rate evolved roughly parallel to the WU rate.

Finally, the UI transition rate (Figure 2e) seemed to follow a slight upward trend from 1992 to 2008, before falling sharply during the Great Recession. It has since then stayed lower than its pre-recession level, just above 2%. The IU rate mirrored the UI rate qualitatively, although with quantitatively larger swings.

3.3. *Job-to-Job Mobility*

Figure 3 plots our job-to-job (WW) transition rate series, i.e., the rate at which either employed or self-employed workers move directly from one job to another without experiencing any period of unemployment or inactivity in between. As for transition rates in and out of work, we use the (rescaled) quarterly job-to-job transition rates from the ONS's X02 data set as benchmark.

¹⁰ In Appendix E, we present an alternative comparison of the ONS and our flow series by attempting to replicate the quarterly time aggregation of UKLFS in our monthly data.

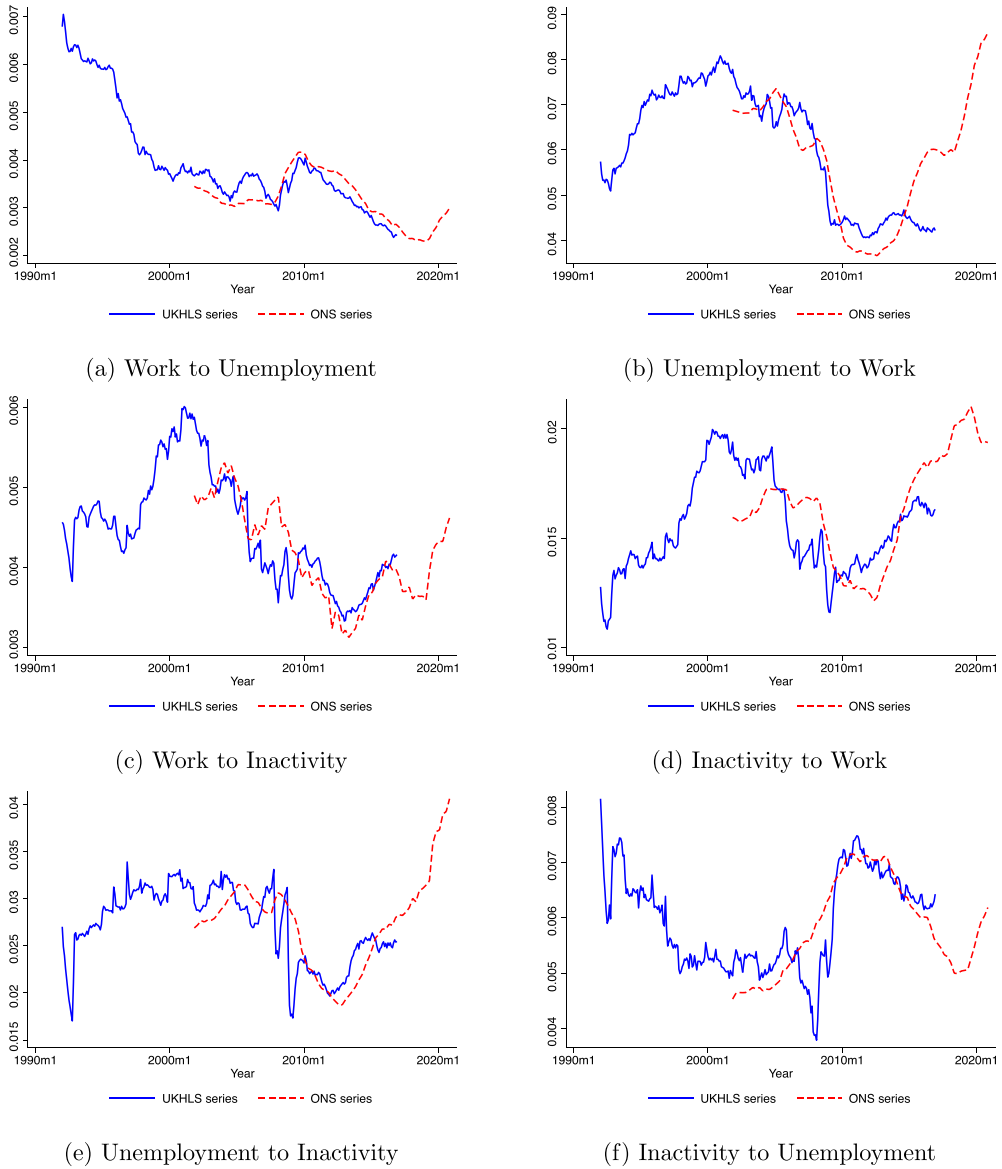


Fig. 2. Separation and Job Finding Rates.

The behaviour of the WW rate over our observation window is qualitatively similar to that of the UW rate (Figure 2b): increasing in the 1990s, reaching a peak around 2000, then gradually declining until 2008 to its early 1990s level, before falling sharply during the Great Recession and staying at historically low levels ever since. Quantitatively, however, the drop in the WW rate during the Great Recession is, in relative terms, much more dramatic than the drop in UW rates.

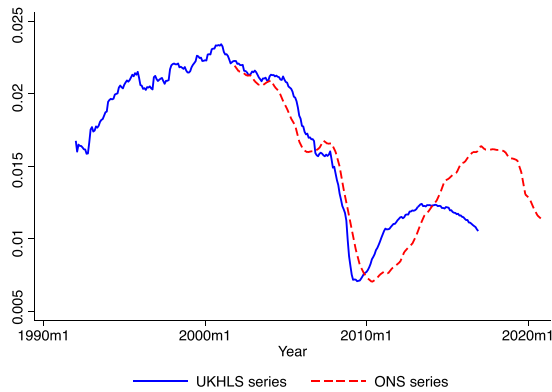


Fig. 3. *Job-to-Job Transition Rate.*

3.4. *Taking Stock*

One consistent message conveyed by Figures 2 and 3 is that all the transition rates in and out of work (WU, UW, WW, WI, and, to a slightly lesser extent, IW) have been on a moderate, but clear downward trend, since around 2000. This echoes similar findings for the United States (see, among others, Fallick and Fleischman, 2004; Fujita *et al.*, 2018), which have fuelled a literature investigating a possible trend decline in business dynamism. The United States' decline in transition rates is generally accepted to have started in the early to mid-1990s, slightly earlier than what our data suggest for the UK. Yet the parallel is striking.

4. Earnings

We construct series for average monthly labour income as the weighted sum of monthly labour income (using the BHPS and UKHLS cross-sectional weights), divided by the weighted sum of respondents reporting non-zero labour income in month t . This process produces estimates of nominal average labour income in each month t . We then construct real average labour income by deflating nominal labour income to 2015 GBP using the Consumer Price Index (CPI) All Items (D7BT) series produced by the ONS. We compare our estimates of real labour earnings to those produced by the ONS as part of its Average Weekly Earnings series (AWE), the series used by the Bank of England and HM Treasury to measure the inflationary pressure emanating from the labour market. Specifically, we use the KAB9: Weekly Earnings series, which is part of the AWE. When we make this comparison, we take the ONS estimate of nominal earnings and deflate using the same CPI series we use for our own BHPS/UKHLS series.

