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Empirical Essays on Recent Patterns in the British Labour Market

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Abstract

This thesis presents three essays, which each address a salient recent pattern in the British labour market. The first essay concerns whether or not men and women experience the business cycle differently, through their labour market outcomes, and why this might be the case. The second essay seeks to explain the cyclical amplification of unemployment duration, in particular the substantial and persistent increase in UK long-term unemployment observed during and since the Great Recession. The final essay studies recent changes in British wage inequality. To shed light on the possible factors driving these changes, it asks simply whether they are mostly determined by increasing or decreasing wage dispersion within or between firms.

Gender and the business cycle: an analysis of labour markets in the US and UK
Starting from an improved understanding of the relationship between gender labour market stocks and the business cycle, we analyse the contributing role of flows in the US and UK. Focusing on the post-2008 recession period, the subsequent greater rise in male unemployment can mostly be explained by a less cyclical response of flows between employment and unemployment for women, especially the entry into unemployment. Across gender and country, the inactivity rate is generally not sensitive to the state of the economy. However, a flows based analysis reveals a greater importance of the participation margin over the cycle. Changes in the rates of flow between unemployment and inactivity can each account for around 0.8-1.1 percentage points of the rise in US male and female unemployment rates during the latest downturn. For the UK, although the participation flow to unemployment similarly contributed to the increase of the female unemployment rate, this was not the case for men. The countercyclical flow rate from inactivity to employment was also more significant for women, especially in the US, where it accounted for approximately all of the fall in employment, compared with only forty percent for men.

Long-term unemployment and the Great Recession: evidence from UK stocks and flows
Although modest by historical standards, long-term unemployment nonetheless more

than doubled during the UK's Great Recession. Only a small fraction of this persistent increase can be accounted for by the changing composition of unemployment across personal and work history characteristics. Through extending a well-known stocks-flows decomposition of labour market fluctuations, the cyclical behaviour of participation flows can account for over two-thirds of the high level of long-term unemployment following the financial crisis, especially the procyclical flow from unemployment to inactivity. The pattern of these flows and their changing composition suggest a general shift in the labour force attachment of the unemployed during the downturn.

Recent changes in British wage inequality: evidence from firms and occupations

Using a linked employer-employee dataset, we study the increasing trend in British wage inequality over the past two decades. The dispersion of wages within firms accounts for the majority of changes to wage variance. Approximately all of the contribution to inequality dynamics from firm-specific factors are absorbed by controlling for the changing occupational content of wages. The modest trend in between-firm wage inequality is explained by a combination of changes in between-occupation inequality and the occupational composition of firms and employment. These results are robust to using weekly, hourly or annual measures of employee pay.

Lay summary

This thesis presents three essays, which each address a salient recent pattern in the British labour market. The first essay concerns whether or not men and women experience periods of economic recession, recovery and boom differently, through how they fare in the labour market. The second essay seeks to explain why the length of time workers spend unemployed during recessions increases so much. In particular it studies the substantial and persistent increase in UK long-term unemployment observed during and since the Great Recession; i.e. since the financial crisis of 2008. The final essay studies recent changes in British wage inequality, or the the differences between workers' pay. To shed light on what could be driving these changes, it asks simply whether they are mostly determined by the increasing or decreasing differences in employees' wages within or between the firms for whom they work.

Gender and the business cycle: an analysis of labour markets in the US and UK
The essay starts by improving our understanding of how the numbers of men and women who are either employed, unemployed and looking for work, or neither employed nor actively seeking work (economically inactive), have changed since the Second World War along with the state of the US and UK economies. To explore these results further, we analyse how changes in the rate at which workers moved between employment and unemployment, economic inactivity and unemployment etc., determined the historical evolution of the number of men and women in work. Focusing on the post-2008 recession period, the greater rise in men's unemployment over this period can mostly be explained by greater changes in the rate at which they moved between employment and unemployment than women. Across gender and country, the rate of economic inactivity is generally not sensitive to the state of the economy. However, studying the dynamics of the labour market reveals a greater importance of movements between economic activity and inactivity through recessions, along with greater gender differences. This has important implications for policy makers, because it highlights not only the way in which recessions can affect some types of workers more than others, namely here men and women, but also shows

that they should look beyond just the headline unemployment rate in assessing the current and future health of the labour market.

Long-term unemployment and the Great Recession: evidence from UK stocks and flows

Although modest by historical standards, long-term unemployment nonetheless more than doubled during the UK's Great Recession. Only a small fraction of this persistent increase can be explained by the changing characteristics of unemployed persons; i.e. it is not explained by a relatively large increase in the unemployment of workers who typically in all periods continuously stay unemployed for a long time. By studying how workers move around the labour market, between either employment, unemployment and economic inactivity (not looking for work), the vast majority of the increase in long-term unemployment can be accounted for by a decrease in the rate at which the unemployed stopped looking for work to become inactive. The pattern of how this rate changes over time, along with other evidence, suggests that during the most recent downturn there was a general increase in how attached to the labour market the unemployed were. Understanding why long-term unemployment increases during recessions has important implications for policy makers, who view it as a particularly adverse social outcome and wish to avoid its persistence following recessions.

Recent changes in British wage inequality: evidence from firms and occupations

Using a dataset covering a large sample of employees and their mostly very large employers, we study the dynamics of British wage inequality over the past two decades. Contrary to other studies, we find little evidence that recent increases in inequality have been driven by differences in the average wages paid by firms. Instead greater wage differences within firms can account for the majority of the overall differences in wages between all workers. After addressing the fact that some occupations are paid more than others, the role of average firm wages is approximately zero; the modestly increasing trend in between-firm wage inequality is explained by a combination of changes in between-occupation inequality and the occupational specialisation of firms. It is possible that previous studies, which assign some of the importance of changes in the between-firm component to industry, have misrepresented a significant role for occupations. These results are robust across measures of hourly, weekly and annual wages. Understanding the determinants of wage inequality trends matters for at least three major reasons. First, there is a long-held view in economics that perceptions of fairness in the workplace, or a lack thereof, can affect productivity. Second, if increases or decreases in inequality occur within or between firms, it could affect how salient those overall changes are to workers, and how likely it is therefore to affect the political economy status quo within that country. Third, for policy makers who seek to affect the level of wage inequality, understanding how it came about could give insights into whatever the most effective policy tools are likely to be.

Declaration

I, Carl Andrew Singleton, confirm that the work presented in this thesis is my own. Where the research was carried out alongside others, or where information has been derived from other sources, I confirm that this has been indicated in the thesis. This work has not been submitted for any other degree or professional qualification.

Acknowledgements

I thank my academic supervisors, Andy Snell and Jan Grobovšek for their patience, support and advice, and I would express similar sentiments to many other academic and non-academic staff members in the School of Economics. I also thank Giovanni Razzu and Daniel Schäfer for productively working alongside me to produce parts of this research. I am grateful for funding support from the Economic and Social Research Council (UK) under Grant No. ES/J500136/1.

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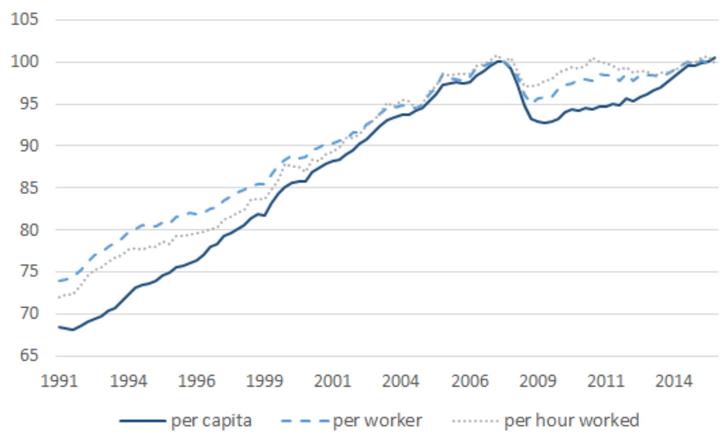
Chapter 1

Introduction

The 2008 global financial crisis precipitated the deepest and sharpest recession in Britain since the Second World War. This downturn has since led to a prolonged slump in GDP per capita, and, unlike the periods following previous recessions, the UK economy has not bounced back to previous long-run trends (Figure 1.1). The British experience of the Great Recession has both been like and unlike that of other major Western economies. For example, the initial contraction in output was similar in relative magnitude to the US, and both countries quickly found themselves pushing against the Zero Lower Bound, the limit on the effectiveness of conventional monetary policy. But the US then adopted a less contractionary fiscal policy stance, not implementing the extent of austerity chosen by the UK Government, and so recovered more quickly (see for example House et al., 2017 for a thorough analysis of the effects of austerity since the Great Recession). UK and US trends and levels of employment, wages, and hours worked, and their distribution across major social groups, were mostly very similar before 2008. However, whilst US labour productivity has increased since, common with what typically happens through recessions, UK productivity has contracted sharply; UK employment has been remarkably resilient by historical standards, given such a prolonged demand deficient slump (see Barnett et al., 2014; Bryson & Forth, 2015 for discussions of "The UK's Productivity Puzzle").

It is largely within this context that the first two essays in this thesis discuss recent patterns in the British labour market. Both make use of longitudinal micro data from the Labour Force Survey, which have been collected since 1993, and therefore only cover the most recent UK recession. These data can be used to document how individual and aggregate transitions (flows) between states explain the performance of the labour market over the economic cycle. Such data have been fundamental in shaping a new generation of research into the role of labour

FIGURE 1.1: UK Whole Economy Output per capita, worker and hour worked, SA, index: 2008q1 = 100



Notes.- own calculations using ONS time series data, accessed 3/4/2017.

markets in the macroeconomy: on accurately modelling responses to events such as the 2008 financial crisis and considering the effects of policy interventions (see Davis et al., 2006; Rogerson & Shimer, 2011 for extended discussions). Besides this line of research, there are still many open empirical questions that labour market flows data can help to address. The first essay here uses this data to revisit an old question: why does male unemployment appear to be more sensitive to the cycle than female, beyond the obvious explanation that men more commonly work in sectors and jobs which are more closely linked to aggregate fluctuations (Hoynes et al., 2012; Peiro et al., 2012). In particular, the flows data can be used to assess whether similar gender responses in economic activity levels could belie greater relative differences in the importance of the participation margin. Thus, the significance of theoretical perspectives on why men and women appear to experience a recession differently can be assessed, such as the so-called Added Worker Effect.

The second essay also uses these flows data to study the large and persistent increase in long-term unemployment during the Great Recession (see Bentolila & Jansen, 2016 for a collection of perspectives on the European experience). Long-term unemployment is a particular concern of policy makers, and the negative hysteresis effects on those who find themselves out of work during downturns have been extensively studied. However, the reason why long-term unemployment increases during recessions is perhaps a surprisingly open question. Is it because individuals find jobs at a slower rate, or is it because the unemployment pool shifts during recessions towards consisting of those who in normal times also take longer to find jobs? A relatively new literature has used flows data to show that the unprecedented increase in US long-term unemployment since 2008 was mostly not about changes in the rate at which individuals moved into work, but was instead determined by a reduction in the rate at which they stopped looking and became inactive, whether that be through discouragement or some other reason, and an increase in the rate at which marginally active workers entered the labour market and began to look for work, albeit with perhaps less effort than those who were losing their jobs (Krueger et al., 2014; Kroft et al., 2016). This distinction matters in terms of framing for policy makers how concerned they should be about long-term unemployment, where most active labour market interventions in Britain have been focused.[1]

The final essay here studies recent changes in British wage inequality. Over the last half century this has increased substantially, mostly doing so before the 1990s, but even since then the trend has remained positive (see Machin, 2011 for a detailed description of British wage inequality trends). Many other developed countries have in recent history experienced large (mostly positive) changes in wage inequality. Various explanations have been put forward to explain these changes, ranging from skill biased technological change to the role of executive pay. A recent and rapidly growing body of research, motivated by access to new sources of administrative or survey based linked employer-employee micro data, has attempted to test the validity of these explanations (see Card et al., 2016 for a survey). At the simplest level, these new datasets allow researchers to observe or estimate whether or not changes in wage inequality have been driven by the extent of differences between firms, as opposed to the differences in wages within firms. This is the focus of the third essay here, where a dataset covering a large sample of employees and their mostly very large employers is used to analyse the determinants of British wage inequality over the last two decades.

[1] See for instance the New Deal programmes, 1998-2011, and their replacement by the Work Programme since.

Chapter 2

Gender and the business cycle: an analysis of labour markets in the US and UK

Note: A version of this essay has also appeared as an article in the March 2016 edition of Journal of Macroeconomics; DOI: 10.1016/j.jmacro.2015.12.006. This article was co-authored with Giovanni Razzu, who is Head of Department and Professor in Economics of Public Policy at the University of Reading; e-mail: g.razzu@reading.ac.uk. Giovanni has agreed that the essay can appear within this thesis, and that it represents a significant contribution on my part. Re-production of the essay here does not infringe the publisher's copyright policies. The version here has been rewritten and reformatted compared with the aforementioned article, and so they are not identical, though the main substance and results are. This work was presented at the 2014 European Association of Labour Economists Conference, and as part of the Centre for Analysis of Social Exclusion (CASE: LSE) and the Department of Economics RiP (University of Reading) Seminar Series.

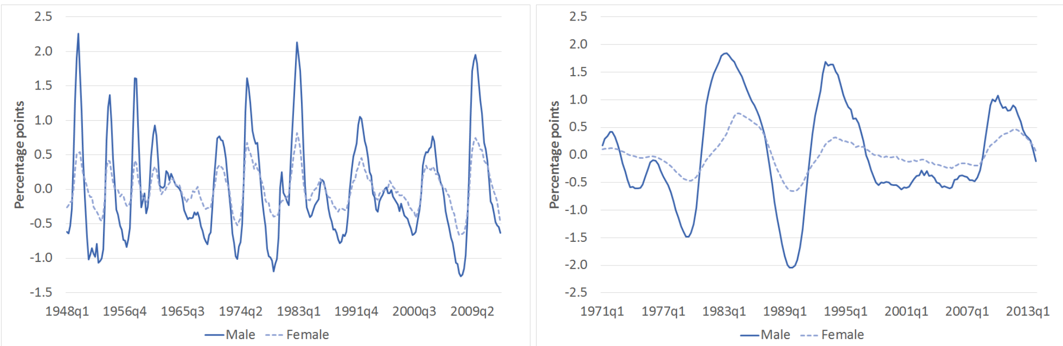
2.1 Introduction

What is the role of labour market flows in explaining the gender dimension of the business cycle? The sparse analysis carried out to date has typically only described how the stocks of men and women in unemployment respond to aggregate fluctuations. Figure 2.1 illustrates for both the US and UK that during economic recessions male unemployment rises faster than female, reducing the gender gap, and in the subsequent recovery, male unemployment falls faster, returning the gender gap to some trend.

The relative resilience of the female unemployment rate during a downturn has been explained by one major factor, at least so far as the US is concerned: men and women tend to be occupied in economic sectors that are differently affected by recessions and booms. Occupations that predominantly hire men are typically more cyclical and, therefore, more severely affected by economic recessions (Wood, 2014).[1] However, the extent to which different responses to the cycle can be related to the fluidity of the labour market has largely been overlooked in the literature.[2] By studying the flows between employment, unemployment and inactivity, we can determine which of the flows into and out of the three states drive the aggregate dynamics of labour market stocks. A flows analysis can tell us something more specific about the sources of the gender business cycle.

FIGURE 2.1: Difference from trend of male and female unemployment rates, 16+

(a) US (b) UK



Notes.- own calculations from seasonally adjusted CPS (US) & Labour Force Survey (UK). Detrended using unobserved component model as described in Section 2.2 with constrained frequency parameter to match estimated cyclical periodicity of log GDP.

Notwithstanding the importance of using stocks to assess the health of the labour market over time, it is now well acknowledged that flows data offer some clear advantages, and the fluidity of the labour market has become the topic of a growing and influential literature since the original contributions of the 1970s.[3] The empirical analysis of flows has guided the development of the search and matching class of

[1]For the UK there is some evidence that where men and women work cannot explain all of recent cyclical differences, and after controlling for this, during the Great Recession, female job losses were more sensitive to the downturn (Rubery & Rafferty, 2013; Perivier, 2014; Razzu & Singleton, 2017). Also, Elsby et al. (2016) tentatively suggest that women's real wages were particularly adversely affected by the latest downturn relative to men. Differences in the response of male and female wages, which may not be sectoral, could also be of some relevance.

[2]For example, see the limited discussion of gender in the most prominent literature on labour market flows, such as Elsby et al. (2010, 2011b); Shimer (2012). These previous papers moreover do not relate flows back to the overall picture of gender differences in the labour market over the business cycle.

[3]See for example Kaitz (1970); Perry (1972). More recently, important methodological contributions have been provided by Shimer (2005, 2012); Petrongolo & Pissarides (2008); Fujita & Ramey (2009); Solon et al. (2009); Elsby et al. (2010, 2015); Gomes (2012); Smith (2011).

models now most commonly used to understand labour market fluctuations. Analysing flows data can give us more detailed insight of how labour market stocks change, and this could underlie differences in how men's and women's outcomes behave over the business cycle. Has a woman become unemployed because she has lost a job, or because she has completed full-time education and become active in the labour market? Similarly, has a man who has left unemployment done so because he has found a job, or because he has withdrawn from the labour market, perhaps due to disability or other reasons for inactivity? These transitions reveal quite dissimilar experiences, but they become hidden when looking only at the stock of unemployed, employed or inactive persons. In the example of the woman above, the two transitions would both result in an increase in female unemployment, but flows data would tell us that in the first case this was due to a job exit, and in the second case because of a positive labour supply response.

This chapter not only builds on but goes substantially beyond previous assessments of the relationship between gender and the business cycle, which have been more limited in scope or indirect, whether based on stocks or flows data.[4] We compare the experiences of the US and UK. These two countries had very similar pre-2008 industry and labour market structures. In both there is extensive and similar gender segregation of work.[5] Both countries experienced a significant narrowing of the employment rate gap between men and women since the 1970s, and the speed of this has slowed similarly since the 1990s (Figure 2.2).

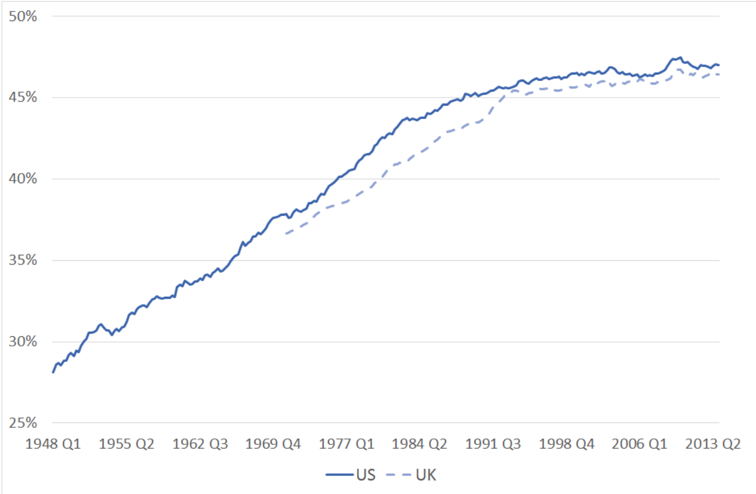
We begin in Section 2.2 by briefly revisiting the reduced form relationship between business cycles and gender labour market population rates. Although other studies have estimated the relationship between unemployment rates and the business cycle over time, there is less direct evidence about the response of gender gaps for other statuses.[6] This broader view is necessary to contrast whether a stocks based view of the labour market reveals less than a flows based approach, specifically with regards gender. The estimated response of the male employment rate is more pronounced than the female, especially during the Great Recession, but this gender gap is not more generally significant. On the other hand, for unemployment rates, business cycles

[4]A notable exception to the lack of focus on gender differentials is Albanesi & Sahin (2013), who analysed the trend and cycle properties of the gender unemployment gap. The authors also concluded that, within recessionary periods, the male unemployment response in the US is stronger than the female, and this difference has been consistent over time, being mostly explained by the distribution of work by industry.

[5]Compare for example BLS (2013) for the US and ONS (2013) for the UK.

[6]See for examples Clark & Summers (1980); Blank (1989); Peiro et al. (2012); Hoynes et al. (2012), who all note the greater cyclical response of male unemployment than female.

FIGURE 2.2: Female share of employment, 16+, SA



Notes.- own calculations from CPS (US) & Labour Force Survey (UK).

are not gender neutral, and affect men more than women. There are no substantial differences in inactivity rate responses to the cycle.

Given this picture for the stocks in both the US and UK, Section 2.3 moves on to the contributing role of flows. One recent contribution to the flows literature, pertinent to the questions posed here, is the identification of a so-called ‘stock-flow fallacy’ in the role of the participation margin in shaping the dynamics of the unemployment rate. Accounting correctly for the flows into and out of activity can explain a third of the rise in US unemployment during the 2007-2012 downturn (Elsby et al., 2015). Theoretical studies of the labour market’s response to the business cycle have tended to place less emphasis on the role of the participation margin, after observing that inactivity rates remain broadly constant. However, this result is due to the offsetting feature of these flows, and in fact the underlying flows are highly cyclical, and their variation could still explain a large fraction of changes in the unemployment rate. We ask whether or not the stock-flow fallacy for the cyclical importance of the participation margin could extend to gender differences. Is the role of flows between inactivity and activity actually relatively important in explaining labour market outcomes by gender? And is the modest cyclicality of the inactivity rate, and insignificant or small gender difference, a case of a stock-flow fallacy?

To address these questions, we decompose the variation in labour market stocks during the economic cycle into contributions from the attributing flow hazard rates using a modest modification on the methods of Fujita & Ramey (2009) & Elsby et al. (2015). Since 1990, as much as a half of the monthly variation in the US gender unemployment rate gap can be accounted for by flows between unemployment and inactivity. This result is robust to adjustments for possible bias in the estimated transition rates. These flows also explain a significant fraction of the evolution of the UK gender gap. Looking specifically at the Great Recession, the majority of the greater rise in male unemployment, between 2007 and 2012 in both countries, can be explained by a more cyclical response of flows between employment and unemployment than for women, especially for the job separation rate. Movements between inactivity and activity were nonetheless relevant in explaining the variation in recent outcomes. In the US, flows between unemployment and inactivity each contributed around 0.8-1.1 percentage points to the rise in the unemployment rate from 2007 for both men and women. However, for the UK, the flow from inactivity to unemployment does not explain the rise in the male unemployment rate, but can account for around half a percentage point for women. This suggests some macro evidence to support the presence and significance of a so-called 'added worker effect', whereby women are more likely to move from inactivity to activity during periods of economic recession, perhaps to compensate for a partner's loss of job and income.[7]

We also consider the possible presence of this effect at the aggregate level by studying heterogeneity in the flow from inactivity to unemployment, across time and conditional on gender. Generally for all groups, the participation margin in the US was equally affected by the downturn for men and women, and an aggregate added worker effect is unlikely to be gender specific. However, in the UK there are starker differences, which suggest a specifically female added worker effect could be a reasonable explanation for the relatively greater importance for women of inactivity to activity flows over the cycle. Although our results focus on unemployment, a notable gender difference also emerges when we consider the contributing role of flows changes to the employment rate. The large and persistent fall in transitions from inactivity to employment, observed during the Great Recession, explains a large and greater share of the female employment rate fall in both countries.

2.2 Reviewing gender business cycles

2.2.1 Data & Methods

For both the US and UK we use seasonally adjusted quarterly chained volume measures of real GDP, and (un)employment levels and population ratios for those aged

[7]See Stephens (2002) for an overview of the literature concerning the added-worker effect, and for recent analysis of its presence using micro data see Juhn & Potter (2007) and Bryan & Longhi (2013) for the US and UK respectively. See also Mankart & Oikonomou (2015) for a novel theoretical discussion and its role at the aggregate level.

16+.[8] We consider all those aged 16+ so as to avoid having to make judgements about what constitutes working age over time and across the two countries, however our results are qualitatively unchanged if we restricted attention to ages sixteen to sixty-four.[9] The series are detrended using both the Hodrick & Prescott (1997) (HP) filter and the unobserved components model (UCM) methodology of Harvey (1989).[10]

In reviewing the relationship between gender outcomes and business cycles, a helpful starting point is Okun's law, which posits that, in response to some external shock, there is a predictable decomposition into the factors which could comprise some output gap identity. This predictability is dynamic also. Since labour market variables respond slowly, these are typically lagging indicators of output gaps, and by construction, vice versa for output per employee. We motivate our method here using the most simple identity relating output and labour market outcomes,[11]

$$Y_t \equiv \frac{Y_t}{E_t}\frac{E_t}{N_t}N_t, \tag{2.1}$$

where Y_t is real GDP, Y_t/E_t is output per employee, E_t/N_t is the ratio of employment to population, and N_t is the total population. Note also that $U_t/N_t = 1 - E_t/N_t - I_t/N_t$ is the ratio of unemployed to population, where I_t denotes the level of economic inactivity. We take a first order log approximation of (2.1) around some trend levels, for example E_t^τ, thus expressing the output gap (or zero sample mean log points from trend of GDP), y_t^c, as a as a tractable additive function of gender (un)employment or inactivity rate trend deviations,

$$y_t^c = \frac{E_t^{\tau,m}}{E_t^\tau}[e_t^{c,m} - n_t^{c,m}] + \frac{E_t^{\tau,f}}{E_t^\tau}[e_t^{c,f} - n_t^{c,f}] + \upsilon_t \tag{2.2}$$

or

$$y_t^c = -\frac{U_t^{\tau,m}}{E_t^\tau}[u_t^{c,m} - n_t^{c,m}] - \frac{U_t^{\tau,f}}{E_t^\tau}[u_t^{c,f} - n_t^{c,f}] - \frac{I_t^{\tau,m}}{E_t^\tau}[i_t^{c,m} - n_t^{c,m}] - \frac{I_t^{\tau,f}}{E_t^\tau}[i_t^{c,f} - n_t^{c,f}] + \zeta_t, \tag{2.3}$$

where $\{m, f\}$ denote male and female respectively, and υ_t & ζ_t capture the behaviour of other variables in the output gap identity such as output per employee, population and an approximation error. Based on (2.2) & (2.3), the cyclical components of male

[8]GDP data from BEA, 1947-2013 and ONS, 1955-2013, respectively, and labour market data obtained from BLS, 1948-2013, and ONS, 1971-2013. The estimation window for the US is therefore longer at 1948-2013 compared with 1971-2013 for the UK.

[9]For brevity, the results form this robustness check are excluded here, but are available on request.

[10]See Appendix A.1 for a brief discussion of detrending methods and data summary statistics.

[11]See Gordon (1993) for a discussion of output identities of this type and their implicit role in Okun (1962, 1965).

and female (un)employment and inactivity rates, weighted by their trend levels relative to total employment, and consequently the gender employment rate gap, could have a predictable relationship with respect to the business cycle and output gaps. Previous empirical studies of gender, such as Peiro et al. (2012), have tended to ignore both the need to weight or adjust (un)employment rates in this way and the possibility of causality between male and female outcomes, as well as typically only focusing on one labour market variable.

2.2.2 Estimation & results

We begin by considering the period of the Great Recession only. Using (2.2) & (2.3), Figure 2.3 represents the cumulative contributions of deviations from logarithmic trend of labour market population rates to the output gap, with the final quarter of 2007 indexed to zero. For the US, changes to the labour market accounted for a much greater share of the output gap than the UK.[12] Changes to male (un)employment accounted for a greater share, with the female contribution in the UK being particularly weak. For both countries and genders there were limited contributions from changes in inactivity rates. Although we could replicate the decomposition of Figure 2.3 for any particular period, and thus describe the gender properties of the business cycle, we also consider a more general approach.

To estimate the general properties of the gender business cycle we use a VAR model for the detrended and subsequently stationary series of the output gap and weighted gender employment rates motivated by (2.2).[13] We also estimate the model to study the general responses of inactivity by gender over the business cycle, a surprisingly neglected issue. To do so, based on (2.3), we replace employment rates in the VAR model with cyclical components of inactivity rates, alongside unemployment population ratios. Finally, to compare our results across the estimated models, we consider impulse responses from an orthogonal shock to GDP which is scaled to give a maximum cumulative output gap increase of approximately one percentage point, and confidence intervals are estimated using non-parametric bootstrapping.[14]

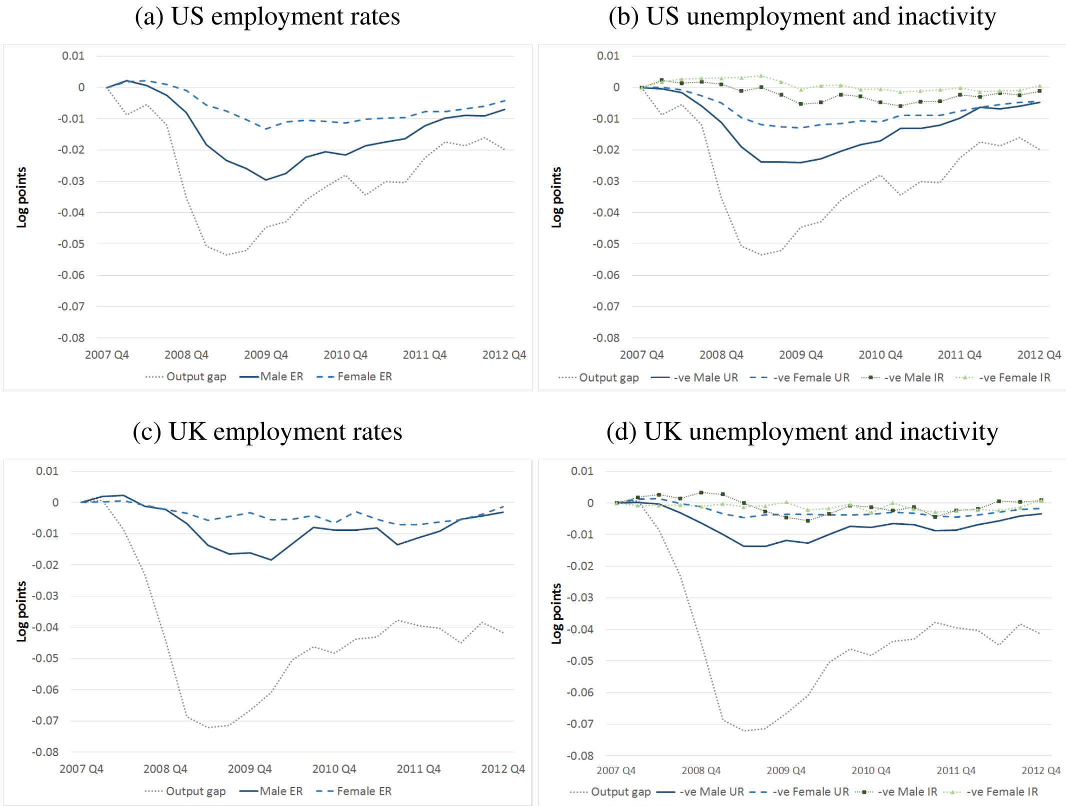
To quantitatively interpret the results of the VAR estimations by gender, we ‘unweight’ the impulse response functions, dividing by the trend weighting factors, e.g. $E_t^{\tau,f}/E_t^{\tau}$. We can approximately assume that population is constant in the short

[12] This is the so-called labour productivity puzzle for the UK observed since the start of the Great Recession, but further discussion here is outside the scope of this study.

[13] Alternatively, see Attfield & Silverstone (1998) for an alternative approach to our own whereby the Okun coefficient could be interpreted and estimated as the cointegrating relationship between variables.

[14] 200 repetitions. See Appendix A.1 for a more complete description of the estimation strategy and cumulative impulse response functions for the estimated models, with a brief discussion thereof.

FIGURE 2.3: Cumulative contribution of changes in labour market variables from trend to the output gap, 2007q4-2012q4



Notes.- all series detrended using HP-1600 filter.

term such that responses give relative changes in levels as well as rates. Table 2.1 shows the maximum cumulative log point changes in the difference from trend of (un)employment and inactivity population rates, following a shock to the output gap which has a maximum cumulative increase of one percentage point, for two time periods: 1975q1 & 2007q1. For the following discussion we focus on results obtained using UCM detrended data and evaluated at 2007 trend levels of gender population rates. The estimated labour market response is typically stronger in the US than the UK, with employment rising 0.6-0.7 & 0.3-0.5 percent above trend respectively. However, there is no suggestion of a significant gender business cycle for employment. The maximum decline in UK male unemployment is more than double the female. The gender response is substantially different also for the US, with male unemployment falling as much as ten percent following such a shock, and only five percent for women. We also see that the implied change in participation over the business cycle is relatively small, as are any gender differences.

Given that this analysis produces results for all three labour market states, direct comparisons with other studies are possible only for the unemployment rate. Peiro

TABLE 2.1: Estimated max. cumulative response of population rates from trend to a one percentage point cumulative increase in the output gap

	U.S.		U.K.	
	HP-1600	UCM	HP-1600	UCM
1975				
Male employment	0.7*	0.6	0.6	0.3
	*(0.5, 0.8)***	*(0.5, 0.8)*	*(0.4, 0.9)*	*(0.1, 0.5)*
Female employment	0.6	0.7	0.6	0.5
	(0.4, 0.8)	*(0.5, 0.9)*	*(0.3, 0.8)*	*(0.2, 0.8)*
2007				
Male employment	0.8	0.7	0.7	0.3
	(0.6, 1.0)	*(0.6, 0.9)*	*(0.4, 1.0)*	*(0.1, 0.6)*
Female employment	0.5	0.6	0.5	0.4
	(0.4, 0.6)	*(0.4, 0.8)*	*(0.3, 0.7)*	*(0.1, 0.6)*
1975				
Male unemployment	-7.6	-5.4	-10.4	-6.9
	(-9.2, -6.0)	*(-6.7, -4.2)*	*(-14.1, -6.7)*	*(-10.3, -3.5)*
Female unemployment	-4.6	-4.4	-4.4	-1.9
	(-5.7, -3.5)	*(-5.6, -3.3)*	*(-6.3, -2.6)*	*(-3.0, -0.7)*
Male inactivity	-0.4	-0.4	-0.7	-0.5
	(-0.6, -0.3)	*(-0.5, -0.2)*	*(-1.0, -0.5)*	*(-0.7, -0.4)*
Female inactivity	-0.1	0.0	-0.2	-0.2
	(-0.2, -0.1)	*(-0.1, 0.0)*	*(-0.3, -0.1)*	*(-0.3, -0.1)*
2007				
Male unemployment	-8.4	-10.0	-7.2	-4.6
	(-10.2, -6.6)	*(-12.3, -7.6)*	*(-9.7, -4.6)*	*(-6.9, -2.4)*
Female unemployment	-5.6	-5.1	-3.7	-1.5
	(-6.9, -4.3)	*(-6.5, -3.8)*	*(-5.2, -2.2)*	*(-2.4, -0.5)*
Male inactivity	-0.4	-0.3	-0.5	-0.3
	(-0.5, -0.3)	*(-0.4, -0.2)*	*(-0.6, -0.3)*	*(-0.4, -0.2)*
Female inactivity	-0.2	-0.1	-0.3	-0.3
	(-0.3, -0.1)	*(-0.1, 0.0)*	*(-0.4, -0.1)*	*(-0.4, -0.2)*

* interpretation: 100 x log points from trend change (or approximate percentage points from trend);
** 90% non-parametric bootstrap confidence intervals.
Notes.- using the intervals here, and whether or not they overlap, is not an appropriate check of whether the estimated difference between male and female is statistically significant. Instead, one should use the graphical response functions in the Appendix, and also note that the length of time before the max. cumulative response can also differ by gender.

et al. (2012) analysed the same countries and roughly similar time periods. They estimated that a four successive quarterly one percentage point increase in the output gap would decrease the US male and female unemployment rates (not detrended) cumulatively by 2.4 and 1.7 percentage points respectively, and 2.7 and 1.0 points for the UK. Although the comparison is not direct, since the estimated impacts here from such a shock are interpreted as log point deviations from trend, the magnitude of the impacts are roughly similar, and not out of step with the updated Okun hypothesis of a two to one percentage point ratio for GDP and unemployment rate changes.[15] Perhaps more interestingly, Peiro et al. (2012) also suggested that the estimated responses for the UK appear to decrease over time, but not for the US, estimating their model over two sub-samples for each country.[16] However, this is also consistent with the significant decline over time in UK average unemployment rates, and less so for the US, between these two time periods, which suggests that this result may not be due to a structural change in the effect of the business cycle, but due to the model design.[17] In fact, when applying the output gap identity model structure, since the average ratio of unemployed to employed has fallen more significantly in the UK than the US for these two periods, and had the cyclical components of unemployment rates not been 'weighted', we might have concluded that the relationship had become stronger over time, when from our own sensitivity analysis over the sample period there is no such evidence.

In summary, focusing on the Great Recession only, there is some evidence of a gender business cycle in both countries. But notably there is little difference in participation response. When considering if this pattern is more general over past decades, there is more limited evidence of a gender business cycle. Women and men in employment are equally affected. Participation changes little and gender differences are small. Unemployment rates respond more for men. Nonetheless, we should not necessarily conclude from these results that the participation margin is not cyclically important, nor that there are no gender differences. To test this further, we also consider the relative importance of flows in and out of participation since these could potentially drive the observed gender difference in unemployment responses to the cycle.

[15] See for example Lee (2000) for detailed estimates of Okun's law for the UK and US. Baseline estimates are a ratio of 1.84 and 1.39 for the US and UK respectively, and 2.0 as an average across a sample of sixteen OECD countries.

[16] 1948-1987 & 1988-2008 for the US, and 1971-1995 & 1996-2008 for the UK; these particular results also suggest that over time in the US, the gender difference reverses.

[17] Likewise, the average US female unemployment rate increases in the latter sample period of Peiro et al. (2012), and is higher than the male.

2.3 Gender labour market flows

2.3.1 Data

We use monthly gross flows from the CPS for the US, and derived from the Labour Force Survey (ONS) Two Quarter Longitudinal datasets for the UK. Both surveys have a rotating sample. For the UK, the total sample of over one hundred thousand individuals is split into five waves, with one wave leaving the sample and another new wave entering each quarter. Thus it is possible to observe changes in labour market status between quarters of approximately eighty percent of individuals that take part in the survey. The CPS has a similar structure but on a monthly rather than quarterly basis. In any given month the CPS has eight groups, six of which will remain in the sample in the next month so that they can be linked longitudinally and individuals' transitions between the three labour market states can be computed. For the UK we use data for men aged 16-64 and women aged 16-59 from 1996 to the second quarter of 2015, smoothing the derived gross flows series with a four quarter moving average. For the US, a research series of seasonally adjusted monthly flows for ages sixteen and over are publicly available from the BLS from February 1990. From these gross flows we compute transition probabilities, namely the probability that an individual moves from one state to another over the period. For example, from the employment to unemployment gross flow, EU_t, the transition probability is measured as $p_{EU_t} = EU_t/E_{t-1}$.

Survey based flows estimates are subject to some methodological problems, most notably biases that arise from time aggregation and classification error.[18] Time aggregation bias arises because of the discrete nature of the data from which we can estimate flow probabilities between states. For instance, a woman might be longitudinally recorded as inactive, followed by employed in the following month or quarter. Whilst we observe only one transition in the data, she could have moved from inactivity to unemployment first, and then from unemployment to employment between responses to the survey. These other transitions are not captured due to the limitation of the data collection frequency. One robust correction to this problem has been provided by Shimer (2012).[19] We apply the equivalent of this correction to our data, denoting these derived continuous time hazard rates by f_{ij_t}, but also present results both with and without this correction.

[18] Non-response bias is also potentially an issue, but this has been addressed in the published CPS flows (Frazis et al., 2005), and is accounted for in the longitudinal weights for the UK two quarter datasets (see relevant user guides).

[19] See also the Appendix in Elsby et al. (2015) on how the Shimer correction takes the analytical form of an eigendecomposition, which then allows for the numerical computation of all of the underlying continuous time hazard rates.

A classification error bias can arise if respondents to the survey are systematically classified as having the wrong labour market status. This problem is known to be particularly relevant in the US data for transitions between unemployment and inactivity. Abowd & Zellner (1985) estimated that more than nine percent of the sample was erroneously classified as inactive instead of unemployed in the original interview. The authors also provided a method to correct for the classification error based on re-interviews of a sub-sample of the CPS. However, re-interview surveys are no longer conducted, meaning that the historical correction might not be applicable to more recent surveys.[20] Here we apply this correction to the US gross flows as per Poterba & Summers (1986) using the re-interview survey tables in Abowd & Zellner (1985), with separate adjustments for male and female. In terms of gender differences, this correction implies a larger reduction in the relative gross flows EU, UE, UI & IU for men, with the reduction for EI & IE greater for women. Importantly for our analysis here, although the correction affects the estimated levels of transitions, and gender gaps, it has little effect on their relative importance in explaining fluctuations in labour market stocks over time. With regards the UK, as noted by Clarke & Tate (1996), there is also evidence of significant classification bias, or at least inconsistencies in the longitudinal flows relative to reported state durations, with male inconsistencies for the IU flow being greater. However, there is no equivalent re-interview survey for the UK, and duration data in the survey, which could also be recorded inconsistently, is not sufficient to correct all of the flows. Therefore, this is a limitation of the UK data and an area for further research.[21]

2.3.2 Methods

To estimate the relative importance of changes in each flow rate to gender patterns in the stocks over time we use a version of the three state, non-steady-state decomposition methodology of Elsby et al. (2015). The original literature in this field tended to ignore inactivity rates and participation flows, whereas the three state approach recognises that a fuller picture of labour market dynamics should also take into account flows in and out of inactivity. Other decompositions of unemployment variation are often based on the assumption that the actual unemployment rate is close to its steady-state value, defined as the value of the unemployment rate that

[20]Elsby et al. (2015) also adopt a novel approach to correct for classification error in the CPS data, which they refer to as "de-NUNification." This is based on the re-coding of unemployment-inactivity flows for each wave over four months so that, for example, if an individual is observed as having the $IIUI$ classification over four periods, this is indiscriminately recoded as $IIII$. However this is intended mainly as a sensitivity analysis of their main results rather than a robust correction of the estimated time series.

[21]See Appendix A.2 for a brief description and Figures of the estimated gender flows time series.

would prevail in the long run if the inflow and outflow rates did not change from their current level.[22] However, this approach could lead to misleading results if the actual unemployment rate deviates persistently from its implied steady-state level, as described for the UK by Smith (2011). To account for this, Smith (2011) proposes a decomposition of changes in the unemployment rate that incorporates the impact of past transition rates, but her method only allows for an analysis of how indirect flows between employment and unemployment via inactivity could explain changes in the stocks. Elsby et al. (2015) note that the discrete time change in the vector of labour market population rates can be rewritten as a distributed lag model of past and present changes in implied steady-state levels, and some initial values, thus allowing for a complete decomposition of the change in each population rate into contributions from each flow hazard rate. Our own approach differs from Elsby et al. (2015) in so far as we do not ignore births and deaths to the labour market population in the decomposition, which could be instructive potentially in their contribution to longer term trends in population rates and their gender gaps.

Let the civilian population be normalised to one in each period, i.e. $E_t + U_t + I_t = 1$, initially ignoring births (labour market entrants at age sixteen, immigration etc.) and deaths (retirement, emigration etc.), p_{ij_t} are discrete transition probabilities, and k denotes each two month/quarter longitudinal period. However, it is possible that $E_{t-1,k} - E_{t-1,k-1} = D_{E,t-1} \neq 0$. When there are more 'births' to employment than 'deaths' $D_{E,t-1} > 0$. We refer to this as a 'demography factor.'[23] When analysing changes in the stocks we consider, $\Delta E_{t,k} = E_{t,k} - E_{t-1,k-1}$, i.e. the difference in the second period stock between consecutive two month/quarter longitudinal periods. The relationship between labour market stocks and flows can then be written as

$$\begin{bmatrix} E \\ U \\ I \end{bmatrix}_{t,k} = \underbrace{\begin{bmatrix} p_{EE} & p_{UE} & p_{IE} \\ p_{EU} & p_{UU} & p_{IU} \\ p_{EI} & p_{UI} & p_{II} \end{bmatrix}_t}_{\mathbf{M}_t} \left(\begin{bmatrix} E \\ U \\ I \end{bmatrix}_{t-1,k-1} + \begin{bmatrix} D_E \\ D_U \\ D_I \end{bmatrix}_{t-1} \right). \tag{2.4}$$

[22]For examples see Petrongolo & Pissarides (2008); Solon et al. (2009); Fujita & Ramey (2009); Gomes (2012); Shimer (2012).

[23]Despite attempts by the statistical agencies to correct for non-response bias in the longitudinal weights applied to the flows, it is still possible that when we disaggregate the data further than intended, i.e. by gender, that these are not perfect, and thus the 'demography factor' may also capture any systematic bias here also. However, we find that this is not a major concern for gender, but when attempting other disaggregations of the labour market, for example types of employment, this can become a greater concern for validity.