There is less information available on monthly pay in UKHLS than in BHPS. Monthly labour earnings are only available in UKHLS for any job the respondent holds *at the time of interviewing*. In BHPS, data on labour income is available for the individual's full employment history, including jobs which were held between the previous and current interviews. For the UKHLS period, we therefore calculate average earnings as the weighted total monthly earnings that we

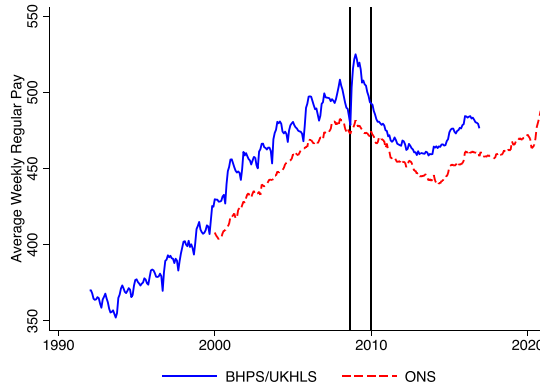


Fig. 4. *Average Real Weekly Earnings Versus ONS Estimates.*

observe, divided by the weighted total of individuals whose labour income we observe—i.e., we ignore individuals who are employed, but whose labour income we do not observe.¹¹

Figure 4 shows the average real weekly earnings series constructed from BHPS and UKHLS against the corresponding ONS series. The latter is only available from January 2000 onwards. Both series have parallel time profiles, and are very close in level. Nevertheless, on average there is a £10–20 difference (in 2015 GBP) between the two series.¹²

Our series confirms that, after over 15 years of steady growth, real labour earnings started falling in 2008 and have been subdued ever since (despite signs of recovery since early 2015), as has been widely documented and discussed in the public debate.

5. Returns to Occupation, Industry and Employer Tenure

We now illustrate the usefulness of our spliced BHPS/UKHLS data set in an application. Key advantages of our data set include its long longitudinal dimension and its reliable tracking of individuals across jobs over extended periods of time. Those attributes make our data set well suited to the study of individual career paths and earnings dynamics over the life cycle. Our specific application is on the comparative wage returns to occupation, industry and employer tenure. Neal (1995) and Parent (2000) have argued that the observed correlation between wages and employer tenure is attributable to the fact that wages grow with industry experience, which in turn is correlated with employer tenure and generally omitted from wage regressions. However, Kambourov and Manovskii (2009) find that tenure in an industry has a very small impact on wages once the effect of occupational tenure is accounted for. Long before that, Shaw (1984) has already argued that investment in occupation-specific skills is an important determinant of earnings. Yet the empirical literature that followed up on her important insight remains surprisingly sparse, and our aim here is to contribute to it in the UK context.

¹¹ This approach is the same as the one we use for BHPS sample members with missing labour earnings for an employment spell. It implies that we tend to be missing the earnings of highly mobile workers (workers who change jobs often), which are likely to be a selected population. However, these workers represent a modest fraction of total employment and their exclusion is unlikely to make any discernible difference to the series plotted in this section.

¹² The ONS series that we use is the average weekly earnings from ONS Table EARN01.

Table 1. *Earnings Function Estimates, OLS.*

	1	2	3	4	5	6
Employer tenure	0.00945*** (0.000113)	0.00532*** (0.000216)	0.00250*** (0.000168)		0.000680*** (0.000233)	0.00136*** (0.000235)
Industry tenure		0.00450*** (0.000201)		0.00272*** (0.000147)	0.00230*** (0.000205)	0.00133*** (0.000209)
Occupation tenure			0.00680*** (0.000122)	0.00665*** (0.000115)	0.00652*** (0.000124)	0.00326*** (0.000193)
Worker FE	No	No	No	No	No	Yes
<i>N</i>	2,511,646	2,511,646	2,511,646	2,511,646	2,511,646	2,511,646
<i>R</i> ²	0.380	0.380	0.381	0.381	0.381	0.131

Notes: Standard errors in parentheses. The dependent variable is the natural logarithm of wages. All tenures measured in years. Additional covariates include 1-digit occupation and industry dummies, year dummies, marital status, education, sex and age. ***statistically significant at the 1 percent tolerance level.

5.1. Wage Function Estimation

In order to assess the respective impact of occupation, industry and employer tenure on wages, we follow Kambourov and Manovskii (2009) and estimate the following wage equation:

$$w_{ijmnt} = x_{it} \cdot \beta_0 + \beta_1 \text{Emp_Ten}_{ijt} + \beta_2 \text{Occ_Ten}_{imt} + \beta_3 \text{Ind_Ten}_{int} + \theta_{it}, \quad (1)$$

where w_{ijmnt} is the natural logarithm of the hourly wage of person i working with employer j in occupation m and industry n in month t . **Emp_ten**, **Occ_Ten** and **Ind_Ten** denote tenure with the current employer, occupation, and industry, respectively. Additional control variables x_{it} include an intercept term, 1-digit occupation and industry dummies, a marital status dummy, year dummies, education, sex as well as age. Finally, θ_{it} is the error term.

We estimate (1) by ordinary least squares (OLS). Both our estimation method (OLS) and our specification of the wage equation (1) are slightly simpler than the preferred estimation method and specification of Kambourov and Manovskii (2009). For the joint sake of parsimony, clarity and brevity, we focus on OLS estimates of (1) in the main body of this paper. However, in Appendix F, we run a series of regressions based on the same specifications as Kambourov and Manovskii (2009), both as robustness checks and to produce results that are more directly comparable to theirs.

5.2. Results

Column 5 in Table 1 reports our OLS estimates of the coefficients of interest—the returns to occupation, employer, and industry tenure—in (1). We find that the returns to occupation tenure, at about 0.65% per year (or 3.3% over five years), are almost three times as large as the returns to industry tenure and an order of magnitude larger than the returns to employer tenure. The fact that occupation tenure is the most important source of wage growth echoes the main findings of Kambourov and Manovskii (2009). However, in contrast to Kambourov and Manovskii (2009), we find that industry tenure also has a sizeable effect on wages though the effect is weaker than the effect of occupation tenure.

In Table 1, column 6, we take advantage of the longitudinal dimension of our data to include worker fixed effects into (1). Doing so roughly doubles the estimated impact of employer tenure on wages, while halving those of industry and occupation tenure. This suggests that high-wage

workers (in a fixed effect sense) tend to have longer occupation tenure. Exactly why that is cannot be inferred from (1),¹³ but the main qualitative conclusion of Kambourov and Manovskii (2009) stands: even though employer and industry tenures have non-negligible positive impacts on wages, the effect of occupation tenure is more than twice as large.¹⁴

The first four columns in Table 1 show estimation results for alternative specifications of the wage equation in which employer, industry and occupation tenure are variously dropped from the list of regressors. Perhaps unsurprisingly, those results suggest that employer tenure picks up a large part of the wage effects of industry and occupation tenure when those are omitted from the regression. Again, those results mostly corroborate the findings of Kambourov and Manovskii (2009) on United States data.

6. Conclusion

In this paper, we combine information from the BHPS and UKHLS to construct consistent time series of aggregate worker stocks, worker flows and earnings in the UK over the 1992–2017 period for all workers as well as for two separate education groups.

We propose a method to harmonise data between the BHPS and UKHLS, which we validate by checking the consistency of some of our headline time series with equivalent series produced from other sources, notably by the ONS. This allows us to put together what, to our knowledge, is the first aggregate analysis of UK labour market stocks, flows, and earnings based on a ‘spliced’ BHPS/UKHLS data set.

Our main findings are summarised in the introduction to this paper. We do not repeat them here. Aside from our substantive results, we hope that this paper will help demonstrate the usefulness of a combined BHPS/UKHLS data set for the study of UK labour markets. While the analysis in this paper is almost entirely confined to the aggregate level, it is based on harmonised individual-level employment history data which is ready to be used for micro-level analysis.

Appendix A. Pre-Panel Employment Histories

As explained in the main text, at each annual interview, respondents are asked to provide retrospective information about their labour market experiences since the last interview. In addition, when they are interviewed for the first time, respondents are also asked to recall their complete employment history since entry into the labour market. In principle, this feature of the survey would allow us to estimate employment rates and transitions in the period before BHPS even started in 1991, and also for new UKHLS members in the period before 2009. However, this retrospective data suffers from two main problems: recall bias and the lack of pre-panel weights.

First, the recall bias is likely to be more severe when more time has passed since the employment spell of an individual is being asked about. Individuals are asked to recall full job histories at their first interview, which means recalling events that often date back several years (or even

¹³ In Appendix F, we decompose the error term θ_{it} and investigate the impact of various sources of heterogeneity a bit further.

¹⁴ Incidentally, in a monumental data harmonisation effort, Donovan *et al.* (2022) show that returns to employer tenure is negatively correlated with GDP per capita in a sample of 42 countries at various levels of development. Their wage equation specification is similar to the one in Table 1, column 1, i.e., it ignores industry and occupation tenure. It would be interesting to determine which of employer, industry or occupation tenure really drives the cross-country differences documented by Donovan *et al.* (2022).

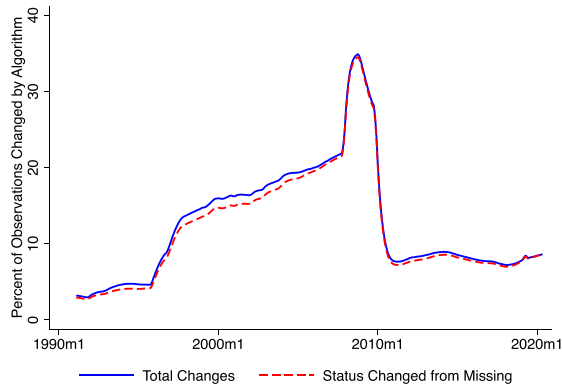


Fig. B1. *Proportion of Employment Statuses Changed by Our Algorithm.*

decades)—typically much longer than the single year individuals are asked to recall at subsequent interviews.

A related problem is that, in many cases, individuals have not reported their full employment history at their first interview. Instead, they only report the start date of their current labour market spell. Because employment spells last much longer on average than non-employment spells, including pre-interview labour market histories in our data would lead us to systematically overestimate the number of employed individuals in the pre-interview period (and underestimate the unemployed and inactive).

Potentially reflecting both of these reasons, we found that including recalled job histories for the period before individuals' first interviews resulted in a significant upward bias in the employment rate (and corresponding downward biases in the unemployment and inactivity rates) relative to national statistics.¹⁵

Second, we use individual weights supplied in BHPS and UKHLS to construct our estimates of aggregate stocks and flows to ensure they are representative of the UK population. Unfortunately, no weights are provided for pre-panel years and therefore it is not possible to make pre-panel years representative.

Appendix B. The Extent of Adjustment by the Algorithm

To check, assess the extent to which our algorithm adjusts the raw data, we reconstructed employment histories without applying the parts of the algorithm which set the start date of spells equal to the end date of previous spells—simply using the start and end dates recorded in the data, without any attempt to resolve inconsistencies or fill gaps. We still dropped all dates for an individual before the first interview and after their most recent one. We then calculated the number of times our algorithm changes the employment status recorded for an individual in a given month.

Figure B1 shows the number of changes our algorithm makes over time, expressed as a proportion of all employment spells recorded in each month. The vast majority of changes made

¹⁵ Elias (1996) and Paull (2002) both studied recall error in BHPS and came to the conclusion that it can have severe effects over periods longer than three years.

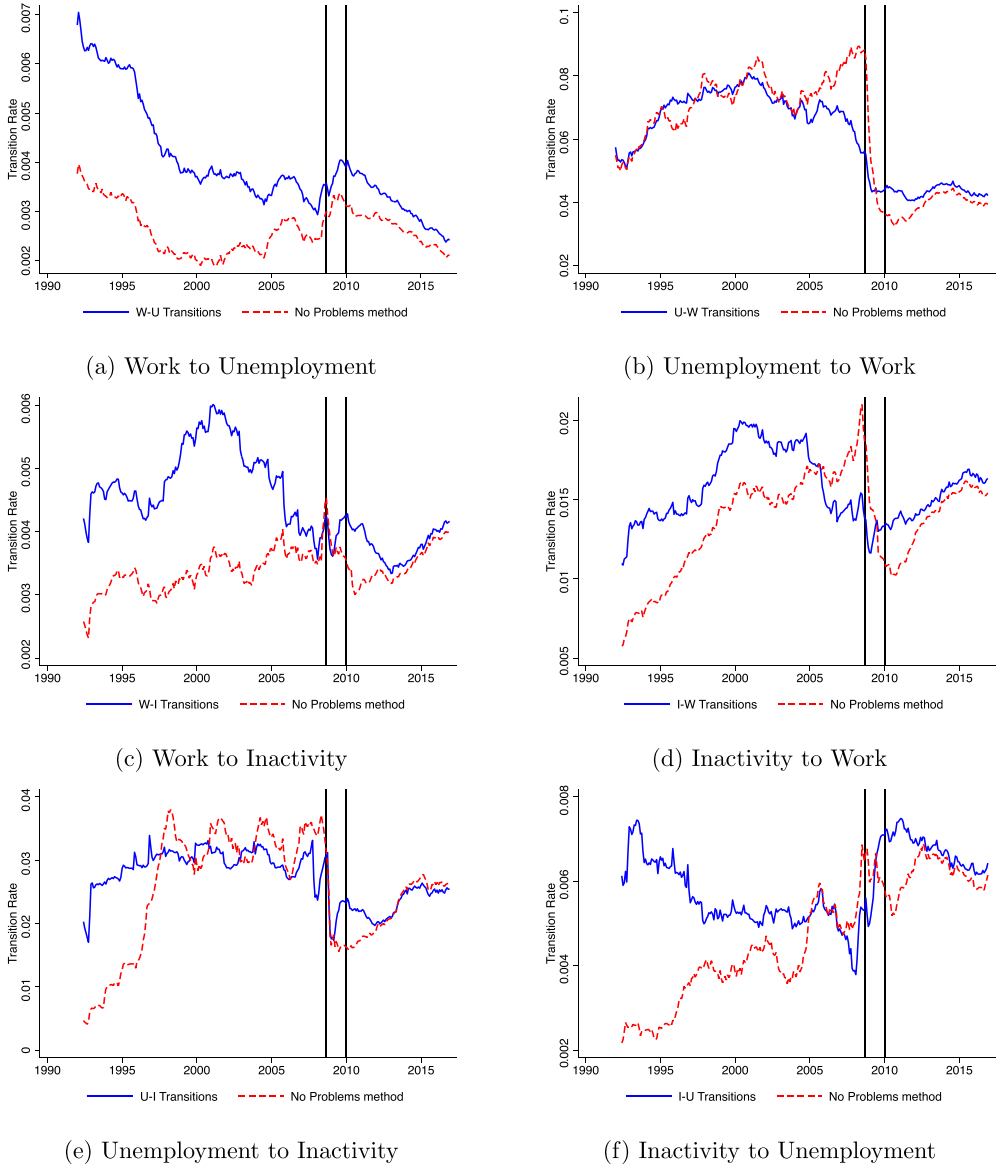


Fig. B2. Separation and Job Finding Rates Using Different Data Correction Methods.

by the algorithm are to fill missing employment spells, meaning that Figure B1 shows the number of job spells we would have to discard without the algorithm.