Which can be reduced to

$$\begin{bmatrix} E \\ U \end{bmatrix}_{t,k} = \begin{bmatrix} 1-p_{EU}-p_{EI}-p_{IE} & p_{UE}-p_{IE} \\ p_{EU}-p_{IU} & 1-p_{UE}-p_{UI}-p_{IU} \end{bmatrix}_t \left(\begin{bmatrix} E \\ U \end{bmatrix}_{t-1,k-1} + \begin{bmatrix} D_E \\ D_U \end{bmatrix}_{t-1} \right) + \begin{bmatrix} p_{IE} \\ p_{IU} \end{bmatrix}_t , \tag{2.5}$$

or equivalently in simplified notation,

$$\mathbf{s}_{t,k} = \mathbf{P_t}[\mathbf{s}_{t-1,k-1} + \mathbf{d}_{t-1}] + \mathbf{q}_t \ . \tag{2.6}$$

The steady-state of this system is then given by

$$\bar{\mathbf{s}}_{t,k} = (\mathbf{I} - \mathbf{P}_t)^{-1}[\mathbf{P}_t \mathbf{d}_{t-1} + \mathbf{q}_t] \ . \tag{2.7}$$

Following Elsby et al. (2015),

$$\Delta \mathbf{s}_{t,k} = (\mathbf{I} - \mathbf{P}_t)\Delta \bar{\mathbf{s}}_t + (\mathbf{I} - \mathbf{P}_t)\mathbf{P}_{t-1}(\mathbf{I} - \mathbf{P}_{t-1})^{-1}\Delta \mathbf{s}_{t-1,k-1}. \tag{2.8}$$

And thus, iterating (2.8) backwards we can write the present change in labour market stocks as a distributed lag function of the change in steady-state values and some initial value for the stocks. Taking a second order approximation of $\bar{\mathbf{s}}_t$ around lagged values,[24] and substituting into (2.8), the change in the stocks in period t is rewritten as an additive function of past and present changes of each transition rate $\mathbf{c}_{ij_t}$, the demography factor $\mathbf{c}_{\mathbf{d}_t}$, and some initial change in the labour market state $\mathbf{c}_{\mathbf{s}_{0_t}}$,

$$\Delta \mathbf{s}_{t,k} \approx \sum_{i \neq j} \mathbf{c}_{ij_t} + \mathbf{c}_{\mathbf{d}_t} + \mathbf{c}_{\mathbf{s}_{0_t}} \ . \tag{2.9}$$

Given this additively separable representation, we can then decompose the variance of the change in the stocks into contributions from changes in present and past transition probabilities, the initial values, and changes in 'demography.' And so, for example, we can compute, the fraction of the variance of the monthly/quarterly change in unemployment explained by changes in p_{EU_t},[25]

$$\beta^U_{EU} = \frac{cov(\Delta U_{t,k}, \{c_{EU_t}\}_2)}{var(\Delta U_{t,k})} \ . \tag{2.10}$$

[24] As used in other studies, a first order approximation is sufficient for a cyclical analysis since the approximation error does not correlate, but we nonetheless find that including second order terms, excluding the cross-derivatives, reduces the size of the errors significantly.

[25] For a complete description of the variance flows decomposition methodology see also Fujita & Ramey (2009).

We could also replace the steady-state in (2.8) with its continuous (or time aggregation bias adjusted) hazard rate, f_{ij_t}, equivalent, where

$$\bar{\mathbf{s}}_t = -\mathbf{F}_t^{-1}\mathbf{g}_t - \tilde{\mathbf{d}}_t \ , \tag{2.11}$$

and terms are continuous time equivalents of those in (2.7). These hazard rates are obtained by solving the ordinary differential equation given by (2.4), noting that the conditions for the existence and uniqueness of the logarithm of $\mathbf{M}_t$ are trivially satisfied (see Davies (2010) for an overview), and whereby it can be shown that

$$\tilde{\mathbf{d}}_t = -(\mathbf{I} - \mathbf{P}_t)^{-1}\mathbf{P}_t\mathbf{d}_{t-1} \ . \tag{2.12}$$

The derivatives in the Taylor approximation then take a different analytical form. To derive a decomposition of changes in the active labour force unemployment rate, as opposed to the share of the population unemployed, we use the first order approximation

$$\Delta urate_{t,k} \approx (1 - urate_{t-1,k-1})\frac{\Delta U_{t,k}}{(U_{t-1,k-1} + E_{t-1,k-1})} - (urate_{t-1,k-1})\frac{\Delta E_{t,k}}{(U_{t-1,k-1} + E_{t-1,k-1})} \ . \tag{2.13}$$

In what follows we also discuss how changes in flow rates account for variation in the percentage point gender (un)employment rate gap. This is derived by subtracting the female decomposition of the change in the population rates (2.9) from the male equivalent.

2.3.3 Results

Unemployment rate variation

Table 2.2 summarizes the results of the above decomposition for the US and UK unemployment rates.[26] Entries for the US show the estimated fraction of monthly variation in unemployment from June 1990 to August 2015 accounted for by covariance with each component of the decomposition, i.e. the βs as per (2.10). UK entries similarly show computed results for quarterly variation between the third quarter of 1997 and second quarter of 2015. The table shows results using flow transition probabilities, p_{ij} and hazard rates which have been adjusted for the presence of time aggregation bias in the flows, f_{ij}. Cyclically this bias tends to lead to a substantial underestimation of the relative importance of flows from unemployment,

[26]For brevity here, and as consistent with the focus of the literature, results and a discussion of the decomposition for the employment rate is included only in Appendix A.3. However, when we focus on the Great Recession period later we do draw out some pertinent gender differences which can only be seen from the employment rate results.

offset by an overestimation for the reverse flows. For example, using unadjusted transition probabilities would for both countries underestimate the UE flow's relative importance in explaining employment and unemployment rate variation by as much as a third. Additionally, for the US we give results including the constant Abowd & Zellner (1985) correction for classification bias. The adjustment implies that the estimated importance of the UI flow for unemployment variation would otherwise be biased downwards, and vice versa for the IU flow. However, although this substantially affects the magnitude of estimated flow rates, it has less impact on the results of the cyclical analysis.[27] For both countries in what follows we focus on results using hazard rates corrected for time aggregation bias, f_{ij}.

TABLE 2.2: Flows decomposition of monthly changes in the unemployment rate and gender gap

		UE	EU	EI	UI	IE	IU	Init. val.	d	approx. err.
US: June 1990 - August 2015										
$p_{i,j}$	All	0.29*	0.27	-0.02	0.16	0.04	0.24	0.00	0.00	0.01
	Male	0.28	0.33	-0.01	0.14	0.03	0.21	0.00	0.00	0.01
	Female	0.25	0.22	-0.03	0.18	0.04	0.33	0.00	0.01	0.01
	Gap**	0.12	0.38	0.01	0.18	0.00	0.30	0.00	0.00	0.00
$f_{i,j}$	All	0.39	0.20	-0.02	0.22	0.03	0.17	0.00	0.00	0.01
	Male	0.37	0.26	-0.01	0.19	0.02	0.15	0.00	0.00	0.01
	Female	0.34	0.15	-0.03	0.25	0.04	0.24	0.00	0.01	0.01
	Gap	0.17	0.33	0.01	0.22	0.00	0.27	0.00	0.00	0.00
$f_{i,j}$ w. AZ corr.	All	0.42	0.22	-0.03	0.25	0.03	0.09	0.00	0.00	0.01
	Male	0.39	0.29	-0.01	0.21	0.02	0.09	0.00	0.00	0.01
	Female	0.36	0.16	-0.03	0.27	0.04	0.18	0.00	0.01	0.01
	Gap	0.17	0.36	0.00	0.21	0.00	0.25	0.00	0.00	0.00
UK: q3 1997 - q2 2015										
$p_{i,j}$	All	0.28	0.32	-0.01	0.14	0.03	0.14	0.07	0.02	0.01
	Male	0.26	0.36	-0.01	0.12	0.01	0.10	0.10	0.04	0.02
	Female	0.28	0.23	0.00	0.16	0.04	0.21	0.02	0.04	0.00
	Gap	0.15	0.35	0.00	0.13	-0.02	0.07	0.13	0.18	0.01
$f_{i,j}$	All	0.36	0.25	-0.01	0.19	0.03	0.08	0.07	0.02	0.01
	Male	0.32	0.31	-0.01	0.15	0.02	0.06	0.10	0.04	0.02
	Female	0.38	0.16	-0.01	0.24	0.05	0.11	0.02	0.05	0.00
	Gap	0.19	0.30	0.00	0.15	-0.03	0.06	0.13	0.18	0.01

* β_{UE}^{urate} is approximated from equivalent components for the unemployment and employment population shares as per (2.13) for current and past changes in the UE transition probability.
** Gender gap computed as male unemployment rate minus female.
Notes.- rows may not sum to one due to rounding errors.

[27] These biases in the estimates can also be discerned by scrutinising the flow rates time series given by Figures A.8- A.13.

When making cross-country comparisons here we must be conscious that we are comparing results using monthly and quarterly derived transitions. By applying the time aggregation bias correction we should theoretically be accounting for this difference. But as noted by Gomes (2015), who applies the correction to US transitions from the CPS at both monthly and quarterly frequencies, the effect on cyclical properties of the estimated flows can differ depending on the frequency of the data. This is because the correction assumes the flow hazard rate is constant over time for all workers. In reality it isn't, varying with tenure and unemployment duration for example. Therefore he suggests comparisons across countries should at least use similar frequency data. However, this critique should not apply to comparisons of gender differences within country; we can assume that the effects of applying the bias correction to flows measured over the same periodicity will be similar for men and women.

For the unemployment rate in the US, over half of the variation in changes for both men and women can be attributed to the combined exits to employment and inactivity. However, the composition of this variance share differs, with the exit to inactivity, UI, being relatively more important in explaining the path of female unemployment. However, this small measured difference in the importance of the UI flow, twenty-five vs nineteen percent, could disguise a larger actual difference in responses to the cycle. If we accept that the labour market attachment of unemployed women is generally lower, and if the procyclical UI hazard rate is largely explained by composition effects on the pool of those unemployed, as hypothesised by Darby et al. (1986) and demonstrated in Elsby et al. (2015), then, we would have expected the importance of the male flow to be greater through this composition channel alone. Differences in the relative importance of flows into unemployment are also greater. The EU flow is almost twice as important for male employment changes than it is for female, and vice versa for the IU flow. For men and women combined flows between unemployment and inactivity explain thirty-four and forty-nine percent of the variance in unemployment rate changes, emphasising again the importance of the labour market participation margin for both genders over the cycle.

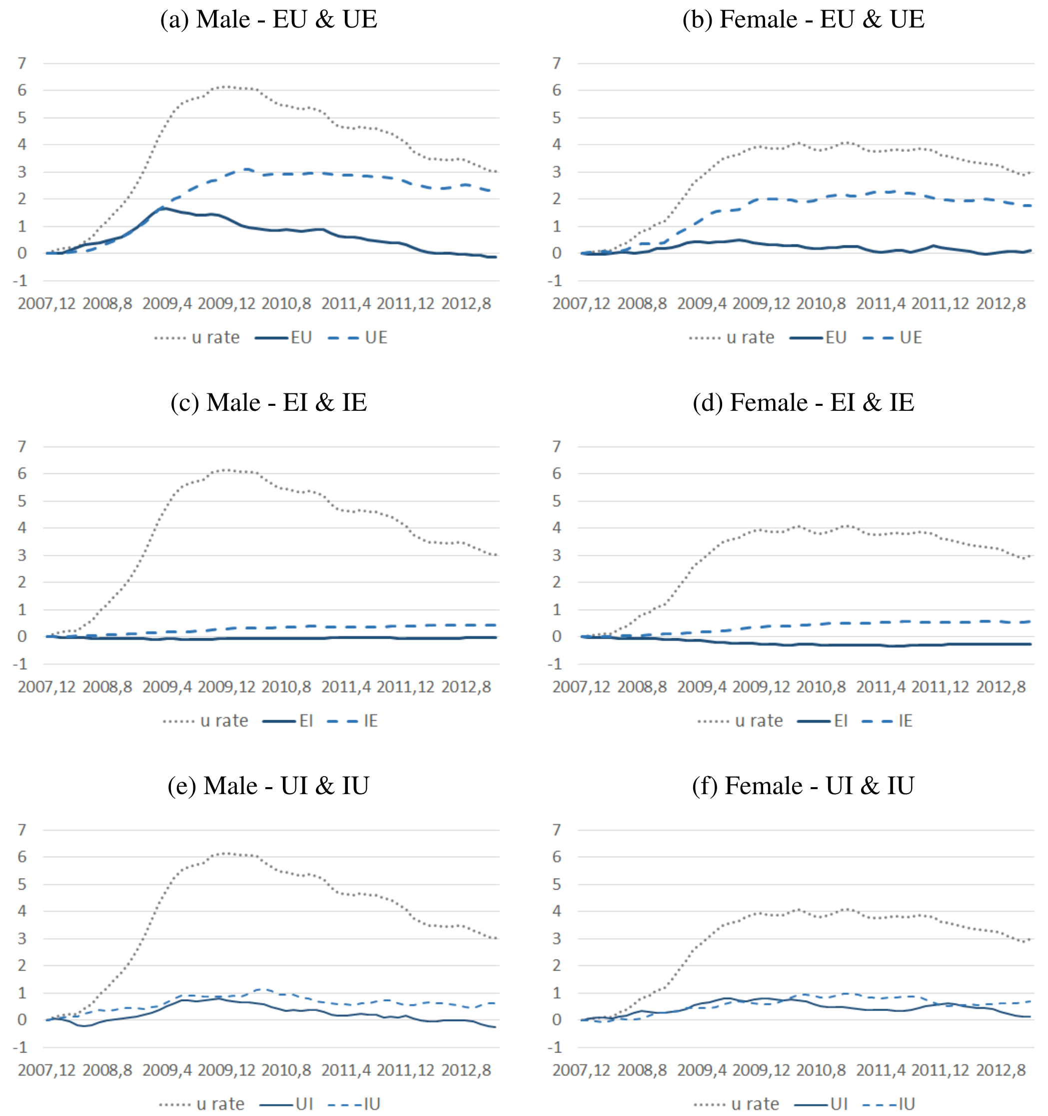
Focusing on the evolution of the US gender unemployment rate gap over the past twenty-five years, around a third of its variation can be explained by greater volatility in male entries from employment, a half by the combined difference in transitions rate changes between unemployment and inactivity, and the remaining sixth by the difference in volatility of exits to employment. Crucially for the robustness of this result, these shares are not substantially altered when we either remove the time aggregation bias correction or add the adjustment for classification error in the gross flows.

The results for the UK are qualitatively similar to the US. Exits explain a greater share of female unemployment variation than male, sixty-two vs forty-seven percent, with the majority of this difference accounted for by the UI rate. The contribution of the reverse IU flow to variation over the last two decades is relatively small, although greater for women. Departures from employment to the unemployment pool explain half as much of the variation in the female unemployment rate as the male. With regards explaining changes in the gender gap, the variance of the entry rates to unemployment is more important than any gender difference in exits. The combined changes in flows between unemployment and inactivity can account for approximately a fifth of the gap's variation. Compared loosely with the US, inactivity flows therefore appear less significant. This is most likely explained by institutional differences and social welfare eligibility conditions, which in the UK encourage individuals to remain active in the labour market continuously. A major conclusion from these stock-flow decompositions is again to reiterate the cyclical importance of the participation margin, and add to the evidence in Elsby et al. (2015) by showing this is not unique to the US.

The Great Recession

Given our short sample period containing only the one major downturn, our results above ought to be driven by the labour market experiences of men and women during the Great Recession. Therefore, using the stocks decomposition as an accounting identity, we can focus more precisely on how the evolution of unemployment rates between 2007 and 2012 was determined by changes in the underlying hazard rates. Figures 2.4 & 2.5 give the cumulative contributions of changes in each of the hazard rates to the percentage point change in the unemployment rate by gender, indexed to zero at the end of 2007. Here the gender differences in the relative importance of the flow rates become clearer, and their contributions to the change in the unemployment rate gap during this time can be read off indirectly.

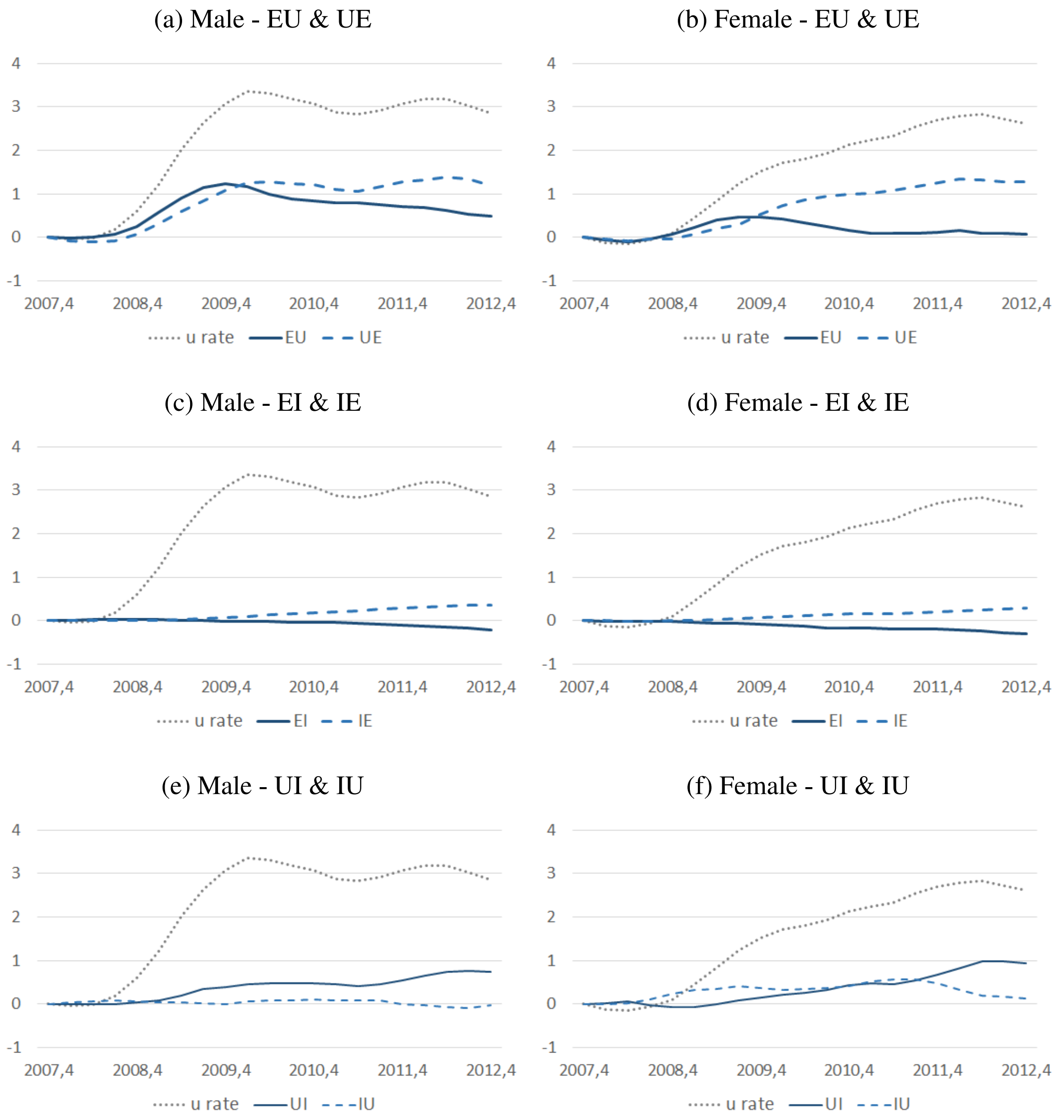
FIGURE 2.4: US cumulative percentage point contributions from changes in hazard rates to the unemployment rate change, 2008-2012



Notes.- hazard rates here are calculated without the Abowd & Zellner (1985) correction for classification error to the gross flows.

For the US, unemployment exits to employment for both men and women explain around a third of the initial rise in unemployment to the end of 2008, with this rising to a half by the time the unemployment rate hits its peak towards the end of 2009. The fall in the unemployment exit rate contribution persists then through to 2010, despite the fall in the unemployment rate seen especially for men. This differing pattern of unemployment over the cycle appears to be driven by the greater contribution of the *EU* rate, which for men peaks with unemployment, and then declines to pre-recession levels. However, the rise in this entry rate to unemployment never substantially contributes to the stock of unemployed women. The procyclical decline in the *UI* flow, and the countercyclical rise in the *IU* flow, contribute each to the unemployment

FIGURE 2.5: UK cumulative percentage point contributions from changes in hazard rates to the unemployment rate change, 2008-2012



rate increase for men and women by around 0.8-1.1 percentage points at its peak level. Thus, despite explaining a greater share of the female unemployment rise within the recession, the rise in the gender gap cannot be significantly explained by the participation margin, whereas over the past twenty-five years more generally, changes in these flows can explain a much larger share of the gap's variation.

Similarly for the UK, the persistent decline in the UE flow can explain a large part of the rise in male and female unemployment rates, and the difference in their evolution since 2007 can largely be accounted for by the relatively muted rise in EU transitions for women. However, unlike for the US, the rise in the participation flow to unemployment for men, IU, explains none of the unemployment rate change, whereas for women it can account for around half a percentage point.

The more significant rise in male unemployment from 2007 in both countries can mostly be accounted for by differences in the magnitude of responses to the downturn of the flows between employment and unemployment. However, the relative insensitivity of the inactivity rate to the business cycle belies the important role that changes in the rates individuals move into and out of the active labour force have in determining the rise in unemployment. Further, for the UK there is some evidence that an aggregate gender specific 'added worker' effect could be present, manifested by a countercyclical *IU* hazard rate for women and absence of the like for men.

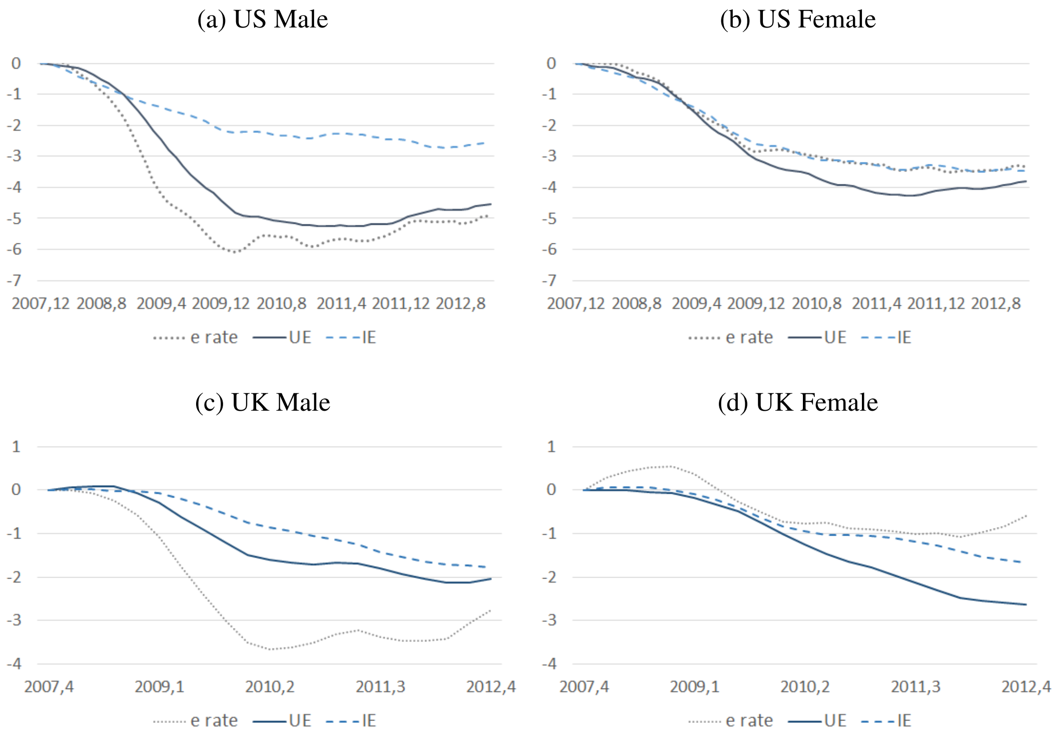
The employment change over the period can likewise be decomposed into its specific flow rate contributions. An interesting feature of the Great Recession has been the relative role of the procyclical *IE* flow. The collapse in this transition rate, and especially the persistence of this fall, is largely a puzzle (Kroft et al., 2016). Figure 2.6 demonstrates how this can account for a large part of the fall in employment to 2012, even as compared with the decline in entries from unemployment, the most cyclically important flow rate. There is also some common gender difference in the significance of this flow across countries. In terms of absolute percentage points, *IE* transitions account for a similar amount of the employment rate fall for both sexes in the UK, and over half a point more for women in the US. However, given the smaller decrease in female employment, it remains a demonstrably more relevant cyclical factor for women. For example, in the US, by the end of 2010 it accounts for approximately all of the female employment fall, notwithstanding the offsetting contributions of other flows, as opposed to only forty percent for men.

Heterogeneity in the *IU* flow rate

We can explore the possible presence of the added worker effect by considering heterogeneity in the *IU* transition rate, across time and conditional on gender. Focusing on individuals aged 20-54, we consider age, the age of the youngest child in the family, the number of dependent children, whether living as a married couple, when an individual left their last job, reasons for leaving, and their more detailed inactivity status.[28] We compute the US monthly and UK quarterly transition probabilities for men and women defined by these various characteristics and we average these probabilities over two broad time periods: one ending before the start of the latest economic downturn, 1997 to 2007, and the second capturing broadly the period of the Great Recession, 2008 to 2012 (see Tables A.3 & A.4). It is not possible to carry out a time aggregation or classification error bias adjustment on these transitions. But especially for time aggregation, we should not expect these biases to be systematic

[28] For the US, survey responses of when an individual left their last job, and reasons for leaving are either not available or reliable for those who are inactive.

FIGURE 2.6: Cumulative percentage point contributions from changes in entry hazard rates to the employment rate change, 2008-2012



Notes.- US hazard rates here are calculated without the Abowd & Zellner (1985) correction for classification error to the gross flows.

with gender and time. If we only consider the pre-recession period, for both countries, across all groups, the male flow probability from inactivity to unemployment is greater than the female. This implies that men, when inactive, are closer to the labour market than women, even controlling for type of inactivity. Looking within types of heterogeneity, the relative difference between the flow probability for men who declare themselves to be inactive because they are looking after the family or home, and other inactivity groups, is higher than for women. Furthermore, in both countries again, the male flow probability decreases with the age of youngest child, as opposed to increasing for women (although only marginally so for the US).

Have these patterns changed since the Great Recession? To answer this we consider changes between the two broad time periods (Table 2.3). For the US, there were large increases in the monthly flow probability for both men and women who are inactive looking after the family or home, as well as for those with young children. Likewise, the probability of transition for married men increased by over fifty percent, and a third for women. These are groups of individuals for whom we might expect to see large countercyclical increases in transition probabilities if a theoretical added worker effect were relevant. Based simply on these unconditional averages over time, it would appear as though this is equally the case for men and women. Those without dependent children, or not living as a married couple, both male and female, appear to be less affected than those with. Generally, across all groups it appears as though the participation margin in the US is equally affected by the downturn for men and women. However, in the UK, there are more stark differences. Younger men, and those in full-time education, see a smaller rise in their likelihood of rejoining the labour market via unemployment than do women. Across most groups, the male flow is less cyclical. More relevant to the hypothesised added worker effect, the rise in the flow probability for those looking after family or home is twenty & thirty-nine percent respectively for men and women, and the equivalent figures for those with children aged zero to one are six and forty-one percent. The differences remain large for those with youngest child aged two to four also. Women living as a married couple are a third more likely to move from inactivity to unemployment during the Great Recession, whereas the male transition barely increases. Like the US, having no dependent children is associated with a relatively smaller increase in the flow probability. Therefore, while in the US these simple average flow probabilities suggest that an added worker effect might not be gender specific, for the UK we find more associated evidence that it is. This may contribute to the aggregate gender difference in the cyclical importance of the participation margin in explaining changes in unemployment rates observed for the UK, and also why this is not the case over the same period for the US.

2.3.4 Further discussion

Our analysis suggests a greater cyclical importance of IU flows for men in the US than in the UK during the Great Recession. Before making too much out of this cross-country result, we must be confident that these observed differences do not emerge from the types of data we have used, in particular the frequency over which we have estimated hazard rates. It is possible that the counter-cyclical US male IU transition and observed cyclical neutrality for the UK could be accounted for by frequent back and forth transitions between unemployment and inactivity for men within the quarter, even after our corrections for other biases in the flow rates. For example, the recorded quarterly UU flow in the UK would be equivalent to the $UNNU$ chain over four months seen in the US data. To check whether this drives our results, we use waves one and five matched with four & eight from the CPS to estimate a quarterly series of gross US flows by gender for each month. In Figure 2.7 we see that the strong counter-cyclicality of the male quarterly transition probability remains, and this appears at least as significant for women over the downturn. The differing cross-country male participation response to the Great Recession could be a result of inactive men in the UK having a particular set of characteristics that put them

TABLE 2.3: Percent change in p_{IU} from 1997-2007 to 2008-2012

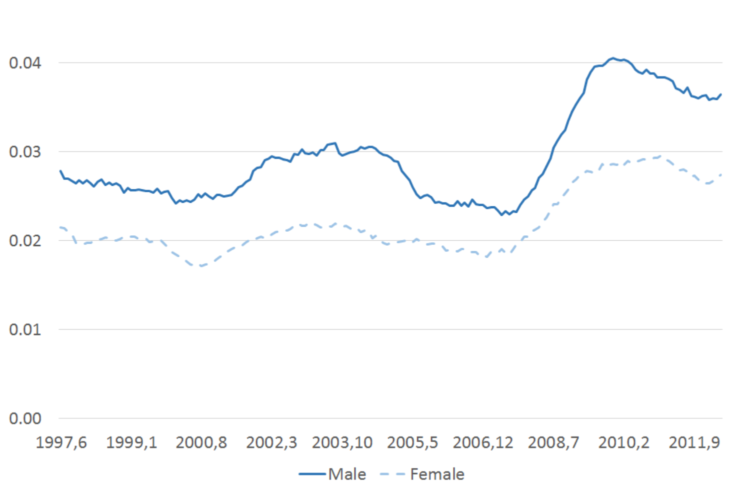
		U.S.		U.K.	
		Male	Female	Male	Female
Age	20-29	20.8	28.1	11.0	33.2
	30-39	52.7	38.1	4.9	28.8
	40-54	52.1	44.6	28.3	26.2
Inactivity reason	Retired	-14.4	1.3	33.1	21.3
	Disabled	23.6	23.9	22.3	41.5
	Family/home	36.9	43.5	20.1	39.2
	Student	28.6	25.3	9.2	25.9
	Other	33.6	43.3	11.6	19.4
When left last job	$\tau \leq 12$			17.0	23.8
(τ months)	$\tau > 12$ / never			24.2	38.3
				0.0	0.0
Reason left last job	Job loser			28.0	17.9
	Job leaver			26.7	35.2
	Temp. job ended			13.5	10.6
Living as a married couple	Yes	49.1	36.6	5.2	33.6
	No	34.7	25.8	15.3	26.5
Age of youngest child	0-2 / 0-1	43.8	48.5	6.6	41.4
	3-5 / 2-4	62.0	54.6	17.8	38.5
	6-13 / 5-9	74.6	28.8	18.0	28.9
N. of dep. children age < 18 / 19	0	39.2	37.7	15.3	28.9
	1	55.2	51.7	38.9	38.5
	2	71.9	41.5	29.2	32.9
	3	57.3	39.7	5.9	24.5
	≥ 4	43.0	13.3	-29.2	33.0

further from the labour market, relative to women, than is the case for those in the US. Future research could assess whether inactive men in the UK and the US, otherwise identical along relevant observable characteristics such as marital status and number of dependent children, have residually different probabilities of moving from inactivity to unemployment.

2.4 Summary

Our main aim in this chapter has been to shed light on the gender dimension of the relationship between labour market stocks and flows during the business cycle. We have built on limited evidence, which tended to focus on what happens to unemployment rates only, by looking at the relationship between the cyclical components of output and all three labour market states, with an analysis motivated by an output gap decomposition. Moreover, the gender dimension of labour market

FIGURE 2.7: Estimated quarterly US transition probability from inactivity to unemployment



Notes.- gross flows estimated using waves one & five matched with four & eight for each month of CPS datasets, un-weighted, and twelve month moving average.

flows has also been overlooked in previous studies. The analysis is structured around one main issue that has emerged from the existing literature: the so-called stock-flow fallacy, whereby a lack of cyclicality in certain stocks, notably the participation rate, does not necessarily imply that flows between this state and others are not significantly cyclical, nor important in driving the labour market response to recessions. We assess whether there is a particular gender dimension to this stock-flow fallacy. Although male and female inactivity rates are not especially cyclical, there could be greater gender differences in the importance of flows in and out of this state over the cycle.

In both the US and UK, the response of male employment rates was at least stronger during the Great Recession, but not more generally over previous downturns. The response of the unemployment rate is not gender neutral. The male rate tends to increase more significantly than the female during economic recessions. There are not substantial gender differences in the response of inactivity rates. When assessing the role fluidity has in shaping stocks, more prevalent gender differences arise than those implied by the stock-based results alone. In the past twenty-five years as much as a half of the variation in the US gender unemployment rate gap can be accounted for by changes in male and female rates of transition between unemployment and inactivity. For the UK these flows can also explain some of the pattern in gender differences. The majority of the difference in the unemployment rate response to the 2008 downturn can be accounted for by a less strong response of the flows between employment and unemployment for women. But changes in the flow rates between inactivity and unemployment were also significant. For the US, these contributed similarly to the unemployment rate rise for both men and women. However, for the UK, unlike for women, the male participation flow to unemployment accounted for none of the rise in the unemployment rate. This suggests that a gender-specific added worker effect was more likely to be present in the UK than in the US at the aggregate level. This is corroborated by an assessment of the heterogeneity of inactivity to unemployment transition probabilities, comparing the period of the Great Recession with the years before. Employment rate responses to the cycle also belie gender differences in the importance of the participation margin. In both countries employment is driven substantially by the procyclical entry rate from inactivity, and more so for women than for men, especially during the latest downturn.

Chapter 3

Long-term unemployment and the Great Recession: evidence from UK stocks and flows

Note: A version of this essay will appear as an article in the Scottish Journal of Political Economy; DOI: 10.1111/sjpe.12139. An older version has also been published as Edinburgh School of Economics Discussion Paper Series N.273. In addition to those already acknowledged, I am especially grateful to Mike Elsby for his advice and comments. The data used in this chapter are accessible from the UK Data Service, having been collected by the Office for National Statistics (ONS). Neither the collectors of the data nor the Data Service bear any responsibility for the analysis and discussion of results in this chapter.

3.1 Introduction

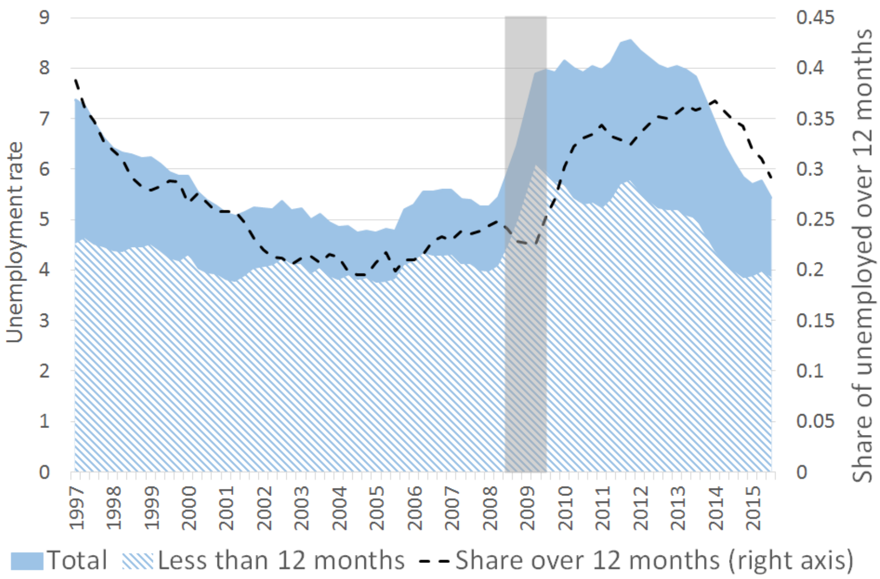
The main aim of this chapter is to describe how the persistent rise in long-term unemployment (LTU) during the UK's Great Recession came about (see Figure 3.1).[1] This countercyclical rise in average duration, which typically persists even after unemployment has begun to fall rapidly, has long been of interest to those studying European labour markets.[2] Renewed international interest has been driven by the significant and less usual rise in US unemployment durations since the 2008-09 downturn, where LTU rose to its highest post-war level, and persisted even after

[1]Throughout this paper, and as most commonly defined in the UK, LTU refers to those unemployed and looking for work for at least twelve months.

[2]See for a comprehensive review Machin & Manning (1999).

short-term unemployment had largely subsided.[3] Using the Labour Force Survey (LFS), I first discuss how much of the recent UK experience can be accounted for by changes to the composition of the unemployment pool, i.e. by the prevalence of personal and work history characteristics amongst the unemployed. I then identify which of the flows between employment, inactivity and unemployment durations can explain LTU's rise and persistence.

FIGURE 3.1: UK unemployment rate and LTU, 1997-2015



Notes.- Labour Market Statistics, Office for National Statistics, ages 16-64, accessed November 2015; shaded area denotes UK officially defined recession, 2008q2-2009q2.

I find that LTU's rise, from 2007 to its prolonged peak in 2010-13, cannot be explained in any large part by changes in the prevalence of observable characteristics amongst those looking for work: including the industry and occupation of previous employment, the reasons for leaving a job, and whether an individual was most recently otherwise employed or out of the labour force. This mirrors similar results from Kroft et al. (2016) for the US over the same period.

A notable recent literature has added to earlier work by Clark & Summers (1979) highlighting the cyclical importance of fluidity at the participation margin. Most prominently, Elsby et al. (2015) (henceforth referred to as EHS) have demonstrated that a third of historical US unemployment rate variation can be accounted for by the cumulative influence of monthly changes in the transition hazard rates between

[3]Examples for the US case include: Elsby et al. (2011a), Kroft et al. (2013), Krueger et al. (2014) and Kroft et al. (2016). A discussion of the features of LTU in several European countries during the Great Recession is provided by a collection of essays in Bentolila & Jansen (2016). Through the case of Spain, Bentolila et al. (2017) have assessed the possible role of institutional factors in accounting for the unprecedented rise in LTU in Southern European countries. In contrast, the UK case is somewhat more similar to the US.

unemployment and inactivity. Applications of their methodology to flows estimates obtained from the UK's LFS have demonstrated that this result generalises to the UK, for a period including the Great Recession (Borowczyk-Martins & Lalé, 2016; Razzu & Singleton, 2016). Specifically for long-term unemployment changes, Krueger et al. (2014) and Kroft et al. (2016) have identified the importance of cyclical patterns in participation flows using calibrated matching models. Both find that allowing for duration dependence in exit rates to employment, as well as transitions between inactivity and unemployment, is crucial in matching the rise and level of US LTU post 2008. Instead of similarly calibrating these models to the UK labour market, I explore thoroughly the underlying flows data and how they have determined patterns of LTU over the past two decades.[4] I do this by extending EHS's stocks-flows decomposition from three to five labour market states: employment, short-, medium- and long-term unemployment, and inactivity. The advantage of this method is not relying on an assumption of the labour market being at or close to its steady state at all times, which would be unreasonable when unemployment is disaggregated into its less dynamic long-term component.

It is not a priori obvious that results for the UK during the Great Recession will be similar to those found in the aforementioned studies of US LTU. There are notable differences in how OECD countries experienced the Great Recession. The reduction in UK GDP, accounting for pre-recession trends, was roughly twice as great as in the US by the end of 2011, but the US nonetheless experienced a greater rise in unemployment (Hoffmann & Lemieux, 2016). The UK's experience was not only distinct from the US, but also something of an outlier both across countries and compared with past UK recessions. Thus, in the context of what has become the "The UK Productivity Puzzle" (Barnett et al., 2014; Bryson & Forth, 2015), it would be striking if the determinants of the recent cyclical and persistent level of LTU in the US and UK were similar.

To preview the results, aggregate transition rates from unemployment exhibit substantial negative duration dependence.[5] Flows at the margin between inactivity and unemployment are important in explaining LTU's rise since 2008, and account for as much as half of its variation since 1998. The relative importance of the procyclical unemployment to inactivity flow is especially robust to the alternative methods used here to estimate transition rates. The pattern of how unemployment exit rates account for LTU in the Great Recession is suggestive of shifts in the composition

[4] As such, this paper relates to several others that have used the LFS to characterise the fluidity of the UK labour market, detailing its advantages and limitations in this regard: Gomes (2012), Sutton (2013) and Carrillo-Tudela et al. (2016).

[5] I use the term duration dependence here more loosely than in the specialist literature, which applies this only to the exit probability of individuals. Duration dependence in the UK has been identified and studied at length previously by amongst others van den Berg & van Ours (1994).

of the unemployment pool, with regards individuals' attachment to the labour force. These exit rates significantly depend on what state individuals entered unemployment from. But more generally, like the stock, the recessionary decrease in transitions from unemployment to inactivity cannot be explained by the prevalence of characteristics one would expect to be correlated with attachment.

The remainder of the chapter is arranged as follows. Section 3.2 details a counterfactual exercise on whether or not the changing composition of the unemployment pool accounts for the Great Recession's rise in LTU. Section 3.3 outlines the methodology used to estimate transition rates, discusses their time series, and briefly gives some detail of the extended EHS stocks-flows decomposition method. Section 3.4 discusses results using this decomposition, and gives additional focus to the unemployment to inactivity transition rate. Finally, Section 3.5 summarises the results and offers some further discussion and implications for future research.

3.2 The composition of the unemployment pool & the long-term share

Before studying the flows data, I assess the possibility that the changing composition of unemployment could account for LTU over the cycle. This could help to nuance any later flows-based conclusions. For instance, if the rise in LTU was accounted for by a collapse in outflows from unemployment at long durations to inactivity, this could be wrongly attributed to a collapse in individual worker hazard rates, when in truth the composition of the long-term unemployed may have shifted towards those who are more attached to the labour market, such as those who were made redundant instead of having resigned form their last job.

I use the Annual Population Survey (ONS, 2004, 2007, 2010, 2013), restricting attention to the historical UK definition of working-age.[6] Short-, medium- and long-term unemployment are defined by those who have been unemployed for up to three, between three and twelve, and over twelve months, denoted respectively by S, M and L.[7] I consider the change in unemployment over three periods: first 2007-10, i.e. before the Great Recession to the peak rise in LTU, second 2007-13, to assess

[6]Male 16-64, female 16-59. This is also consistent with the age groups for which it is possible to extract a consistent series of gross flows from published Two-Quarter Longitudinal LFS (ONS, 1997-2014) datasets.

[7]Only these three duration types are considered to be consistent throughout with the set of labour market transition rates that I can reliably estimate from longitudinal survey data later. These particular duration band choices also have the nice result of roughly splitting the unemployment pool evenly, on average, over the period studied, 1997-2014.

the possibility that composition might have had a greater role during the persistent phase of unemployment, and third 2004-07, to serve as a baseline. I define types of the unemployed over sex, age groups, region of residence, industry and occupation of the last job, reason for leaving previous employment, type of employment sought, and the time since leaving the last job relative to the length of the current unemployment spell. These types account for individuals who have never worked nor had paid employment. Relative to 2004 and 2007, I construct a counterfactual unemployment pool, holding constant the distribution over $\{S,M,L\}$ for each type of the unemployed, but applying the aggregate level of unemployment and its distribution over the different types for 2007, 2010 and 2013. That is, the counterfactual for 2010 only differs from the actual observed unemployment pool in one respect: types are apportioned to $\{S,M,L\}$ according to their 2007 shares thereof.[8]

Table 3.1 demonstrates the results of this analysis between 2007 and 2010/13 (see also Figure B.1), showing actual and counterfactual levels of LTU, and changes in the share of those unemployed over twelve months. Each row addresses a single type characteristic in the composition of unemployment, including its interaction with both sex and age group types. The final row interacts more characteristics.

TABLE 3.1: Counterfactual levels and increases in the share of the unemployed who are long-term, 2007-10/13

	Number over 12 months (000s)			*Increase in share*	
	2007	*2010*	*2013*	*2007-10*	*2007-13*
Actual	370	740	850	0.08	0.12
Counterfactuals: composition change only					
1. Region		590	580	0.01	0.01
2. Prev. job industry		570		0.01	
3. Prev. job occupation		570		0.01	
4. Reason left prev. job		580	580	0.01	0.01
5. Type of job sought		600	580	0.02	0.01
6. When left last job		580	570	0.01	0.01
Characteristics 1. & 4-6.		560	590	0.00	0.01

Notes.- author calculations using UK Annual Population Survey, ages 16-64/59, January-December 2007, 2010 & 2013. Counterfactuals give levels and increases in shares for 2010 and 2013 holding constant the distribution over $\{S,M,L\}$ for each stated type of heterogeneity, interacted with sex and age groups, from 2007, and applying the overall distribution of types in the unemployment pool from 2010 or 2013.

[8]See Appendix B.1 for a more detailed description of the data, variables and methodology used in this analysis, as well as full counterfactual results for the baseline 2004-07 case and long-term shares of unemployment across the various personal characteristics accounted for.