To further illustrate the impact of our adjustment algorithm, we compare the transition rates described in Section 3 to those we would have obtained if, instead of using the closest interview method, we simply discarded all observations with missing information or inconsistencies. This method is useful to illustrate the consequences of selection bias. Figure B2 shows that mobility between work and either unemployment or inactivity is almost systematically, and quite severely,

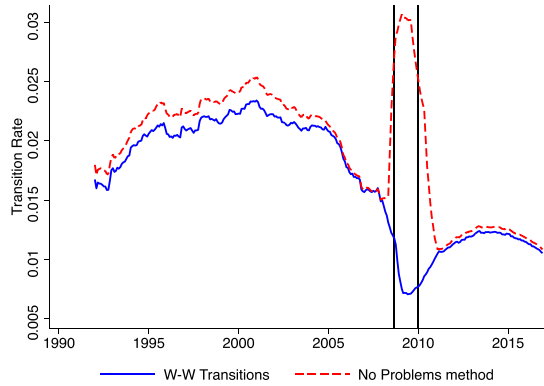


Fig. B3. *Job-to-Job Transition Rate Using Different Data Correction Methods.*

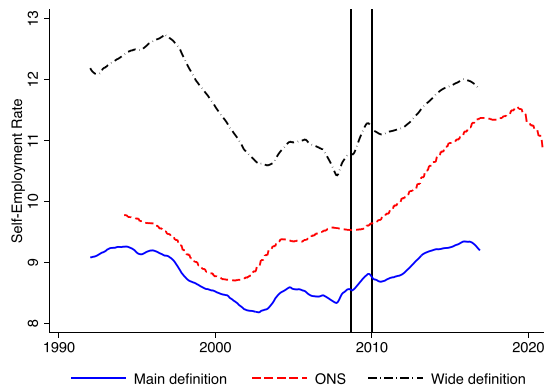


Fig. C1. *Monthly Self-Employment Rate.*

underestimated during the period covered by BHPS. The impact of the algorithm is much more limited on data from the UKHLS. Interestingly, Figure B3 shows that the bias caused by missing and inconsistent spells on direct employment-to-employment transitions is small. The rate at which such transitions occur is slightly overestimated by ignoring the inconsistent spell date problem, mainly because some work to non-employment, then back to work sequences are then misclassified as direct work to work transitions.

Appendix C. Self-Employment

In this Appendix, we illustrate the extent to which different ways of counting self-employed workers affect the aggregate measure of the stock of self-employed workers. As a reminder, our own definition of self-employment consists of only counting as self-employed workers who report themselves to be self-employed. Alternatively, a wider definition of self-employment could be to count as self-employed any worker who reports a self-employment income, even if their main income comes from paid employment and they do not report themselves as self-employment.



Fig. D1. *Aggregate Monthly Rates: BHPS/UKHLS Versus ONS.*

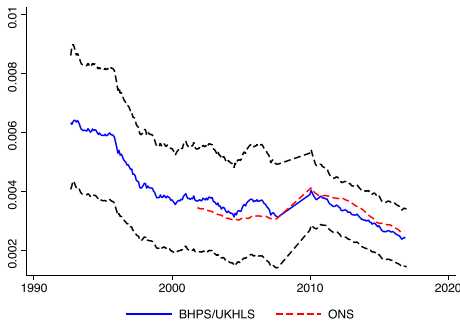
The time series of self-employment rates obtained by both methods are plotted on Figure C1, together with the ONS self-employment rate. As expected, the series using the ‘wider definition’ is everywhere well above our own series, and the ONS series is in between the two.

Appendix D. Confidence Intervals of 95% Around the Main Aggregate Series

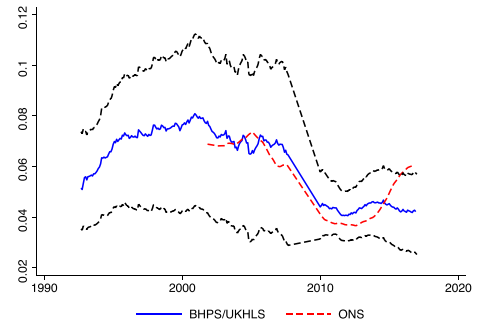
Figures D1 to D4 are replicas of Figures 1 to 4 from the main text, with 95% confidence bands superimposed. Confidence bands were constructed by regressing the variable of interest on month dummies, clustering standard errors at the individual respondent level.

Appendix E. Quarterly Transitions

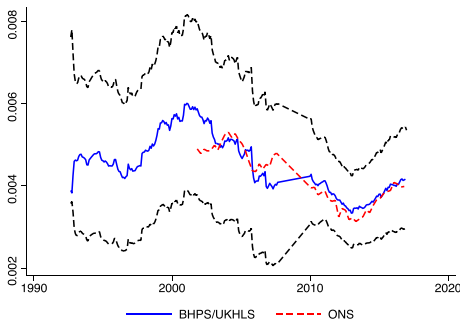
In this Appendix, we present an alternative comparison of labour market flow rates obtained from our new data set with those produced by the ONS. As explained in the main text, the ONS series are based on quarterly data from the UKLFS, and are therefore subject to time aggregation. While we do not know the details of the methods used by the ONS to construct its aggregate series from UKLFS worker-level data, we can attempt to replicate the UKLFS quarterly time aggregation in our monthly data. The resulting flow rate series are plotted in Figures E1 and E2,



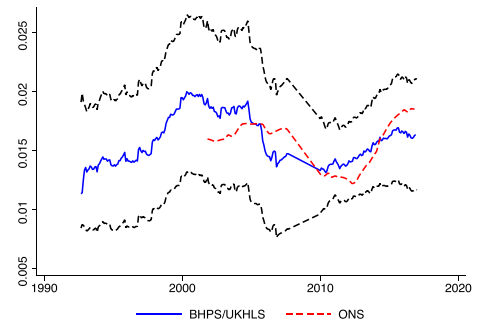
(a) Work to Unemployment



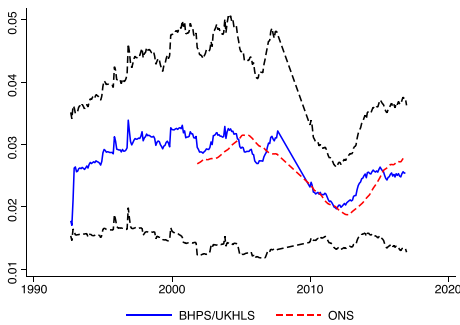
(b) Unemployment to Work



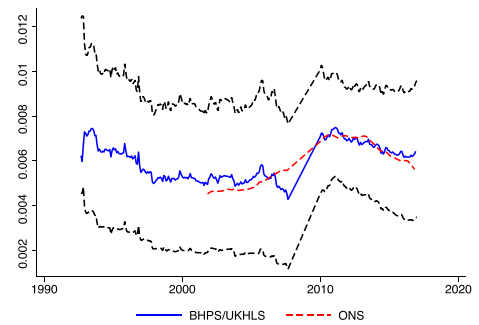
(c) Work to Inactivity



(d) Inactivity to Work



(e) Unemployment to Inactivity



(f) Inactivity to Unemployment

Fig. D2. Separation and Job Finding Rates.

together with the raw ONS data. As can be seen on the figures, the levels and trends of both sets of series coincide, although the ONS series has somewhat higher volatility.