The changing composition of the unemployed was not significant in accounting for the rise in the long-term share of unemployment from around a quarter to a third since 2008.[9] For example, although LTU's share of unemployment increased twelve percentage points between 2007 and 2013, the change in composition along the reason for leaving a previous job, sex and age groups accounts for only one point. Similarly, other characteristics only account for a small fraction of the increase. In terms of the level of LTU, by 2013 the counterfactuals leave an increase of over 250,000 unaccounted for. Not only is this an observed fact of the initial stage of the downturn to 2010, where we might expect composition to have had a more minor role, but also is the case as LTU persisted through to 2013 and the beginning of the labour market recovery. This is in spite of large pre-recession differences in the likelihood of different types finding themselves in LTU (see Table B.2). This conforms with the findings of Kroft et al. (2016) for the US over the same period. In addition to the characteristics accounted for by Kroft et al., the length of time since an individual left their last job, relative to the duration of their current unemployment spell, cannot explain a perceptible part of the rise in the LTU share. In other words, changes in the extent to which the unemployed entered form employment or inactivity are not significant.[10] However, this is not to say that the participation margin is not important, only that changing the composition along where individuals enter unemployment from cannot alone explain recessionary LTU.

A concern of this analysis, and how to interpret the results, is that upon conditioning on some observable characteristics, those who are long-term unemployed will become increasingly characterised by something unobservable which tends towards longer spells of unemployment. And given that average durations rise in recessions, dynamic selection of the unemployment pool in this regard will also be cyclical. In spite of this, it remains a surprising result that so little of the change in the distribution of unemployment across $\{S,M,L\}$ can be accounted for by observables. Ahn & Hamilton (2016) have provided a methodology to potentially account for unobserved heterogeneity. They conclude that the employment history characteristics of the unemployed are likely to explain more of the rise in average duration than coarser observable information. I have found that this is not the case in so far as employment history can be observed in the LFS. EHS have shown that during

[9]See Figure B.2 for confirmation that this is not an anomalous result for this time period. LTU during more normal times, 2004-07, is similarly uninfluenced by the composition of those looking for work.

[10]The duration of unemployment in the LFS is derived from the minimum response to when an individual left their last job and the stated length of time looking for work. Where these differ it is implied that an individual has been economically inactive since leaving their last job. In practice this also includes new entrants to the working-age labour force at age 16, who directly become unemployed, though this should be accounted for by age group and never having had paid employment characteristics.

recessions the US unemployment pool does shift towards consisting of those who are more attached to the labour force, such as job losers rather than labour force entrants, and that this is at least a relevant factor in explaining cyclical patterns in exit rates, especially the flow to inactivity. A cautious look at the distribution of personal characteristics across unemployment durations over time, combined with the results of the counterfactual exercise, suggests that recessionary LTU in the UK is not so discriminating.

3.3 Flows data & methodology

So far I have shown that changes in the composition of unemployment alone cannot account for recent changes in UK LTU. By identifying the flows and specific transition rates between labour market states which do account for these changes, I can develop a more complete picture of LTU in the Great Recession.

I derive estimates of quarterly gross flows between five labour market states from the Two Quarter Longitudinal LFS datasets, between the fourth quarters of 1997 and 2014.[11] The five states are defined as follows: employment, inactivity, short-, medium- and long-term unemployment, denoted by $X \in \{E,N,S,M,L\}$. The LFS has a five wave rotational structure, such that in any quarter the labour market status of roughly eighty percent of respondents can be compared with their record from the previous quarter. I use population weights provided by the ONS which address non-response bias in the longitudinal sample. Simple transition rates can be estimated, for example from employment to short-term unemployment, as $\tilde{p}_{ES,t} = \tilde{ES}_t/\tilde{E}_{t-1}$, where $\tilde{ES}_t$ is the gross number of transitions, and where $\tilde{E}_{t-1} = \sum_X \tilde{EX}_t$ gives an estimate of the stock in employment.

3.3.1 Employment status classification errors

A major concern when estimating flows by unemployment duration is that the data are potentially rife with classification errors. If labour market status was recorded accurately and conclusively, from one quarter to the next, then zero gross flows from employment to LTU should be observed, or from long- to medium-term unemployment for example. These measured flows in labour force surveys are typically significantly different from zero.[12] This could be explained by the incorrect recollection on the part

[11]These are subsequently seasonally adjusted. See Appendix B.2.1 for adjustment method.

[12]These gross flows within the US Current Population Survey (CPS), and their cyclical behaviour, are discussed in Elsby et al. (2011a). Also, the matching model calibrated in Kroft et al. (2016) recognises this and allows for empirically observed flows into unemployment at longer durations. See Clarke & Tate (1996) for a thorough analysis of inconsistencies between recorded states and subsequent duration responses in early panels of the LFS.

of respondents regarding the length of time they have been employed or unemployed, or that their own interpretation of their past state is different from the International Labour Organization (ILO) definition assigned to their previous responses. My own reading of the data is that the first explanation is unlikely, as individuals who remain in the same state provide very few duration inconsistencies. There is also no concentration of inconsistent transitions with unemployment durations of four to five months. Furthermore, flows between employment and unemployment have relatively few inconsistencies compared with those at the participation margin.

For robustness I address this empirical phenomenon and consistency concerns in reported transitions in three ways. Actual stocks are obtained from national labour market statistics and are given by the state vector $\mathbf{z}_t = [e,s,m,l]'_t$, with lower case denoting population rates, and where the state space is reduced by noting that the population rates across all five states sum to one. First, I measure transition rates as they are given directly by the data, and make only the standard adjustment that they should support the observed quarterly change in $\mathbf{z}_t$, abstracting from entry to and exit from the working-age population.[13] In what follows this is referred to as the 'naïve' approach, or specification (I). Second, using the measured rates, I compute the aggregate state-transition matrices for every quarter, which are not only consistent with the observed actual changes in stocks, but also conform to restrictions that some of the quarterly transition probabilities ought to have been zero: $p_{EM} = p_{EL} = p_{SL} = p_{LM} = p_{NM} = p_{NL} = 0$. In what follows this is referred to as the 'restricted' approach, or specification (II). Third, based on an assumption that the ILO employment status is most likely to have been recorded accurately, some observed transitions are reassigned before computing alternative estimates of the gross flows and transition rates. The latter are then adjusted as per (II) and subsequently referred to as 'cleaned', or specification (III).[14]

A further concerning source of potential classification errors is not addressed by (III). Using re-interview surveys of the CPS, Abowd & Zellner (1985) found that flows between unemployment and inactivity are the most likely source of these errors in individuals' longitudinal records. This was also corroborated by Clarke & Tate (1996) within the LFS, who further noted that inconsistencies are greater for groups with characteristics which are likely to be correlated with lower labour market attachment. This latter point is of particular concern when conducting a cyclical analysis of

[13]See Razzu & Singleton (2016) for a version of the EHS decomposition which does not abstract from working-age entry and exit: the different stocks individuals enter to or exit from can potentially affect the cyclical behaviour of those stocks, though in practice this is negligible.

[14]See Appendix B.2.2 & B.2.3 for more details of these adjustments, or Borowczyk-Martins & Lalé (2016) and EHS for similar applications.

flows, since the composition of the inactive and unemployed pools can be expected to change over the economic cycle, thus leading to correlation between changes in these classification errors and labour market stock measures, potentially biasing any results substantially. EHS suggested a robustness check to demonstrate the direction and potential magnitude of this bias in monthly US data. They referred to this as 'de-NUN-ification.' Transitions between unemployment and inactivity are ignored in what would otherwise have been continuous spells in one state or the other over four months. I carry out a similar recoding procedure using up to four consecutive quarters of observations for an individual, but only where it is unambiguous that transitions could not be genuine. For example, an individual who is observed as *NNSN* is not re-assigned to continuous inactivity, whereas individual *NNLN* is. This procedure is carried out subsequent and in addition to the recoding exercise described for (III), and transition rates are again adjusted as per (II). This is referred to in what follows as the 'deNUN' approach, or specification (IV).[15] In each specification the adjusted rates are then used to populate a state-transition matrix $\mathbf{P}_t$ for each quarter. For completeness, a set of continuous time equivalent hazard rates, adjusted to account for potential time aggregation bias, are also estimated using a standard procedure.[16] This is referred to in what follows as specification (V).

3.3.2 Transition rate time series and interpretation

Figure 3.2 compares the estimated exit rate series from LTU across specifications. The restrictions imposed on the non-naïve specifications imply a significant decrease in the level of exits, to off-set the lack of entries other than from medium-term unemployment. Despite this, the qualitative pattern since the Great Recession remains similar. Specifications (III) and (IV) do not substantially alter the estimated series relative to (II), especially with regards their cyclical pattern. The level adjustments in estimated transition rates of the 'restricted' specifications are somewhat extreme. It is impossible to identify whether the adjustment is mainly driven by incorrect duration records, or an individual having a different interpretation of their previous labour market status as compared with the statistical agency. Adjustments of this kind rely on arbitrary assumptions and only provide a sense of the direction or size of any classification error bias in results. As such, despite some impossible observed transitions, in what follows the naïvely estimated transition rates are mainly studied.

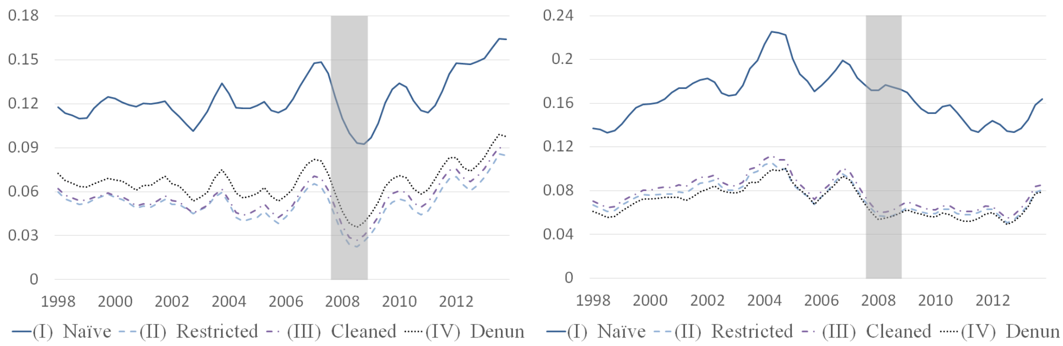
Figure 3.3 compares the estimated exit rates from specification (I) across unemployment durations, where U more generally denotes unemployment. For p_{UE},

[15] Tables B.4-B.6 give details on the extent and effect of the recoding in (III) and (IV) on the measured numbers of gross flows.

[16] See for example Shimer (2012) and also brief discussion in Appendix B.2.4.

FIGURE 3.2: Estimated long-term unemployment exit rates, 1998-2014: comparison of methodologies/specifications

(a) p_{LE} (b) p_{LN}

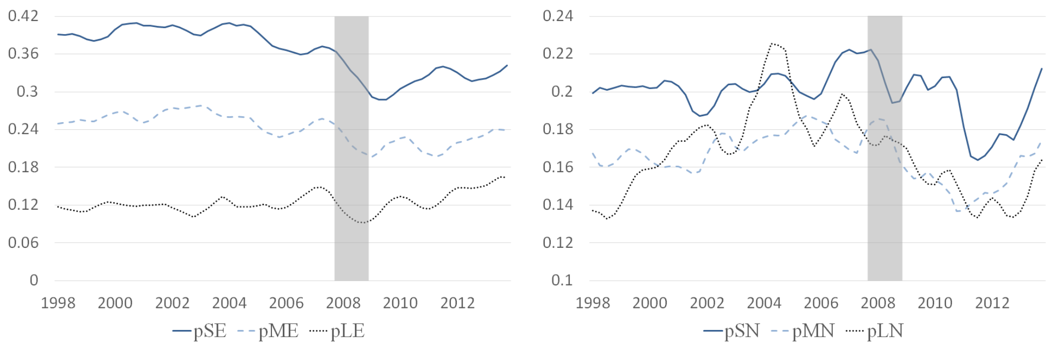


Notes.- author calculations using Two Quarter Labour Force Survey, ages 16-64/59, 1997q2 - 2015q2, after seasonal adjustment, and with a centred moving average to smooth.

exits to employment decline steeply across all durations in 2008, but although there is some recovery for long-term rates, this is less apparent at shorter durations, where the decline appears to have been more persistent. The levels of these aggregated transition rates suggest negative duration dependence. Further, this appears to reduce during the downturn. The estimated levels of transition rates for medium- and long-term unemployed to inactivity are close, and their patterns since 2008 are similar. These rates declined in 2008, but remained persistently low thereafter, and began to recover from 2013 onwards. However, the exit rate to inactivity for the short-term unemployed, being over twice as high as at longer durations pre-recession, saw a sharp decrease in 2011, before recovering to its pre-recession level by 2014.

FIGURE 3.3: Estimated unemployment exit rates by duration using specification (I), 1998-2014

(a) p_{UE} (b) p_{UN}



Source: Author calculations using Two Quarter Labour Force Survey, ages 16-64/59, 1997q2 - 2015q2, after seasonal adjustment, and with a centred moving average to smooth the series.

Interpretation of these exit rates is not straightforward. Although the composition of the unemployment pool does not generally explain the rise in LTU, this conclusion cannot simply be extended to these exit rates. Besides personal characteristics and employment history changes there is a more obvious composition challenge. Even if the unemployed were identical other than their duration, given the theoretical negative duration dependence of exits, and how $\{S,M,L\}$ are defined, the average rise in durations during a recession would contribute to some of the observed fall in measured transition rates within the grouped duration states.

3.3.3 Decomposition method

I can also derive statistics to assess the relative importance of each transition rate in explaining the change in the observed labour market stocks. The stocks-flows decomposition used here is directly extended to five states from EHS. This method has the advantage over others in so far as it does not rely on an approximation of the labour market to its steady state.[17] Whilst this latter simplification might be valid for the US, it is decreasingly so for less fluid labour markets such as the UK, or for LTU, which could be persistently away from the steady state stocks implied by current estimated transition rates.

Given the estimated transition rates populating $\mathbf{P}_t$ for each specification, the reduced form of the Markov process governing a five state labour market is given by

$$\underbrace{\begin{bmatrix} e \\ s \\ m \\ l \end{bmatrix}_t}_{\mathbf{z}_t} = \underbrace{\begin{bmatrix} 1-\sum\limits_{X\neq E} p_{EX} - p_{NE} & p_{SE}-p_{NE} & p_{ME}-p_{NE} & p_{LE}-p_{NE} \\ p_{ES}-p_{NS} & p_{SS}-p_{NS} & p_{MS}-p_{NS} & p_{LS}-p_{NS} \\ p_{EM}-p_{NM} & 1-\sum\limits_{X\neq M} p_{SX}-p_{NM} & p_{MM}-p_{NM} & p_{LM}-p_{NM} \\ p_{EL}-p_{NL} & p_{SL}-p_{NL} & 1-\sum\limits_{M\neq L} p_{MX}-p_{NL} & 1-\sum\limits_{X\neq L} p_{LX}-p_{NL} \end{bmatrix}_t}_{\Pi_t} \underbrace{\begin{bmatrix} e \\ s \\ m \\ l \end{bmatrix}_{t-1}}_{\mathbf{z}_{t-1}} + \underbrace{\begin{bmatrix} p_{NE} \\ p_{NS} \\ p_{NM} \\ p_{NL} \end{bmatrix}_t}_{\pi_t} . \tag{3.1}$$

I exclude p_{SM} & p_{ML}, since otherwise the variation in these unemployment survival rates could largely obscure the role of entries and exits at shorter durations in the evolution of LTU. However, p_{MM} then still has a somewhat strange interpretation and cannot be trivially excluded. Although the process is memoryless, its effect on long-term unemployment is similar to a decline in exit rates, in so far as it then captures a rise in average duration within M, and the mass of workers here moving closer to L,

[17] See for such examples Solon et al. (2009); Shimer (2012); Gomes (2012). For an alternative non-steady state decomposition, using flows estimates from the British Household Panel Survey, see Smith (2011).

i.e. then experiencing a p_{ML} transition. The steady-state of (3.1) is given by

$$\bar{\mathbf{z}}_t = (\mathbf{I} - \Pi_t)^{-1}\pi_t \ . \tag{3.2}$$

The change in the labour market state can be re-written as a weighted sum of its lagged value and the change in the present steady-state;

$$\Delta\mathbf{z}_t = (\mathbf{I} - \Pi_t)\Delta\bar{\mathbf{z}}_t + (\mathbf{I} - \Pi_t)\Pi_{t-1}(\mathbf{I} - \Pi_{t-1})^{-1}\Delta\mathbf{z}_{t-1} \ . \tag{3.3}$$

Iterating (3.3) back to some initial value of the labour market state, $\mathbf{z}_0$, and using a Taylor expansion around each transition rate contained in Π_t, with easily obtained analytical derivatives, the change in labour market state can approximately be written as

$$\Delta\mathbf{z}_t \approx \sum_{ij \notin \{EE,SM,ML,LL,NN\}} \mathbf{c}_{ij,t} + \mathbf{c}_{\mathbf{z}_0,t} \ , \tag{3.4}$$

where $\mathbf{c}_{ij,t}$ is a vector containing the independent contribution of past and present changes in transition rate p_{ij} to the current change in each labour market state, and $\mathbf{c}_{\mathbf{z}_0,t}$ is the contribution of some initial value.[18] In practice I also distribute the contribution from Δp_{MM}, noting that it ought to be in reality a function of changes in gross flows from between three to nine months unemployed to states $\{E,N,S\}$; i.e. for contributions to $\Delta\mathbf{z}_t$ from $\{\Delta p_{ME}, \Delta p_{MN}, \Delta p_{MS}\}_t$ I use

$$\begin{bmatrix} \widehat{\mathbf{c}_{ME}} \\ \widehat{\mathbf{c}_{MN}} \\ \widehat{\mathbf{c}_{MS}} \end{bmatrix}_t = \begin{bmatrix} \mathbf{c}_{ME} + \alpha_{ME}\mathbf{c}_{MM} \\ \mathbf{c}_{MN} + \alpha_{MN}\mathbf{c}_{MM} \\ \mathbf{c}_{MS} + (1 - \alpha_{ME} - \alpha_{MN})\mathbf{c}_{MM} \end{bmatrix}_t \ , \tag{3.5}$$

where values for each α are estimated using gross flows data from the LFS.[19] As well as being able to study the outcome of this decomposition over specific time periods, a more general measure of each transition rate's importance in determining the change in the stocks can be derived with a variance decomposition. For example, the share of the variance of changes in long-term unemployment explained by its covariance with $\{c_{ES,t}\}_4$ (i.e. the fourth row element of the vector $\mathbf{c}_{ES,t}$; the contribution of past and

[18]To improve accuracy additional polynomial terms are included in the expansion though cross-derivatives are set to zero.

[19]For example, the share attributed to the exit rate p_{ME} is estimated as the centred median over nine quarters of $\tilde{\alpha}_{ME,t} = \Delta\left(\frac{M_{3-9mE}}{M}\right)_t / \Delta\sum_{Y\in\{E,N,S\}}\left(\frac{M_{3-9msY}}{M}\right)_t$. I take the median over a range of t because the series for $\tilde{\alpha}_{ME,t}$ contains outliers which could distort the decomposition, due to the denominator occasionally being very small. I experimented with several ways to make this approximation, but the variance decomposition results were not sensitive to these.

present changes in p_{ES}) is given by

$$\beta^{l}_{ES} = \frac{cov(\Delta l_t, \{c_{ES,t}\}_4)}{var(\Delta l_t)} \ . \tag{3.6}$$

Given (3.4), the sum of the β^{l}'s for each transition rate contained in Π_t, in addition to the variance shares accounted for by the contribution of the initial labour market state and approximation errors, will necessarily sum to one. Using (3.4)-(3.6) it is straightforward to similarly derive the contributions of transition rates to changes in other labour market variables, such as the overall unemployment population share and its rate of the economically active, by adding rows and linearising. A continuous time equivalent decomposition for use with the estimated hazard rates of specification (V) is a trivial extension of the above.

3.4 Stocks-flows decomposition results

I implement the EHS style decomposition described above for quarterly changes between the second quarter of 1998 and the fourth of 2014, with the initial value of the labour market state being the first quarter of 1998.

3.4.1 Variance decomposition

Table 3.2 gives the complete variance decomposition results for quarterly changes in LTU's population share, and other labour market stocks, for the naïve and restricted specifications of estimated transition rates: i.e. values for the β_{ij} described above. Appendix B.2 contains equivalent results for specifications (III)-(V), which are viewed as robustness checks. The final rows sum unemployment flow contributions across all durations; i.e. Δp_{EU} gives the contribution from quarterly changes in the aggregate transition rate from employment to all unemployment durations. Initially focusing on the naïve results, Δp_{NL} and Δp_{LN} together explain a third of the variation of changes in LTU. When combined with changes in transition rates between inactivity and other unemployment durations, i.e. Δp_{NU} and Δp_{UN}, this increases to almost a half. This is especially accounted for by the pro-cyclical Δp_{LN}. These same flows changes account for less than a third of total unemployment's fluctuations. Contrasting the cyclical importance of Δp_{UN} with Δp_{UE}, the former is approximately half as important than the latter for total unemployment. This relative difference is however reversed for LTU. Thus, the participation margin appears relatively more important in explaining the cyclical behaviour of long-term unemployment than the total level.

TABLE 3.2: Stocks-flows decomposition: 'naïve' and 'restricted' transition rates, 1998q2-2014q4

	(I)*				(II)†			
	Δe	Δu	Δu_{rate}‡	Δl	Δe	Δu	Δu_{rate}‡	Δl
Δp_{ES}	0.20§	0.25	0.26	0.03	0.25	0.34	0.34	0.08
Δp_{EM}	0.06	0.08	0.08	0.01				
Δp_{EL}	0.00	0.02	0.02	0.06				
Δp_{EN}	0.16	0.00	0.00	0.00	0.16	0.01	0.01	0.01
Δp_{SE}	0.07	0.10	0.10	0.02	0.06	0.08	0.08	0.00
Δp_{SS}	0.00	0.00	0.00	0.01	0.03	0.05	0.05	0.07
Δp_{SL}	0.00	0.00	0.00	0.04				
Δp_{SN}	0.00	0.08	0.07	0.01	-0.01	0.06	0.05	0.00
Δp_{ME}	0.12	0.14	0.14	0.14	0.14	0.19	0.20	0.25
Δp_{MS}	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.09
Δp_{MN}	0.00	0.05	0.04	0.11	0.01	0.07	0.07	0.15
Δp_{LE}	0.07	0.08	0.09	0.10	0.10	0.14	0.14	0.15
Δp_{LS}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
Δp_{LM}	0.00	0.00	0.00	0.04				
Δp_{LN}	0.00	0.04	0.04	0.21	0.01	0.09	0.08	0.12
Δp_{NE}	0.30	0.01	0.03	0.00	0.32	0.00	0.03	0.00
Δp_{NS}	0.00	0.04	0.04	0.01	-0.01	0.08	0.07	0.01
Δp_{NM}	-0.02	0.07	0.06	0.02				
Δp_{NL}	-0.01	0.03	0.02	0.13				
Initial val.	0.01	0.01	0.01	0.03	0.01	0.02	0.02	0.05
Approx. err.	0.02	0.01	0.01	0.01	-0.08	-0.12	-0.12	0.00
Δp_{EU}	0.27	0.36	0.36	0.10	0.25	0.34	0.34	0.08
Δp_{UE}	0.26	0.32	0.32	0.26	0.30	0.41	0.41	0.40
Δp_{UN}	0.00	0.17	0.15	0.33	0.02	0.22	0.20	0.28
Δp_{NU}	-0.03	0.14	0.12	0.16	-0.01	0.08	0.07	0.01
Δp_{UU}	0.00	0.01	0.01	0.10	0.03	0.05	0.05	0.15

* 'Naïve' transition probabilities, i.e. with no zero value restrictions when adjusting $\tilde{\phi}_t$: see Appendix B.2.2.

† Transition probabilities adjusted according to restrictions $p_{EM} = p_{EL} = p_{SL} = p_{LM} = p_{NM} = p_{NL} = 0$.

‡ $u_{rate} = u/(u+e)$

§ Interpretation: Share of variance in the change in the employment rate accounted for by past and present changes in p_{ES}, i.e. $\beta^e_{ES} = \frac{cov(\Delta e_t, \{c_{ES,t}\}_1)}{var(\Delta e_t)}$.

Notes.- author calculations using Two Quarter Longitudinal Labour Force Survey & Labour Market Statistics, ages 16-64/59.

Comparing results using the estimated restricted transition rates, in terms of accounting for the unemployment rate, the 'outs' become more dominant, explaining sixty percent of the variation in the stock. This is driven by the restriction that all gross flows must enter short-term unemployment. These restrictions do not affect the combined importance of the participation margin, but give more weight to Δp_{UN}. Results for the change in LTU with the restricted set of possible transitions do differ more substantially from the naïve. Instead of explaining almost a half of the variance, transitions between inactivity and unemployment account for less than a third. This difference is mostly explained by a greater relative importance of Δp_{UE}. The importance of Δp_{UN} though remains unchanged.

The additional reassignment of some gross flows data to assess the role of possible classification errors have anticipated effects on the results (see Table B.7). With regards the unemployment rate, the effect of using the 'cleaned' flows series is to marginally reduce the importance of the participation margin. This is further reduced through 'de-NUN-ification'. However, through all specifications the pro-cyclical Δp_{UN} (and Δp_{LN}) remains a major factor, explaining a third of the variance in LTU's changes in the past sixteen years to 2015.

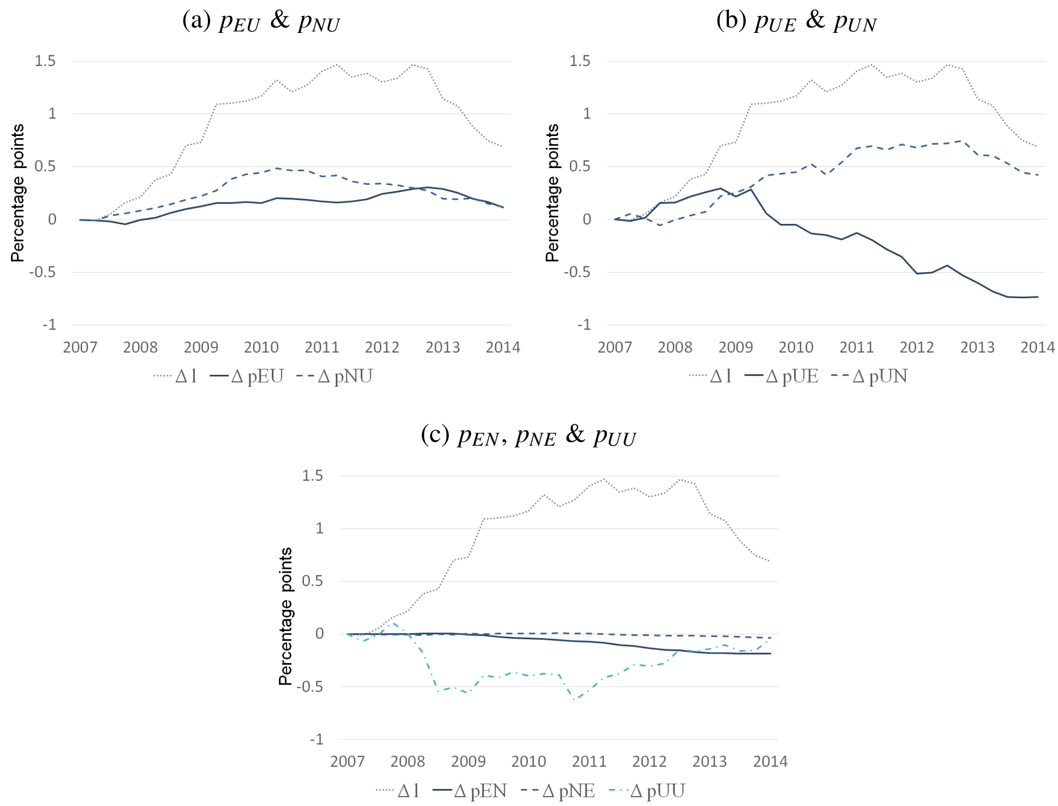
As a further robustness check, I compare results using naïve transition rates with those using their time aggregation bias adjusted hazard rate equivalents (see Table B.8). With regards the unemployment rate, the share of the variance attributed to changes in the exit rates rises relative to the non-adjusted baseline, from a half to two-thirds, in line with the expected direction of the bias. But addressing this does not alter the principal qualitative result: the participation margin is crucial in accounting for LTU variation.

3.4.2 Focusing on the Great Recession

Figure 3.4 plots the cumulative rise in the working-age LTU population share from the final quarter of 2007, and the estimated contributions from past and present changes in the underlying naïve transition rates, using equations (3.4) & (3.5). By the beginning of 2012 the population share had reached a peak of 2.5%, more than doubling with an increase of 1.4 percentage points. The majority of the initial rise in 2008 is explained by the pro-cyclical Δp_{UE}. However, this contribution disappears by 2010, and by 2012 changes in the exit rates to employment alone would have implied a lower long-term level than pre-recession, despite the actual level being at its peak. Entries to unemployment from employment contribute a small amount, but this is never substantial. Conversely, by 2010 entries from inactivity can explain almost half a percentage point of the increase, though this subsequently declines to pre-recession levels even as LTU persists. To account for the majority of the persistent and prolonged rise in LTU we must focus on the decline in exit rates to inactivity.

These flows patterns, and their contributions to the stock of long-term unemployed, would strongly suggest a compositional change in the unemployment pool. Intuitively, the initial fall in the exit rate to employment affected the already unemployed going into the Great Recession. However, as the downturn persisted, the composition of

FIGURE 3.4: Decomposition of the cumulative change in long-term unemployment, 2008-14: contributions from individual transition rates



Notes.- author calculations using Two Quarter Labour Force Survey & Labour Market Statistics, ages 16-64/59. Transition rates calculated using specification (I). Series indexed to zero in 2007q4. Interpretation is the cumulative increase in long-term unemployment's population share since 2007 accounted for by past and present changes in transition rates. Flows contributions may not appear to exactly sum to the change in the stock due to accumulated approximation errors. The initial state value contribution is negligible.

this pool shifted towards individuals with higher job finding rates. Similarly, these displaced workers are likely to have had a stronger attachment to the labour force, potentially accounting for the procyclical exit rate to inactivity.

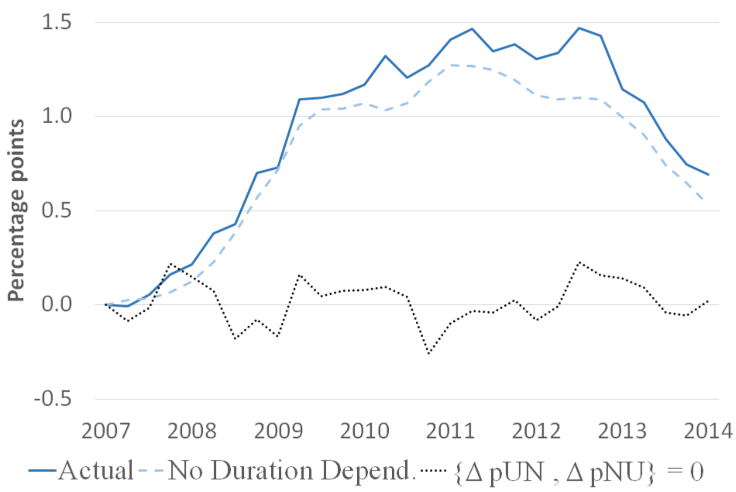
3.4.3 Duration dependence or participation flows?

The methodology used here introduces both the limited duration dependence of unemployment exit rates and the role of participation flows in accounting for LTU changes. I can assess the importance of each in turn during the Great Recession. To simplify the problem, for the former I use the restricted transition rate series. With these, which are consistent with actual changes in unemployment, I project forwards the LTU population share as if there was in fact no duration dependence. That is, given some initial value for LTU, l_0, I can recursively update the stock as follows,

$$\Delta l_t = \sum_X \left[x_{t-5} p_{XS,t-4}\right] \prod_{i=0}^{3} (1 - \sum_{X \neq M,L} p_{UX,t-i}) - l_{t-1} \sum_{X \neq M,L} p_{UX,t} \,, \tag{3.7}$$

where x is the population rate corresponding to the stock X, and $\sum_{X \neq M,L} p_{UX,t}$ is the total exit rate from unemployment, including restarts. The initial value is chosen as early as possible, 1998q4. Figure 3.5 compares the actual cumulative rise in LTU, from 2008, with this 'no duration dependence' counterfactual. Clearly the limited aggregate duration dependence studied here is not significant in matching the counter-cyclical propagation of LTU, as the two series are almost identical.[20]

FIGURE 3.5: Cumulative long-term unemployment change and two counterfactuals: no duration dependence and no changes in participation flows, 2008-14



Notes.- author calculations using Two Quarter Labour Force Survey & Labour Market Statistics, ages 16-64/59. Series indexed to zero in 2007q4. Interpretation is the cumulative increase in long-term unemployment.

Using the full decomposition results with naïve transition rates, Figure 3.5 also demonstrates the implied rise in LTU assuming instead no contemporaneous or past changes in transition rates between unemployment and inactivity: i.e. setting Δp_{UN} and Δp_{NU} equal to zero in all periods. This picture simply reinforces results already discussed. Over two-thirds of recessionary LTU is accounted for by changes in flows at the participation margin.

3.4.4 Composition and unemployment to inactivity flows

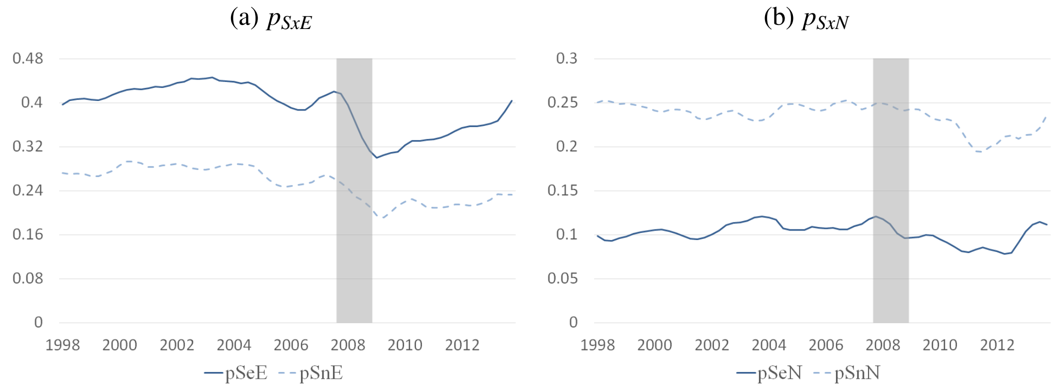
As previously studied for the stocks above, I can assess the role of composition along some observable characteristics in explaining these flows patterns. One

[20]Though as in Kroft et al. (2016); Krueger et al. (2014) it is highly significant in terms of matching levels of LTU over the whole sample period.

distinction of interest is whether individuals entered unemployment from inactivity or employment, as this will correlate strongly with labour force attachment. Although this could to some extent be observed using the five successive waves of the LFS, it can be studied for a larger sample using responses to when an individual left their last job, and whether or not the time since is strictly greater than the derived unemployment duration. Due to sample sizes it would not be robust to disaggregate the long-term unemployed gross flows series further. However, if S and M are combined, it turns out that approximately over the sample period similar numbers in this combined stock entered from employment and inactivity. The level of those unemployed zero to twelve months, for whom the time since they left their last job is strictly greater than these grouped duration categories, is denoted by Sn, and for those where this matches, by Se. For these two new states, as well as $\{E, L, N\}$, I derive seasonally adjusted gross flows and estimated transition rate series, which are adjusted to match observed changes in population rates, as in the naïve specification described before.

Figure 3.6 shows estimated exit rate series for those unemployed for less than twelve months, conditional on whether they entered from employment or inactivity. Unsurprisingly, the exit rate to employment is significantly higher for employment entrants, and vice versa, the exit rate to inactivity is higher for inactivity entrants. Pre-recession, p_{SnN} was over twice as high as p_{SeN}. Therefore, just through differences in these levels, if the unemployment pool had shifted during the Great Recession towards entrants from employment, this could account for some of the importance of changes in the p_{UN} rate relative to p_{UE}.

FIGURE 3.6: Short-term unemployment exit rates conditional on where entered from, 1998-2014



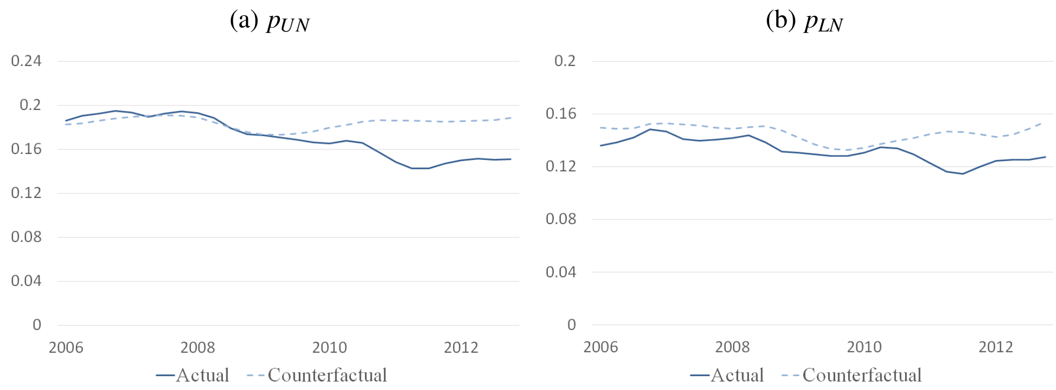
Source: Author calculations using Two Quarter Labour Force Survey, ages 16-64/59, 1997q2 - 2015q2, after seasonal adjustment, and with a centred moving average to smooth. Transition rates adjusted to be consistent with observed changes in stocks.

Specifically with respect to LTU, and the contributions of changes in exit rates, I can use the gross flows, conditional on point of entry to unemployment, to test the suspicion that my main results are related to composition changes. Figure B.3 repeats panel (b) of Figure 3.4, but overlays the share of gross flows into LTU which were employed prior to becoming unemployed. There is a notable increase in this share by 2009 and onwards, which coincides with the decreasing and increasing contributions of Δp_{UE} and Δp_{UN} respectively. However, we have already seen from the stocks counterfactual exercise that the composition over this particular employment history characteristic does not explain LTU and its persistent rise. The implication being that whilst there is some correlation, much larger shifts in the unemployment pool along these observables would be required to explain the overall rise of the stock and the contributing pattern of the flows.

To see this more generally, I consider whether the changing composition of the unemployment pool can explain the procyclical p_{UN} and p_{LN} transition rates. I derive counterfactual series of these rates that would have occurred had the exit rates of types of unemployed, defined by all possible combinations of some personal and work history characteristics, remained at pre-recession levels, but only the composition of unemployment changed. I estimate these pre-recession exit rates for each type as the arithmetic mean of raw unadjusted quarterly transition rates observed for 2006-07. I use characteristics and categories considered in the counterfactual exercise in Section 3.2 sex, age groups, type of employment sought, reason for leaving last job, and when the individual left their last job relative to the reported length of the unemployment spell. Figure 3.7 plots the actual estimated transition rate series along with these counterfactuals. Although the actual unemployment to inactivity transition rate declined steadily from around 0.2 to 0.15 between 2008 and 2011, the counterfactual series only shows a small decline in 2009 and 2010, but thereafter is approximately at pre-recession levels. The long-term to inactivity rate demonstrates a similar pattern. The counterfactual also initially matches the actual series, but cannot then match a greater decrease from 2011 onwards. Thus, the changing composition of the unemployment pool across these particular characteristics, which are strongly correlated with labour force attachment in terms of the levels of stocks and flow rates, cannot account for the cyclical importance of unemployment to inactivity flows.

It is possible that changes in UK Government labour market policy during the Great Recession are responsible for some of the results here. However, in Appendix B.3 I demonstrate that changes to the eligibility of welfare payments, which could potentially affect flows between active and inactive types, cannot account for the procyclical p_{UN} rate.

FIGURE 3.7: Counterfactual unemployment exit rates to inactivity: changing the composition of unemployment only, 2006-13



Notes.- author calculations using Two Quarter Labour Force Survey, ages 16-64/59, 2005q4 - 2015q2. Using raw transition rates, not seasonally adjusted but smoothed using centred four quarter moving average. Personal characteristics accounted for in counterfactual: sex, age groups, type of employment sought, reason left previous employment and when left last job relative to length of unemployment spell. See Appendix B.1 for details and derived categories of these characteristics.

3.5 Summary and further discussion

Some observed and derived facts discussed in this chapter regarding long-term unemployment and the UK labour market during the Great Recession are as follows:

(i) The changing composition of unemployment, along relevant observable personal and employment history characteristics, cannot account for the significant and persistent rise in LTU since 2008.

(ii) Changes in transition rates between unemployment and inactivity can explain as much as half of the variation in LTU between 1998 and 2014. The flow from unemployment to inactivity's relative importance is robust to various different approaches used to estimate these transition rates.

(iii) Despite (i), the pattern of how changes to flows contributed to the rise in LTU remains consistent with an unemployment pool which shifted towards workers more attached to the labour force.

(iv) Unemployment exit rates exhibit both level and cyclical dependence on whether workers entered from employment or inactivity.

(v) However, procyclical transition rates from unemployment to inactivity are mostly not accounted for by changes to the observable composition of the unemployment pool.

A significant challenge to the validity of these results remains the longitudinal inconsistencies between states and durations in the LFS. However, it seems a reasonable stance, as others have taken in the literature, to in the first instance take these simply as given, and then for robustness study in what direction any measurement errors would tend to bias results. One way to corroborate would be to use administrative claimant flows data for those receiving out of work payments from government. But at least so far as the UK is concerned, the available data are typically incomplete, and thus prone to sampling bias, and individuals claiming most major benefits do not fall strictly within ILO employment status definitions.

This paper reinforces that the participation margin is likely to be crucial in accounting for the observed amplification of long-term unemployment during recessions, as also demonstrated in Krueger et al. (2014) & Kroft et al. (2016) for the US experience of the Great Recession. An interesting extension of the matching models in these aforementioned studies would be the inclusion of exit rate dependence on employment history, namely depending on which state workers entered unemployment from. As shown here, this could be significant. The shift of the unemployment pool towards entrants from employment in recessions could potentially off-set a stronger procyclical response and importance of negative duration dependence.

The results of the flows decomposition lead to a strong suspicion that a shift in the composition of the unemployment pool, towards more attached workers, could explain the UK's recessionary rise in LTU. However, counterfactual analyses of the stock and contributing flows, along some observed characteristics expected to be correlated with attachment, have not confirmed this. This points towards the likelihood that levels of attachment are challenging to identify from observables. Alvarez et al. (2016a) have modelled transitions between employment and non-employment and found that unobserved heterogeneity across workers, affecting their degrees of negative duration dependence in exit likelihood, and the resulting dynamic selection of the stocks over time, must play a significant role in accounting for the evolution of the aggregate job finding rate from non-employment. Using a similar model, it would be an interesting direction for future research to consider whether this extends to unemployment to inactivity flows, and how in this way we might account for LTU increases during recessions.

Chapter 4

Recent changes in British wage inequality: evidence from firms and occupations

Note: The latest working paper version of this essay is publicly available at SSRN: https://ssrn.com/abstract=2816868. An older version has also been published as Edinburgh School of Economics Discussion Paper Series N.277. This research was co-authored with Daniel Schaefer, who is a PhD candidate at the University of Edinburgh; daniel.schaefer@ed.ac.uk. Daniel has agreed that it represents in the majority my work, and none of the work directly related to this research/essay will appear in his future thesis submission. By the time of final submission this research will have been presented at the RES Symposium of Junior Researchers (April 2017, Bristol), IAAEU Workshop on Labour Economics (April 2017, Trier), Society for Economic Dynamics Annual Meeting (June 2017, Edinburgh), and European Association of Labour Economists Annual Conference (September 2017, St. Gallen); versions may appear on the scientific programmes of these events. I am grateful to the Scottish Economic Society for funding support in carrying out this research. This chapter is mostly based on data from the New Earnings Survey Panel Dataset (Crown copyright 2016), having been funded, collected and deposited by the Office for National Statistics (ONS) under secure access conditions with the UK Data Service.

4.1 Introduction

The long-term trend of rising wage inequality in Great Britain has been extensively documented (Hills et al., 2010; Machin, 2011; Belfield et al., 2017). As in the US and several other countries, the majority of this increase in Britain occurred in the 1980s, but stagnant real median wages in the past two decades have refocused attention on where the proceeds of growth are ending up. Although well-studied, some ambiguity remains over what principally drives changes in the wage distributions of labour markets such as Britain's. One explanation points towards pay setting practices and the increasingly generous remuneration of executives and senior managers (Piketty, 2013). Others have identified rising skill and occupational wage premiums, associated with skill-biased technological change (Katz & Murphy, 1992; Machin & van Reenen, 1998). Further explanations highlight changing institutions, with examples in Britain being the decline in unionisation (Card et al., 2004) and the introduction of a minimum wage in 1999 (Machin, 2011). One way to potentially disentangle these explanations is to ask how much have the differences between firms, relative to within, accounted for recent inequality trends. We answer this question for the last two decades in Great Britain.

Among full-time employees over eighty percent of the increase in the variance of log weekly wages between 1996 and 2005 occurred within firms. In the subsequent decade to 2015 overall inequality decreased, whereas the dispersion of average firm wages increased. For measures of annual or hourly wages we similarly find that within-firm inequality changes predominantly accounted for overall changes. Faggio et al. (2010) find that rising British wage inequality in the fifteen years prior to 1999 was almost entirely accounted for by an estimate of between-firm variance. A contribution of this chapter is to extend their results, using the same survey data of wages and hours, but by instead matching a representative sample of employees to the majority of large firms. This provides us with a more robust sample of employer-employee linked jobs, as opposed to using some separate source to estimate firm average wages; Faggio et al. (2010) lacked data on the wages within firms. Mueller et al. (2016) also study British wage inequality from the firm's perspective. Using data on average pay at hierarchy levels in 880 firms, they find not only substantial within-firm inequality in the years 2004-13, but that this tended to increase as firms grew. They suggest that overall wage inequality trends could be related to an increasing concentration of employment in large firms.

Several recent studies have documented that trends in employee wage inequality and the dispersion of firm productivity or average wages tend to coincide (see among others for the US: Davis & Haltiwanger, 1991; Dunne et al., 2004; Barth et al., 2016; Song et al., 2016. For Sweden: Nordström Skans et al., 2009; Akerman et al., 2013. For West Germany: Card et al., 2013. For Brazil: Alvarez et al., 2016b; Benguria, 2015; Helpman et al., 2017. See also the literature review by Card et al., 2016). At first look our results for Britain would appear to conflict with this wider literature. The data are a one percent random sample of employees, and so we limit attention to mostly large firms, representing approximately forty percent of all UK employment. The overall trends in wage inequality for this forty percent are not dissimilar to the whole economy. But Song et al. (2016) have demonstrated that the contribution of between-firm wage dispersion to overall changes is smaller among large US firms. Although our results are robust to varying the sample selection and resulting average firm size, we can only cautiously compare them to those found elsewhere using more widely representative data.

These British data do however offer some clear advantages. They are generally considered to be accurate records from firms' payrolls (Nickell & Quintini, 2003), giving measures of annual and weekly earnings, and their constituent components, including hours worked. They also contain a detailed classification of occupations. We use this to ask how much of the estimated contribution to inequality changes from firm-specific differences can be accounted for by changes to the occupational content of wages. The answer is approximately all. Some combination of changes to between-occupation inequality and the sorting of occupations across firms accounts for the role of dispersion in firm-specific wages over the last two decades in Britain.

It is well-known that the polarisation of employment across occupations, the increase in shares of employment in high- and low-skilled occupations, accounts for a significant part of long-run wage inequality changes in the UK, US and elsewhere (Goos & Manning, 2007; Autor et al., 2008; Williams, 2013). Song et al. (2016) suggest that while skill-biased technological change could account for overall wage inequality increases and the polarisation of employment, across firms there has perhaps been greater specialisation and concentration of occupations, explaining some part of the rising dispersion in average firm wages. This theory has been largely untested due to a lack of comprehensive data covering long periods of employee wages, detailed occupations and firm identities. A notable exception is Weber-Handwerker & Spletzer (2016), who do make some progress on this for the US for 2000-11, finding that the changing composition of employment over occupations, as opposed to industry, accounts for almost half of between-establishment wage growth. They also specifically find that occupational concentration in firms, measured by Herfindahl indices, explains only a small part. In contrast, we also allow for changing occupational wage premiums as well as their composition over firms and employment, and as such we are able to account for approximately all of the change in firm-specific inequality throughout the wage distribution. We view this as suggestive evidence that the estimated importance of between-firm inequality found elsewhere could similarly represent an important role for the occupational transformation of firms and labour markets.

The remainder of the chapter proceeds as follows: Section 4.2 describes the data, Section 4.3 presents the results from decompositions of wage variance over the last two decades in Britain, Section 4.4 describes the dynamics of inequality throughout the wage distribution, Section 4.5 briefly summarises the related literature, and Section 4.6 concludes. Further information concerning the data, sample construction, mathematical details and additional results is presented in Appendix C.

4.2 Data

The data we use are from the New Earnings Survey Panel Dataset (NESPD), 1975-2015, which is distributed under secure license access by the UK Data Service, with the permission of the data owners, the Office for National Statistics (ONS). It is a continuing sample of approximately one percent of all Pay As You Earn (PAYE) taxpayers in Britain, with the sample selected using the same last two digits of worker National Insurance numbers, covering up to 180,000 employee jobs per year.[1] A small number of jobs not registered for PAYE, which tend to be of very low pay, are not sampled. Employees who are not paid in the reference period are also excluded. These are both potential sources of composition bias in measuring inequality changes, which could vary over the economic cycle. But it is certainly an advantage that the dataset is a long-running panel, since we can expect many repeated observations of employer-employee matches.[2] The data are collected via a questionnaire issued to employers, who are required by law to respond and complete it with reference to payrolls. They return the gross weekly earnings and hours worked of employees, and their detailed components, as well as an employee's occupation and other information related to remuneration, such as pensions and collective agreements. The reference period for the survey is always a week in April. Gross annual earnings for the year to April have been recorded since 1999.

It is a significant advantage of these data that we can consider the robustness of results across different frequencies of pay. For example, the compositional differences in two jobs samples from the NESPD which contain either non-missing observations of weekly or annual wages could be large, given that for the latter individuals must have been with the same employer for at least twelve months. Related, the timing of bonus

[1] National Insurance numbers are issued to all individuals in the UK who have the right to work. For UK nationals these are typically issued when turning sixteen.

[2] We do not exploit this feature fully since in the current publicly available form of the dataset employers can only be robustly identified over time for 2002-2015.

payments tends to be seasonal in Britain. Approximately half of all such payments economy-wide and over seventy percent in the financial and insurance activities sector occur in the 'bonus season' of December-March.[3] This seasonal pattern is consistent across years. Therefore the measures of weekly and hourly wages in April will only capture a small part of this pay component. The fraction of total employee remuneration which is from bonus payments has been fairly constant at 6-7 percent over the last two decades, but in the financial and insurance activities sector this has fluctuated between 20 and 35 percent around the Great Recession. If bonus payments have significantly affected trends in the employee wage distribution, then we could expect our results to differ between using annual vs. weekly or hourly measures.

Information on employer size and industry classification was added to the NESPD from 1996 onwards by the ONS, using Her Majesty's Revenue and Customs' Inter-Departmental Business Register (IDBR), an administrative census of all UK registered companies. Only tiny businesses consisting of the self-employed are not found on the IDBR. The employer reporting unit observed in the NESPD is generally the enterprise or a local unit thereof. For the vast majority of the data used in the analysis that follows the 'firm' is an enterprise.[4] For a sub-period, 2002-15, the enterprise of all jobs is identified, and we use this as a robustness check of whether our less precise definition of a firm could qualitatively affect any main results. We can do this using the annual cross-section datasets of the Annual Survey of Hours and Earnings, from which the NESPD in later periods is derived. This earnings survey is considered to be unusually accurate, at least when compared with household based surveys (Nickell & Quintini, 2003). The NESPD has undergone minor methodological changes over its lifetime, but the principal aim of collecting detailed and precise information on hours, pay and occupations has remained consistent. In Appendix C.1 we briefly summarise the relevant changes, as well as providing greater detail than what follows on the construction of our analysis sub-samples and variables.

4.2.1 Creating a large firms sample of the NESPD

For sub-samples of the NESPD we include only those aged 16-64 and exclude jobs where pay in the reference week has been affected by absence or leave. For weekly

[3]See ONS statistical bulletin: "Average weekly earnings, bonus payments in Great Britain: financial year ending 2016".

[4]We are comfortable that the enterprise is a typical definition of the firm, as defined for UK government administrative purposes. IDBR definition: 'An Enterprise can be defined as the smallest combination of legal units (generally based on VAT and/or PAYE records) that is an organisational unit producing goods or services, which benefits from a certain degree of autonomy in decision-making, especially for the allocation of its current resources. An enterprise carries out one or more activities at one or more locations. An enterprise may be a sole legal unit.'

wages and hours worked we use the reported values excluding overtime. We drop a tiny number of jobs with records of over a hundred hours worked in the reference week. Hourly rates of pay are derived from gross weekly pay and basic (usual) hours worked. From 1999 we drop less than half a percent of observations in each year whose hourly rate of pay is less than eighty percent of the applicable National Minimum Wage. When considering annual earnings we use only observations where the employee has been in the same job for at least a year. All monetary values are deflated to 1997 prices using the ONS' Retail Price Index from April, to match the reference period of the NESPD.[5] To analyse and estimate a within-firm component of wage dispersion we have to match sufficient numbers of employees to each observed firm. Hence we construct a large firms sample of the NESPD. We consider only jobs in each year at enterprises with 250 employees or more according to the IDBR.[6] In the baseline sample we keep only full-time jobs, defined as working over thirty hours in a week before overtime, and in each year then keep firms for which there are ten or more job observations with non-missing values of pay and hours worked. This firm-based selection imposes a de facto minimum firm size of more than a thousand employees. We construct several other sub-samples, which are discussed in the results, where we vary the minimum number of job observations required per firm and add part-time workers.

Throughout the following analysis and results one can generally replace any reference to 'firms' with 'large firms,' or even 'very large firms.' This is clear when we compare the enterprise size distributions in 2013 of the UK population and the firms in our baseline NESPD sub-sample (Table C.1). Over seventy percent of UK enterprises with at least 250 employees have less than a thousand employees. But in our baseline sample such firms are only five percent of the total number. On the other hand, firms with more than two thousand employees are relatively over represented: the sample includes a similar number of firms with over five thousand employees as there are such UK enterprises.[7] Though we cannot represent the whole firm size distribution of Britain, we can nonetheless claim to sample employees from practically all very large enterprises. As such we are able to study a significant fraction of jobs and wages: in 2013 the firms in our sample represented approximately forty percent of employee jobs.[8]

[5]Accessed from the ONS website 25/05/2016.

[6]The cut-off between the definition of Small and Medium Enterprises (SMEs) and Large firms in the UK is typically at 250 employees.

[7]Part of the non-sampling discrepancy is due to the NESPD being British as opposed to UK. In 2013 ONS data suggests there were thirty enterprises in Northern Ireland with over a thousand employees. Using enterprise identifiers from the ASHE to define firms in 2013, and otherwise the same criteria to construct the baseline large firms sample, gives us 598 enterprises with over five thousand employees.

[8]According to the ONS Labour Market Statistics Workforce Jobs series, there were approximately 27.5 million employee jobs in Great Britain in 2013.

Given we are studying the dynamics of wage inequality, we briefly document how the baseline sample's firm size distribution has evolved over time, between 1997 and 2007 for example (Table C.2). The share of firms with more than two thousand employees increased by over thirteen percentage points in this period, with the largest increase among those with five thousand or more. The share of employee observations in very large firms similarly increased. The true distribution of these firms was relatively unchanged over the period, according to their administrative IDBR enterprise level of employment. We believe this difference reflects a shift since 2004 in the employer reporting unit of the earnings survey towards more commonly being the enterprise, as opposed to the local unit.[9] We also describe the sample's changing industrial make-up over the same ten years (Figure C.1).[10] The share of firms associated with the manufacturing sector decreases notably, while real estate and business services firms are increasingly represented. We observe similar trends in the represented labour shares of sectors, though in this case there is also a decline in the share of employees in public administration and defence.

An advantage of our data over those used in similar studies is the presence of employer descriptions of jobs and their assignment to a detailed occupational classification. Throughout, occupations refer to the International Standard Classification of Occupations 1988 (ISCO88), unless stated otherwise. Due to inconsistencies in source data classifications we only consider occupations for the sub-period 1996-2010. Comparing the incidence of major occupation groups in the sample over time, some occupations are less prevalent in 2007 than in 1997, with a large decrease for professionals (Table C.3). At the same time the share of elementary occupations has increased by almost the same amount. This sample of large British firms, and a further sample of their employees, would appear to have some different characteristics over time. Partially this could reflect long-run trends of structural change in the labour market.

4.2.2 Describing wages in large firms and the NESPD

Since economy-wide trends in wages have been extensively documented elsewhere using the NESPD (e.g. Machin, 2011), here we focus on whether recent patterns among jobs in large firms have been notably different. Figure 4.1 compares selected percentiles of real log wages for full-time employees between our baseline sub-sample and the whole NESPD. Figure C.2 similarly compares mean values. All measures of

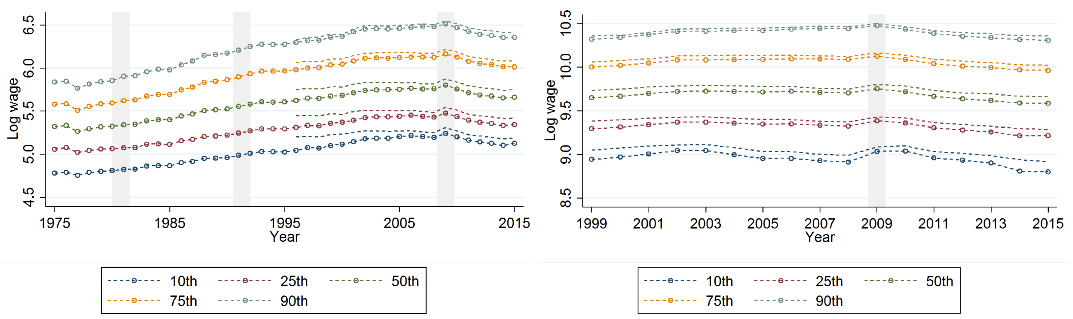
[9]This coincides with the replacement of the NESPD with the ASHE. Despite studying the documentation we cannot find any noteworthy reason for such a sizeable shift. As we show in what follows, we are confident that this does not qualitatively drive any of the main results.

[10]Throughout the chapter industry sectors refers to the Standard Industrial Classification (SIC) 2003.

real wages were relatively stagnant during the 2000s. They have also seen a substantial decline since 2008, especially compared with the periods following other downturns. The variance of log weekly wages increased for the whole NESPD persistently from 1975 to 1995 (Figure 4.1a). The variance of wages in our baseline sample is somewhat lower than in the whole NESPD. This is due to a tighter distribution of wages above the median among those working in larger firms. Generally though the pattern of wages across the large firms distribution is similar to the whole NESPD: for example, both show a steep increase in hourly and weekly wages for top earners in the early 2000s, as well as a decline in variance at the onset of the Great Recession, driven by relatively higher earnings at the bottom. Figure 4.2a further demonstrates these changes by plotting weekly wages relative to 1996 for selected percentiles of the large firms sample.

FIGURE 4.1: Percentiles of real log wages in large firms, full-time employees only, and comparison with the whole NESPD sample, 1975-2015

(a) Weekly (b) Annual

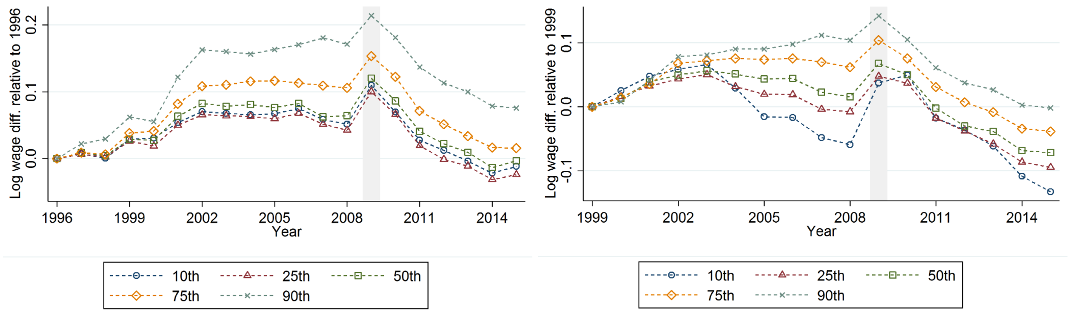


Notes.- author calculations using the NESPD, age 16-64 and full-time employees only. ‘Weekly’ exclude overtime. ‘Annual’ are for employees with the firm at least one year. See the text for further details of sample construction. Shaded areas represent official UK recessions. Dashed lines without markers are the series for a large firm sub-sample of the NESPD.

The increase in the variance of log annual wages, which include all performance related payments, was more substantial between 1999 and 2007. As shown in Figures 4.1b and 4.2b, this is explained by real wages falling at the lower percentiles and only marginally rising at the median, while the ninetieth percentile increased consistently through this period. Much of the increase in variance during the preceding decade was reversed in 2008 by a relatively greater increase in log wages at the bottom. This large increase in real wages in 2008 partly reflects our choice of price deflator, which includes the slashing of mortgage interest costs during the financial crisis, as well as the well-understood cyclical composition bias in aggregate wage measures, which was large in the UK during the Great Recession (Elsby et al., 2016). These patterns and comparisons are similar when we consider all employees and not only those working full-time (Figures C.3-C.5).

FIGURE 4.2: Percentiles of real log wages in large firms, full-time employees only: differences relative to 1996/9

(a) Weekly (b) Annual



Notes.- see Figure 4.1.

4.3 Wage inequality trends: the role of between-firm variance

To account for how much of the variance in employee wages is explained by differences in the average wages paid by firms, we use the decomposition of Davis & Haltiwanger (1991). The total variance of the natural logarithm of wages across a set of firms and their employees, V_e, can be decomposed into a within-firm component, V_{wf}, and the variance of average log wages between firms, V_{bf}. We estimate this decomposition as follows. Denoting the total number of firms in a given year by J, and the number of employees we observe in firm $j = 1,...,J$ by N_j, such that the total sample number of employees is $N = \sum_{j=1}^{J} N_j$, then we can write

$$\underbrace{\frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{N_j}(w_{ij}-\overline{w})^2}_{\text{Overall - }V_e} = \underbrace{\frac{1}{N}\sum_{j=1}^{J}\sum_{i=1}^{N_j}(w_{ij}-\overline{w}_j)^2}_{\text{Within-firm - }V_{wf}} + \underbrace{\sum_{j=1}^{J}\frac{N_j}{N}(\overline{w}_j-\overline{w})^2}_{\text{Between-firm - }V_{bf}}, \tag{4.1}$$

where w_{ij}, $\overline{w}$, and $\overline{w}_j$ denote respectively the log wage of employee i in firm j, the sample mean of log wages, and the sample mean of log wages within firm j.[11] For convenience we leave implicit the dependence of j on i throughout the paper. The term capturing the between-firm component of wage dispersion weights by employment

[11]Sampling errors in the measures of firm average wages (or hours) will generally induce a positive bias in between-firm variance estimates and their shares of the overall variance. We do not attempt to correct this, and instead rely on our analysis being focused on trends, since the size of this bias is unlikely to vary significantly over the period studied. The literature in this area, such as Card et al. (2013), also acknowledges the bias from sampling error, and similarly tends to ignore it, by arguing that trends are unlikely to be affected. Here we are especially reliant on any changes to the NESPD/ASHE sample frame or method not affecting the level of bias over time. We are confident that this is qualitatively the case, given our knowledge of the timing of any such changes, as discussed in Appendix C.1.

share the observed distance of a firm's estimated average wage to the overall average wage, such that larger firms have a potentially greater influence on wage dispersion than smaller firms. There are two potential choices for how to weight firms: by their shares of employee observations in the sample, or by their relative size as indicated by the IDBR recorded numbers of employees. Our preference throughout is the former, but we find the choice has no qualitative effect on results (see for example Figure C.6).

Table 4.1 summarises the decomposition results discussed throughout this section. Since the data are not top-coded and a small sample, we exclude the top one percent of all earners from the variance calculations in this section. Throughout the remainder of the chapter we mostly focus on weekly wages, as these are recorded in the data independently of an employer's response for the hours worked of their employees. Further, this sample includes jobs which are less than a year old. These jobs would be excluded from an analysis of annual wages and their importance within the true wage distribution could vary over time. Figure 4.3 plots the estimated components of (4.1) for each year between 1996 and 2015 for full-time employees. Overall wage dispersion is increasing when measured over the entire sample period (column (9), Table 4.1). However there is an observable difference pre and post the 2008 financial crisis. The latter period experienced falling inequality, mostly accounted for by the decreasing variance of wages within firms, whilst at the same time between-firm inequality continued to increase. Prior to 2008, the increase in within-firm inequality explained the majority of the overall trend (over 80 percent: column (7), Table 4.1). The overall variance of log weekly wages mirrors closely the pattern of the within-firm component, as can be seen in Figure 4.3a. It is clear that the pre-2008 increase and the post-2008 decrease in inequality were driven mostly by the within-firm component in Britain (see also Figure C.7a). A similar conclusion holds for annual wages in Figure 4.3b (see also Figure C.9a). Just over forty percent of the long-run increase in annual wage inequality was accounted for by between-firm variation, compared, for example, with sixty percent found by Song et al. (2016) for jobs in large US firms. The decrease in wage dispersion during the financial crisis is also more pronounced in annual wages, and accounted for mostly within firms.

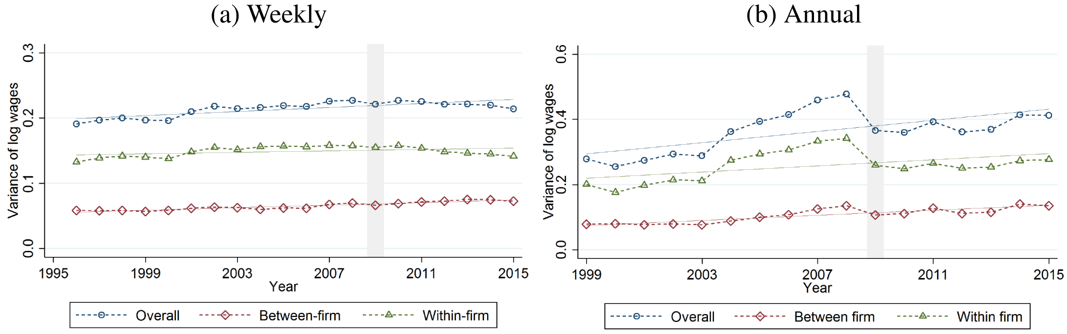
TABLE 4.1: Summary of decomposition results for the variance in log employee wages

		1996/9*		2005		2015		Change 1996/9-2005		Change 1996/9-2015	
		Level (1)	Share (2)	Level (3)	Share (4)	Level (5)	Share (6)	Level (7)	Share (8)	Level (9)	Share (10)
Full-time employees	Raw weekly wages:	0.191		0.219		0.214		0.028		0.023	
	Between: total	0.058	0.305	0.062	0.284	0.072	0.339	0.004		0.014	
	Hourly wages bf	0.074	0.387	0.072	0.331	0.083	0.389	-0.001	-0.056	0.009	0.002
	Usual hours bf	0.005	0.029	0.004	0.016	0.004	0.016	-0.002	-0.012	-0.002	-0.012
	Covariance bf	-0.021	-0.110	-0.014	-0.063	-0.014	-0.067	0.007	0.047	0.007	0.043
	Within: total	0.133	0.695	0.157	0.716	0.141	0.661	0.024	0.021	0.009	-0.034
	Hourly wages wf	0.138	0.723	0.161	0.734	0.139	0.650	0.023	0.011	0.001	-0.073
	Usual hours wf	0.003	0.016	0.006	0.027	0.006	0.028	0.003	0.011	0.003	0.012
	Covariance wf	-0.008	-0.044	-0.010	-0.045	-0.003	-0.016	-0.001	-0.001	0.005	0.027
	Unobs. weekly wages:	0.082		0.090				0.008			
	Between	0.024	0.277	0.019	0.211			-0.005			
	Within	0.058	0.713	0.071	0.789			0.013	0.076		
	Raw annual earnings:	0.279		0.393		0.412		0.115		0.133	
	Between	0.078	0.281	0.010	0.254	0.135	0.328	0.022		0.057	
	Within	0.201	0.719	0.293	0.746	0.277	0.672	0.093	0.027	0.076	-0.047
	Unobs. annual earnings:	0.202		0.303				0.101			
	Between	0.039	0.189	0.047	0.157			0.008			
	Within	0.163	0.811	0.256	0.843			0.093	0.032		
All employees	Raw weekly wages:	0.574		0.629		0.601		0.055		0.027	
	Between: total	0.204	0.356	0.204	0.325	0.218	0.363	0.000		0.014	
	Hourly wages bf	0.092	0.160	0.090	0.143	0.099	0.165	-0.002	-0.018	0.007	0.005
	Usual hours bf	0.051	0.090	0.050	0.080	0.049	0.082	-0.001	-0.009	-0.002	-0.008
	Covariance bf	0.061	0.106	0.064	0.102	0.070	0.116	0.003	-0.004	0.009	0.010
	Within: total	0.370	0.644	0.424	0.675	0.383	0.637	0.055	0.031	0.013	-0.007
	Hourly wages wf	0.169	0.295	0.171	0.272	0.139	0.231	0.002	-0.023	-0.031	-0.064
	Usual hours wf	0.133	0.232	0.199	0.316	0.188	0.312	0.066	0.085	0.055	0.081
	Covariance wf	0.068	0.118	0.055	0.087	0.056	0.094	-0.013	-0.030	-0.011	-0.024

* Weekly values refer to 1996, annual to 1999.

Notes.- author calculations using the NESPD. See text for further description of the data sample and methods. *bf* and *wf* refer to the between- and within-firm components of the total variance. Unobserved wages control for 3-digit occupations. Relevant rows may not sum exactly due to rounding.

FIGURE 4.3: Within- and between-firm components of the variance in log employee wages, 1996-2015



Notes.- author calculations using the NESPD, age 16-64 and full-time employees only. 'Weekly' exclude overtime. 'Annual' wages are for employees with the firm at least one year. The data is for all large firms in the NESPD who have at least ten full-time employee wage observations in that year. The top one percent of wage values in each year are excluded from calculations here. Shaded areas represent official UK recessions. Lines without markers are linear trends.

It is apparent that over the last two decades any short or medium-term inequality changes are not driven by the between-firm component. Overall wage inequality exhibits stronger co-movement with its within-firm component than the between, implying that the latter is less important in driving any overall changes. This result also holds when we consider three sub-samples, each consisting of approximately a third of the employee observations: the public sector, SIC 2003 sectors G-H (wholesale, retail, hotels, restaurants etc.), and the remainder of the private sector (Figure C.7). Given we consider only full-time employees up to this point, unsurprisingly the results are qualitatively unchanged for hourly wage inequality (Figure C.8). Where we can identify firms exactly at the enterprise level, using the ASHE datasets for 2002-15, results are also not qualitatively different (Figure C.10).

The changes in weekly wage variance are small in magnitude compared with those measured for annual earnings. Two potential reasons for this difference are not plausible. First, employees with less than a year of tenure in jobs, not represented in the annual earnings decomposition, could have had increasingly similar wages. However, their sample weight is not large enough for this to be a plausible explanation, even if it were the case. Barth et al. (2016) find that ignoring job changers' wages in fact relatively dampens the measured change in US annual wage inequality. Second, though the share of bonuses in total pay was approximately constant over the period, there could have been increasing variance in these payments. If this were an important factor, we would expect to see greater increases at the top of the annual wage distribution when compared with the weekly, which we do not see in Figure 4.2. A third likely explanation, which we cannot precisely identify in this data, is that hours worked in jobs throughout the year have become more variable, especially in low-paying jobs.

Although our sample of annual wages conditions on workers who are full-time in April, their hours could fluctuate over the year, including any overtime. Our view is that this explanation is the most likely.

For weekly measures we can also identify the determinants of actual wage inequality, as opposed to earnings, by further decomposing gross weekly wages into the components which account for the variance in log hourly wages, θ, log weekly hours worked, h, and their covariance:

$$V_{wf} = V_{wf}^{\theta} + V_{wf}^{h} + 2cov_{wf}(\theta, h), \tag{4.2}$$

$$V_{bf} = V_{bf}^{\theta} + V_{bf}^{h} + 2cov_{bf}(\theta, h) \tag{4.3}$$

(see Appendix C.2.1 for exact definitions and derivations of these terms). The covariance terms are potentially large, since both individual and firm average wages and hours are known to be strongly correlated.[12]

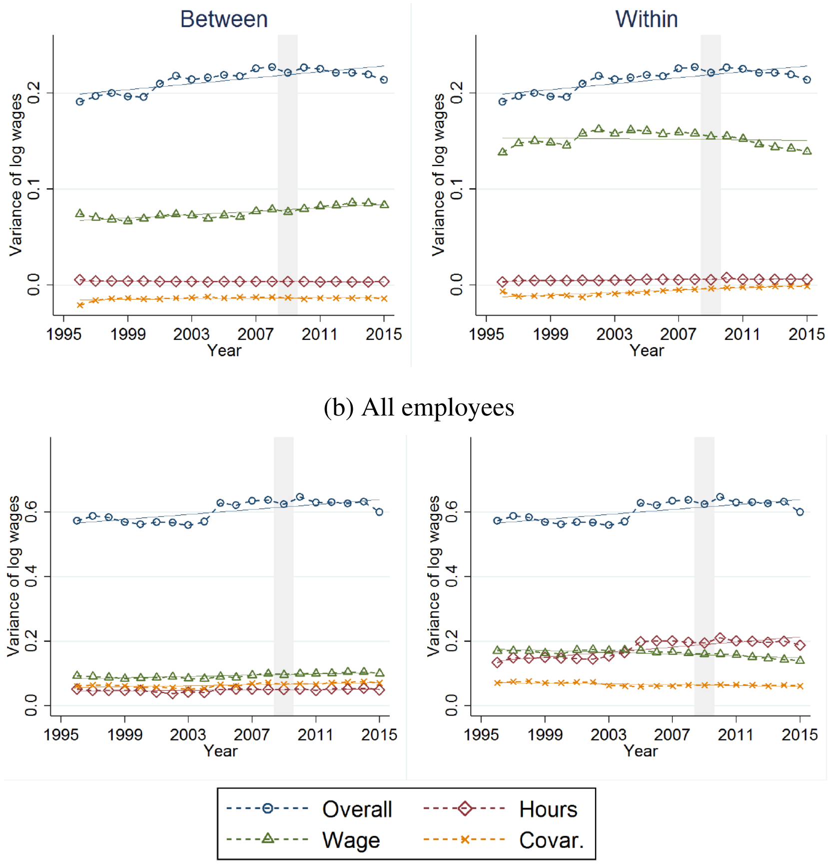
Figure 4.4 plots the decomposition described by (4.2)-(4.3) for weekly wages. Unlike other related studies, we can show explicitly that the variation in hours worked does not affect the decomposition results for full-time employees. Both between- and within-firm hours variance components together account for less than five percent of weekly wage variance throughout the period (column (2), Table 4.1). This offers some support to results in other studies which cannot directly observe hours, but restrict their attention to full-time employees, such as in Card et al. (2013). When we contrast this with a decomposition of weekly wage variance which includes those working part-time, changes in the variance of hours worked within firms most closely determine overall inequality changes: in the last two decades firms have been increasingly using a mix of part- and full-time employees. However, the sharp increase in wage variance amongst all employees in 2004-05 measured here coincides with a methodological shift in the survey, where more low-paid and part-time jobs without PAYE numbers were sampled. We discuss this further in the Appendix, but it is a good reason why we mostly focus on only full-time workers here. In terms of levels, the combined hours components account for as much as forty percent of overall wage inequality. The covariance in hours and wages, both within and between firms, is also a significant part, accounting for as much as twenty percent, reflecting the tendency of part-time jobs to be more commonly low-wage.

[12]This advantage of our data is emphasised in a recent study by Belfield et al. (2017). Using potentially less accurate household survey data for all employees, they find that a sixth of the increase in male log weekly earnings variance over the past two decades in Britain is accounted for by greater hours variation. The increased tendency of low wage work to accompany low hours accounts for a further thirty percent. They also find that the entire fall in female wage inequality is explained by these factors, and not by any change in wage rate variance.

FIGURE 4.4: Within- and between-firm, hourly rate and usual hours components of the variance in log weekly employee wages, 1996-2015

(a) Full-time

(b) All employees



Notes.- author calculations using the NESPD, age 16-64 only. Wages and hours exclude overtime. The top one percent of wage values in each year are excluded from calculations here. The data is for all large firms in the NESPD who have at least ten (full-time) employee observations in that year. The 'Covar.' series represent twice sample covariance terms. The "Overall" series, in both left and right panels, is the total sample variance. As such, all other series across both panels sum within year to this total variance. See the text for further details of how the sample is constructed. Shaded areas represent official UK recessions. Lines without markers are linear trends.

4.3.1 Observed vs unobserved wage inequality

In Section 4.2 we described how the baseline sample has changed over time in terms of firm size, and the industry sectors and occupations represented. Further, we cannot be certain that the results are unaffected by changes in how much some characteristics of jobs are rewarded: for example, the recent rise in the London wage premium, which could potentially manifest as greater between-firm inequality.[13] To account for this, we regress log wages in each year of our sub-samples of the NESPD on employee characteristics, and then describe inequality in the resulting unobservable

[13]For example, ONS published results from the ASHE for the nominal median weekly pay of full-time employees show an increase between 1997 and 2007 of forty-five percent in London, compared with thirty-five percent in the North East.

part: i.e. for each year, sample and measure of wages we estimate

$$w_{ij} = \mu + \beta' \mathbf{x_{ij}} + \underbrace{\alpha_j + \varepsilon_{ij}}_{\text{unobs. - } \psi_{ij}} , \tag{4.4}$$

where in each wage regression we include a minimum set of controls in the vector $\mathbf{x_{ij}}$ for sex, age and its square, and the region of employment, and β is a vector of coefficients. What we call the unobservable part of wages is given by ψ_{ij}, and includes a firm-specific component α_j and the remaining heterogeneity in wages, which is left in the error term ε_{ij}. We use the estimated values of ψ_{ij} for each year to study how additional controls included in $\mathbf{x_{ij}}$, in particular for employee occupations, could allow us to more precisely determine the sources of wage inequality trends.[14]

At this point we acknowledge a limitation of our approach. What we call firm-specific effects are not comparable to the firm wage premiums identified by job-switching in Card et al. (2013) and Song et al. (2016) among others. Instead estimates $\hat{\alpha}_j$ should be interpreted as measuring the composition-adjusted differences of firm average wages from the overall employee sample mean, in each year. Their absolute levels and variance are surely biased upwards by not addressing unobservable worker heterogeneity and its distribution across firms. Several other studies in this literature have estimated firm premiums using variants of the two-way worker- and firm-fixed effects model of Abowd et al. (1999). However, as discussed at length by Card et al. (2016), estimates obtained form this model are prone to several sources of bias. We anticipate that these would be large using one percent samples of firm employees, making the interpretation of any results a significant challenge. For example, there is a well-known and typically substantial negative bias in small sample settings on the estimated correlation of worker- and firm-effects, with a coinciding positive bias on the variances of these individual effects. Our approach however has the advantage of allowing the sample and firm-specific effects to vary each year. It is also a tractable way to assess the combined roles of the changing observable composition of employment and wage premiums.

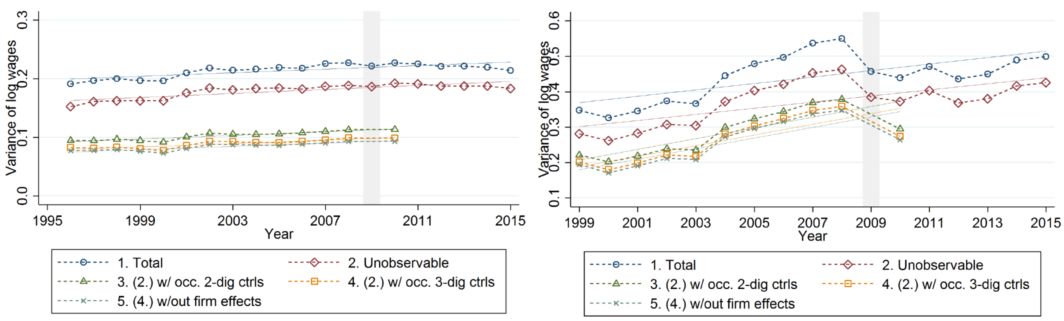
Figure 4.5 compares the total variance of log weekly and annual wages with the variance of the estimated values for their unobservable parts, using alternative specifications of the wage regression described above: we compare $var(w_{ij})$ and $var(\hat{\psi}_{ij})$, with the difference between these values being the sum of variance in the

[14]We do not have information on years of education, or some other explicit proxy for levels of human capital. The only way we can mitigate the resulting concern, that this missing information would be correlated with occupation controls, is by considering the robustness of any results whilst varying the detail of the occupational classification used.

estimated observable part of wage heterogeneity and twice its covariance with the firm-specific effects. For both measures of wages, the patterns over time appear to be mostly unaffected by the inclusion of controls in (4.4) for regions, age groups and gender (comparing series 2. with 1.). This implies that any dynamic changes in the overall composition of our baseline sample of the NESPD and/or wage premiums for these observable employee characteristics are insignificant. In other words, the changes in British wage inequality over this period are to some extent unobservable changes, occurring within sex, age groups and regions. However, adding controls for the occupational content of wages not only significantly explains a large part of the level, but also decreases the amount of the increase in wage inequality in the decade prior to the Great Recession which is accounted for by greater variance in unobservable heterogeneity (comparing series 3. and 4. with 1. and 2. in Figure 4.5, or column (7) in Table 4.1). This is increasingly the case when we control for a more detailed group of occupations. Changes in between-occupation inequality and the sorting of workers across occupations are important contributors to total changes in earnings inequality. We also show estimates of the residual variance, excluding firm effects from the estimated wage regressions. Though these are less robust, since they overestimate the role of occupations in the overall level, and potentially in the changes over time, the results show a similar pattern to those which include firm-specific effects.

FIGURE 4.5: Variance of estimated unobservable log employee wages, 1996-2015

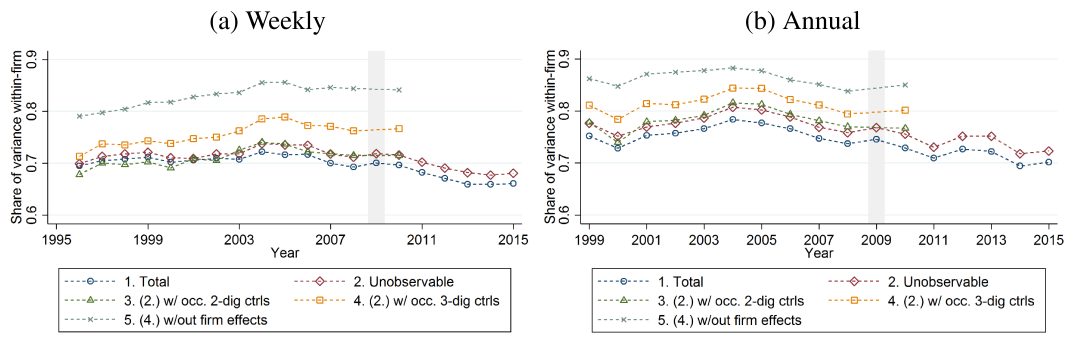
(a) Weekly (b) Annual



Notes.- author calculations using the NESPD, age 16-64 and full-time employees only. 'Weekly' exclude overtime. 'Annual' are for employees with the firm at least one year. The top one percent of wage values in each year are excluded from calculations here. The data is for all firms in the NESPD who have at least ten full-time employee observations. 'Total' gives the total variance. All unobservable log wages are estimated using regressions with controls for sex, age, age squared and major regions. (2.)-(4.) include estimates of firm-specific effects, and respectively (3.) and (4.) add controls for ISCO 2- and 3-digit groups. (5.) is the variance of residuals from an estimation of the wage regression without firm-specific effects.

We can also account for the role of between-firm differences in unobservable wage inequality changes, by replacing the values and statistics for w with estimates $\hat{\psi}$ in (4.1). Figure 4.6 shows that by conditioning on 3-digit occupation groups the share in the overall variance level of the between-firm component, $var(\hat{\alpha}_j)$, is reduced on average from a third to a quarter for weekly wages, and from a quarter to a fifth for annual earnings (comparing series 4. with 1. and 2.). Unsurprisingly, a part of the difference in average wages across firms is accounted for by the types of workers they employ. More important for our focus on trends, the share of unobservable wage variance which is within-firm, $var(\hat{\varepsilon}_{ij})$, is increasing over time, relative to the equivalent share of total wage variance, addressing the role of changing occupation-specific wage premiums and their composition in our sample. This suggests that measured changes in the actual between-firm component represent changes to between-occupation inequality and the distribution of occupations across firms.

FIGURE 4.6: Share of within-firm component in the variance of estimated unobservable log employee wages, 1996-2015



Notes.- see Figure 4.5.

4.4 Inequality changes throughout the wage distribution

In analysing the dynamics and components of an aggregate measure of wage inequality we could be neglecting a more complex evolution of the cross-sectional wage distribution. To determine the role of firms in changes across and within the distribution of wages, we employ a graphical method popularised by Juhn et al. (1993), and subsequently adapted by Song et al. (2016) and Benguria (2015) among others. Simply we can write employee log wages as

$$\underbrace{w_{ij}}_{\text{Employees}} = \underbrace{\overline{w}_j}_{\text{Firms}} + \underbrace{\left[w_{ij} - \overline{w}_j\right]}_{\text{Employee/firm}}. \tag{4.5}$$

We then compute estimates of the averages of each term in (4.5) within each percentile bin of the employee wage distribution in every year. By considering the resulting differences across percentiles and between years, we can then account for the role of firm average wages, as opposed to the relative difference between employees' wages and their firms' averages, in driving wage inequality changes. We also report a heuristic measure of what moves the wage distribution, which captures the share of the variance across percentiles in average wage changes accounted for by covariance with changes in the 'Employee/firm' (within-firm) component:

$$\gamma = \frac{cov(\Delta\{\overline{w_{ij} - \overline{w}_j}\}_p,\, \Delta\overline{w}_p)}{var(\Delta\overline{w}_p)} \,, \tag{4.6}$$

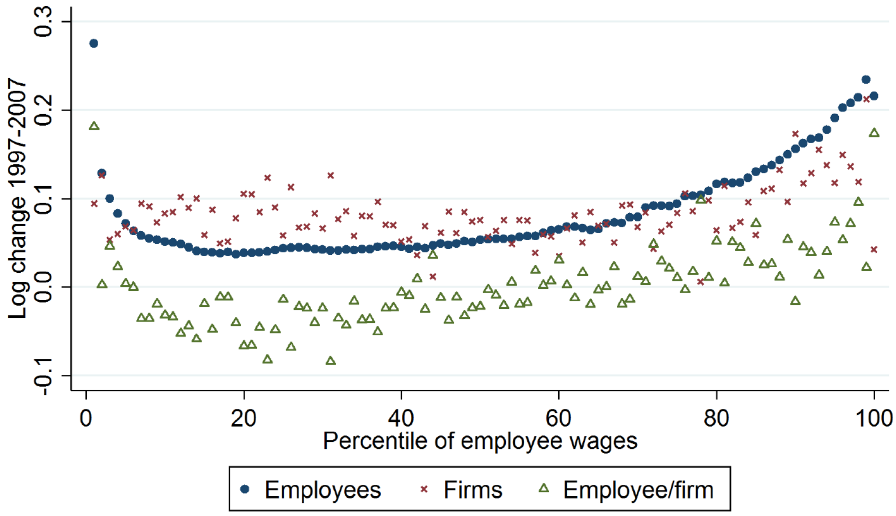
where $\Delta\overline{w}_p$ gives the change between two periods in the sample average log employee wage in percentile bin p.

4.4.1 Actual employee wages

Figure 4.7 represents this graphical decomposition for the change in real log weekly wages between 1997 and 2007, using the baseline sub-sample of full-time employees. The relatively smooth 'Employees' series plots the change in the average log wage of workers in each percentile between the two years. To avoid confusion, these are unlikely to be the same individuals: this is a comparison of annual cross-sections. Each percentile is decomposed using around four to five hundred job observations in each year. A positive slope across percentiles indicates that in some portion of the wage distribution inequality has increased. For example, wages at the median increased by 5 log points (5%) over this period, but by 10 points (11%) at the seventy-fifth percentile, and 20 points (22%) at the ninety-fifth.

Representing the evolution of wage inequality in this way shows that small changes in the time series of overall log wage variance can belie starker inequality dynamics. For instance, here we see that inequality fell among the very lowest earners, potentially due to the introduction of the National Minimum Wage in 1999. By construction, the average level of the 'Firms' components across percentiles is the same as that for 'Employees', and the 'Employee/firm' component is centred about zero. For the graphical analysis it is the slopes of these series across the percentiles which concern us. The firms component contributes somewhat to the rise in wage inequality at the top of the wage distribution, but the employee/firm component also contributes, increasing across the percentiles from the twentieth onwards. This is consistent with results for the US in Song et al. (2016), that among large firms the between-firm component appears to not be wholly driving wage dynamics. However, in Great Britain for this period, for smaller firms than what are considered large in Song et al. (2016), the

FIGURE 4.7: Change 1997-2007 in the average real log weekly wage by percentile of employees, and the contribution from firms



Notes.- author calculations using NESPD, age 16-64, full-time employees only. Weekly exclude overtime. The data is for all firms in the NESPD who have at least ten full-time employee observations. The 'Employees' values are computed by taking the average log real wages of employees within each percentile, increasingly ordered by the level of wages in each year, and taking the difference between years. The 'Firms' values are computed by taking the average across workers, in each percentile, of the average log wages of the firms they work for, in each year, and then taking the difference across years. The 'Employees/Firms' values are the residual difference between these other two lots: equivalently, the average across workers, in each percentile, of the log difference in employee wages from their firms' average value, in each year, and taking the difference across years. $\gamma = 0.68$.