Appendix F. Returns to Tenure: Robustness Analysis

In this Appendix, we investigate the robustness of the results on the estimation of the relative returns to employer, occupation and industry tenure presented in Section 5. Specifically, we

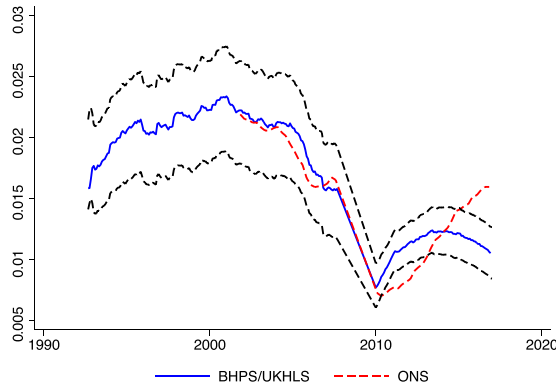


Fig. D3. Job-to-Job Transition Rate.

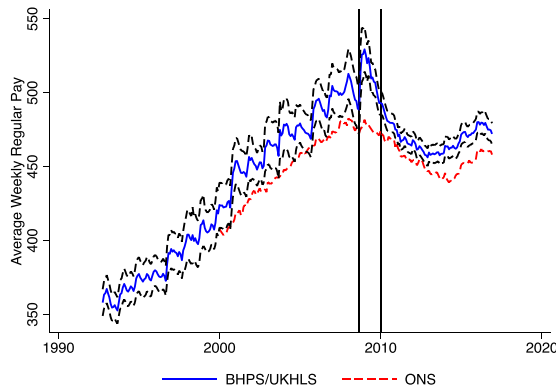
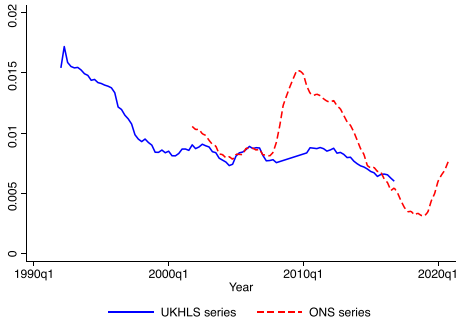


Fig. D4. Average Real Weekly Earnings Versus ONS Estimates.

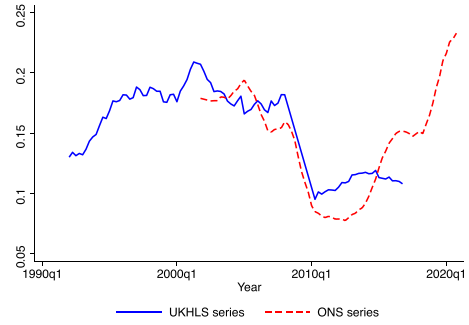
implement the full specification of the wage equation estimated by Kambourov and Manovskii (2009) on our data set and comment on the ways in which results are affected by this change of specification. The full specification of Kambourov and Manovskii (2009) is as follows:

$$\begin{aligned}
 w_{ijmnt} = & x_{it} \cdot \beta_0 + \beta_1^{(1)} \text{Emp_Ten}_{ijt} + \beta_1^{(2)} \text{Emp_Ten}_{ijt}^2 + \beta_4 \text{OJ}_{ijt} \\
 & + \beta_2^{(1)} \text{Occ_Ten}_{imt} + \beta_2^{(2)} \text{Occ_Ten}_{imt}^2 + \beta_2^{(3)} \text{Occ_Ten}_{imt}^3 \\
 & + \beta_3^{(1)} \text{Ind_Ten}_{int} + \beta_3^{(2)} \text{Ind_Ten}_{int}^2 + \beta_3^{(3)} \text{Ind_Ten}_{int}^3 \\
 & + \beta_5^{(1)} \text{Work_Exp}_{it} + \beta_5^{(2)} \text{Work_Exp}_{it}^2 + \beta_5^{(3)} \text{Work_Exp}_{it}^3 + \theta_{ijmnt}. \quad (\text{F1})
 \end{aligned}$$

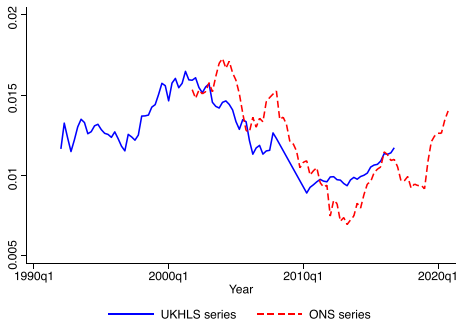
Compared to our simpler specification (1), Kambourov and Manovskii (2009) include the following additional regressors. First, they add a cubic polynomial in overall labour market experience, Work_Exp_{it} (we simply allow for a linear age effect). Second, they allow for non-linear effects of the various measures of tenure (employer, occupation, industry). Specifically, they include squared and cubed terms in industry and occupation tenure, a squared term in employer tenure,



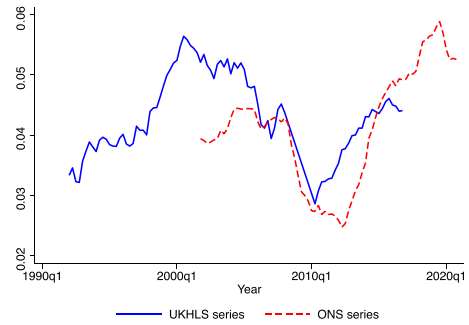
(a) Work to Unemployment



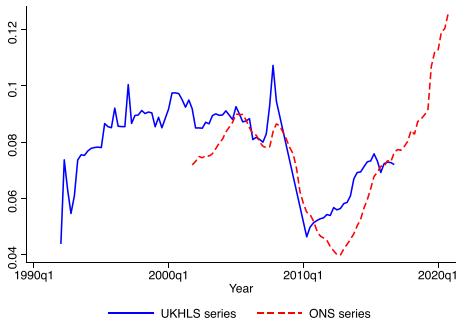
(b) Unemployment to Work



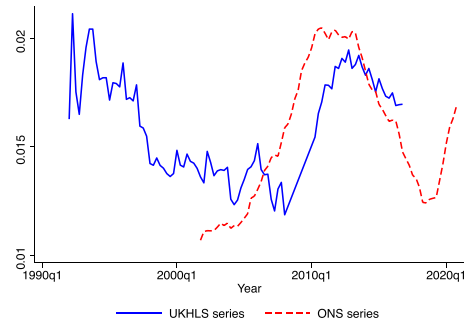
(c) Work to Inactivity



(d) Inactivity to Work



(e) Unemployment to Inactivity



(f) Inactivity to Unemployment

Fig. E1. Separation and Job Finding Rates.

and a term OJ_{ijt} which is an indicator variable of individual i not being in their first year of employment with their current employer j . Exactly why possible non-linear effects of employer tenure are specified differently than those of occupation or industry tenure is not entirely clear to us.¹⁶

¹⁶ Altonji and Shakotko (1987) and Parent (2000) also use a similar term in the specification of their wage equations. Altonji and Shakotko (1987) write that they include it ‘so that the wage response to the first year of tenure is not restricted

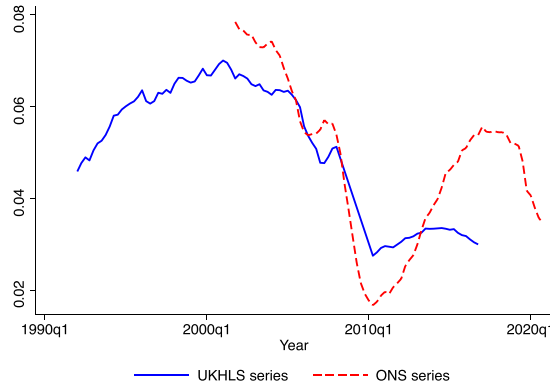


Fig. E2. Job-to-Job Transition Rate.