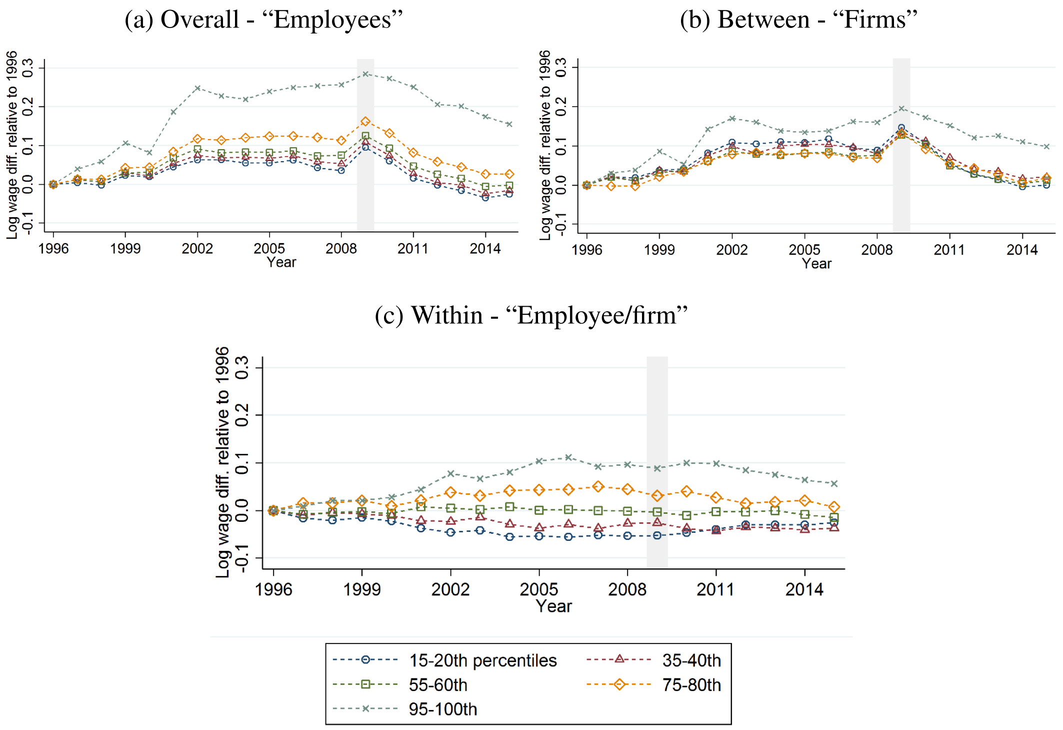
firms component is weaker. The within-firm change accounts for over two-thirds of the overall movement at percentiles across the distribution: $\gamma = 0.68$.

For this graphical decomposition we retain the top one percent of earners in the sample. The very top of the income and wage distribution has drawn significant attention recently, especially in the US (see Piketty, 2013; Song et al., 2016). Although based on a small sample of these top earners in Britain, we can see from Figure 4.7 that average weekly wages in the top one percent for 1997-2007 did not experience greater relative increases than those in the top decile. However, over eighty percent of the log wage increase for the top one percent occurred within firms, notably higher than for all other percentiles besides the bottom one percent.

Before progressing further, we also represent the change in inequality since the Great Recession, for 2008-2015, in the same way (Figure C.11). We demonstrate here that our results are unaffected if we instead use the administrative definition of an enterprise from the ASHE datasets to define firms. Real wages decreased across the whole distribution since the financial crisis, but inequality also fell. However, there is no suggestion in the data that this can be accounted for by changes in the differences in average wages between firms. In fact, the within-firm component more than explains the changes across the distribution: $\gamma > 1$.

We consider how consistent these results are across the whole time period. Still focusing on full-time weekly wages, Figure 4.8 plots the changes for selected ventiles of the employee weekly wage distribution relative to 1996. The average wages paid by firms can account for some of the relatively greater increase in the top five percent of employee wages in the early 2000s. But dispersion within firms explains most of the overall inequality dynamics over the last two decades.

FIGURE 4.8: Average real log weekly wage of employees in selected ventiles, relative to 1996, and contributions from firms



Notes.- see Figure 4.7.

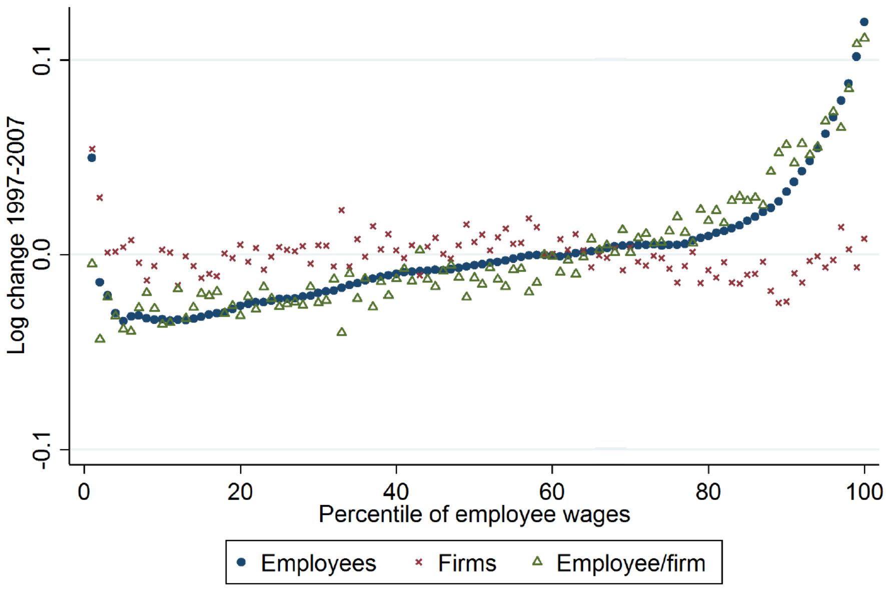
4.4.2 Unobservable wage heterogeneity

Figure 4.9 shows an equivalent decomposition for 1997-2007 as Figure 4.7, but only for the estimated unobservable part of wages $\hat{\psi}_{ij}$, including firm-specific effects, and controlling for occupation groups:

$$\underbrace{\hat{\psi}_{ij}}_{\text{Employees}} = \underbrace{\overline{\hat{\psi}}_j}_{\text{Firms}} + \underbrace{\left[\hat{\psi}_{ij} - \overline{\hat{\psi}}_j\right]}_{\text{Employee/firm}}, \tag{4.7}$$

where $\overline{\hat{\psi}}_j = \hat{\alpha}_j$ and $\left[\hat{\psi}_{ij} - \overline{\hat{\psi}}_j\right] = \hat{\varepsilon}_{ij}$.

FIGURE 4.9: Change 1997-2007 in the average real unobservable log weekly wage by percentile of employees, and the contribution from firms



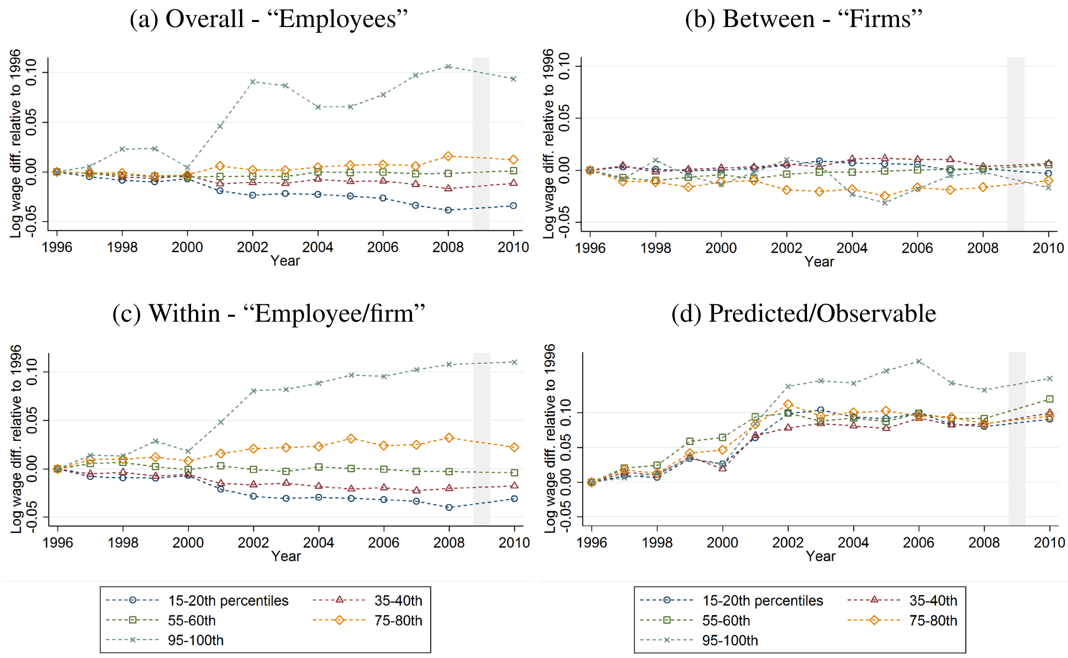
Notes.- author calculations using NESPD, age 16-64, full-time employees only. Weekly exclude overtime. The data is for all firms in the NESPD who have at least ten full-time employee observations. Unobservable log wages are estimated using a regression with controls for sex, age, age squared, major regions, ISCO 3-digit groups and firm-specific effects. $\gamma = 1.00$. See notes for Figure 4.7 or the text for a description of how series are calculated and interpretation.

The pattern of unobservable employee wage changes across percentiles noticeably differs. There is rising inequality across the distribution, with the slope becoming steeper from the eightieth percentile upwards. Firm average unobservable wages did not account for these dynamics: neither for rises below the eightieth percentile, nor the greater increase in the highest wages, $\gamma = 1.00$.[15] In Figure C.12 we consider alternative estimates of unobservable wages. In panel (a), we can see that other controls, including the firm-specific effects, are not driving this result. In panel (b), controlling for less detailed occupation groups still relatively reduces the estimated role for firm-level differences. In panels (c) and (d) we show that not including firm-specific effects would lead us to overestimate the role of occupational inequality. This leads us to conclude that any change in the differences in average wages between large firms is mostly due to some combination of between-occupation inequality and the concentration of high- or low-wage occupations within firms. Further, given that the main result here does not qualitatively depend on firm-specific controls, it is possible that results in other studies, which assign some of the importance of changes in the between-firm component to industrial change, are to an extent misrepresenting a more significant role of occupations.

[15]Where γ, with the inclusion of firm-specific effects, is measured by $cov(\Delta\bar{\hat{\varepsilon}}_p, \Delta\bar{\hat{\psi}}_p)/var(\Delta\bar{\hat{\psi}}_p)$.

Figure 4.10 replicates Figure 4.8 but instead for unobservable wages. There is no substantial contribution from between-firm inequality to the dynamics of the unobservable part of the wage distribution since 1996. Panel (d) also includes the contribution from the observable or predicted part of the real wage distribution, $\Delta\{\overline{\hat{\mu} + \hat{\beta}'\mathbf{x_{ij}}}\}_p$. Here we can see explicitly how wage premiums and the prevalence of high paying occupations in our sample particularly account for the rise in inequality at the top of the employee wage distribution. Figure C.13 further demonstrates the robustness of this result across all percentiles, considering changes over other ten-year periods, each beginning in a year between 1996-2000.

FIGURE 4.10: Average real (un)observable log weekly wage of employees in selected ventiles, relative to 1996, and contributions from firms



Notes.- see Figure 4.9.

4.4.3 Additional results and robustness checks

So far in this section we have only discussed the dynamics of weekly wages for full-time employees working for firms with at least ten job observations in the NESPD in any given year. We can also check whether results change for the period 1997-2007 when we alter these aspects of the sample. Figures C.14-C.16 decompose the log change in the weekly wages of full-time employees who are employed by large enterprises with at least one, five or twenty employee job observations. For actual wages, as we increase the sample size and include some smaller firms, it becomes clearer graphically that the firms component cannot explain inequality dynamics.

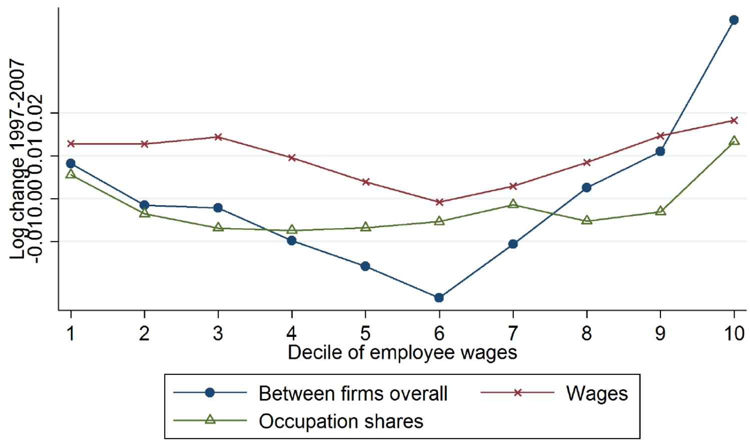
Considering the unobservable part of wages, with controls for occupations, the results are also qualitatively unchanged as we vary the average firm size in our sample.

In Figure C.17 we return to our baseline sample, but now study only private sector employees. Again the results are unaffected. Further, Figure C.18 shows that there is no qualitative difference in results if we decompose hourly wage dynamics as opposed to weekly. For annual wages, Figure C.19 demonstrates that for actual wage inequality the majority of the dynamics across percentiles are explained by the changing picture within firms. This is also the case when we turn to the inequality in unobservable annual wages. Finally, we also consider the picture for weekly wages including part-time employees, and after conditioning on employee characteristics, there is no suggestion in Figure C.20 that firm average wages have driven inequality dynamics in this case also.

Returning to weekly wages and our baseline sample, Figure C.21 looks at changes across all percentiles for five-year sub-periods. Notably for robustness, these are periods where the classification of occupations used in the NESPD is constant, and thus cross-walking was not necessary. As also seen above, the majority of recent increases in employee wage inequality occurred in the five years to 2001. There is no contribution to this from the firms component for unobservable log wages. This is also the case for actual wage inequality, apart from some contribution to greater changes above the ninety-fifth percentile. For 2002-07 and 2005-10, the rise in wage inequality is small, and is driven by greater wage changes for only the highest earners. But in both later sub-periods, once we account for the observable content of wages, the role of firm average wage differences is reduced.

To expand on these findings further, we focus on the 'Firms' component of the change between 1997 and 2007 in weekly wage residuals for full-time employees, represented by Figure C.12(a): i.e. the estimated firm-specific effects, with controls for some employee observables but not occupations in the log wage regression. Averaging these across employee wage percentiles, we carry out a shift-share decomposition. This accounts for the role of the changing occupational structure of the firms represented in each decile (see Online Appendix C.2.2 for details). Figure 4.11 shows the results of this decomposition. The 'Wages' component, which is computed by holding the occupational structure of firms representing the employees in each decile constant, and allowing only wages to change, does correlate across percentiles with the overall 'Firms' component. However, the between-firm inequality increase through the top deciles is mostly accounted for by the changing occupational structure of the firms who pay the highest wages, holding occupation wages constant.

FIGURE 4.11: Decomposing the firm component of employee wage inequality patterns, 1997-2007: the role of changing firm occupation shares vs wages



Notes.- this figure takes the average over deciles of the firm component of wage changes in Figure C.12(a) (circle markers), and carries out a shift-share decomposition. The two components thereof reported here are as follows: first holding the average across employees of firm occupation shares constant, and considering only average occupational wage changes (cross markers), and second holding the average across employees of firm average occupational wages, in a decile, constant, but varying only firm occupation shares (diamond markers).

4.5 Related literature

There is now an extensive empirical literature concerning the role of firms in explaining trends in wage inequality. Early studies noted that large increases in the US through the 1970s, and into the 1980s, coincided with similar patterns at the establishment level. Davis & Haltiwanger (1991) documented that the trend in the manufacturing sector was just as much driven by differences in the dispersion of average plant earnings as it was by the variance of wages within them.[16] They also highlighted that worker heterogeneity, and changes in the composition of types across plants, could be important to identify the drivers of inequality. Using the same data and methodology, but studying an extended time period to 1992, Dunne et al. (2004) further found that between-plant variance could almost completely account for the trend in US manufacturing wage inequality.

More recent studies exploit data where employees can be matched to their employers. Barth et al. (2016) use unemployment insurance files, for nine US states, to document rising inequality and the extent to which this was explained by the changing differences in average wages between establishments. Between 1992 and 2007, over two-thirds of the increased wage variance is accounted for by between-establishment variance. Song et al. (2016) extend these results, via data covering around a hundred million workers per year, from 1981 to 2013, across the whole US. Although the

[16]Given the lack at this time of matched employer-employee records, the within-plant component of wage variance could only be estimated as a residual rather than directly measured.

employers in this latter study are somewhat closer to the definition of a firm than an establishment or plant, and are studied over a longer period, they also find that over two-thirds of the increasing inequality in annual earnings for full-time workers was accounted for by what happened to the differences in average wages between firms. However, this share falls to a half when considering only those employed by the very largest firms (over ten thousand employees), and in this part of the economy changes to pay differences within firms remain important. Given the data cover a virtual universe of US employees, they can confirm that this is robust across demographics, detailed industry sectors and regions. By estimating worker and firm-specific fixed effects, using the econometric wage model of Abowd et al. (1999), they further find a substantial and increasing amount of assortative matching of worker and firm wage premiums, and that this accounts for the between-firm component of increasing inequality. They discuss an explanation whereby skill-biased technological change drives the overall trends in wage inequality, whereas outsourcing, for various reasons, might account for the lack of increase in within-firm dispersion. This would be consistent with firms over time having developed a more occupation focused structure. Using the US Occupational Employment Statistics survey, Weber-Handwerker & Spletzer (2016) show that increasing occupational concentration can explain some of the level of between-establishment wage variation. However, this increasing concentration since 2000 cannot account for any significant part of the trend in wage inequality.

Similar observations have also been made for other countries. Using a near census of employees in the Brazilian formal sector, Alvarez et al. (2016b) and Benguria (2015) demonstrate that the majority of declining wage inequality, for 1988-2012 & 1999-2013 respectively, is accounted for by reduced variance between firms. They also estimate variants of the model suggested by Abowd et al. (1999). Benguria (2015) finds that decreasing between-firm inequality is mostly accounted for by the variance of average unobservable worker heterogeneity across firms, and not by firm-specific fixed effects. Alvarez et al. (2016b) conclude that patterns in Brazil may also owe more to changes in institutions affecting the nature of wage setting in the economy. Helpman et al. (2017) also use this Brazilian dataset, focusing on the manufacturing sector and the period 1986-95. They find that two-thirds of earnings inequality and its increase occurred within groups of workers characterised by an interaction of twelve sub-sectors and five occupation categories. After conditioning on observable worker characteristics, changes in between-firm differences can explain eighty-six percent of the observed rise in this within-sector-occupation inequality.

Elsewhere, Nordström Skans et al. (2009) use a database covering all workers and their employers in Sweden for 1985-2000. They find that between-plant variance accounts for the entire increase in earnings dispersion. Even accounting for variation across industries, they nonetheless find that plant-level variance remains the main driver of overall wage inequality. Sweden is also studied by Akerman et al. (2013), who use data for over a hundred occupations in manufacturing, and find results similar to Helpman et al. (2017) for Brazil: within-sector-occupation wage inequality accounts for the majority of recent trends. However, they find that this is instead mostly accounted for by increased within-firm inequality, and suggest that the difference compared with Brazil could be due to Swedish institutions dampening between-firm differences through collective wage agreements. Highlighting further the possibility that European inequality trends may owe less to between-firm differences, Cardoso (1997, 1999) finds that a substantial increase in wage inequality in Portugal is accounted for by changes within firms. More specifically, she suggests that this can be explained by changes to wage progression policies, which began to reward certain skills, as opposed to a more traditional basis on tenure or seniority.

Wage inequality in Germany has also been extensively studied (Dunstman & Schönberg, 2009; Baumgarten, 2013). Card et al. (2013) use the Integrated Employment Biographies (IAB) data file, containing social security records for West Germany from 1985 to 2009. The IAB contains only very limited information on hours worked, i.e. full or part-time status only, and the top ten to twelve percent of male earnings observations are censored each year. They note that the degree of sorting of different education and occupation groups across establishments increased over this period and could account for some share of increasing establishment effects in a wage model; i.e. employees in higher paid occupations are increasingly concentrated at establishments that pay all workers a higher wage, whereas those in lower-paid occupations are increasingly concentrated at low-wage establishments. The authors also apply the methodology of Abowd et al. (1999), including controls in the wage equation for occupation and industry. A quarter of the increase in wage dispersion is due to the rising variance in wage premiums across establishments. As much as forty percent is explained by an increased tendency of high wage workers to work for high wage establishments. They also show that sixty percent of the rise in between-occupation wage inequality is accounted for by this sorting effect.

4.5.1 British firms and wage inequality

The changing nature of wage inequality in Great Britain is documented by Machin (2011). Gaps opened up considerably in the 1980s and the picture has since become somewhat more complex. The New Earnings Survey (NES) dataset is used by Faggio et al. (2010), who combine it with business survey data from Financial Analysis Made Easy (FAME), to study the increase in wage inequality and the role of firm-level productivity differences from 1984 to 1999. To decompose the overall increase in wage dispersion, Faggio et al. (2010) compute the total variance of wages from the NES and the between-firm component from the FAME database; within-firm inequality is obtained as the residual. Their results suggest that the between-firm component accounts for almost all of the increase in wage inequality during this time, and cannot be explained by the changing industry distribution of employment. Mueller et al. (2016) study the within-firm component of pay inequality in almost nine hundred mostly large UK firms, over a decade since 2004. Although they cannot decompose overall wage inequality, and their pay data refers to firm hierarchy levels rather than individual employees, they nonetheless find that the importance of within-firm wage variation is correlated with firm size, consistent with Song et al. (2016) for the US. Lee (2016) has used the ASHE for 2002-2014 to estimate the Abowd et al. (1999) model, and assesses the role of firm and worker differences in the level of UK wage inequality. Notwithstanding the robustness concerns in estimating such a model, and how to interpret and compare the level of estimated variance shares when observing only one percent of employee wages in firms, she finds that firm-level differences are less important than found in almost all other studies of other countries, such as Card et al. (2013). There is also some evidence in this analysis to suggest that firm pay levels are type-specific, with type referring to occupation or skill levels.

Other studies of British labour market inequality have discussed the role of the changing occupational structure of employment (Williams, 2013). In Goos & Manning (2007) three-digit occupation codes and hourly wage rates from the NES, are combined with data on the task composition of occupations in the US from Autor et al. (2003). They show that from 1975 to 1999 the British labour market became polarised, and that the shares of workers and hours in the highest and lowest wage occupations greatly increased. This pattern can account for a third of the rise in the wage gap between the median and the tenth percentile, and half of the rise in the gap between the ninetieth and the median. These results are obtained simply by holding the average wage within each occupation constant, whilst allowing employment shares across occupations to mirror their observed trends. They conclude that: "It seems likely that much of these wage gaps between plants can be explained in terms of the characteristics (in gender, age, education, and occupation) of the workers within them." Perhaps related to this trend of occupational polarisation, and its effect on inequality, Cortes & Salvatori (2016) find that since 1998 the share of UK establishments in which more than half of the workers are employed in the same occupation has increased by ten percentage points.

4.6 Summary and further discussion

We have used well-known methods to answer whether recent trends in British wage inequality, viewed through a sample of employees at mostly very large firms, can be accounted for by between-firm inequality. We have found substantial evidence that in the last two decades this has not been the case. This is also clear when we consider estimates of unobservable wage heterogeneity, controlling for changes to occupational premiums and firm-specific effects. At first look, this would appear to contradict what is becoming a stylised fact, across several countries, that between-firm wage inequality is the most important driver of overall trends. But this is not the first study to suggest that some part could be accounted for by the changing supply and demand of occupations across firms and labour markets (see Card et al., 2013; Song et al., 2016). We further believe our results can be reconciled with some of these previous studies. The analysis here is dominated by the very largest firms in Britain. Already Song et al. (2016) have shown that in the US firm size matters. Larger firms come from the starting point of having more diverse workforces and complex pay structures, and so there is far more scope for changes over time in the dispersion of wages within as they evolve. Second, we believe our results chime with another hypothesis from Song et al. (2016): the reason why within-firm inequality cannot account for overall dynamics, in most studies, could be due to the increasing occupational concentration, or specialisation, of firms, coinciding with falling costs of outsourcing work tasks, and their greater tendency to focus on so-called 'core-competencies.' The very large and long-lived firms, which dominate our sample, are where we might expect such changes in specialisation to mostly occur. Adding to this the continued trend of increasingly polarised demand for occupations in the British labour market (Goos & Manning, 2007; Williams, 2013), it is then not surprising that once we focus on the inequality dynamics of the estimated unobservable part of wages, with controls for changing occupational premiums and the composition of the workforce, the role of firm-specific differences becomes markedly weaker, or even non-existent.

The results here suggest that future analyses of this kind should attempt to seek out data which can address the possible role of the changing occupational structure of firms. Otherwise it could be challenging to identify whether inequality changes are accounted for by some greater segregation of workers across firms, or whether this to some extent reflects only the combined effects of changes to the occupational polarisation of employment and firm-level specialisation. In other words, the estimated role of assortative matching over innate firm and worker productivities could be overstated, if firms simultaneously alter their demand for occupations and skills.

A limitation of the analysis here is that we are restricted to studying repeated cross-sectional data of jobs and wages, since employers cannot be identified reliably across time for an extended period in the NESPD. Furthermore, the results only reflect what has happened for wages in mostly very large firms. We believe this is the limit of what can be achieved using current available British data sources, without small sample biases totally confounding any analysis. We hope that existing UK administrative earnings data, for all employees and their employers, will be made available for research in the near future. Only then can the continuing large evidence gap regarding the determinants of British wage inequality be more completely addressed, with the NESPD's more detailed records of job characteristics, such as hours and occupations, serving as a useful supplementary data source.

Appendix A

Gender and the business cycle: an analysis of labour markets in the US and UK

Appendix A.1 Estimating the gender business cycle

A challenge of estimating an Okun gap type relationship as described in the main text is in identifying trends. Okun (1962) originally assumed that for the US four percent was a reasonable estimate of the trend unemployment rate, and used GDP data to back out potential output. However, algebraic manipulations of this kind can be improved upon (Plosser & Schwert, 1979). One common approach in the literature is to apply a dynamic filter to the series, such as the Hodrick & Prescott (1997) (HP) or Band-pass class of filters (see for example Giorno & den Noord, 1994). However, these methods are often criticised since they rely on arbitrary smoothing parameter choices (Gordon, 1993), may generate cycles where data are trend or difference stationary (Cogley & Nason, 1995), generate a significant bias in the trend at the endpoint of the series, and may produce unrealistic or theoretically inconsistent estimates of trend and gap (Gordon, 2010). Another common de-trending method is the decomposition of an integrated series into stochastic trend and cyclical components (Beveridge & Nelson, 1981) (see for related examples Evans, 1989; Attfield & Silverstone, 1998). Alternatively, a theoretical approach could employ an expectations augmented Phillips Curve model and Kalman filtering algorithm to identify time varying trend components of output and unemployment (Gordon, 1997, 2010). Both the HP and Beveridge & Nelson (1981) approaches have been shown to place a specific set of restrictions on the data generating process within the more general structural time series, or unobserved components model (UCM) methodology of Harvey (1989). As shown by Harvey &

Jaeger (1993), for US GDP the HP filter with standard quarterly smoothing parameter can produce a very similar trend cycle decomposition to the less restricted UCM with stochastic trend and cycle. However, this is often not the case for other macroeconomic variables and the GDP of other countries. Canova (1998) provides a thorough description of the impact of the common detrending methods on the estimated business cycle properties of various US macroeconomic time series, and concludes that the information lost by the different methods varies greatly, and it is dangerous to use only one approach, such as the HP filter. For robustness here we have presented results based on two approaches. First we use the most common method of the HP filter with a quarterly smoothing parameter of 1600. Lee (2000) analyses the robustness of Okun's law across sixteen OECD countries, and considers the sensitivity of the gap approach estimates to the use of the HP filter, Beveridge-Nelson decomposition and Kalman filter. He shows that the estimated relationship tends to be weaker with the use of the HP filter. Second, for each seasonally adjusted level of the output gap we estimate using maximum likelihood a standard stochastic trend-cycle UCM for GDP, and predict the estimated components using all observations with a Kalman filter. We then estimate the UCM for each labour market in turn, with the constraint that the frequency parameter is set to that estimated for GDP. We do this to account for some spurious estimations of the stochastic cycle component if we allow this as a free parameter. Whilst the structural approach could be used to estimate the seasonal component, we prefer to use data already seasonally adjusted by the national statistical agencies. The actual estimated UCM for each variable depends on whether or not a first or second order stochastic trend is more appropriate, the models estimated then being respectively 'random walk with drift' or 'random trend.' We confirm that the cyclical components of US quarterly GDP and unemployment generated by the HP filter are an almost perfect replication of those obtained using the structural model, with an estimated central periodicity of the cycle component of just under five years. However, this is not always the case. The HP filter underestimates the volatility of the UK business cycle and labour market, with the UCM estimate being a somewhat smoother trend and a cycle periodicity of thirteen years.

Table A.1 contains brief summary statistics of the data for the cyclical components for the two detrending methods. Almost all male components, weighted relative to overall trend employment, are more volatile than female, and this is only reversed for the inactivity rate. The US labour market cycle is also more volatile relative to GDP. We can also see that these qualitative comparisons are sensitive to appropriately weighting the cyclical components as implied by an output gap decomposition. For brevity we exclude cross-correlation statistics of lags and contemporaneous values for our cyclical components, though these are also available on request.

The estimated VAR models are motivated from equations (2) and (3) as described in the main text. For employment rates we can write

$$\mathbf{a}_t = \mathbf{B}(L)\mathbf{a}_{t-1} + \varepsilon_t \ ,$$

where $\frac{E_t^{\tau,f}}{E_t^{\tau}}[e_t^{c,f} - n_t^{c,f}] = e_t^{*,c,f}$, $\mathbf{a}_t = \left[y_t^c, e_t^{*,c,f}, e_t^{*,c,m}\right]'$ and $B(L)$ is $3x3$ where each i,j th element is the lag polynomial $b_{ij}(L) = (\beta_{i,j,0}L^0 + \beta_{i,j,1}L^1 + \cdots + \beta_{i,j,p}L^p)$. We estimate the covariance matrix using a small sample correction to the degrees of freedom. The constant is suppressed since the variables are zero mean cyclical components. To identify the system and generate impulse response functions we use a recursive VAR. Although there is no clear theoretical justification for any particular ordering, except that it is an accepted business cycle fact that labour market variables tend to be a lagging indicator, we use the recursive order as listed above in the description of $\mathbf{a}_t$ (i.e. with deviations from trend of male employment rates being contemporaneously correlated with both the output gap and female deviations). To justify this ordering we consider the lagged cross-correlation statistics and Granger causality results across all the models estimated here. Also, an alternative ordering, such as $\mathbf{a}_t = \left[y_t^c, e_t^{*,c,m}, e_t^{*,c,f}\right]'$ does not produce realistic impulse responses, particularly for the output gap. Although recursive identification removes some of the advantages of the system based approach over separate regressions for male and female as per Peiro et al. (2012), we still believe it is an improvement, and identification using sign restrictions would be an empirical complication unlikely to qualitatively affect the results.

For the estimated VAR model with unemployment and inactivity rates in place of employment, all results described in the main text are identified using ordering $\mathbf{a}_t = \left[y_t^c, u_t^{*,c,f}, u_t^{*,c,m}, i_t^{*,c,f}, i_t^{*,c,m}\right]'$. As before, though it is difficult to justify one ordering over another, orderings of male rates before female, and inactivity before unemployment, both produce unrealistic responses for the output gap. Inactivity rates also tend to lag unemployment over the business cycle. The lag orders of the models are chosen to whiten the residuals. Although it is possible that even after detrending we could be left with near MA unit roots in the series to whiten the residuals, a low lag order tends to be sufficient. For example a highest order of thirteen is chosen for the HP filter & UCM detrended model with unemployment and inactivity rates for the UK.

Estimating the VAR models for the output gap and gender outcomes, Figures A.1 - A.6 show the cumulative impulse response functions, for the full sample, following an orthogonal shock to the output gap. We also estimate and obtain impulse responses for a restricted period to the end of 2006 as a sensitivity check and to guard against any abnormal effects of the Great Recession. For reasons of brevity, we do not show figures here, but restricting the sample size and excluding the most recent data has no qualitative effect. We see that there are some differences between the detrending methods, though this does not affect our description of the gender business cycle, and so for simplicity we focus mainly on results obtained with the UCM detrended data. To assess simply whether or not the business cycle response of male and female labour market variables differ significantly, we note that the ninety percent confidence intervals for male and female employment rates substantially overlap for both countries. Conversely, they do not overlap at their respective peak cumulative impacts for unemployment rates, with the male response being of greater magnitude. The unemployment response to the cycle for women is notably weak, both compared with UK men and US women. For the US there is a small but significant from zero countercyclical response for the male inactivity rate, but none for women. For the UK, inactivity also has some counter-cyclical response but their is no gender difference.

TABLE A.1: Summary statistics for cyclical components

		US				UK			
		HP-1600		UCM		HP-1600		UCM	
			adj.[*]		*adj.*		*adj.*		*adj.*
Real GDP	std dev.	1.66[***]		1.63		1.53		2.35	
	max.	3.73		3.86		5.09		6.26	
	min.	-6.24		-6.22		-3.49		-4.78	
Male employment[**]	std dev.	1.17[†]	*0.70*[‡]	1.11	*0.67*	1.11	*0.63*	1.75	*1.00*
	max.	2.61	*1.39*	2.43	*1.42*	3.19	*1.79*	4.43	*2.49*
	min.	-3.50	*-1.98*	-3.32	*-1.83*	-2.49	*-1.37*	-3.76	*-2.21*
Female employment	std dev.	1.16	*0.44*	1.35	*0.52*	0.83	*0.35*	1.59	*0.68*
	max.	2.46	*0.90*	2.69	*1.13*	2.13	*0.93*	3.92	*1.72*
	min.	-4.35	*-1.36*	-4.52	*-1.41*	-2.76	*-1.14*	-4.35	*-1.79*
Male unemployment	std dev.	16.41	*0.59*	16.01	*0.64*	10.85	*0.51*	14.79	*0.83*
	max.	55.46	*1.79*	51.57	*2.63*	18.99	*1.17*	27.18	*2.18*
	min.	-33.53	*-1.07*	-32.55	*-0.72*	-27.66	*-1.34*	-29.28	*-1.30*
Female unemployment	std dev.	11.73	*0.29*	11.17	*0.28*	5.39	*0.19*	6.31	*0.25*
	max.	34.95	*0.80*	32.52	*0.78*	10.81	*0.54*	13.99	*0.76*
	min.	-43.51	*-0.66*	-38.52	*-0.63*	-12.94	*-0.48*	-13.75	*-0.45*
Male inactivity	std dev.	1.26	*0.20*	1.22	*0.19*	1.15	*0.23*	1.65	*0.34*
	max.	4.01	*0.54*	3.99	*0.51*	3.40	*0.68*	4.83	*0.92*
	min.	-4.51	*-0.64*	-4.49	*-0.64*	-2.59	*-0.53*	-4.74	*-1.01*
Female inactivity	std dev.	0.56	*0.27*	0.42	*0.21*	0.58	*0.26*	1.02	*0.45*
	max.	1.65	*0.99*	1.26	*0.76*	2.64	*1.26*	3.85	*1.77*
	min.	-1.21	*-0.71*	-1.05	*-0.61*	-1.19	*-0.49*	-2.79	*-1.21*

* Cyclical variables weighted as per e.g. $\frac{E_t^{\tau,f}}{E_t^{\tau}}[e_t^{c,f} - n_t^{c,f}]$ etc.

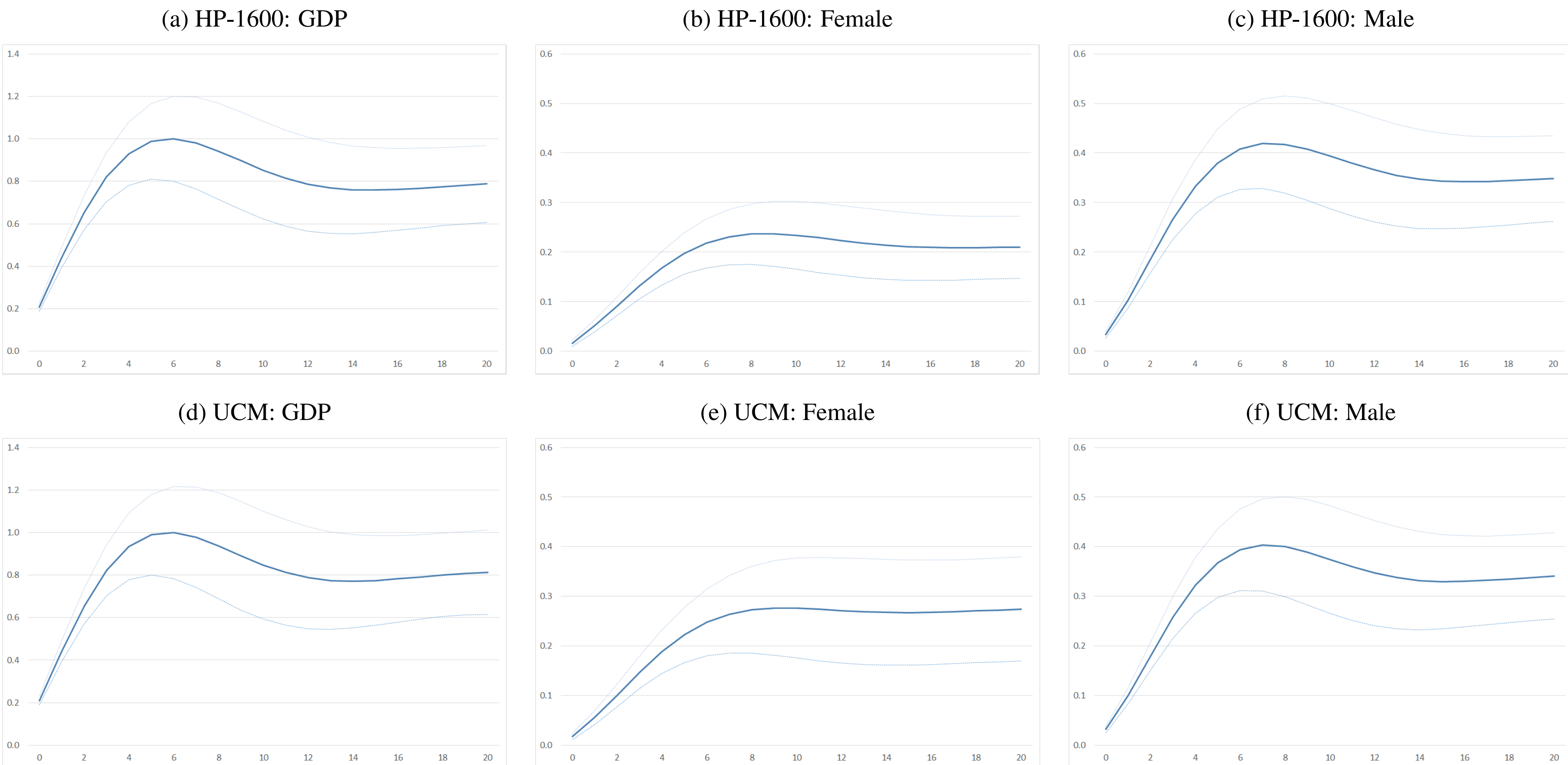
** all labour market variables expressed as population ratios

*** interpretation: % output gap

† interpretation: 100 x log points from trend

‡ interpretation: (100 x log points from trend) x $\frac{E_t^{\tau,m}}{E_t^{\tau}}$.

FIGURE A.1: US real output gap and weighted employment rates - cumulative impulse response functions

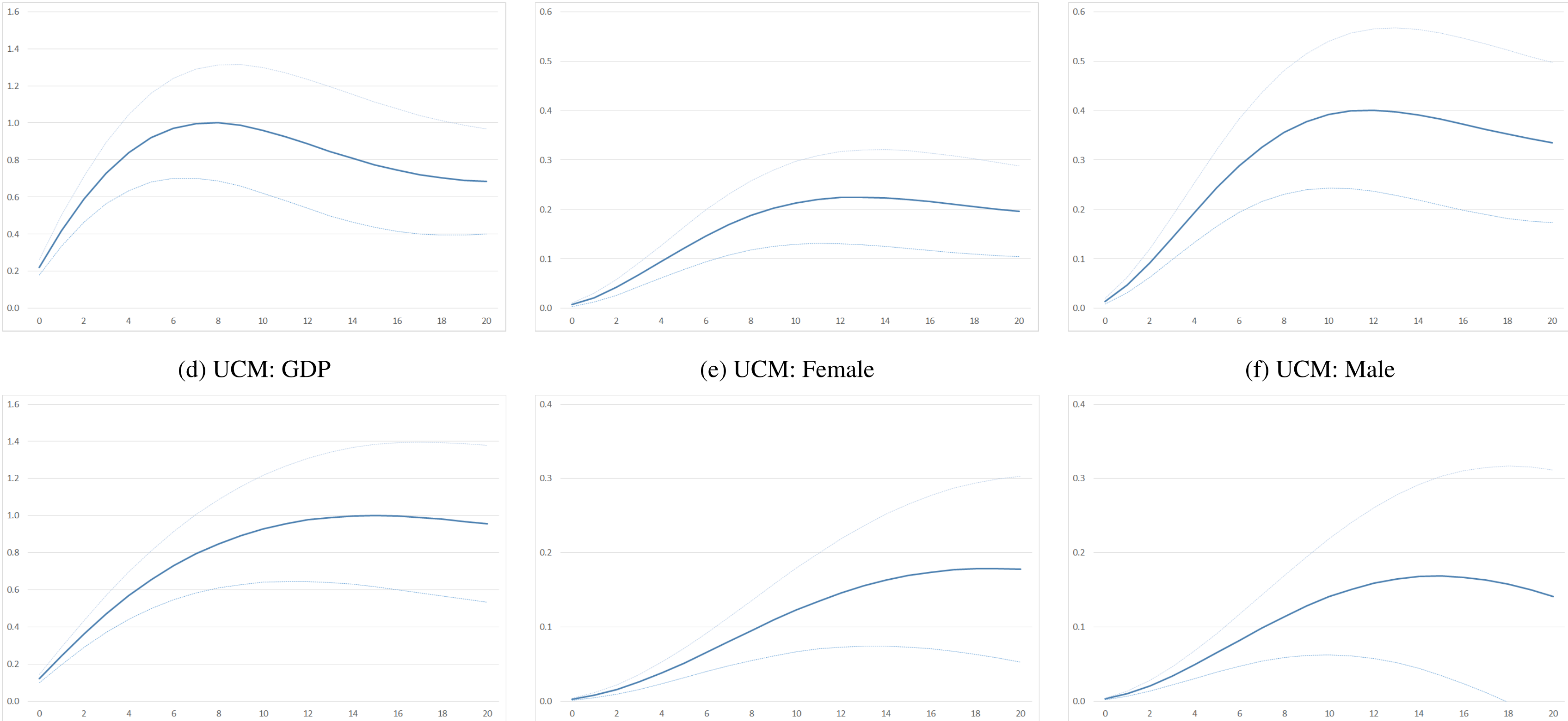


Notes.- responses are from an orthogonal shock/impulse to the output gap which generates a max. cumulative increase of one percentage point; 90% confidence intervals from bootstrapping.

FIGURE A.2: UK real output gap and weighted employment rates - cumulative impulse response functions

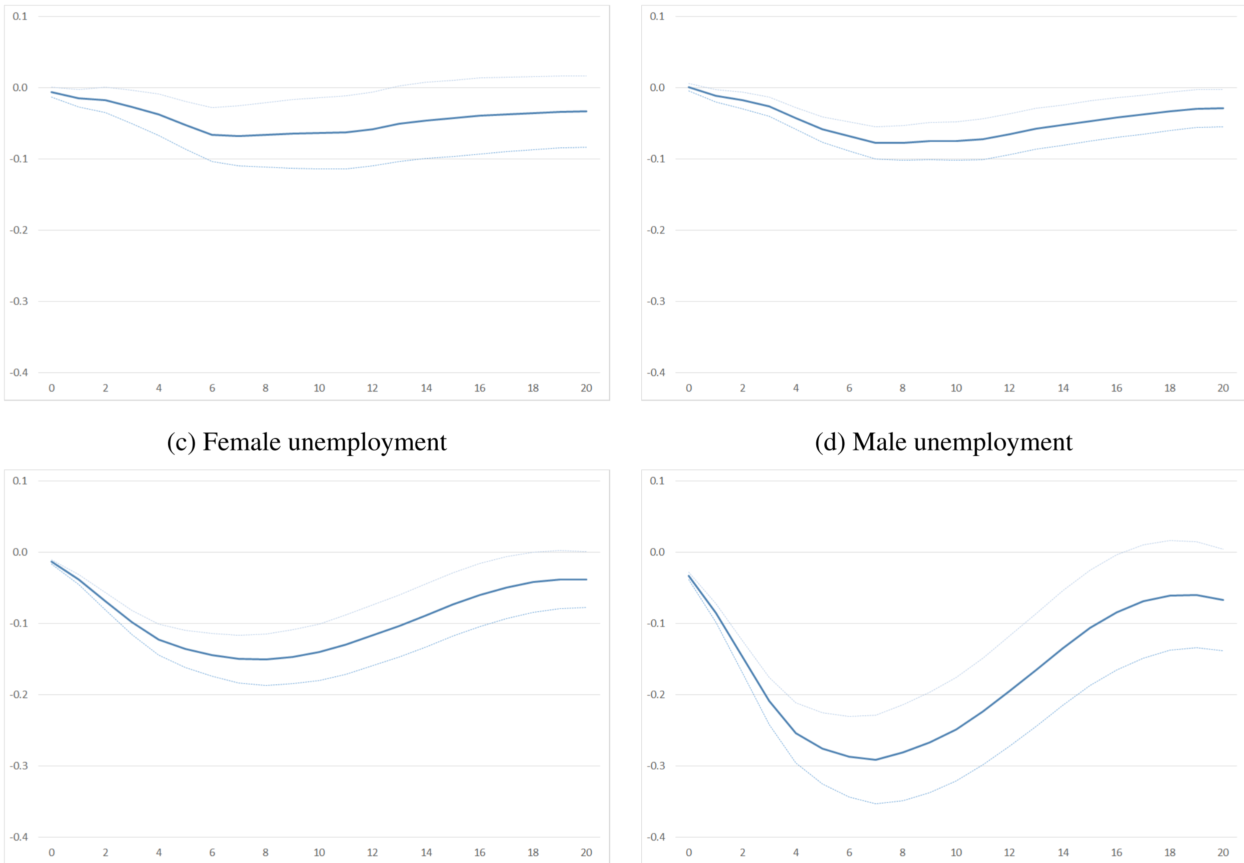
(a) HP-1600: GDP (b) HP-1600: Female (c) HP-1600: Male

(d) UCM: GDP (e) UCM: Female (f) UCM: Male



Notes.- responses are from an orthogonal shock/impulse to the output gap which generates a max. cumulative increase of approximately one percentage point over twenty periods; 90% confidence intervals from bootstrapping.

FIGURE A.3: US weighted, unemployment and inactivity population rates - cumulative impulse response functions (HP filter detrended data)



(a) Female inactivity

(b) Male inactivity

(c) Female unemployment

(d) Male unemployment

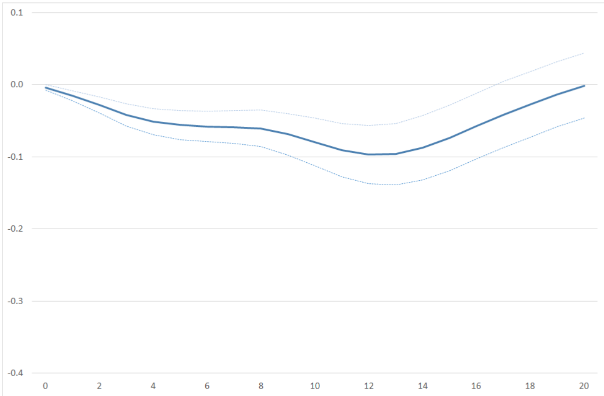
Notes.- responses are from an orthogonal shock/impulse to the output gap which generates a max. cumulative increase of approximately one percentage point over twenty periods; 90% confidence intervals from bootstrapping.

FIGURE A.4: US weighted, unemployment and inactivity population rates - cumulative impulse response functions (UCM detrended data)

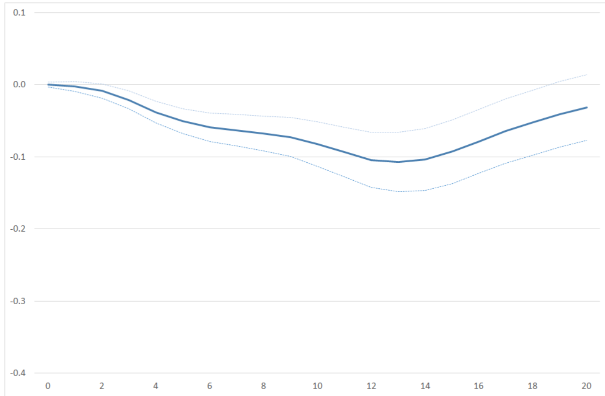
Notes.- responses are from an orthogonal shock/impulse to the output gap which generates a max. cumulative increase of approximately one percentage point over twenty periods; 90% confidence intervals from bootstrapping.

FIGURE A.5: UK weighted unemployment and inactivity population rates - cumulative impulse response functions (HP filter detrended data)

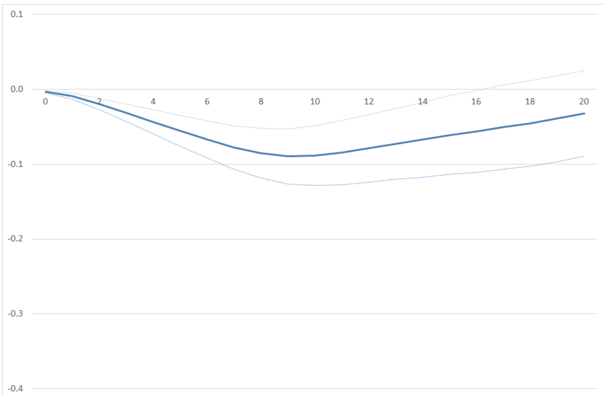
(a) Female inactivity



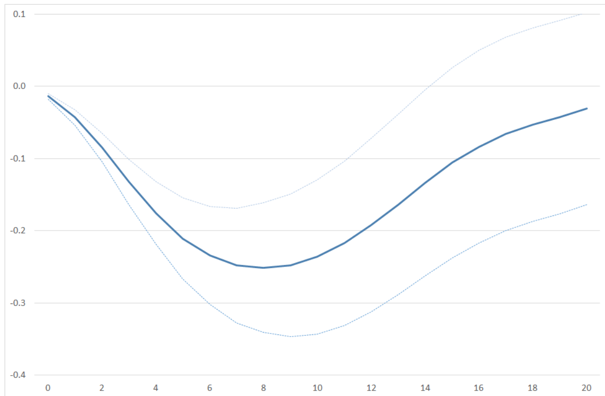
(b) Male inactivity



(c) Female unemployment



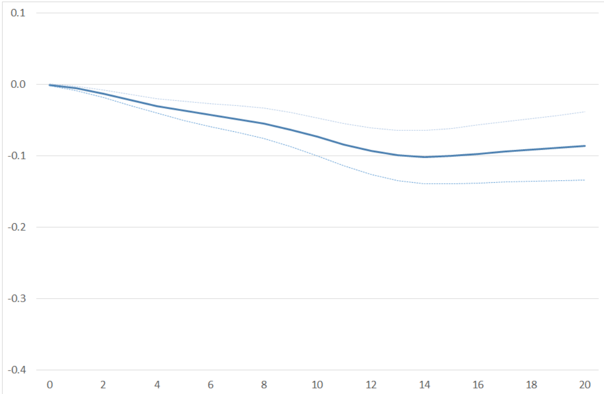
(d) Male unemployment



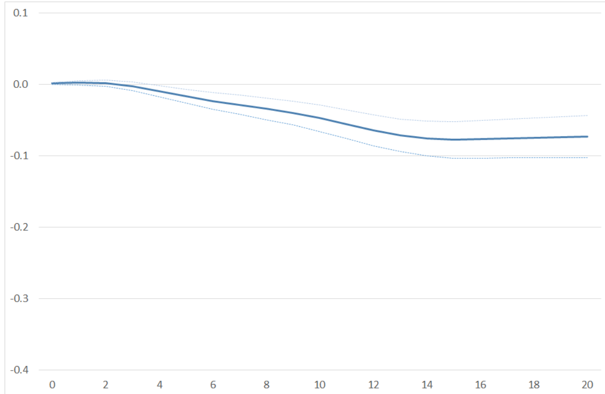
Notes.- responses are from an orthogonal shock/impulse to the output gap which generates a max. cumulative increase of approximately one percentage point over twenty periods; 90% confidence intervals from bootstrapping.

FIGURE A.6: UK weighted unemployment and inactivity population rates - cumulative impulse response functions (UCM detrended data)

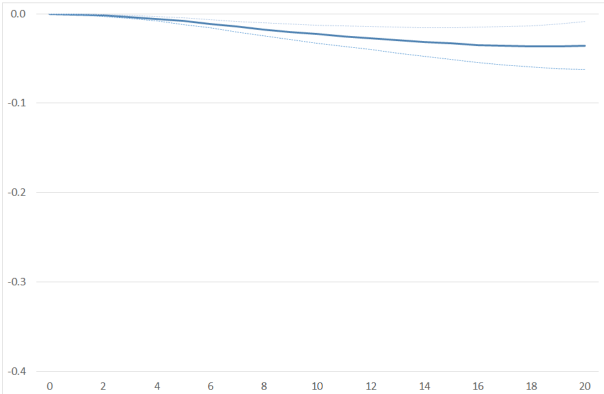
(a) Female inactivity



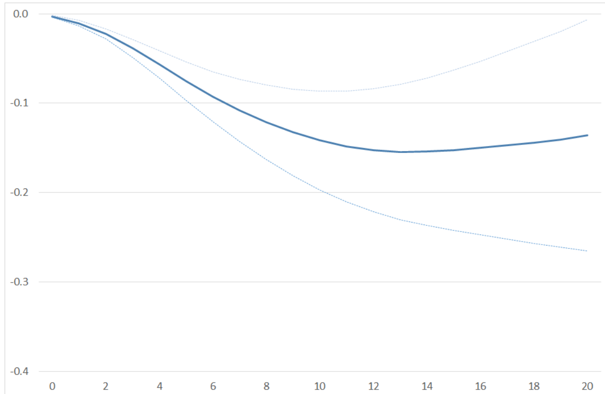
(b) Male inactivity



(c) Female unemployment



(d) Male unemployment

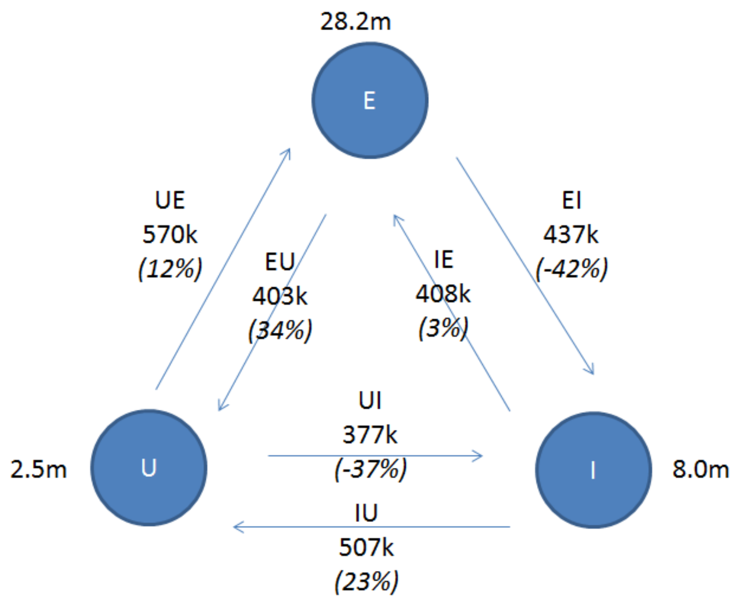


Notes.- responses are from an orthogonal shock/impulse to the output gap which generates a max. cumulative increase of approximately one percentage point over twenty periods; 90% confidence intervals from bootstrapping.

Appendix A.2 Brief description of gender flows data

Figure A.7 reproduces the basic relationship between employment (E), unemployment (U) and inactivity (I) stocks, and the possible inflows and outflows for the UK in 2013, abstracting at this point from 'births' and 'deaths.' As an illustration, the large gender differences in these raw transition probabilities for the UK first and second quarters of 2013 are also demonstrated in parentheses in Figure A.7. For example, the male p_{EU_t} transition probability for this period was thirty-four percent greater than the female, and the flow probabilities from unemployment and employment to inactivity were thirty-seven and forty-two percent smaller for men respectively.

FIGURE A.7: Gross labour market flows, Male & Female, UK 2013 quarter 1-2



Notes.- In this representation we have ignored 'births' and 'deaths', and stocks are for the first quarter. In brackets, gender differences in transition probabilities are expressed as $(male/female-1)$.

Figures A.8 - A.10 report the US transition probabilities and hazard rates by gender used in the analysis in Section 2.3, including the correction for classification error, while Figures A.11 - A.13 report the corresponding information for the UK. The overall EU & IU counter-cyclicality and the UE & UI pro-cyclicality are clear, as reported in other studies. For comparable derived flows series and adjustments for all workers for the US see Elsby et al. (2015). For UK hazard rates also estimated using the LFS and a discussion of their properties see Gomes (2012). The latter also provides a brief comparison of transition rates with the US which is analogous with these flows series here. The labour market flow response to the cycle appears to be stronger in the US than in the UK, which is consistent with what is observed for the stocks. One notable pattern in the UK flows series is that the inactivity to unemployment rates show a notable U-shape over time, with the low point towards the mid 2000s. During this time there have been substantial changes to the UK welfare system and eligibility for inactivity benefit payments, and we cannot rule out that these changes could explain this trend. However, we abstract from this in our results since these principally relate to disability classifications, and less so for lone parents, and thus should not have a significant gender dimension.

Focusing on within country gender differences, the rate of moving from employment to unemployment has tended to be larger for males than females over the time period studied here, with the gender differences narrowing in the US towards the end of the 1990s and beginning of the 2000s, whereas the gender gap has remained similar across the time period in the UK. The pro-cyclicality of this flow is also clearly more pronounced for men than women in both countries. On the other hand, the probability of moving from unemployment to employment displays narrower gender gaps, and the response during the Great Recession appears to be more similar. Although flows between employment and inactivity appear not especially sensitive to the economic cycle, and there is little difference in the flow from inactivity to employment, the reverse flow is consistently greater for women in both countries, making up for some of the difference in the *EU* flow. This observation can be used to indicate a lower level of labour market attachment for working women than men. However, we also see for the US the extent to which classification error could bias this result, with the gender gap narrowing substantially when the Abowd & Zellner (1985) correction is applied. The transitions between unemployment and inactivity show pronounced and consistent gender differences in both countries, though particularly so for the UK. Women are more likely to move from unemployment to inactivity than men, while the opposite is true for *IE* flow rates. The relative counter-cyclical increase in the *IU* flow rate appears to have been more marked for men than for women during the latest economic recession for the US only.

FIGURE A.8: US flow probabilities and rates between employment and unemployment

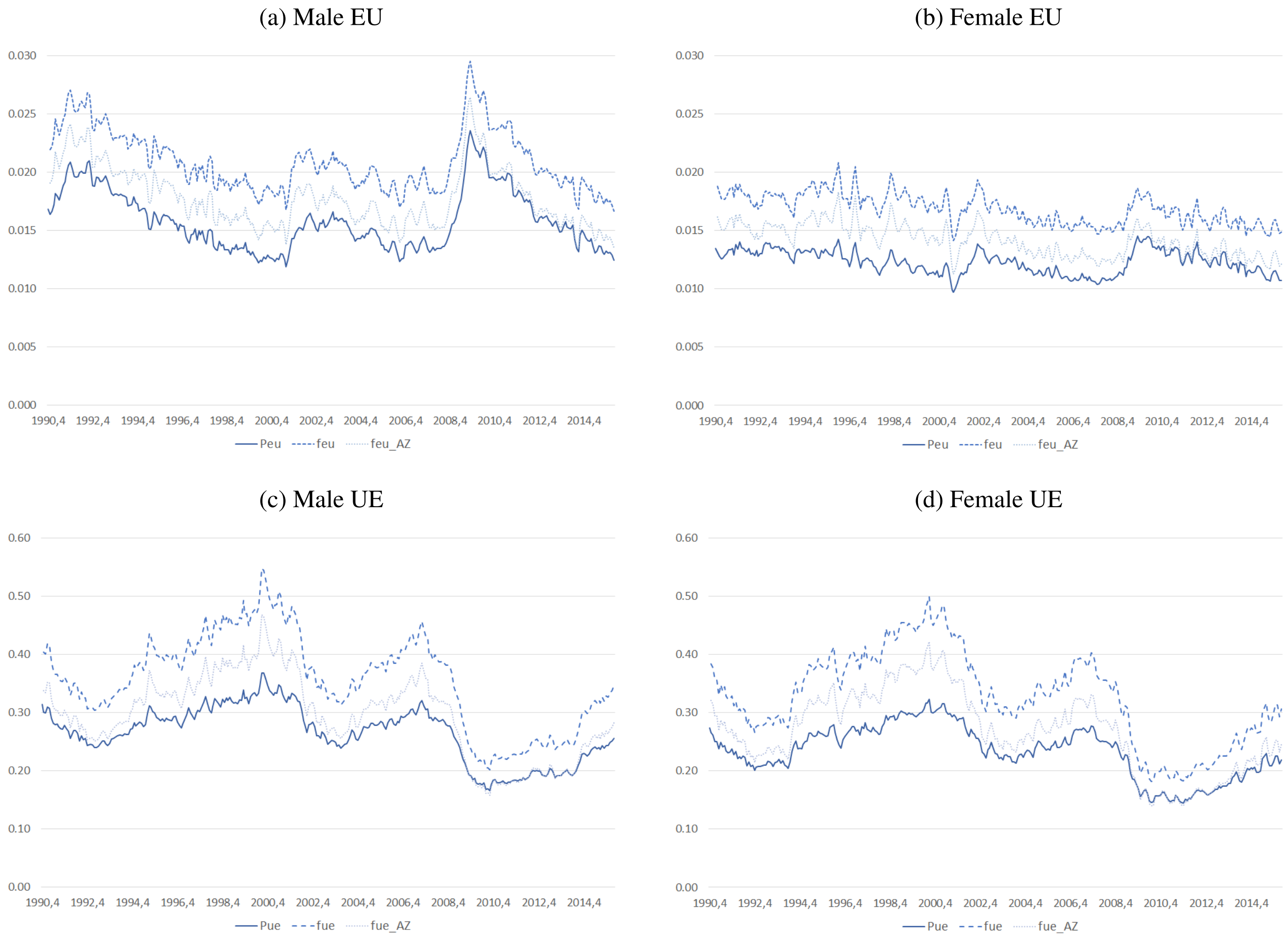
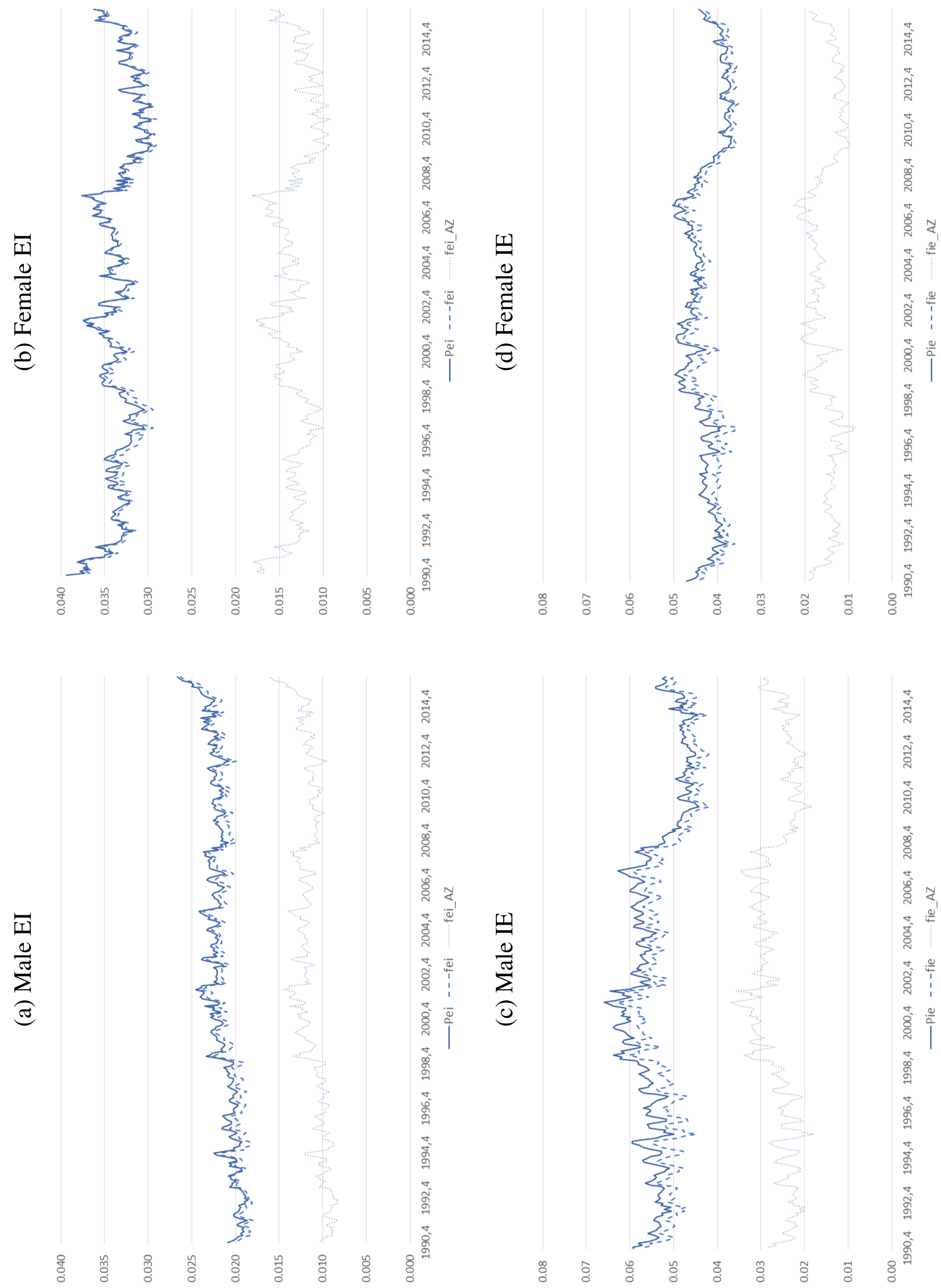


FIGURE A.9: US flow probabilities and rates between employment and inactivity



(a) Male EI

(b) Female EI

(c) Male IE

(d) Female IE

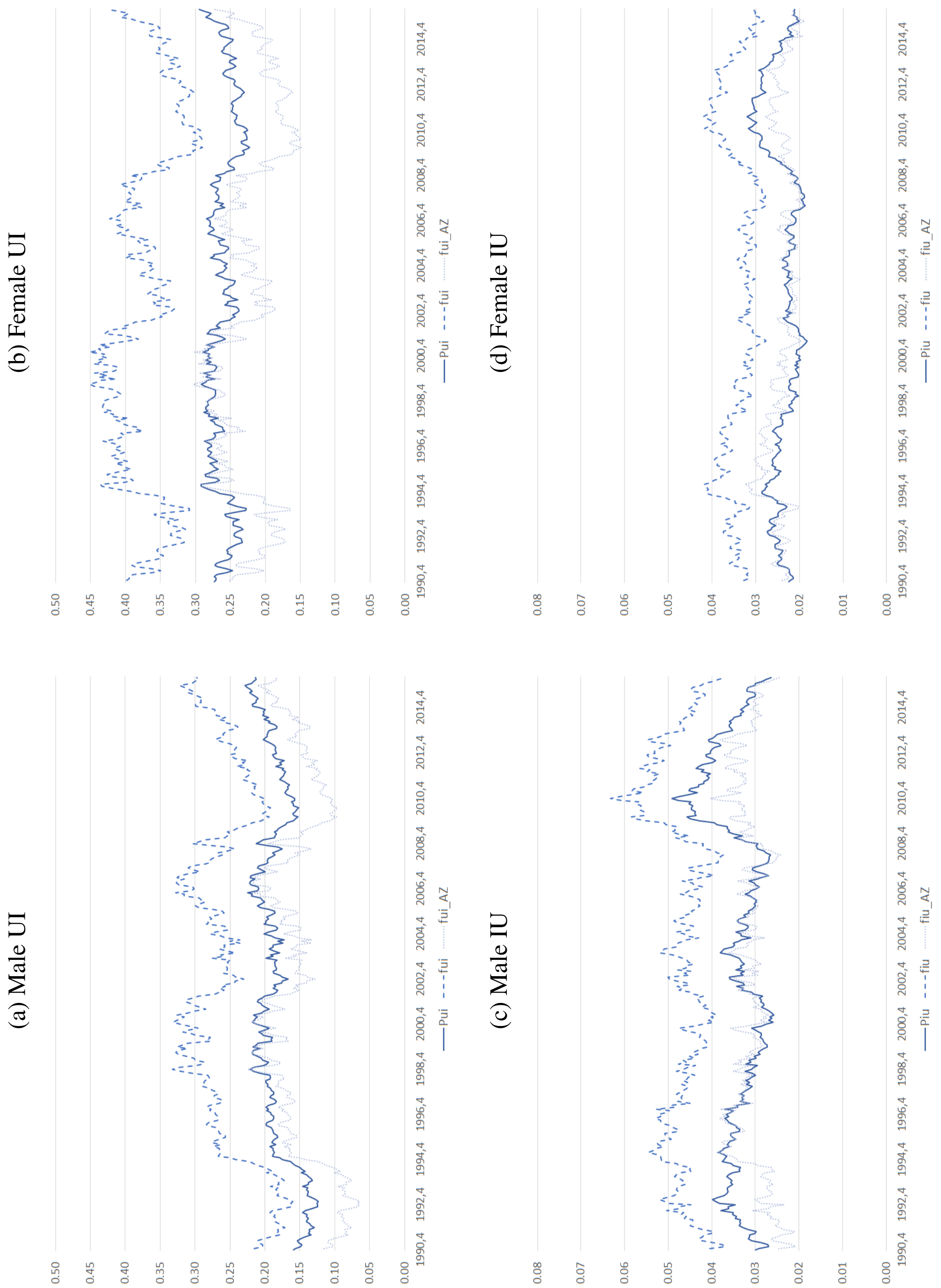


FIGURE A.10: US flow probabilities and rates between unemployment and inactivity

FIGURE A.11: UK flow probabilities and rates between employment and unemployment

(a) Male EU

(b) Female EU

(c) Male UE

(d) Female UE

FIGURE A.12: UK flow probabilities and rates between employment and inactivity

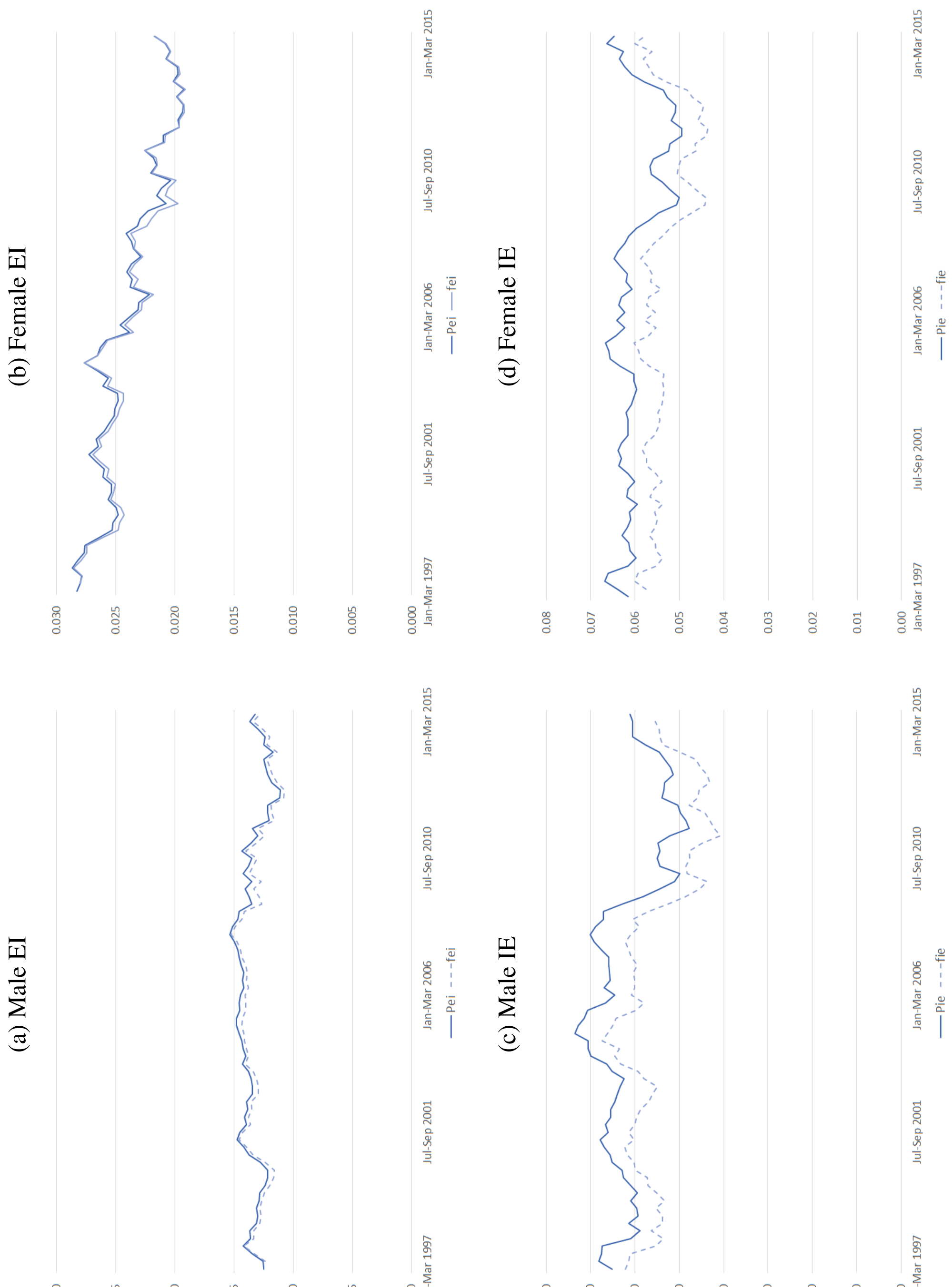
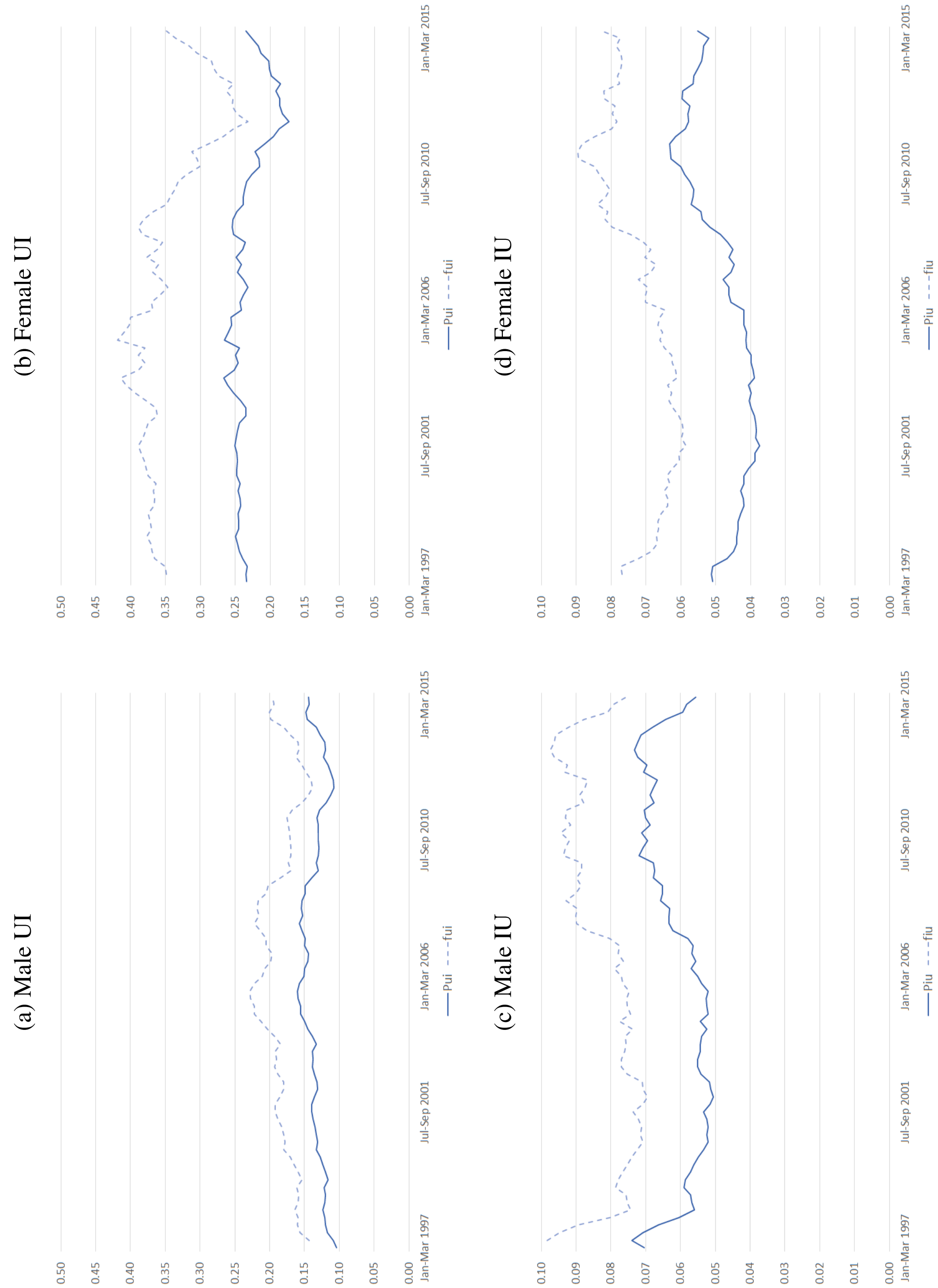


FIGURE A.13: UK flow probabilities and rates between unemployment and inactivity



Appendix A.3 Results of employment rate flows decomposition

Table A.2 below gives the decomposition results for employment rate variation accompanying the equivalent Table 2.2 in the main text. For the US, focusing on the hazard rate results $f_{i,j}$, combined exits to unemployment and inactivity account for eighty-two percent of variation for men, and sixty-five percent for women. This difference is accounted for by a lower importance of employment to unemployment flows for women, explaining only thirteen percent of variation for women compared with thirty-four percent for men. This is offset by a greater female variance share attributed to the procyclical IE rate. As much as half of female employment rate variation can be explained by changes in this flow rate alone. Perhaps surprisingly, the procyclical UI rate also attributes to employment variation. As this flow falls during a downturn, it offsets the decline in employment to some extent since individuals who remain in the unemployment pool are far more likely to move to employment. Specifically for the employment rate gap, half of its variation over the past twenty-five years is accounted for by the flows between employment and inactivity, and the other half between employment and unemployment. Generally, these results demonstrate the significance of the participation margin in explaining labour market changes over the cycle to an extent that is not identified when we consider patterns in the levels of inactivity. Further, they also highlight potentially greater gender differences in the importance of the participation margin over the cycle than observed from an analysis of the stocks alone. These differences can otherwise be lost in the offsetting nature of the various flows between states.

The UK results are qualitatively similar to the US. The gender difference in the relative importance of changes in the traditional ‘In’ and ‘Out’ rates, EU and UE, are again offset by greater cyclical importance of the IE rate for women, with this latter flow explaining thirty-two percent of the variation against thirteen percent for men. Unlike for the US, changes in the UI rate are not significant, implying either that there is less difference in attachment between the unemployed and inactive pools for the UK, or that this flow rate is less cyclically sensitive. The initial value and demography components can explain a sizeable fraction of the variance in employment rates for the UK. This is expected for the former, given hazard rates are smaller than for the US, and thus the labour market can be more persistently away from its implied steady-state. The small but notable importance of the demography effect, which is not seen either for unemployment rates nor for the US, can be explained by trend changes in employment since 1998, primarily before 2008. Given the rising participation rate of women, the gap between employment rates of those exiting and entering the working-age population here has narrowed over time. Closer inspection of the time series for this component of the gender gap decomposition shows that pre 2008 and post 2012 this accounts for the majority of the gap's change, but does not account for the within recession fall. (But even if this effect were present for the US, we would not expect to observe it here since the BLS flows derived form the CPS used here are for ages 16+.)

TABLE A.2: Flows decomposition of monthly changes in the employment rate and gender gap

		UE	EU	EI	UI	IE	IU	Init. val.	d	approx. err.
US: June 1990 - August 2015										
p_{ij}	All	0.40*	0.33	-0.01	-0.09	0.48	-0.14	0.01	0.01	0.01
	Male	0.33	0.37	0.11	-0.08	0.34	-0.09	0.01	0.00	0.01
	Female	0.34	0.17	0.07	-0.05	0.56	-0.11	0.00	0.01	0.00
	Gap**	0.16	0.26	0.37	-0.02	0.21	0.01	0.01	0.00	0.00
$f_{i,j}$	All	0.60	0.29	-0.01	-0.20	0.42	-0.12	0.01	0.01	0.01
	Male	0.48	0.34	0.09	-0.15	0.29	-0.07	0.01	0.00	0.01
	Female	0.52	0.13	0.07	-0.12	0.50	-0.10	0.00	0.01	0.00
	Gap	0.20	0.27	0.34	-0.03	0.18	0.02	0.01	0.00	0.00
$f_{i,j}$ w. AZ corr.	All	0.61	0.32	-0.10	-0.29	0.43	0.00	0.01	0.01	0.01
	Male	0.47	0.37	0.01	-0.21	0.31	0.01	0.01	0.01	0.01
	Female	0.56	0.15	0.01	-0.20	0.48	-0.02	0.00	0.02	0.00
	Gap	0.21	0.29	0.30	-0.03	0.18	0.03	0.01	0.00	0.01
UK: q3 1997 - q2 2015										
p_{ij}	All	0.32	0.37	-0.02	0.01	0.26	-0.10	0.11	0.04	0.01
	Male	0.28	0.38	0.00	0.00	0.15	-0.05	0.08	0.14	0.01
	Female	0.31	0.25	-0.05	0.01	0.34	-0.14	0.09	0.18	0.00
	Gap	0.15	0.25	0.03	-0.01	-0.04	-0.01	0.02	0.62	0.00
f_{ij}	All	0.46	0.35	-0.05	-0.03	0.24	-0.12	0.11	0.04	0.01
	Male	0.37	0.36	-0.02	-0.02	0.13	-0.06	0.08	0.14	0.01
	Female	0.46	0.23	-0.08	-0.02	0.32	-0.19	0.09	0.18	0.00
	Gap	0.19	0.23	0.02	-0.02	-0.07	0.01	0.02	0.61	0.00

* $\beta^E_{UE} = \frac{cov(\Delta E_{t,k}, \{c_{UE_t}\}_1)}{var(\Delta E_{t,k})}$, where $\{c_{UE_t}\}_1$ is the component of the decomposition accounting for current and past changes in the UE transition probability.
** Gender gap computed as male employment rate minus female.
Notes.- rows may not sum to one due to rounding errors.

Appendix A.4 Heterogeneity tables for the IU transition

TABLE A.3: Average US transition probabilities from inactivity to unemployment, p_{IU}, age 20-54

		Male		Female	
		1997-2007	2008-2012	1997-2007	2008-2013
Age	20-29	0.08	0.10	0.05	0.06
	30-39	0.06	0.10	0.03	0.04
	40-54	0.04	0.06	0.02	0.04
Inactivity reason	Retired	0.02	0.02	0.01	0.01
	Disabled	0.01	0.01	0.01	0.01
	Family/home	0.13	0.18	0.03	0.05
	Student	0.06	0.08	0.05	0.06
	Other*	0.19	0.25	0.11	0.16
Living as a married couple	Yes	0.05	0.07	0.02	0.03
	No	0.06	0.08	0.05	0.06
Age of youngest child	0-2	0.08	0.12	0.03	0.04
	3-5	0.07	0.12	0.03	0.05
	6-13	0.06	0.10	0.03	0.04
N. of dep. children age < 18	0	0.06	0.08	0.03	0.05
	1	0.06	0.10	0.03	0.05
	2	0.06	0.11	0.03	0.04
	3	0.07	0.11	0.03	0.04
	$\geq$4	0.08	0.11	0.03	0.04

* Includes those who are temporarily ill.

TABLE A.4: Average UK transition probabilities from inactivity to unemployment, p_{IU}, age 20-54

		Male		Female	
		1997-2007	2008-2012	1997-2007	2008-2013
Age	20-29	0.09	0.10	0.05	0.07
	30-39	0.07	0.07	0.04	0.05
	40-54	0.04	0.05	0.03	0.04
Inactivity reason	Retired	0.02	0.02	0.01	0.01
	Disabled	0.02	0.03	0.01	0.02
	Family/home	0.07	0.08	0.04	0.05
	Student	0.09	0.09	0.07	0.09
	Other*	0.17	0.19	0.09	0.10
When left last job	$\tau \leq 12$	0.14	0.17	0.09	0.11
(τ months)	$\tau > 12$ / never	0.05	0.06	0.03	0.05
Reason left last job	Job loser	0.12	0.15	0.08	0.09
	Job leaver	0.07	0.09	0.05	0.06
	Temp. job ended	0.15	0.17	0.09	0.10
Living as a married couple	Yes	0.05	0.05	0.03	0.04
	No	0.07	0.08	0.05	0.07
Age of youngest child	0-1	0.09	0.10	0.03	0.05
	2-4	0.07	0.08	0.04	0.06
	5-9	0.06	0.07	0.05	0.07
N. of dep. children age < 19**	0	0.06	0.07	0.04	0.05
	1	0.07	0.10	0.05	0.07
	2	0.07	0.09	0.04	0.06
	3	0.06	0.06	0.04	0.05
	≥ 4	0.07	0.05	0.03	0.03

* Includes those who are temporarily ill.
** All children aged 15 and under and those aged 16-18 in full-time education.

Appendix B

Long-term unemployment and the Great Recession: Evidence from UK stocks and flows

Appendix B.1 Composition of the unemployment pool - data and methodology

The UK's nationally representative Annual Population Survey (APS) combines responses from waves one and five of the LFS, for the whole year, as well as incorporating local and regional boosts to the sample to match its aim of providing representative data at the local authority level. To obtain more reliable estimates of working-age (male 16-64, female 16-59) unemployment levels across the duration distribution, I prefer this larger sample size dataset to the Quarterly Labour Force Survey. The increased sample size is also useful when specifying heterogeneous types of unemployed individuals over multiple levels (e.g. sex, age groups, duration of unemployment and industry of previous job). An indicative reference for the APS datasets is as follows: Office for National Statistics. Social and Vital Statistics Division. (2015). Annual Population Survey, January - December, 2004. [data collection]. 6th Edition. UK Data Service. SN: 5334. Table B.1 contains notes on the variables used and how these have been transformed into the heterogeneous types used in the analysis. Table B.2 gives the long-term shares of unemployment across the various sets of personal characteristics for some of the years used here.

The counterfactual levels of unemployment by duration $\{\tilde{S}, \tilde{M}, \tilde{L}\}_t$, that would have occurred had each type i's distribution over unemployment duration remained constant relative to three years previously, but allowing for the actual change over those years in the overall composition of types within the total unemployment pool, where $U = \sum_i U_i$, are similarly given by

$$\tilde{L}_t = \sum_i \left(\frac{L_i}{U_i}\right)_{t-3} \left(\frac{U_i}{U}\right)_t U_t. \tag{B.1}$$

By definition the counterfactual is consistent with the realised total level of unemployment, i.e. $\tilde{S}_t + \tilde{M}_t + \tilde{L}_t = U_t$. If there were no unemployed of type i at some duration three years previously, I simply retain their current distribution over duration in the counterfactual: this will make little quantitative difference since such types will have an insignificant weight.

Results for the counterfactual LTU share in 2007 relative to 2004, had each type's duration shares within unemployment remained constant, and likewise for 2010 and 2007, are given by Figures B.1 & B.2. Each panel accounts for both the age and sex composition of the unemployed, as well as one other level of heterogeneity. The small rise in the share of working-age unemployed who have been looking for work for over twelve months between 2004 and 2007, 21% to 24%, cannot be explained by these definitions of the composition. The change in composition with regards the occupation and industry of an individual's previous job marginally predicts a fall in the LTU share. The composition over when an individual left their last job has no effect.