Table F1. Returns to Tenure, Specification of Kambourov and Manovskii (2009).

		6 months	1 year	2 years	4 years	5 years
Employer	OLS	0.0028*** (0.00027)	0.0054*** (0.00054)	0.0134*** (0.00128)	0.0211*** (0.00179)	0.0240*** (0.00205)
	IV	0.0013*** (0.00039)	0.0021*** (0.00077)	-0.0166*** (0.00182)	-0.0220*** (0.00276)	-0.0276*** (0.00318)
Industry	OLS	0.0029*** (0.00038)	0.0058*** (0.00072)	0.0113*** (0.00130)	0.0120*** (0.00208)	0.0252*** (0.00232)
	IV	0.0106*** (0.00047)	0.0206*** (0.00090)	0.0386*** (0.00163)	0.0670*** (0.00265)	0.0778*** (0.00298)
Occupation	OLS	0.0065*** (0.00033)	0.0127*** (0.00062)	0.0239*** (0.00112)	0.0420*** (0.00178)	0.0493*** (0.00198)
	IV	0.0080*** (0.00039)	0.0155*** (0.00074)	0.0294*** (0.00135)	0.0524*** (0.00218)	0.0620*** (0.00244)

***statistically significant at the 1 percent tolerance level.

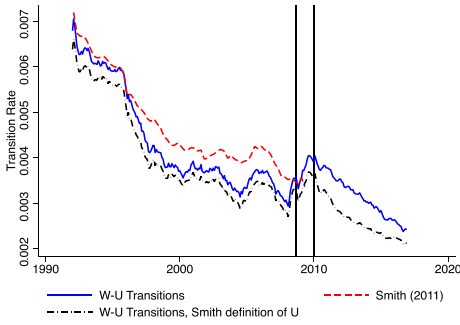
Finally, Kambourov and Manovskii (2009) assume the following structure for the disturbance term:

$$\theta_{ijmnt} = \alpha_i + \gamma_{ij} + \phi_{im} + \psi_{in} + \epsilon_{it}. \tag{F2}$$

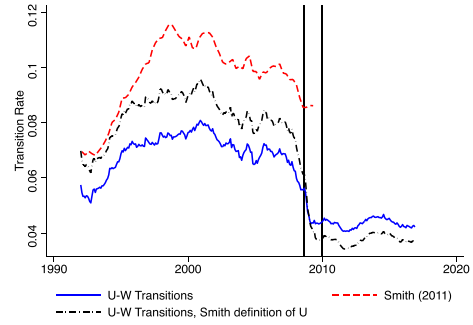
In other words, they decompose the disturbance term θ_{ijmnt} into an individual worker effect α_i , a worker–employer match effect γ_{ij} , a worker–occupation match effect ϕ_{im} , a worker–industry match effect ψ_{in} , and an error term ϵ_{it} . While Kambourov and Manovskii (2009) start by estimating (F1) by OLS, they also worry about the possibility that ‘good’ matches, in the sense of matches with high specific effects γ_{ij} , ϕ_{im} or ψ_{in} , may tend to be more stable, implying that the various measures of tenure might each be correlated with at least one of the components of θ_{ijmnt} . To address that particular concern, Kambourov and Manovskii (2009) apply an instrumental variable procedure adapted from Altonji and Shakotko (1987) and Parent (2000).¹⁷ We do not

by the quadratic specification of the tenure profile’. Parent (2000) says ‘the rationale for the inclusion of such a variable is that the first year of tenure might be of special significance in terms of investments in job-related skills’.

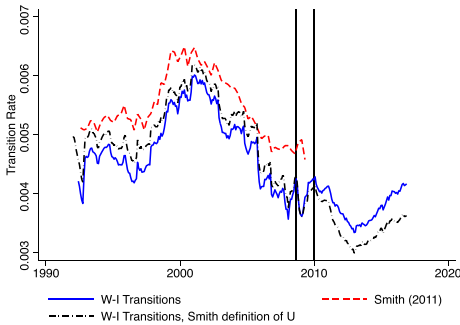
¹⁷ Take employer tenure for example. Emp.Ten_{ijt} is instrumented by $\text{Emp.Ten}_{ijt} - \overline{\text{Emp.Ten}_{ijt}}$, where $\overline{\text{Emp.Ten}_{ijt}}$ is the average tenure of individual i during their current spell of work at employer j . For example, if an individual has a job for five months, the employer tenure variable will take values {1, 2, 3, 4, 5} over the five months. The average employer



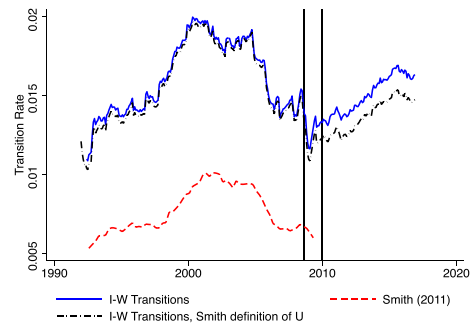
(a) Work to Unemployment



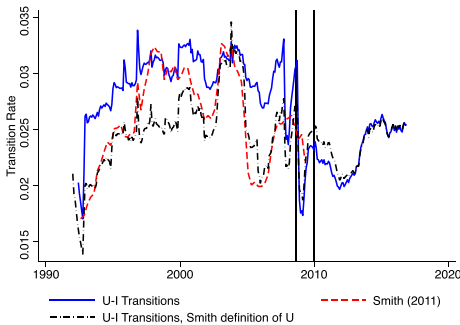
(b) Unemployment to Work



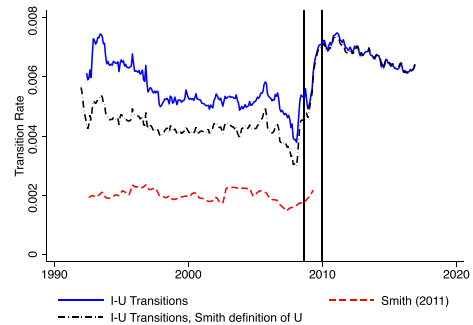
(c) Work to Inactivity



(d) Inactivity to Work



(e) Unemployment to Inactivity



(f) Inactivity to Unemployment

Fig. G1. Dashed Line: Transition Rates from Smith (2011), Solid Line: Transition Rates Using Spliced BHPS/UKHLS, Dash-dot line: transition rates using Spliced BHPS/UKHLS with Smith (2011) definitions of stocks.

comment on the properties of that particular IV protocol in this paper: we only apply it to our own data set for comparability with Kambourov and Manovskii (2009).

tenure for that spell is three, and so the IV takes values $\{-2, -1, -0, 1, 2\}$. All tenure variables (including the non-linear terms and the variable OJ_{ijt}) are instrumented in the same way.

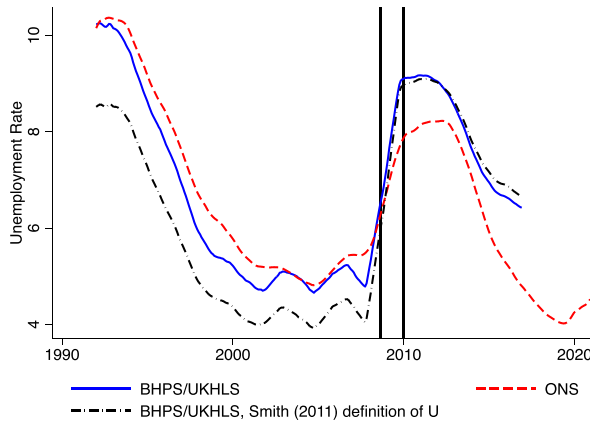


Fig. G2. *Unemployment Rates.*

Results are summarised in Table F1. Because Kambourov and Manovskii (2009) specify wages as non-linear functions of employer, industry and occupation tenure, we present the returns of each type of tenure at various horizons as estimated either by OLS or IV. Estimates of the returns to employer tenure factor in the OJ_{ijt} indicator of tenure greater than one year, which is part of the specification in Kambourov and Manovskii (2009). Full regression results are available on request.

When estimated by OLS on our UK data, the non-linear specification of Kambourov and Manovskii (2009) continues to suggest that occupation tenure is the most highly correlated with wages. However, it also suggests that employer and industry tenure both play non-negligible—and quantitatively roughly comparable—roles as drivers of wages. This corroborates the results obtained from our simpler, linear specification (Table 1), although the non-linear specification tends to assign a quantitatively larger role to employer tenure. Next turning to IV estimates, we see that instrumenting the various tenure measures as described in Altonji and Shakotko (1987), Parent (2000) and Kambourov and Manovskii (2009) largely wipes out employer tenure as a determinant of wages, while inflating the coefficients on industry and occupation tenure, which are now of roughly equal magnitude.¹⁸

Our reading of those results is that, while specification seems to matter quantitatively, Kambourov's and Manovskii's result about occupation tenure being a much more important driver of wage growth than employer tenure is also found in our UK data. However, contrary to Kambourov and Manovskii (2009), our data suggests that industry tenure plays a quantitatively non-negligible role as a determinant of wage growth. Note that, in addition to the fact that our data pertains to a different country than Kambourov's and Manovskii's, it is also the case that we have a considerably larger, and representative, data set. Moreover, we have data on a much longer time horizon compared to their study and we also keep all workers (we only exclude self-employed workers) in our sample, whereas Kambourov and Manovskii (2009) only keep white male workers who are heads of household and aged between 16 and 64.

¹⁸ The impact of employer tenure even appears to become negative after a couple of years, owing to a large, negative estimated coefficient on the OJ_{ijt} indicator. Details are available on request.

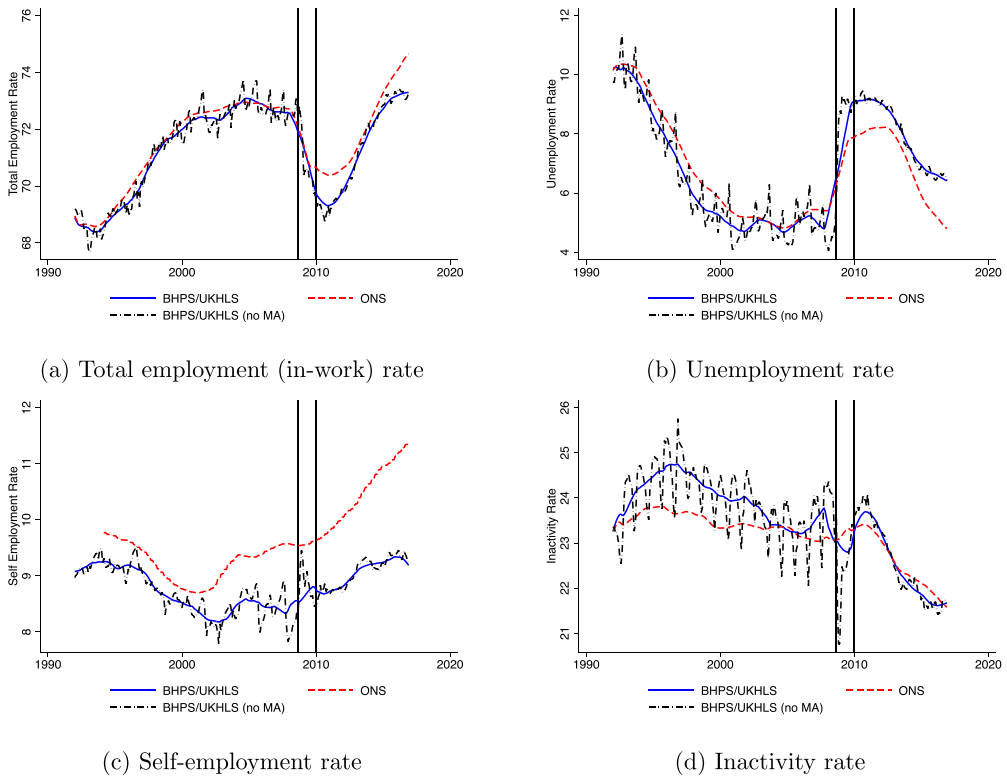


Fig. H1. *Aggregate Monthly Rates: BHPS/UKHLS Versus ONS, with Raw MA Data.*

Appendix G. Comparison with Smith (2011)

Figures G1 and G2 show the comparison between flow rates and aggregate unemployment rate using our definitions of variable versus Smith (2011) definitions. Regarding the difference in transition rates with Smith (2011), these differences are partly caused by our different way of defining employment statuses, especially inactivity. In Smith's definition, inactivity includes retirement, family care, long-term sickness or disability, full-time education, national or war service, and 'anything else' (approximately 32% of her sample). By contrast, we also require individuals to have not searched for work or claimed unemployment benefits in the four weeks prior to their interview. This narrower definition of inactivity results in lower average inactivity rates compared to Smith (2011) (around 24% of our sample) and higher transition rates from inactivity to unemployment and work. The dividing line between inactivity and unemployment is inevitably somewhat arbitrary. We chose our definitions of unemployment and inactivity on two grounds. First, our definitions are closer to those upon which the ONS bases its own aggregate labour market series. Given that those ONS series are the reference measures of employment and unemployment rates in the UK, it is important that our own series match those measures. Second, while Smith's IW transition rates (Figure H2f) stayed roughly constant around 0.2% up until 2008, our series have a downward trend from 1992 to 2008 followed by a sharp increase