TABLE B.1: Notes on variables used from the Annual Population Survey, 2004-2013

	APS (2004) variable	*Notes*	*Transformations/categories*
Age groups	*age*		Groups as follows: 16-24, 25-34, 35-44, 45-54, 55-64/59.
Unemp. duration	*durun*	Minimum of the stated length of time looking for work and length of time since respondent's last job (*wnleft*). From the APS the small share of the weighted unemployed (less than 1%) who have no duration response is dropped from the sample.	Three categories used: 0-3 mths, 3-12 mths, 12 mths +
Region	*govtof*	Thirteen UK Government office regions - all respondents.	Create ten categories by combining *North East* and *Yorkshire and Humberside*, *North West* and *Merseyside*, *East Midlands* and *West Midlands*.
Prev. job industry	*inds92l*	Standard Industrial Classification (SIC) 1992, industry divisions . From 2008 onwards, interviewers in the Labour Force Survey would classify occupations using the SIC2007. Details of how this differs from previous classifications can be found on the ONS website. To generate a consistent time series of employment by industry sector I make use of the conversion variable in the APS 2010, *in0792sl*. This was generated by the ONS by matching SIC2007 sub-class to a higher level of aggregation, i.e. division, in SIC1992, but is not available for 2013.	Create new categories from 19 divisions and missing values: (D) - Manufacturing, (F)- Construction, (G) - Wholesale/retail, (H-I) - Hotels, restaurants, transport, comms, (J-K) - Finance & real estate etc., (L-N) - Public sectors, (A-C, G, O-Q, outside UK) - Others, *Does not apply* (includes those with no previous job).
Prev. job occupation	*sc2klmj*	Standard Occupational Classification (SOC) 2000 - major occupation groups.	Retain nine occupation groups and include category for *Does not apply* (includes those with no previous job).
Reason left prev. job	*redylft*	Applies to all respondents who are not working and left job in 8 years before reference week.	Create five categories: (1-2) - Redundant/dismissed, (3) - Temporary job, (4-8) - Resigned/gave up work/early retirement, (9) - Other, (-9) - Does not apply (includes those with no previous job).
Type of employment sought	*tyemps*	Applies to all respondents looking for employment. Large majority responded (2-3). Other categories *No preference, Self-employment* etc.	Create three categories: (2) - Full time employee, (3) - Part-time employee, (1, 4-11) - Other.
When left last job (relative to unemp. spell starting)	*wnleft*	May differ from *durun* where there have been spells since last job where an individual has not looked for work, or where they have never had a job.	Three categories: Same time - *wnleft=durun*, Strictly longer - *wnleft>durun*, Never had paid employment.

Notes.- author notes, but see also relevant dataset user guides held by the UK Data Service.

TABLE B.2: Long-term shares of unemployment

		2004	*2007*	*2010*
Sex	Male	25.1	28.0	36.2
	Female	15.5	18.2	24.5
Age groups	16-24	12.5	16.0	23.5
	25-34	20.9	23.1	33.0
	35-44	27.4	31.0	36.0
	45-54	31.7	32.3	39.1
	55-64/59	37.6	37.7	43.0
Region	North East & Yorks.	41.9	37.9	42.8
	North West & Mersey.	20.9	26.4	34.4
	Midlands	22.6	24.4	30.2
	Eastern	20.6	25.2	34.2
	London	16.0	21.8	29.8
	South East	23.8	26.0	33.0
	South West	14.3	18.3	25.6
	Wales	16.8	17.7	30.2
	Scotland	20.1	22.3	30.4
	Northern Ireland	24.6	22.8	29.2
Industry of prev. job	Manufacturing	27.3	29.8	38.8
	Construction	23.6	22.3	36.3
	Wholesale, retail	15.6	17.4	29.8
	Finance, real estate	15.9	17.4	27.6
	Hotels, restaurants, transport, comms.	19.0	20.3	29.0
	Public sectors	13.3	18.4	25.1
	Other	18.4	21.6	28.1
	Does not apply	24.3	30.1	34.5
Occupation of prev. job	Managers and Senior Officials	19.9	19.0	28.1
	Professional occupations	17.3	16.1	22.3
	Associate Professional and Technical	15.6	18.2	24.4
	Administrative and Secretarial	12.8	15.3	28.1
	Skilled Trades Occupations	25.8	27.2	36.3
	Personal Service Occupations	11.8	18.9	26.1
	Sales and Customer Service Occupations	9.8	14.5	20.9
	Process, Plant and Machine Operatives	26.0	27.8	39.2
	Elementary Occupations	21.6	24.4	34.9
	Does not apply	24.4	30.1	34.8
All		21.2	23.8	31.6

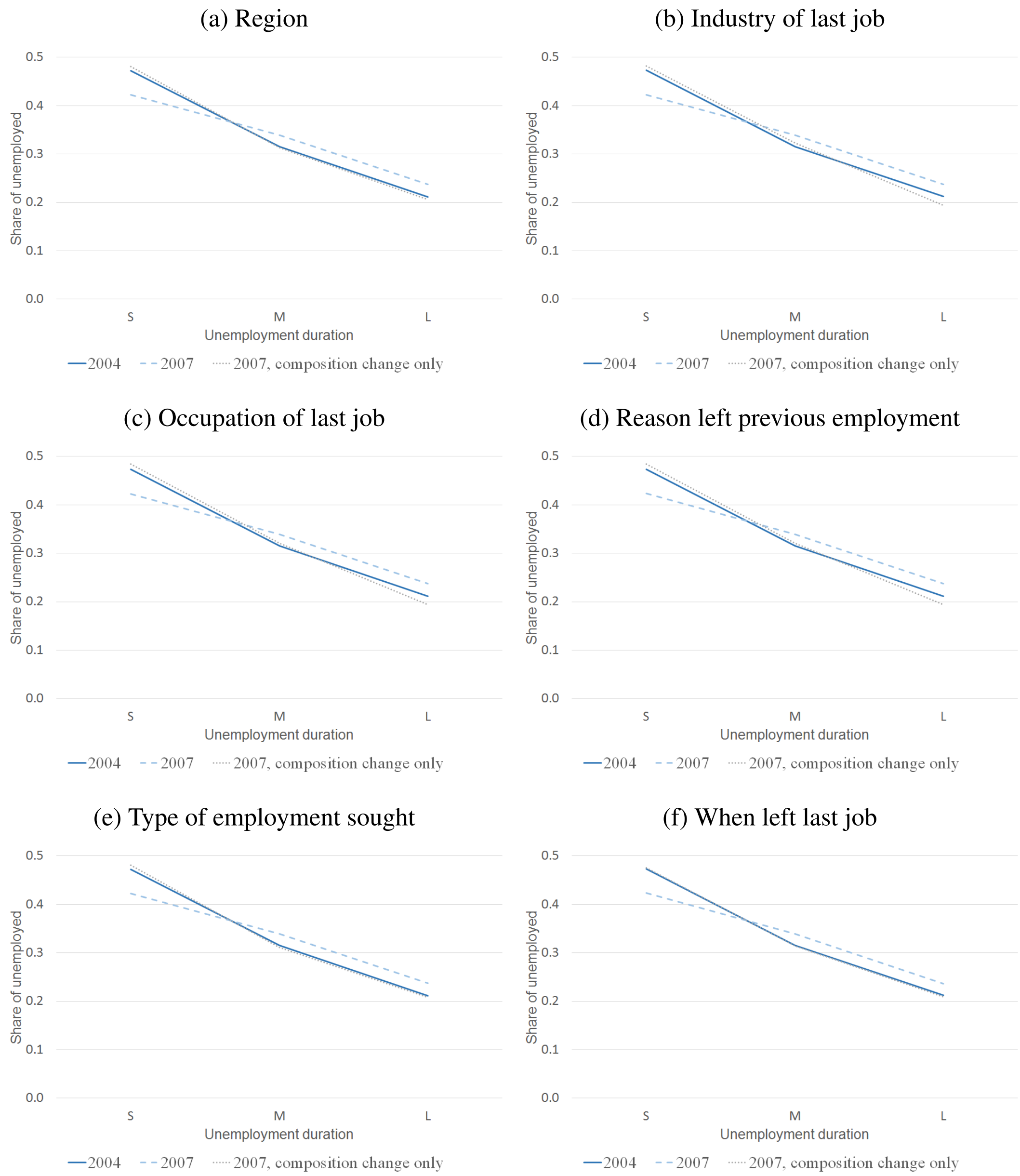
Notes.- author calculations using UK Annual Population Survey, ages 16-64/59, January-December 2004, 2007 & 2010.

TABLE B.3: Table A.2 (cont.): Long-term shares of unemployment

		2004	*2007*	*2010*
Reason left prev. job	Redundant, dismissed	23.3	25.1	34.6
	Temporary job	16.3	19.6	24.4
	Resigned, gave up work, early retirement	15.2	18.4	29.1
	Other	21.4	20.2	29.3
	Does not apply	24.5	30.3	34.5
Type of employment sought	Full-time employee	23.2	24.9	33.9
	Part-time employee	13.0	15.9	21.8
	Other	23.1	29.8	35.2
When left last job (relative to unemployment spell starting)	Same time	26.1	27.8	38.9
	Strictly before	16.6	18.7	23.4
	Never had paid employment	20	24.4	28.4
All		21.2	23.8	31.6

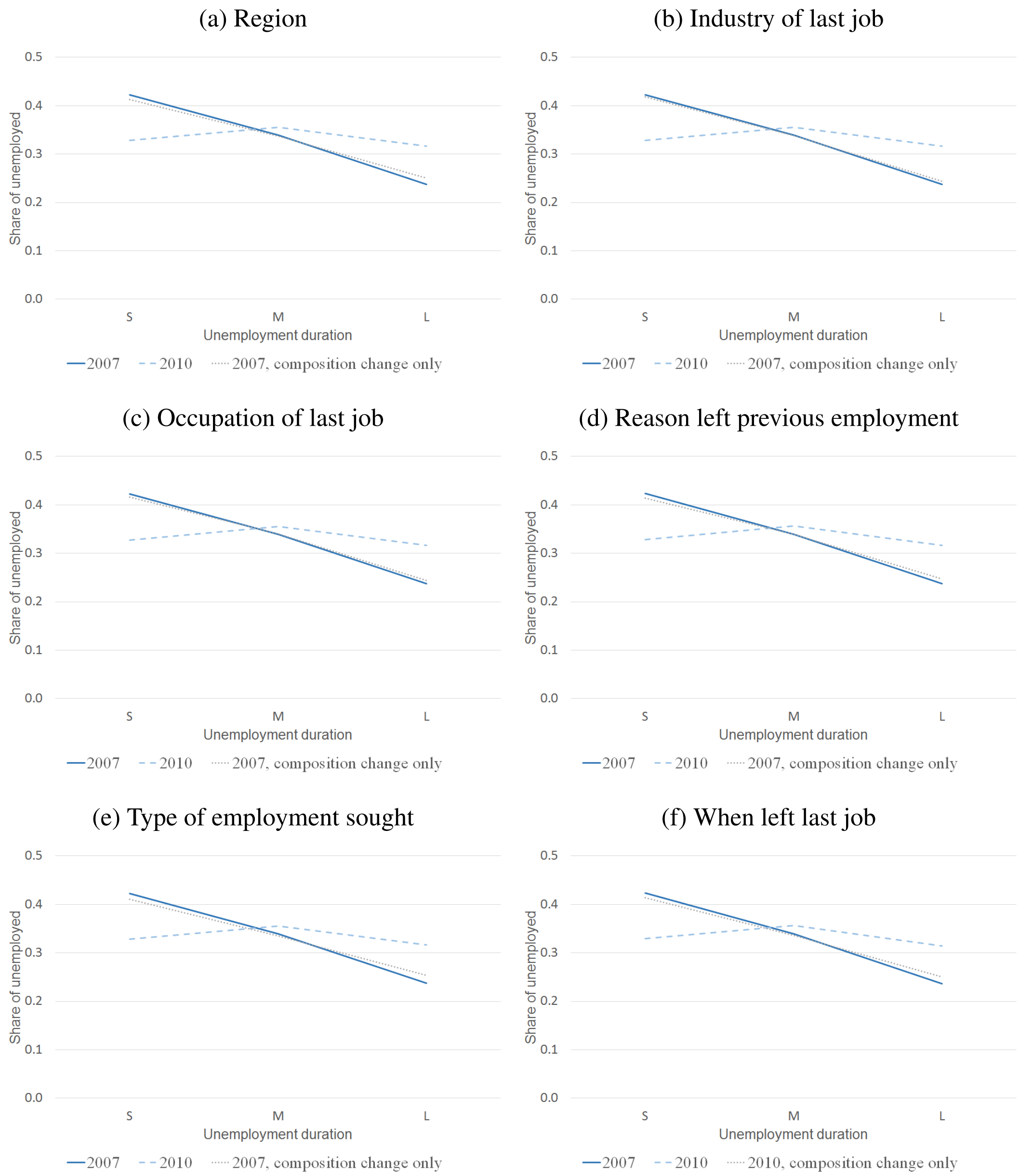
Notes.- author calculations using UK Annual Population Survey, ages 16-64/59, January-December 2004, 2007 & 2010.

FIGURE B.1: Distribution of unemployment over duration in 2004 and 2007, and the role of composition changes in between



Notes.- author calculations using UK Annual Population Survey, ages 16-64/59, January-December 2004 & 2007. Counterfactual gives unemployment shares for 2007 holding constant the distribution over $\{S, M, L\}$ for each stated type of heterogeneity, interacted with sex and age groups, from 2004, and applying the overall distribution of types in the unemployment pool from 2007.

FIGURE B.2: Distribution of unemployment over duration in 2007 and 2010, and the role of composition changes in between



Notes.- author calculations using UK Annual Population Survey, ages 16-64/59, January-December 2007 & 2010. Counterfactual gives unemployment shares for 2010 holding constant the distribution over $\{S, M, L\}$ for each stated type of heterogeneity, interacted with sex and age groups, from 2007, and applying the overall distribution of types in the unemployment pool from 2010.

Appendix B.2 Labour market flows - data & adjustments

B.2.1 Seasonal adjustment

Given quarterly gross flows between states $\hat{XY}_t$ for $1997q2 \leq t \leq 2015q2$, measured from the longitudinal datasets, I first take the log difference from the series centred using a four quarter moving average,
i.e. $\ln \bar{XY}_t = \ln \hat{XY}_t - \ln\left[(0.125\hat{XY}_{t-2} + 0.25\hat{XY}_{t-1} + 0.25\hat{XY}_t + 0.25\hat{XY}_{t+1} + 0.125\hat{XY}_{t+2})\right]$. I then regress this on a set of quarterly dummies, as well as additional dummies for $t = 2000q4, 2001q1$, since there is a reduced sample of reported unemployment durations in the final quarter of 2000, which can be accounted for at this stage. Using the residuals/predicted values ε_t from these regressions, the seasonally adjusted gross flows series for $1997q4 \leq t \leq 2014q4$ are then given by $\tilde{XY}_t = \hat{XY}_t / \exp(\ln \bar{XY}_t - \varepsilon_t)$.

B.2.2 Stocks-flows consistent adjustment for measured transition rates

To adjust the measured transition rates to be consistent with national labour market statistics measures of the stocks I solve the following problem for each t:

$$\min_{\phi_t} (\phi_t - \tilde{\phi}_t)' \tilde{\mathbf{W}}_t^{-1} \left(\phi_t - \tilde{\phi}_t\right) \tag{B.2}$$

$$s.t. \quad \Delta \mathbf{z}_t = \mathbf{Z}_{t-1}\phi_t, \quad \{\mu_t\} \tag{B.3}$$

$$\mathbf{R}\phi_t = \mathbf{0} \qquad \{\nu_t\}; \tag{B.4}$$

i.e. I choose ϕ_t, a $(20x1)$ vector of transition rates between states, to minimise its distance from the equivalent $\tilde{\phi}_t$ estimated from the survey data, and where $\tilde{\mathbf{W}}_t^{-1}$ is proportional to the covariance matrix of $\tilde{\phi}_t$. This is subject to (B.3), which states that the change in population rates should be equal to the normalised gross flows, where $\mathbf{Z}_{t-1}$ is a $(4x20)$ matrix populated accordingly with population shares, and (B.4), where $\mathbf{R}$ contains the restrictions $p_{EM} = p_{EL} = p_{SL} = p_{LM} = p_{NM} = p_{NL} = 0$. The solution is given by

$$\begin{bmatrix} \phi \\ \frac{1}{2}\mu \\ \frac{1}{2}\nu \end{bmatrix}_t = \begin{bmatrix} \tilde{\mathbf{W}}_t^{-1} & \mathbf{Z}_{t-1}' & \mathbf{R}' \\ \mathbf{Z}_{t-1} & 0 & 0 \\ \mathbf{R} & 0 & 0 \end{bmatrix}^{-1} \begin{bmatrix} \tilde{\mathbf{W}}^{-1}\tilde{\phi} \\ \Delta \mathbf{z} \\ \mathbf{0} \end{bmatrix}_t. \tag{B.5}$$

B.2.3 'Cleaned' transition rates - specification (III)

As described in the main text, the primary assumption behind this robustness check is that an individual's employment status is most likely to have been recorded accurately. Starting from this strong assumption, all employment to unemployment flows are then recoded to *ES*. Then, where it is unambiguous, allowing for the possibility of unemployment restarts, if an individual is observed as unemployed up to three quarters consecutively subsequent durations are recoded accordingly. Further, observed transitions to a shorter duration between two quarters of LTU are reassigned to *LLL*, and the continuous observed unemployment spell *SMLL* is reassigned to *SMML*. Table B1 details the number of observed transitions reassigned as such.

B.2.4 Time aggregation bias correction - specification (V)

It is common in the literature to set out the stocks-flows decomposition in terms of continuous time equivalent hazard rates instead of transition probabilities. This is intended to have the advantage of accounting for time aggregation bias in measured transitions; i.e. movements between states, which could be important in explaining the cyclical behaviour of labour market rates, are ignored due to the frequency of data collection. Adjustments to account for this implicitly assume that hazard rates are constant and identical for all workers within a state and period. However, given the analysis of limited duration dependence of transition rates here, implicitly assuming that there is none within $\{S, M, L\}$ is somewhat counter-intuitive. Nonetheless, since I isolate short-term unemployment as a separate state, where the majority of the time aggregation bias would be expected to occur, it would be remiss not to account for it in some way. As computed in EHS, the continuous time generator or hazard rate version of $\mathbf{P}_t$ is its principal logarithm, $\ln \mathbf{P}_t = \mathbf{F}_t$. However, this only exists and is unique under certain conditions on $\mathbf{P}_t$.[1] Fortunately, these conditions are always met for the series of naïve transition rates estimated here. The effect of the adjustment is substantial on the levels of transition rates to and from short-term unemployment. The implied hazard rates for the *ES* and *SE* flows are both approximately doubled. Given the much greater level of the latter transition rate, it follows mechanically that time aggregation would bias the β shares of the variance decomposition downwards for unemployment exits.

The computed hazard rates can then be used to replace the steady-state (3.2) with its continuous time equivalent,

$$\bar{\mathbf{z}}_t = -\Lambda_t^{-1} \lambda_t$$

where Λ_t and λ_t are equivalents of Π_t and π_t. The derivation of (3.4) and (3.6) is then identical besides the derivatives of the Taylor expansion taking a different analytical form.

[1] If $\mathbf{P}_t$ is 'embeddable' (non-singular) the only generator matrix is given by its principal logarithm when its eigenvalues are real, distinct and positive.

TABLE B.4: 'Clean' flows - unweighted number of quarter to quarter transition observations changed on account of reassignments, 1997q2-2015q2

	Freq.	*Percent*
Unchanged	3,093,122	99.69
EM, *EL*, *EU* to *ES*	7,769	0.25
ESL to *ESM*	673	0.02
ESML to *ESMM*	188	0.01
SMLL to *SMML*	324	0.02
LSL, *LML*, *LUL* to *LLL*	510	0.02

Notes.- author calculations using Two Quarter Longitudinal Labour Force Survey, ages 16-64/59. Information on how these values vary over time is available on request. *U* here refers to the small number of observations where no duration data was recorded.

TABLE B.5: 'De-*NUN*-ification' - unweighted number of quarter to quarter transition observations changed on account of reassignments, 1997q2-2015q2

	Freq.	*Percent*
Unchanged	3,097,667	99.84
NNLN or *NNMN* to *NNNN*	1,854	0.06
NLNN or *NMNN* to*NNNN*	1,536	0.04
LLNL to *LLLL*	420	0.02
LNLL to *LLLL*	288	0.00
MLNL MLLL	68	0.00
MMNL to *MMLL*	176	0.00
ENMN ENLN to *ENNN*	160	0.00
ESNM to *ESMM*	210	0.00
ESNL to *ESMM*	29	0.00
MNLL to *MMLL* (ambiguous)†	178	0.00

† Although this small number of observation remains ambiguous, it was decided on the balance of likelihood to reassign them.

Notes.- Author calculations using Two Quarter Longitudinal Labour Force Survey, ages 16-64/59. Information on how these values vary over time is available on request.

TABLE B.6: Ratio of unweighted flows observations after adjustments to before, 1997q2-2015q2

	'Clean'	*'Clean' + 'deNUN'*
EE	1.00[†]	1.00
EL	0.00	0.00
EM	0.00	0.00
EN	1.00	1.00
ES	1.25	1.25
EU	0.00	0.00
LE	0.94	0.94
LL	0.99	1.02
LM	0.78	0.78
LN	0.98	0.78
LS	0.90	0.90
LU	0.57	0.57
ME	0.93	0.93
ML	0.95	0.99
MM	0.97	0.98
MN	0.97	0.80
MS	0.93	0.93
MU	0.91	0.91
NE	1.00	1.00
NL	1.00	0.75
NM	1.00	0.87
NN	1.00	1.01
NS	1.00	1.00
NU	1.00	1.00
SE	1.06	1.06
SL	0.90	0.90
SM	1.11	1.12
SN	1.03	1.02
SS	1.02	1.02
SU	1.19	1.19
UE	0.72	0.72
UL	0.64	0.64
UM	0.83	0.83
UN	0.94	0.94
US	0.80	0.80
UU	0.94	0.94

[†] # of observations after / # of observations before.

Notes.- author calculations using Two Quarter Longitudinal Labour Force Survey, ages 16-64/59. Information on how these values vary over time is available on request. U here refers to the small number of observations where no duration data was recorded.

TABLE B.7: Stocks-flows decomposition: including adjustments for classification errors, 1998q2-2014q4

	(III)*				(IV)**			
	Δe	Δu	Δu_{rate} †	Δl	Δe	Δu	Δu_{rate} †	Δl
Δp_{EU}	0.25§	0.35	0.35	0.06	0.25	0.35	0.35	0.07
Δp_{EN}	0.14	0.00	0.00	0.01	0.14	0.00	0.00	0.01
Δp_{UE}	0.32	0.41	0.41	0.39	0.31	0.42	0.43	0.40
Δp_{UN}	0.01	0.21	0.19	0.32	0.01	0.19	0.17	0.29
Δp_{NE}	0.32	0.00	0.03	0.00	0.31	0.00	0.03	0.00
Δp_{NU}	0.00	0.05	0.04	0.01	-0.01	0.05	0.04	0.01
Δp_{UU}	0.01	0.02	0.02	0.10	0.01	0.02	0.02	0.10
Initial val.	0.01	0.02	0.02	0.05	0.01	0.02	0.02	0.05
Approx. err.	-0.05	-0.06	-0.06	0.04	-0.04	-0.05	-0.05	0.07

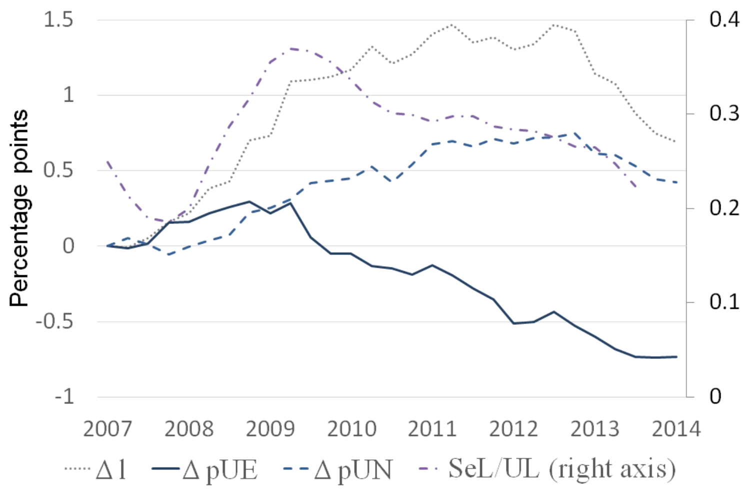
* (II) and using classification error adjusted transition probabilities as $\tilde{\phi}_t$.
** (III) and using 'de-NUN-ified' transition probabilities as $\tilde{\phi}_t$.
† $u_{rate} = u/(u+e)$
§ Interpretation: Share of variance in the quarterly change in the employment rate accounted for by past and present quarterly changes in p_{ES}, i.e. $\beta^e_{EU} = \frac{cov(\Delta e_t, \{c_{EU,t}\}1)}{var(\Delta e_t)}$.
Notes.- author calculations using Two Quarter Longitudinal Labour Force Survey & Labour Market Statistics, ages 16-64/59.

TABLE B.8: Stocks-flows decomposition: including time aggregation bias adjustment, 1998q2-2014q4

	(I)*				(VI)**			
	Δe	Δu	Δu_{rate} †	Δl	Δe	Δu	Δu_{rate} †	Δl
Δp_{EU}	0.27§	0.36	0.36	0.10	0.28	0.26	0.27	0.10
Δp_{EN}	0.16	0.00	0.00	0.00	0.12	-0.01	0.00	0.00
Δp_{UE}	0.26	0.32	0.32	0.26	0.32	0.39	0.39	0.29
Δp_{UN}	0.00	0.17	0.15	0.33	-0.01	0.29	0.26	0.41
Δp_{NE}	0.30	0.01	0.03	0.00	0.28	0.01	0.03	0.00
Δp_{NU}	-0.03	0.14	0.12	0.16	-0.05	0.05	0.04	0.12
Δp_{UU}	0.00	0.01	0.01	0.10	0.02	0.03	0.03	0.05
Initial val.	0.01	0.01	0.01	0.03	0.01	0.01	0.01	0.03
Approx. err.	0.02	0.01	0.01	0.01	0.02	-0.03	-0.02	0.00

* 'Naïve' transition probabilities, i.e. with no zero value restrictions when adjusting $\tilde{\phi}_t$.
** 'Naïve' hazard rates, i.e. with time aggregation bias adjustment.
† $u_{rate} = u/(u+e)$
§ Interpretation: Share of variance in the quarterly change in the employment rate accounted for by past and present quarterly changes in p_{ES} (or hazard rate equivalent), i.e. $\beta^e_{EU} = \frac{cov(\Delta e_t, \{c_{EU,t}\}1)}{var(\Delta e_t)}$.
Notes.- author calculations using Two Quarter Longitudinal Labour Force Survey & Labour Market Statistics, ages 16-64/59.

FIGURE B.3: Cumulative long-term unemployment contributions from exit rates and the share of gross in-flows previously employed, 2008-2014



Notes.- author calculations using Two Quarter Labour Force Survey & Labour Market Statistics, ages 16-64/59. Transition rates calculated using specification (I). Series indexed to zero in 2007q4. Interpretation of series on left axis is the cumulative increase in long-term unemployment's population share since 2007 accounted for by past and present changes in transition rates.

Appendix B.3 The potential role of labour market policy changes

It is possible that changes in UK Government labour market policy are responsible for some of the results. Upon becoming unemployed in the UK, the typical process for many individuals is to first 'sign on' to Jobseeker's Allowance (JSA). This is an active benefit in so far as claimants must look for work and be available to start at short notice, meaning that a LFS respondent receiving such payments would in most cases be classified as ILO unemployed.[2] After signing on, eligibility for other alternative benefits is considered, such as Income Support (primarily for lone parents) and allowances related to disability or care. If eligibility is confirmed there is no monitored requirement to look for work. Although individuals in receipt of such payments could be classified as ILO unemployed instead of inactive, this is less likely.[3] If there was a tightening of eligibility criteria for inactive benefit payments since the Great Recession, this could manifest itself in the aggregate flow rates as observed. Tightening criteria could immediately lead to a reduction in UN flows, but the effect on the reverse flow would be drawn out as reviewing eligibility and the fitness to work of those receiving disability or carer benefits is a slow process. There was such a tightening in the UK, with the stricter Employment Support Allowance (ESA) gradually replacing Incapacity Benefit towards the end of 2008. Furthermore,

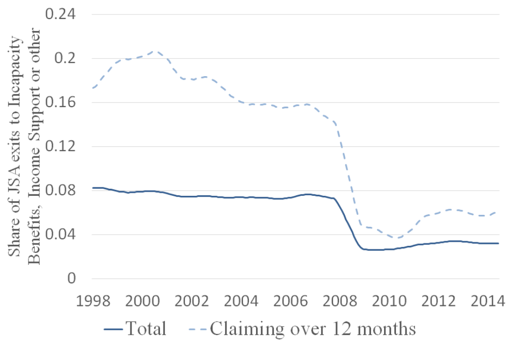
[2]Using the January-December 2007 Annual Population Survey, 21% of JSA recipients were classified as ILO inactive.

[3]Using the January-December 2007 Annual Population Survey, 13% of Income Support recipients were classified as active.

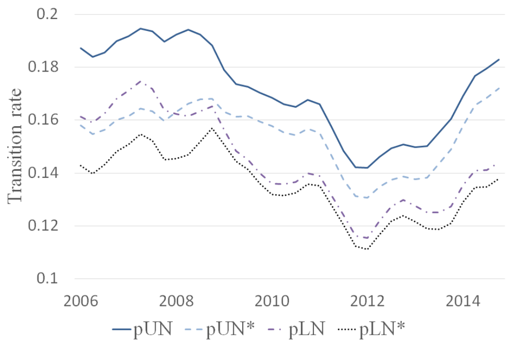
in November 2008, the age limit of the youngest child for lone parents to be eligible for Income Support was lowered to twelve for all new claimants. Out-of work parents would have had to claim JSA instead and actively look for work.[4] Panel (a) of Figure B.4 demonstrates the effect of these policy changes, using administrative data, through the immediate downward shift concurrently in the share of all off-flows from JSA to either Income Support, incapacity benefits or some other benefit, for both all claimants and those claiming for over twelve months.[5] The majority of the fall is in off-flows to Incapacity Benefit. Although many of these claimants may have eventually moved to ESA, this is not recorded. To assess whether this could have affected the estimated cyclical behaviour of transition rates, I imagine a counterfactual whereby all JSA off-flows to other benefits are simply subtracted from the actual number of observed UN and LN gross flows, not accounting for the introduction of the replacement ESA. Panel (b) of Figure B.4 compares actual transition rates with imagined ones which negate these JSA off-flows, p_{UN^*} and p_{LN^*}. The policy changes could account for a not insignificant amount of the cumulative decline in exit rates from 2008, but the cyclical pattern remains. Given that this represents the absolute upper limit of any potential policy effects occurring concurrently, the actual effect is likely to have been much smaller.

FIGURE B.4: Share of JSA off-flows to inactive benefits and an estimate of the maximum potential policy impacts on estimated flows series p_{UN} and p_{LN}

(a) JSA off-flow shares



(b) Imagined counterfactual



Notes.- author calculations using Two Quarter Labour Force Survey, ages 16-64/59, 1997q2 - 2015q2, and NOMIS, ONS off-flows series from Jobseeker's Allowance - using raw transition rates.

[4]The age limit was gradually lowered for existing claimants, starting the following year, to five by October 2011.

[5]Off-flows series accessed from NOMIS, ONS, 10/02/2016. Although these administrative flows data are detailed in terms of the destinations following and reasons for a claim ending, they are incomplete in so far as the destination of some claimants is unknown, and the rate at which claimants complete exit questionnaires is not constant over time, having reduced in recent years.

Appendix C

Recent changes in British wage inequality: evidence from firms and occupations

Appendix C.1 Further description of the data and sample construction

In what follows we give some additional details regarding the datasets used, and how we have constructed the sub-samples thereof. All the relevant documentation and variable descriptions attached to these datasets are publicly available from the UK Data Service. The ONS has also published various documents concerning the data quality and consistency of the NESPD and ASHE. We will publish our replication files for the analysis and sample construction.

We focus on methodological details through the period 1996-2015. From 1975 to 2003, under its guise as the NESPD, very little changed in the methodology and construction of the longitudinal panel dataset. Throughout this period, it should be a true random sample of all employees in employment, irrespective of employment type, occupation, size of employer etc. Given the legal obligation of employers to respond, and their use of payrolls, it has a very high response rate and is believed to be accurate. There is also no cumulative attrition from the panel, as any individual not included in the NESPD in any year, for whatever reason, remains in the sampling frame the following year. Conditional on a hundred percent response, the NESPD would be a true one percent random sample of employees. However there are two major sources of undersampling, both occurring if individuals do not have a current tax record. This could occur for some individuals who have recently moved job, or for those who earn very little (mostly part-time), and so do not have to pay tax or National Insurance. From 2004 the ASHE replaced the NESPD. This aimed to sample some of those employees under-represented in the NESPD. It added supplementary responses for those without a PAYE reference, and also attempted to represent employees whose jobs changed between the determination of the sampling frame in January and the reference period in April. Since the ONS states that the bias these amendments were introduced to address were actually small, we do not believe they could affect our results substantially. The ASHE also introduced some imputations, using similar matched ‘donor’ observations where responses were, for example, missing an entry of basic hours but had recorded pay. These imputations were added for weighting purposes. We ignore these weights throughout our analysis because they are based only on employee data (age, sex, occupation and region of work place) to match population estimates obtained form the Labour Force Survey. Therefore using them would no longer allow us to claim that the ASHE and our results are based on random samples of employees within firms. From 2005, a new questionnaire was also created which was intended to reduce the latitude for respondents’ own interpretations of what was being asked of them. From 2007 there were further notable changes. Beforehand, occupations were classified as follows: either, if the respondent stated an employee’s job had not changed in the past year, the previous year’s occupational classification was applied. Otherwise, it was manually coded. Afterwards an automatic coding, text recognition, tool was used. “The effect of using ACTR was to code more jobs into higher paying occupations. The jobs that tended to be recoded into these higher paying occupations generally had lower levels of pay than the jobs already coded to those occupations. Conversely, they tended to have higher levels of pay than the other jobs in the occupations that they were recoded out of. The impact of this was to lower the average pay of both the occupation group that they had moved from and that they had moved to.” As such, this would certainly increase within occupation wage inequality for the highest earners, and reduce it for the lowest earners. Nonetheless, we do not believe this is significant in affecting our results. In the main text, we focus the graphical analysis on changes across the period 1997-2007, but also find our results are unchanged for the periods 1996-2006 and 1996-2001. From 2007, the sample size of the ASHE was reduced by twenty percent, with reductions targeted on those industries that exhibit the least variation in their earnings patterns. However, we do not believe this could have affected our results substantially.

To construct the sub-samples from the panel dataset for 1975-2015, for the analysis of hourly or weekly pay, we first drop a few cases of duplicates over all variables. Then, using the panel identifier, year, the information from the IDBR concerning enterprise status and number of employees, industry classification and gross weekly pay including overtime, we also drop some cases which are then determined to be the same job. We do not drop observations where an individual has multiple jobs. We keep only observations for individuals aged 16-64, and which have not been marked as having a loss of pay in the reference period through absence, employment starting in the period, or short-time working, and which are marked as being on an adult rate of pay (i.e. dropping trainees and apprenticeships). This is practically the same filter applied for ONS published results using the NESPD or ASHE. We also drop all observations with zero or missing values for basic hours, and hourly or weekly pay excluding overtime. Basic hours are intended to be a record for the employee in a normal week, excluding overtime and meal breaks. Gross weekly pay is the main recorded value in the survey, and from this overtime records are then simply subtracted. Hourly rates are then derived from dividing by basic hours worked. We drop observations with over a hundred basic hours worked, as these could reflect measurement error and inclusion of overtime. Full-time is defined as working over thirty basic hours in a week. But there are a tiny number of discrepancies in some years, we believe relating to teaching contracts, where the definition applied by the ONS differs. We however recode these such that for all observations the thirty hours threshold applies. To further address some potential for measurement error, especially in the recorded basic hours, we drop observations whose hourly rate of pay excluding overtime is less than eighty percent of the National Minimum Wage (NMW) which applies each April, with allowance for the different age-dependent rates of the NMW over time. We set the threshold lower to avoid dropping observations where employers have rounded figures about the NMW, where the degree of rounding could vary with the actual value of the NMW, a behaviour which has been hypothesised by the ONS. To then construct the large firms sample, we drop all employers whose exact enterprise reference number of employees from the IDBR, which is only available from 1996 onwards, is less than 250. We also drop observations where the IDBR status, number of employees or industry classification is missing. We then identify each employer in the dataset using the combination of their 5-digit industry code, IDBR status and exact number of IDBR enterprise employees, within each year. For large firms we are confident this can uniquely identify the reporting organisation of the NESPD. The large firms samples we subsequently analyse then condition on there being a minimum number of remaining job observations per firm in a year. For annual pay, we construct the large firms samples in the same way, except we additionally filter out observations where the employee is reported to not have been in the same job for twelve months, and drop observations with zero or missing values of annual gross pay in place of hours or weekly pay. When handling the ASHE annual cross-section datasets we use the exact same approach, except here there is a unique enterprise level identifier which we can use to identify the firms within each year.

For 1996-2001 occupations are classified using the 3-digit ONS 1990 Standard Occupational Classification (SOC). For 2002-2010, this is replaced with the 4-digit SOC 2000, and for 2011-2015, with the SOC 2010. We experimented using the ONS' publicly available cross-walk from 2010 and 2000 to 1990 classification, but discovered that this causes a large structural break in the distribution of occupations. In particular, it causes a substantial additional degree of polarisation of work from 2002 onwards, which would potentially generate erroneous and large increases in within occupation inequality around this date. To address this we rely on a conversion of SOC 1990 and 2000 to the 1988 International Standard Classification of Occupations (ISCO). We obtain these conversions from the Cambridge Social Interaction and Stratification Scale (CAMSIS) project. For the industry classification, we convert ONS Standard Industrial Classification (SIC) 2007 to 2003, using files made available by the UK Data Service. This conversion uses the 2008 Annual Respondents Dataset where both classifications were applied, and where any 2007 code mapping to multiple 2003 codes is decided using whichever of the two bore a greater share of economic output. For 1996-2002, the work region of the employee is missing, and so we derive this ourselves consistent with the ONS geo-maps, using the more detailed work area variable.

TABLE C.1: Comparison of baseline sample firm size distribution, and represented employees, with UK population of enterprises, 2013

	Number of obs.		Total employees in enterprises (000s)†	
Enterprise size†	Sample firms‡	UK enterprises	Sample firms	UK enterprises
250 - 999	92	6,400	69	2,927
1,000 - 1,999	308	1,050	469	1,455
2,000 - 4,999	644	830	2,098	2,612
5,000+	596	635	8,204	8,805
Total	1,640	8,915	10,804	15,799

† Values for sample firms use the IDBR record of the number of employees in the enterprise, which includes the firm. This is not the number of observations of employee jobs in the sample.
‡ All firms in the baseline sample with a minimum of ten full-time employee observations in the NESPD in 2013, and subject to the other sampling criteria described in the text.
Notes.- author calculations using the NESPD. UK enterprises population figures from UK Business: Activity, Size and Location (IDBR, March 2015).

TABLE C.2: Baseline sample number of firm and employee observations by employer size, 1997 & 2007

	Firms			Employees			IDBR ent. employees (000s)†		
Enterprise size†	1997	2007	Change in share	1997	2007	Change in share	1997	2007	Change in share
250 - 999	125	43	-0.05	1,729	497	-0.03	89	32	0.00
1,000 - 1,999	352	214	-0.08	5,322	2,814	-0.06	539	328	-0.02
2,000 - 4,999	512	548	0.05	10,068	9,789	-0.03	1,612	1,817	0.03
5,000+	485	569	0.09	26,915	36,242	0.12	9,431	8,350	-0.01
Total	1,474	1,374		44,034	49,342		11,671	10,525	

† Values use the IDBR record of the number of employees in the enterprise, which includes the firm.
Notes.- author calculations using the NESPD.

TABLE C.3: Baseline sample incidence of ISCO88 major occupation groups

Major group†	1997	2007	Change
1	0.12	0.15	-0.02
2	0.22	0.16	0.06
3	0.09	0.14	-0.05
4	0.24	0.20	0.03
5	0.11	0.14	-0.03
6 & 7	0.08	0.04	0.04
8	0.08	0.05	0.03
9	0.05	0.11	-0.06

† Key: 1. Legislators, senior officials and managers, 2. Professionals, 3. Technicians and associate professionals, 4. Clerks, 5. Service workers and shop and market sales workers, 6. Skilled agricultural and fishery workers, 7. Craft and related trades workers, 8. Plant and machine operators and assemblers, 9. Elementary occupations.
Notes.- author calculations using the NESPD.