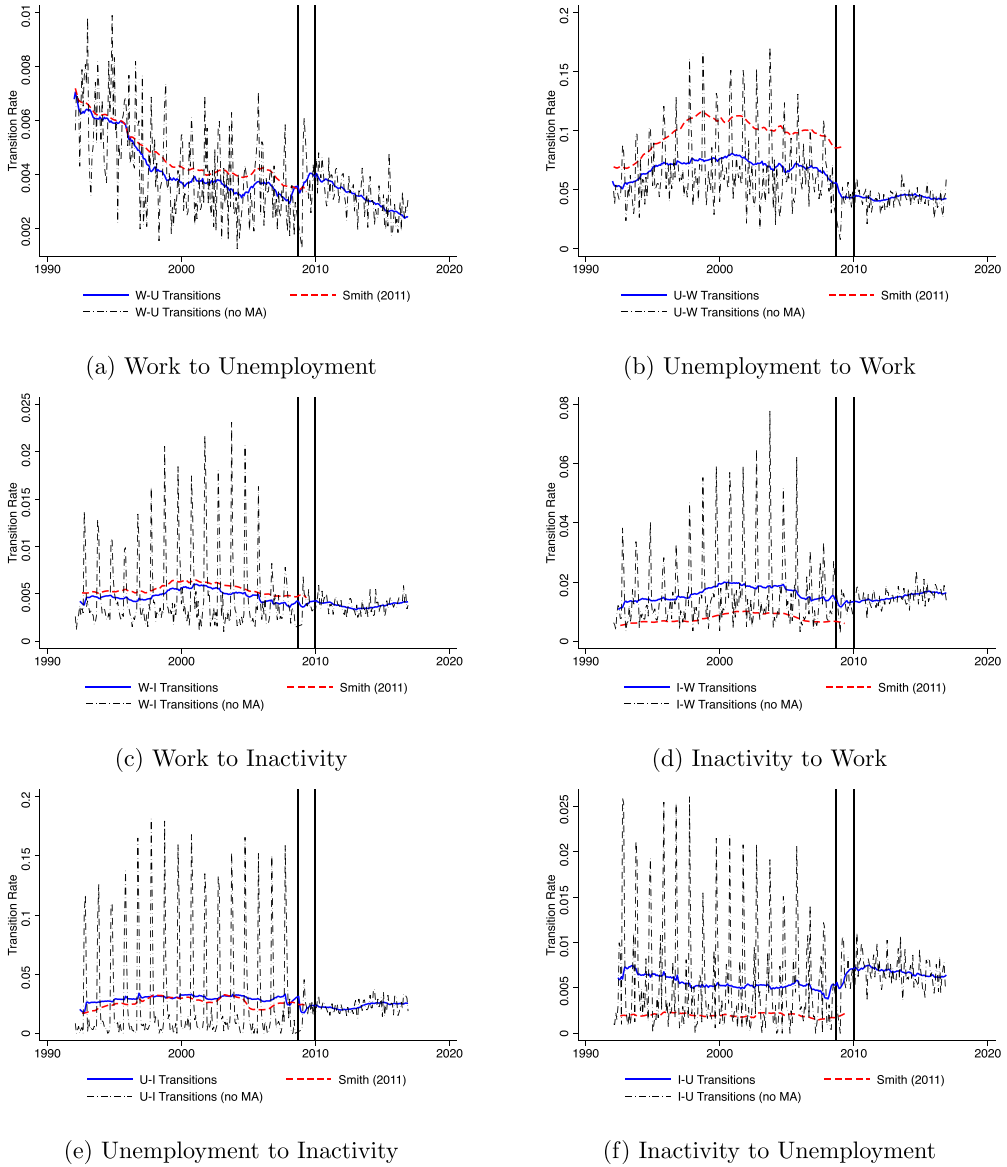


Fig. H2. Transition Rates with No Moving Average.

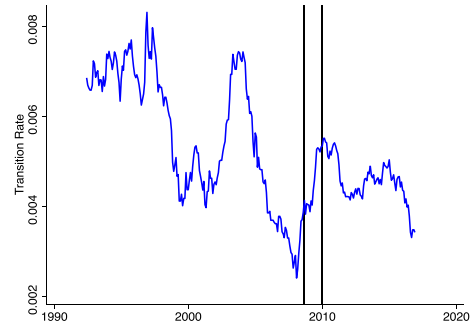
during the Great Recession, which is consistent with the findings of Elsby *et al.* (2009) that IU transitions intensify during downturns.

Appendix H. Raw Data

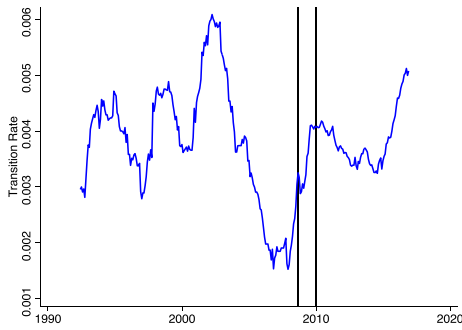
Figures H1 and H2 contain the aggregate and transition rates including raw data.



(a) Self-employment to Unemployment



(b) Unemployment to Self-employment



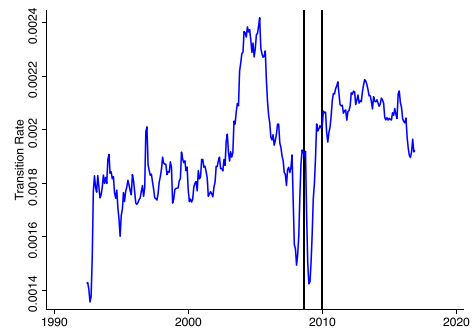
(c) Self-employment to Inactivity



(d) Inactivity to Self-employment



(e) Self-employment to Employment



(f) Employment to Self-employment

Fig. 11. *Self-Employment Transition Rates.*

Appendix I. Transitions in and Out of Self-Employment

Figure 11 shows all transition rates into and out of self-employment. Transition rates between self-employment and unemployment (SU and US rates, Figures 11a, b) evolve in a qualitatively similar way to their WU and UW counterpart rates (Figures D2a, b). In particular, both the SU and US rates trend down over most of the observation window, even though the decline in SU and US rates appears to have started a few years earlier than the corresponding decline in WU

and UW rates. Another difference is that the US rate is more volatile than the UW rate, showing a few sizeable spikes, notably one towards the end of the Great Recession.

Transition between self-employment and inactivity (Panels IIc, d), although somewhat volatile, show no particular trend over the period considered.

Finally, Panels IIe and II f show transition rates between self-employment and employment. The SE rate is hump-shaped over the pre-recession period, much like the general WW rate (Figure 3) but, unlike the WW rate, it does not collapse during the Great Recession: rather, it seems to have started on a slow downward trend around 2008. As for the ES rate, it has been on a slow but steady upward trend since the start of the sample.

Summing up, the U-shape of the self-employment rate over period 1992–2017 documented on Figure 1c in the main body of the paper results from a somewhat complex combination of various inflows and outflows: a fall in transitions from unemployment into self-employment, partly compensated by fewer transitions into unemployment and by more transitions from employment. Zooming in on the aftermath of the Great Recession, a period during which the self-employment rate has increased in the UK (Figure 1c), we can see that this increase in the stock of self-employed workers came with increased ‘impermeability’ of the state of self-employment, i.e., with a fall in all the associated inflow and outflow rates. Yet clearly, over that period, the impact of the combined fall in outflow rates from self-employment into unemployment, inactivity and employment dominated the contemporaneous fall in inflow rates.

University College London & Institute for Fiscal Studies, UK
University of Bristol, UK

Additional Supporting Information may be found in the online version of this article:

Online Appendix Replication Package

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