Appendix C.2 Mathematical details

C.2.1 Variance decomposition - hours and wages

From the main text, we can re-write (4.1), the total variance of log weekly wages as follows, where ω and η denote the hourly non-log wage rate and hours worked respectively, θ denotes the log hourly wage rate, and h denotes log hours. Recalling from the main text that i denotes a worker and j a firm, terms with a bar above refer to average values within the given subscript. For example, $\overline{h_j}$ refers to the sample mean of log weekly hours worked for the employees within firm j. Terms without a subscript but a bar above refer to averages in the whole sample, across all employees and firms.

$$\underbrace{\frac{1}{N}\sum_{j}^{J}\sum_{i}^{N_j}\left[\ln(\omega_{ij}\eta_{ij})-\overline{\ln(\omega_{ij}\eta_{ij})}\right]^2}_{\text{Overall - }V_e}=\underbrace{\frac{1}{N}\sum_{j}^{J}\sum_{i}^{N_j}\left[\ln(\omega_{ij}\eta_{ij})-\overline{\ln(\omega_{j}\eta_{j})}\right]^2}_{\text{Within-firm - }V_{wf}}$$
$$+\underbrace{\sum_{j}^{J}\frac{N_j}{N}\left[\overline{\ln(\omega_{j}\eta_{j})}-\overline{\ln(\omega\eta)}\right]^2}_{\text{Between-firm - }V_{bf}}, \quad \text{(C.1)}$$

with

$$V_{wf}=\underbrace{\frac{1}{N}\sum_{j}^{J}\sum_{i}^{N_j}\left[\theta_{ij}-\overline{\theta_j}\right]^2}_{V_{wf}^{\theta}}+\underbrace{\frac{1}{N}\sum_{j}^{J}\sum_{i}^{N_j}\left[h_{ij}-\overline{h_j}\right]^2}_{V_{wf}^{h}}+\underbrace{\frac{2}{N^2}\sum_{j}^{J}\sum_{i}^{N_j}\left[\left(\theta_{ij}-\overline{\theta_j}\right)\left(h_{ij}-\overline{h_j}\right)\right]}_{2cov_{wf}(\theta,h)} \quad \text{(C.2)}$$

and

$$V_{bf}=\underbrace{\sum_{j}^{J}\frac{N_j}{N}\left[\overline{\theta_j}-\overline{\theta}\right]^2}_{V_{bf}^{\theta}}+\underbrace{\sum_{j}^{J}\frac{N_j}{N}\left[\overline{h_j}-\overline{h}\right]^2}_{V_{bf}^{h}}+\underbrace{2\sum_{j}^{J}\frac{N_j}{N^2}\left[\left(\overline{\theta_j}-\overline{\theta}\right)\left(\overline{h_j}-\overline{h}\right)\right]}_{2cov_{bf}(\theta,h)}. \quad \text{(C.3)}$$

C.2.2 Shift-share analysis of the change in the firm component of employee wages

Let each decile be denoted by d, where N^d is all employees observed in a period in that decile of the unobservable wage distribution. Let k denote an employment type, with K types in total. The share of all employees, irrespective of decile, in type k in the firm of an employee i is given by λ_{ki}, where the dependence of k on i is implicit. The mean log weekly wage of type k in the firm of employee i is given by $\hat{\psi}_{ki}$. We let this value be zero where a firm does not employ anybody of type k. Taking the estimated firm-specific component of the log wage $\hat{\alpha}_j$, we can write the mean of these values for employees within a decile of the distribution of estimated unobservable wages $\hat{\psi}_{ij}$ as

$$\begin{aligned}\frac{1}{N^d}\sum_{i\in d}^{N^d}\{\hat{\alpha}_j\}_i &= \frac{1}{N^d}\sum_{k}^{K}\sum_{i\in d}^{N^d}\lambda_{ki}\hat{\psi}_{ki} \\ &= \sum_{k}^{K}\left[\underbrace{\left(\frac{1}{N^d}\sum_{i\in d}^{N^d}\lambda_{ki}\right)}_{\overline{\lambda}_k}\underbrace{\left(\frac{1}{N^d}\sum_{i\in d}^{N^d}\hat{\psi}_{ki}\right)}_{\overline{\hat{\psi}}_k}+\underbrace{\frac{1}{N^d}\sum_{i\in d}^{N^d}\left(\lambda_{ki}-\overline{\lambda}_k\right)\left(\hat{\psi}_{ki}-\overline{\hat{\psi}}_k\right)}_{cov(\lambda_k,\hat{\psi}_k)}\right].\end{aligned} \tag{C.4}$$

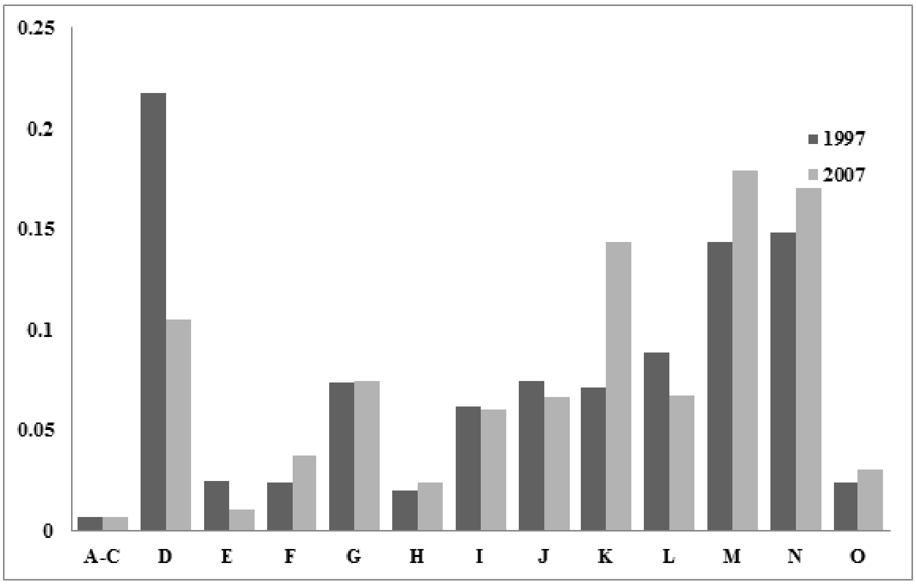
Using (C.4), denoting historical values by $'$, and representing the difference operator by Δ, we can write the change over time (between two years) in the mean of firm-specific log wages for employees in some decile as

$$\sum_{k}^{K}\left[\underbrace{\overline{\lambda}'_k\Delta\overline{\hat{\psi}}_k}_{\text{Wages effect}} + \underbrace{\overline{\hat{\psi}}'_k\Delta\overline{\lambda}_k}_{\text{Shares effect}} + \underbrace{\Delta\overline{\lambda}_k\Delta\overline{\hat{\psi}}_k}_{\text{Interaction effect}} + \underbrace{\Delta cov(\lambda_k,\hat{\psi}_k)}_{\text{Covar. effect}}\right]. \tag{C.5}$$

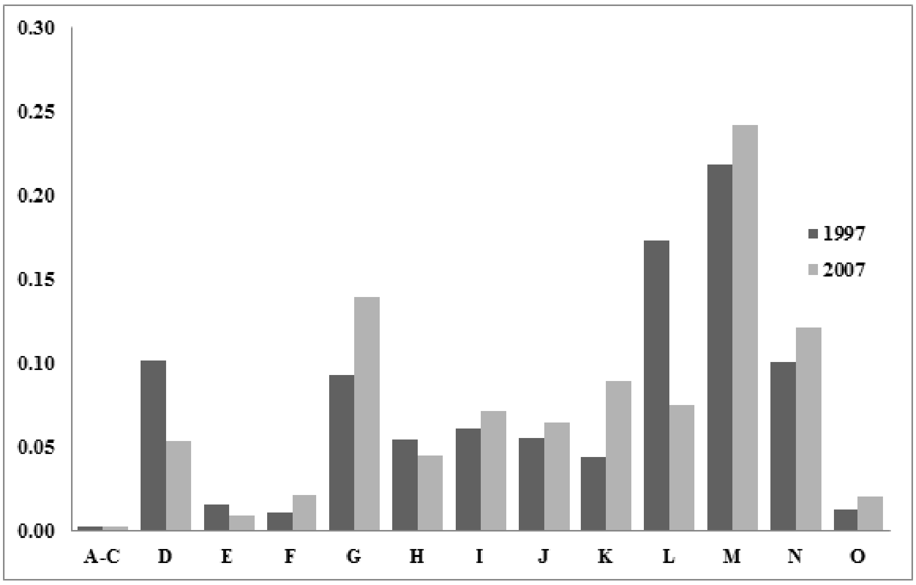
Appendix C.3 Additional figures

FIGURE C.1: Shares of firms and employees in the baseline sample in SIC 2003 sectors, 1997 & 2007

(a) Firms

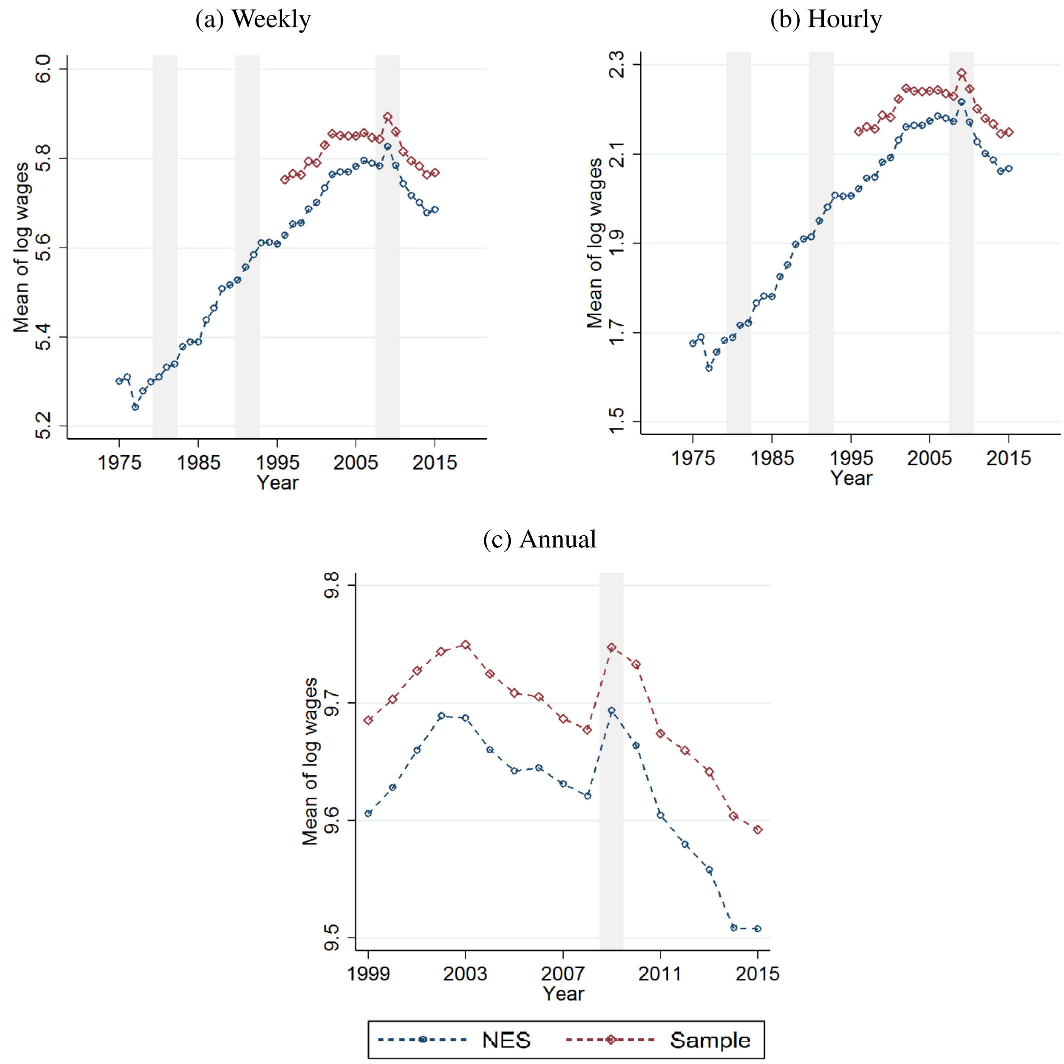


(b) Employees



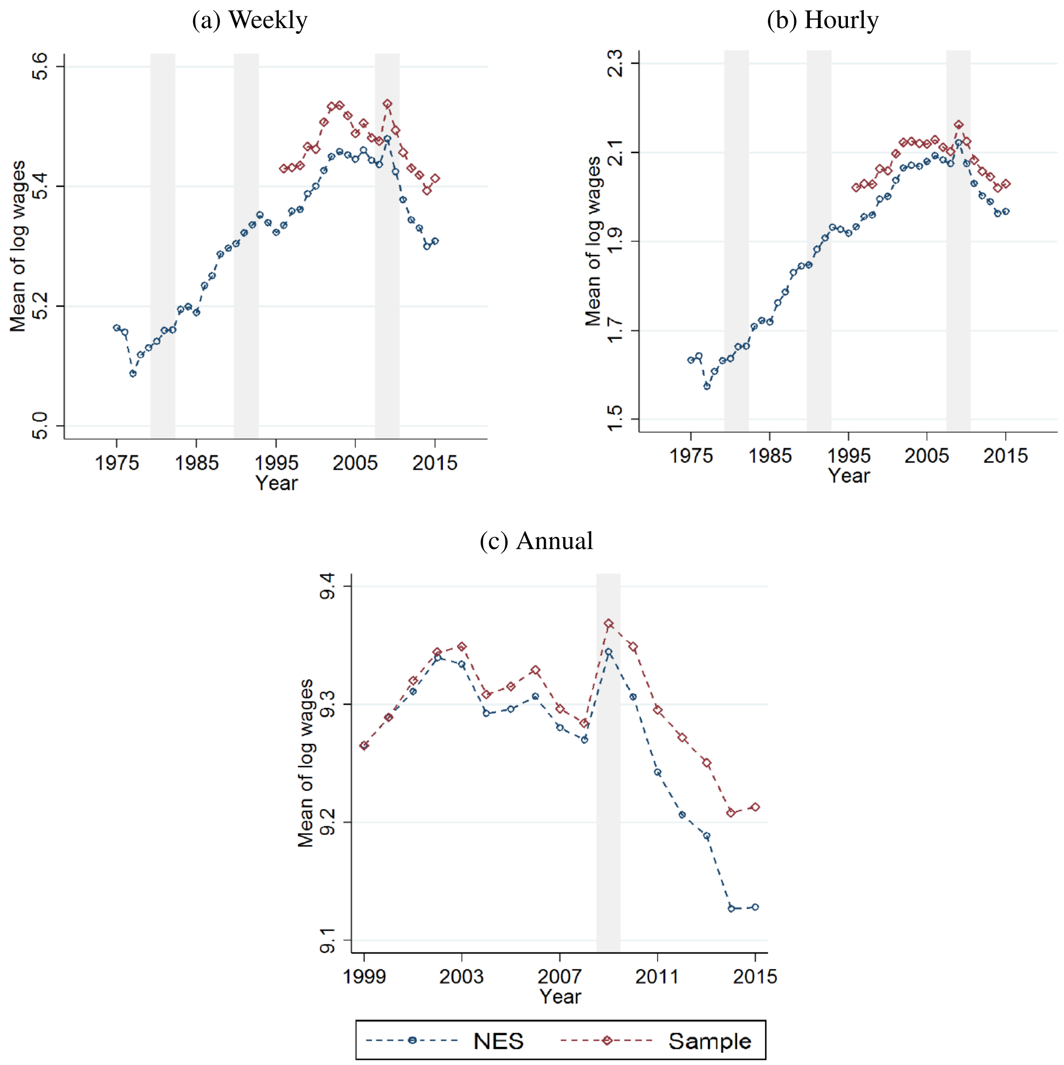
Notes.- author calculations using New Earnings Survey. See the text for description of the sample. SIC2003 codes: A. Agriculture, hunting and forestry; B. Fishing, C. Mining and quarrying, D. Manufacturing, E. Utilities, F. Construction, G. Wholesale and retail, H. Hotels and restaurant, I. Transport and telecommunication, J. Financial intermediation, K. Real estate, business services, L. Public admin and defence, social security, M. Education, N. Health and social work, O. Other comunnity and social services.

FIGURE C.2: Mean of real log wages in large firms, full-time employees only, and comparison the with the whole NESPD sample, 1975-2015



Notes.- see Figure 4.1. The top one percent of wage observations in any year are excluded from all calculations here.

FIGURE C.3: Mean of real log wages in large firms, all employees, and comparison with the whole NESPD sample, 1975-2015



Notes.- see Figure 4.1, except here is with all employees. The top one percent of wage observations in any year are excluded from all calculations here.

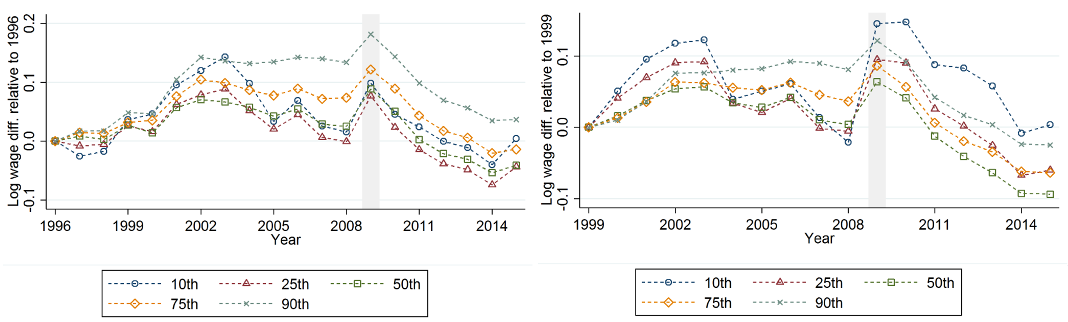
FIGURE C.4: Percentiles of real log wages in large firms, all employees, and comparison with the whole NESPD sample, 1975-2015

(a) Weekly (b) Annual

Notes.- see Figure 4.1, except here is with all employees. Dashed lines without markers are the series for the large firms sample of the NESPD.

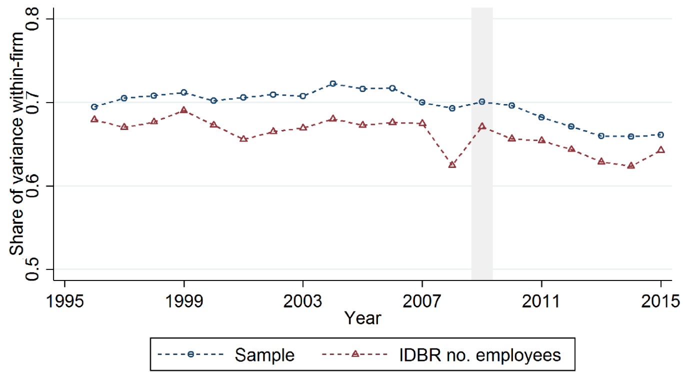
FIGURE C.5: Percentiles of real log wages in large firms, all employees: differences relative to 1996/9

(a) Weekly (b) Annual



Notes.- see Figure 4.2, except here is with all employees.

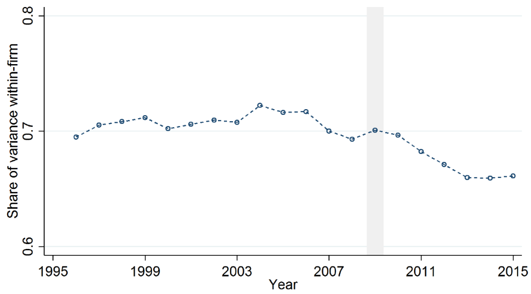
FIGURE C.6: Share of variance in log weekly employee wages from within-firm component, 1996-2015: comparison of firm weights



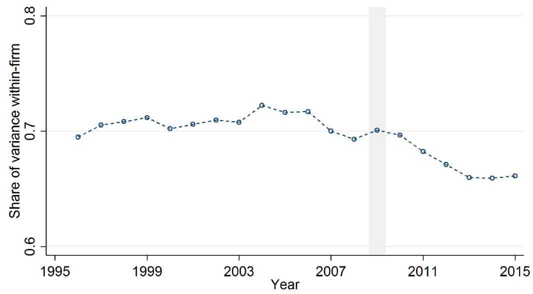
Notes.- see Figure 4.3. 'Sample' gives results where firms are weighted using their share of sample observations in that year. 'IDBR...' gives results where firms are weighted using their administrative record of enterprise size from the IDBR.

FIGURE C.7: Share of variance in log weekly employee wages from within-firm component

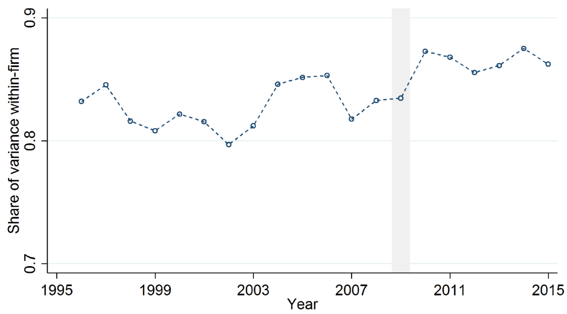
(a) All firms



(b) Private sector excl. wholesale, retail, hotels, restaurants etc.



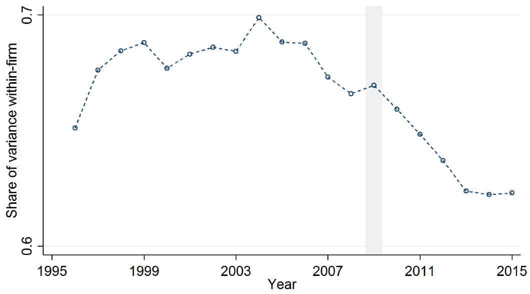
(c) Public sector only



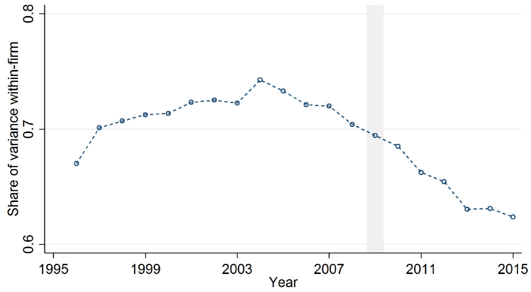
Notes.- see Figure 4.3. Panel (b) excludes major SIC 2003 sectors G & H. Public sector is represented by public corporation or nationalised industry, central government and local authority employers.

FIGURE C.8: Share of variance in log hourly employee wages from within-firm component

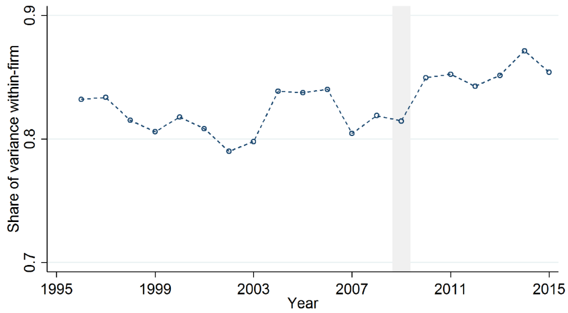
(a) All firms



(b) Private sector excl. wholesale, retail, hotels, restaurants etc.



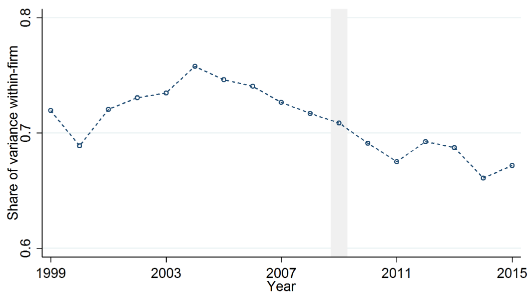
(c) Public sector only



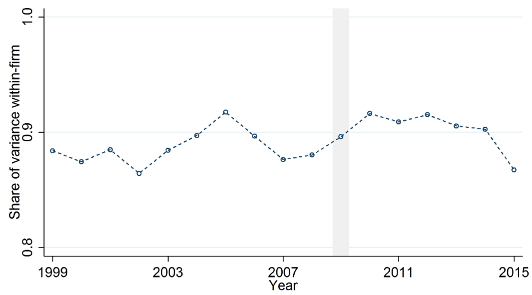
Notes.- see Figure C.7

FIGURE C.9: Share of variance in log annual employee wages from within-firm component

(a) All firms

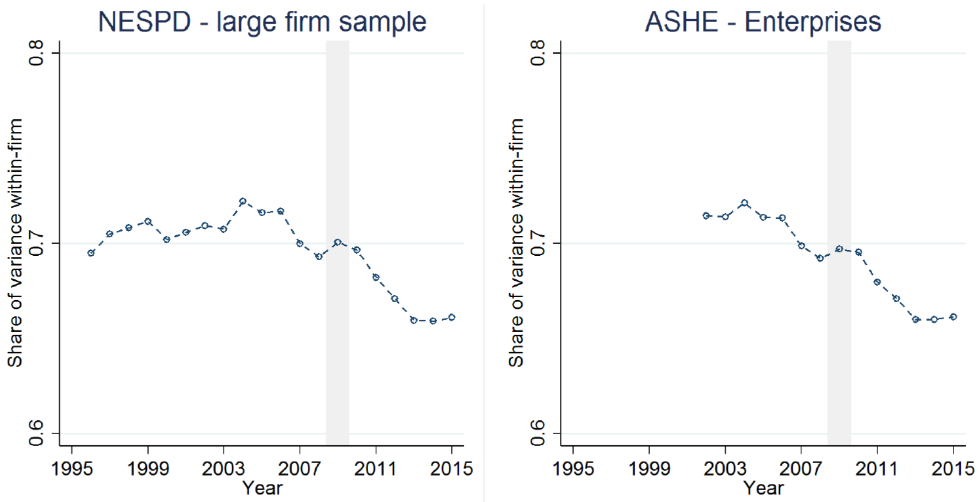


(b) Public sector only



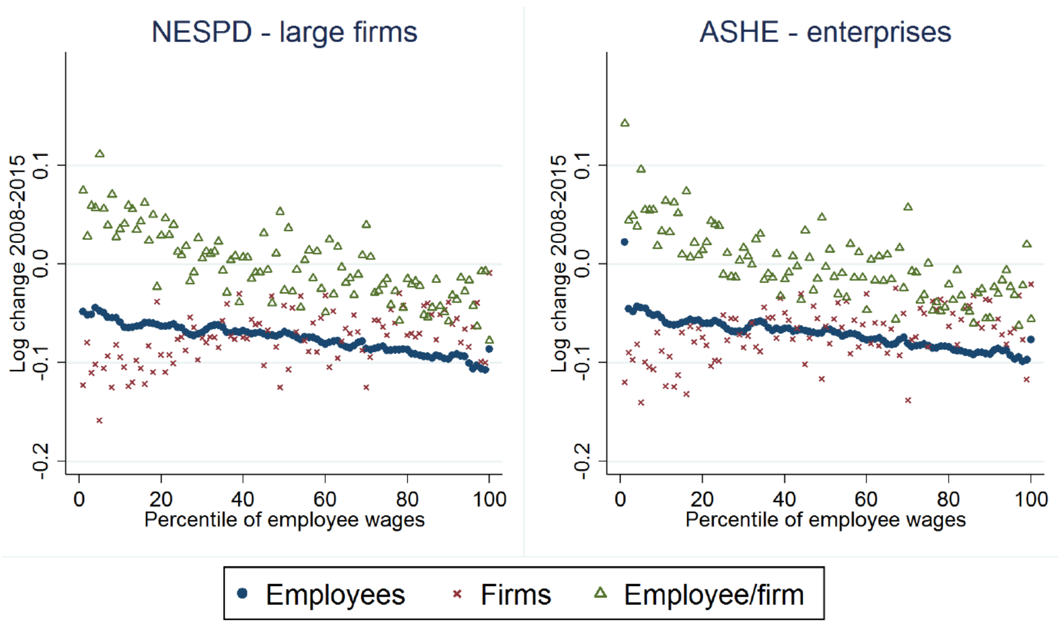
Notes.- see Figure 4.3 and see Figure C.7.

FIGURE C.10: Share of variance in log weekly employee wages from within-firm component: NESPD large firms sample vs ASHE enterprises



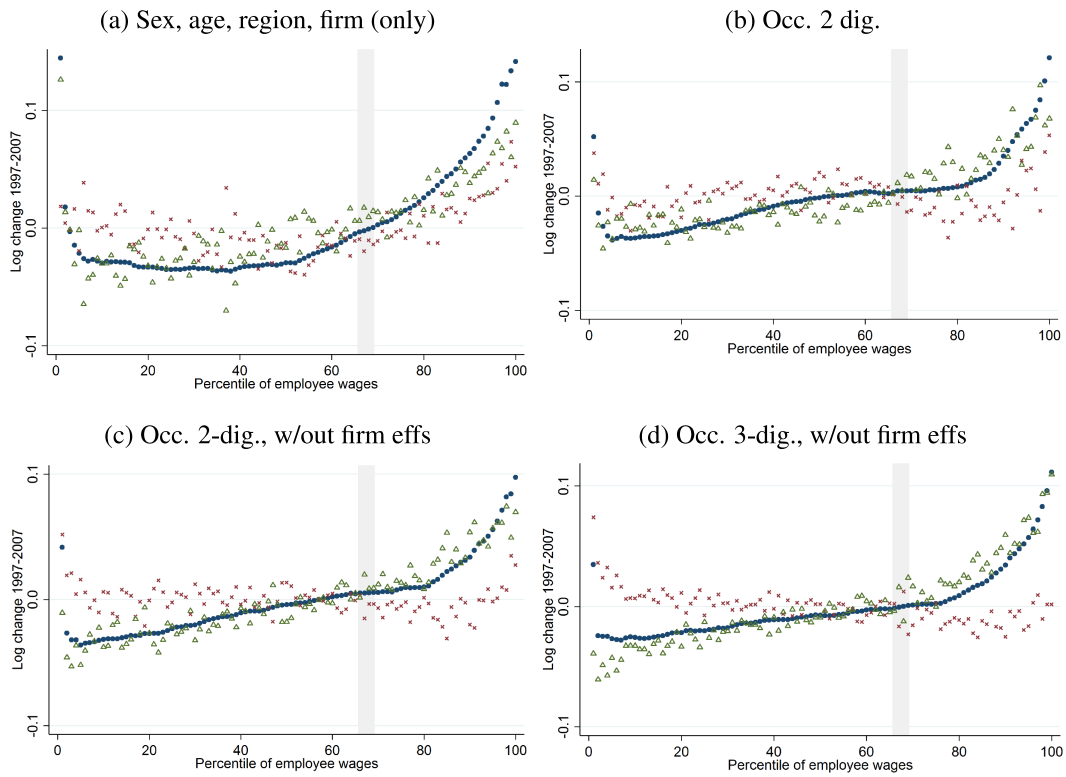
Notes.- author calculations using the New Earnings Survey and Annual Survey of Hours and Earnings, age 16-64 only, all employees. Weekly wages exclude overtime. In the left panel the data is for all large firms in the NESPD who have at least ten employee observations in a year. The right panel is the equivalent but using IDBR enterprise identifiers in the ASHE, instead of a broader definition of a 'firm'. Shaded areas represent official UK recessions.

FIGURE C.11: Change 2008-2015 in the average real log weekly wage by percentile of employees and the contribution from firms: NESPD large firms sample vs ASHE large enterprises



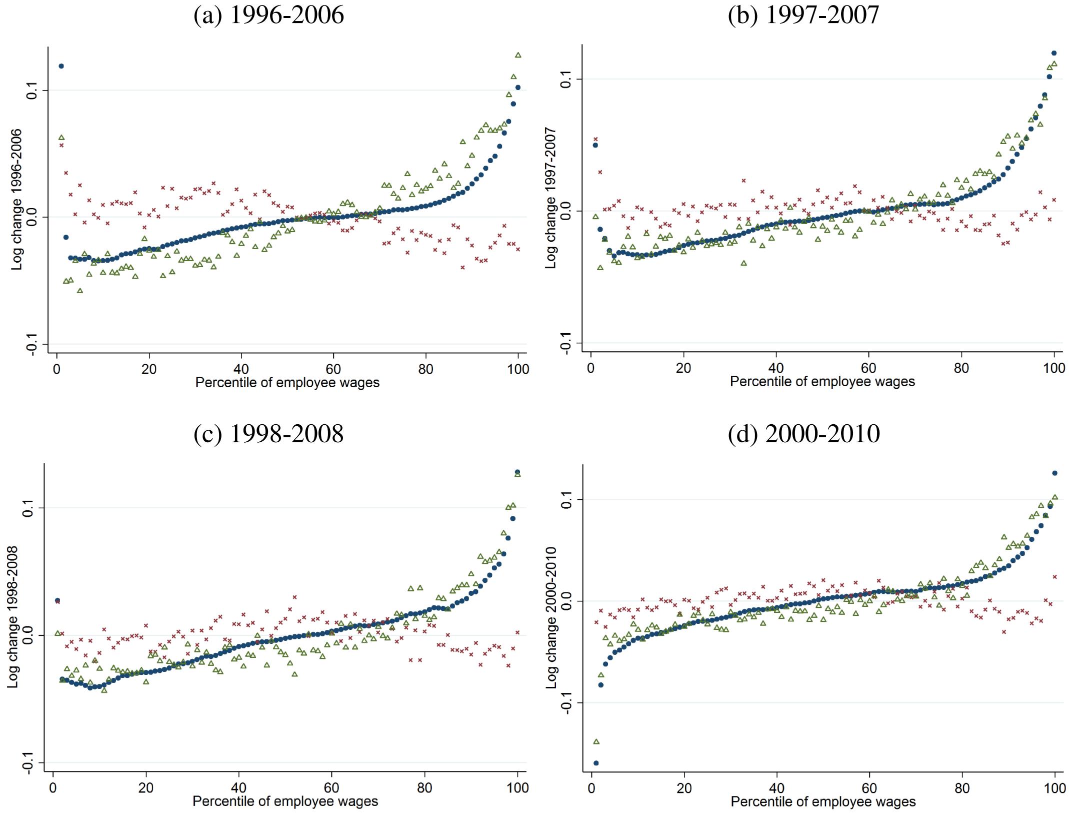
Notes.- see Figure 4.7 and Figure C.10: for NESPD $\gamma = 1.87$, for ASHE $\gamma = 1.72$

FIGURE C.12: Change 1997-2007 in the average real unobservable log weekly wage by percentile of employees and the contribution from firms



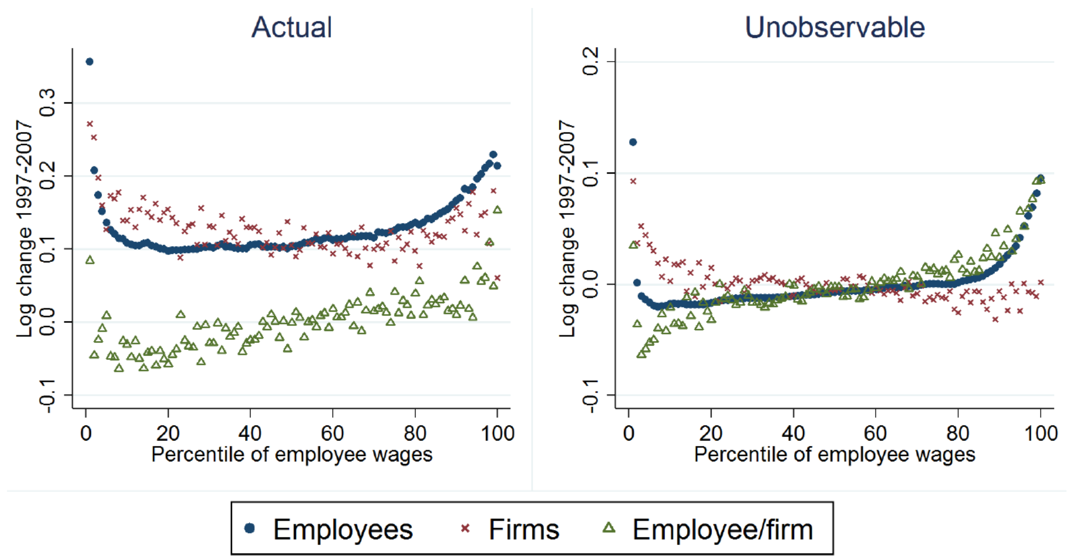
Notes.- see Figure 4.7. Unobservable log wages are estimated using a regression with controls for sex, age, age squared, major regions and firm fixed effects, in addition to those labelled above each panel. (a): $\gamma = 0.67$. (b): $\gamma = 0.81$. (c): $\gamma = 0.96$. (d): $\gamma = 1.14$.

FIGURE C.13: Change in the average real unobservable log weekly wage by percentile of employees and the contribution from firms: other ten year time periods



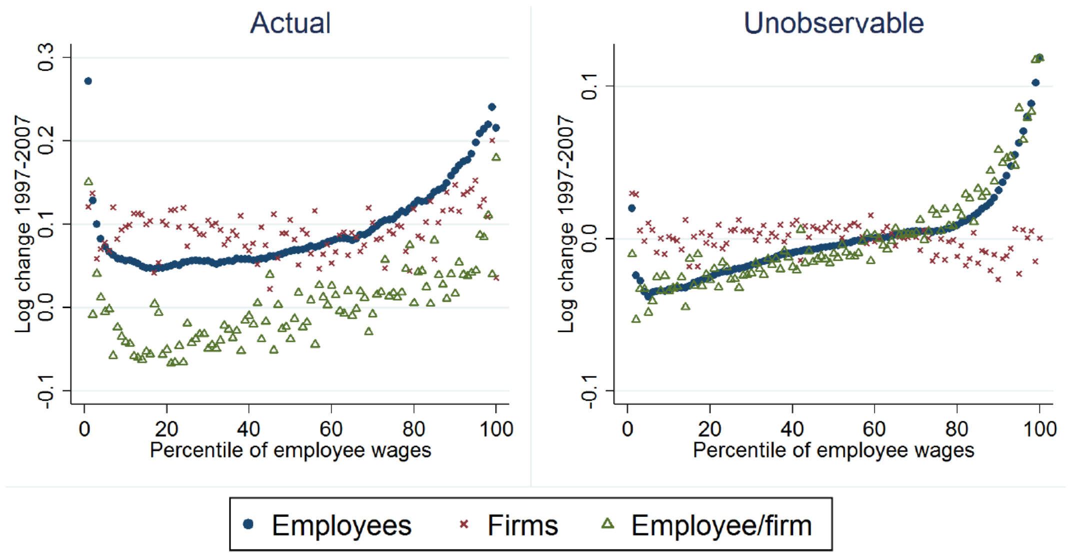
Notes.- see Figure 4.7 and Figure 4.9. (a): $\gamma = 1.30$. (b): $\gamma = 1.00$. (c): $\gamma = 1.03$. (d): $\gamma = 0.96$.

FIGURE C.14: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms: all large firms in the NESPD with 1+ employee observations



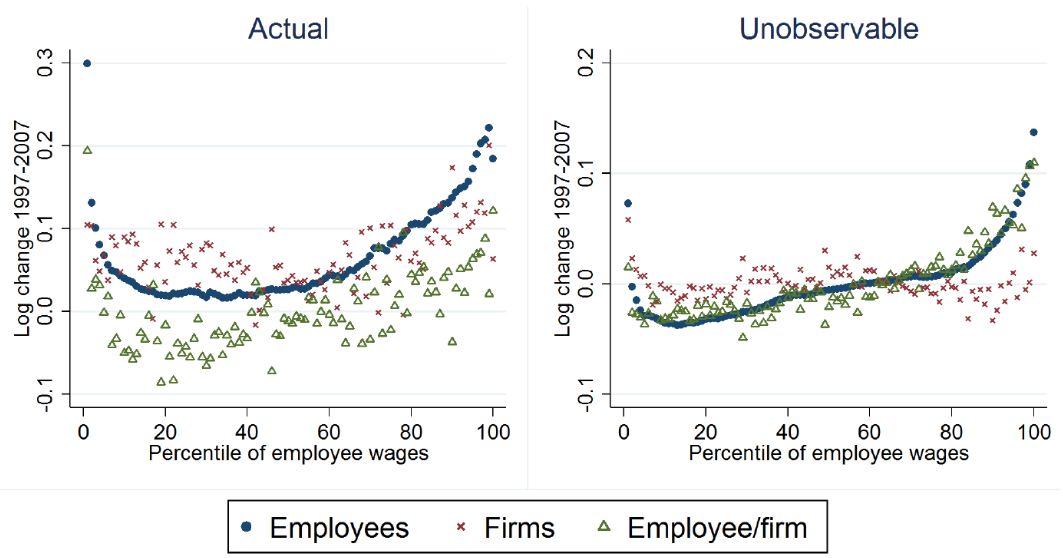
Notes.- see Figure 4.7 and Figure 4.9. The data used here is for all large firms who have at least one employee observation in the NESPD in a year. (a): $\gamma = 0.61$. (b): $\gamma = 0.98$.

FIGURE C.15: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms: all large firms in the NESPD with 5+ employee observations



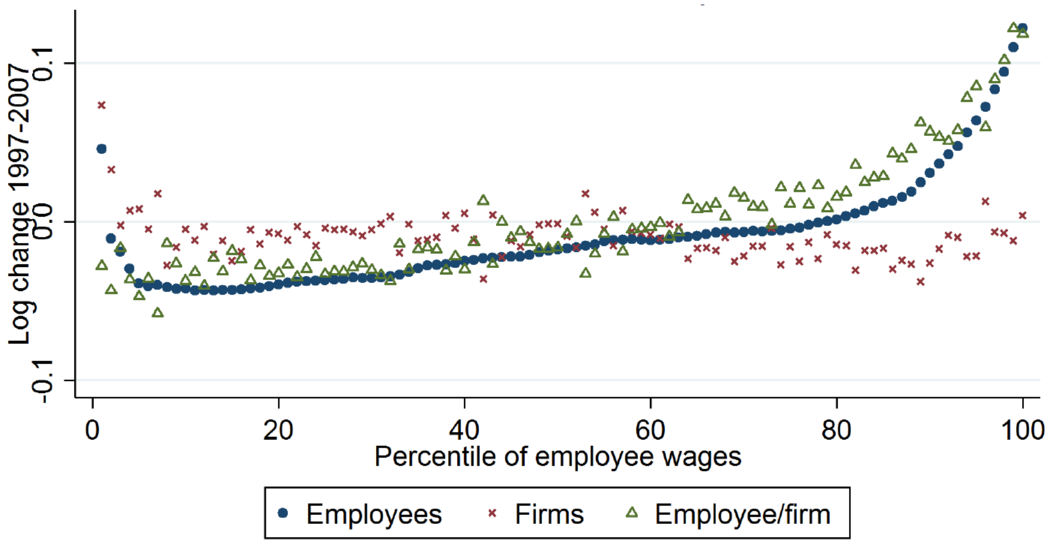
Notes.- see Figure C.14, except the data used here are for all large firms who have at least five employee observations in the NESPD in a year. (a): $\gamma = 0.75$. (b): $\gamma = 1.08$.

FIGURE C.16: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms: all large firms in the NESPD with 20+ employee observations



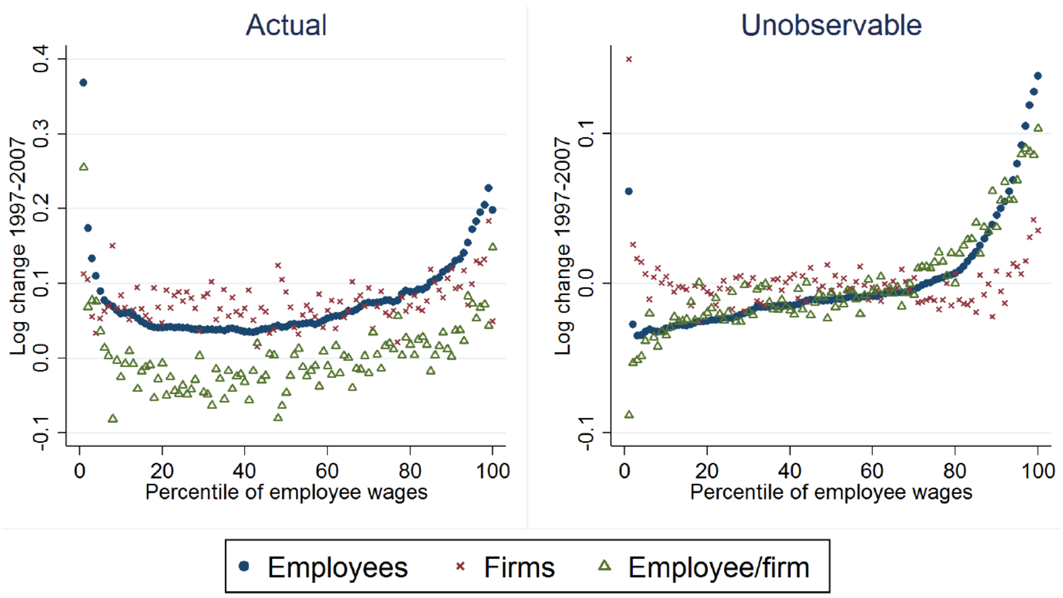
Notes.- see Figure C.14, except the data used here are for all large firms who have at least twenty employee observations in the NESPD in a year. (a): $\gamma = 0.61$. (b): $\gamma = 0.93$.

FIGURE C.17: Change 1997-2007 in the average real unobservable log weekly wage by percentile of employees and the contribution from firms: private sector only



Notes.- see Figure 4.7 and Figure 4.9, except the data used here is for all large private sector firms in the NESPD who have at least ten full-time employee observations in a year. $\gamma = 1.00$.

FIGURE C.18: Change 1997-2007 in the average real log hourly wage by percentile of employees and the contribution from firms: comparison with unobservable wages



Notes.- see Figure 4.7 and Figure 4.9. (a): $\gamma = 0.75$. (b): $\gamma = 0.80$.

FIGURE C.19: Change 1997-2007 in the average real log annual wage by percentile of employees and the contribution from firms: comparison with unobservable wages

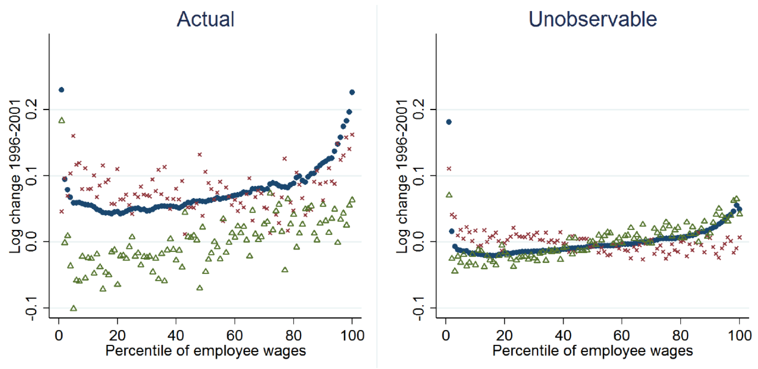
Notes.- see Figure 4.7 and Figure 4.9, except the data used here is for all large firms who have at least ten employee observations in the NESPD in a year, who have been with the firm at least a year. (a): $\gamma = 0.75$. (b): $\gamma = 0.77$.

FIGURE C.20: Change 1997-2007 in the average real log weekly wage by percentile of employees and the contribution from firms, full & part-time workers: comparison with unobservable wages

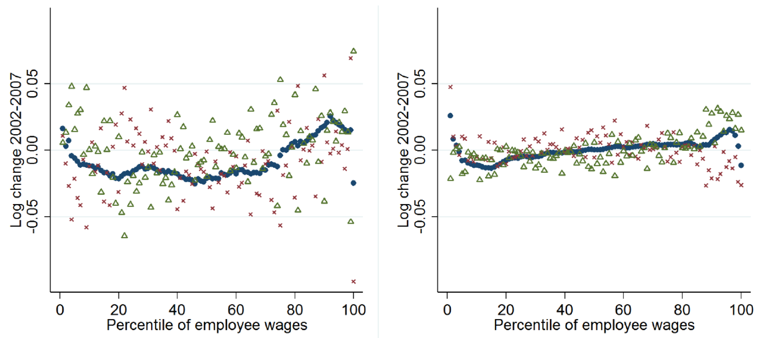
Notes.- see Figure 4.7 and Figure 4.9, except here the data is for all employees, not full-time only. (a): $\gamma = 0.52$. (b): $\gamma = 1.25$.

FIGURE C.21: Change in the average real unobservable log weekly wage by percentile of employees and the contribution from firms: other five year time periods

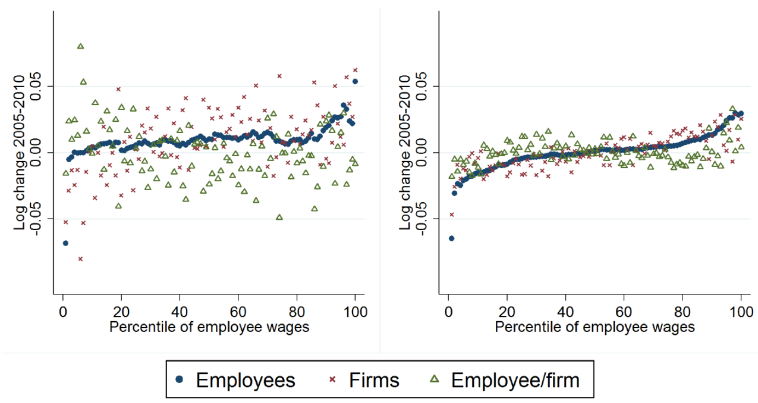
(a) 1996-2001



(b) 2002-2007



(c) 2005-2010



Notes.- see Figure 4.7 and Figure 4.9. (a1): $\gamma = 0.73$. (a2): $\gamma = 0.77$. (b1): $\gamma = 0.45$. (b2): $\gamma = 0.82$. (c1): $\gamma = -0.14$. (c2): $\gamma = 0.27$.

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