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Chapters in this compendium

1. Overeducation and hourly wages in the UK labour market; 2006 to 2017
2. Analysis of job changers and stayers
3. Contributions to earnings growth in the UK: 2018
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Compendium

Overeducation and hourly wages in the UK labour market; 2006 to 2017

This article examines overeducation in the UK labour market using Annual Population Survey (APS), for 2006 to 2017 including analysis on the relationship between overeducation and wages.

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1 . Main points

- In 2017, around 16% of all those in employment aged 16 to 64 years were overeducated (had more education than required for their job); the corresponding figure for graduates (with first degree or equivalent) was around 31%.

- In 2017, 21.7% of those who graduated before 1992 were overeducated, whereas the corresponding figure for those who graduated in 2007 or later was 34.2%.

- There is a wage penalty associated with overeducation, although overeducated employees earn positive return on wages, this is significantly lower compared with those who are matched to their jobs.

- In 2017, the overeducation rate was similar for women and for men, however the wage penalty for overeducation was somewhat higher for men than for women; this suggests that overeducation does not contribute to gender pay gap.

- Recent graduates experience lower pay penalty on overeducation compared with non-recent graduates.

2 . Introduction

This article examines overeducation in the UK labour market using Annual Population Survey (APS), for 2006 to 2017. Overeducation is a form of mismatch where a person can be overeducated if they possess more education than required for the job. Overeducation is a form of resource underutilisation, which may have implications for the individual, firm and the economy. It can also be seen as a form of underemployment, hence contributing to the extent of labour market slack.

The existence of overeducation has been explained by drawing emphasis on the role of human capital. This means that workers may substitute education for the lack of previous work experience, accepting jobs requiring less education than they possess, until they acquire further experience.

This explanation is consistent with the career mobility argument, whereby individuals may forgo higher wages in the early stage of their careers, only to experience upward income mobility later in their careers. Both the human capital and career mobility explanations perceive overeducation as a temporary situation, which is likely to cease once the worker has gained sufficient experience.

An alternative explanation for the existence of overeducation, put forward by the dynamic labour market view, relates to the presence of information asymmetries which may cause search frictions. In other words, and according to dynamic labour markets view there will always be some degree of mismatch between education achievement and job requirements due to incomplete information which prevents efficient matches between educated workers and employees. Some peoples' education will exceed requirements and they will be overeducated (underemployed), others will be in the opposite situation.

Overeducation may also arise in the context of labour market distortions if the supply of graduates exceeds the demand and crowds out job opportunities for the less educated. Employers may prefer hiring graduates as this is likely to reduce training costs, while less educated workers may become unemployed. In this case overeducation could be a more long-term phenomenon.

At the individual level the relationship between overeducation and productivity is often captured through its impact on wages. Existing evidence shows that overeducated workers are likely to earn lower returns relative to similarly educated individuals whose jobs match their education (Hartog, 2000; Green and Henseke, 2016). At the firm level, there is some evidence to suggest that overeducation is associated with lower productivity (McGuinness, 2006; Green, 2016). McGowan and Andrews (2015) find a similar negative relationship at the industry level, for a large sample of Organisation for Economic Co-operation and Development (OECD) countries.

Our article starts with a detailed evaluation of the extent of overeducation in the UK, accounting for age, gender, and regional differences. We also present a detailed analysis by type of first degree and status of younger graduates. The cost of investing in tertiary education and uncertainties related to future job opportunities, make this extension particularly relevant.

Our study aims to answer the following research questions:

- what is the incidence of overeducation in the UK labour market by sex, age and region?
- what is the incidence and persistence of overeducation for graduates (with first degree or equivalent) by type of degree subject?
- what is the relationship between overeducation and wages? Do results for women and men differ?
- are younger (recent) overeducated graduates earning lower wages, compared to older (non-recent) overeducated graduates?

Two main assumptions underlie our analysis. First, we assume that education is a measure of workers' abilities, hence we do not directly distinguish between overeducation and over-skilling. This distinction can be important if highly educated workers are employed in low-level jobs because they only possess low skills, despite their level of education.

Second, we take wages as our measure of productivity, hence this article does not analyse the impact of overeducation on productivity measured in terms of output per worker or hour worked or total factor productivity.

In this article, using the Annual Population Survey (APS), we broadly follow a statistical method used by the International Labour Organisation (ILO) to compare the distribution of educational attainment of those in employment in the UK against the average educational attainment level for their occupation.

Each individual is assigned a status based on whether their own level of education falls within or outside of the range for their particular occupation and age group. The range is defined as being one standard deviation above and below the mean level of educational attainment.

This method, will, by construction, always result in a proportion of workers who can be classified as:

- matched (individuals whose highest qualification falls within one standard deviation of the average level of educational attainment for their occupation)
- overeducated (individuals whose highest qualification is above one standard deviation of the average level of educational attainment for their occupation)
- undereducated (individuals whose highest qualification is below one standard deviation of the average level of educational attainment for their occupation)

Aggregating these groups over all occupations gives an estimated matched, over and undereducated rate for the whole economy.

Notes for Introduction:

1. A different type of mismatch, which we shall not pursue in our analysis, is that of “horizontal mismatch” where the subject or type of education does not match the job requirements.

2. We should emphasise that the statistical method, by its construction, permits the average educational attainment to increase across all occupations if participation in education and the average level of educational attainment in the population increases. The effect on the degree of matching across the whole economy is therefore dependent on the age composition of each occupational group and the distribution of older and younger workers across occupations. So, to mitigate a potential age composition bias, we construct estimates of average educational attainment by three-level Standard Occupational Classification (SOC) group and by two age groups: 16 to 35 years and 36 to 64 years. We present our methodology for measuring education mismatch and overeducation in Appendix 1.

3 . Results-descriptive analysis

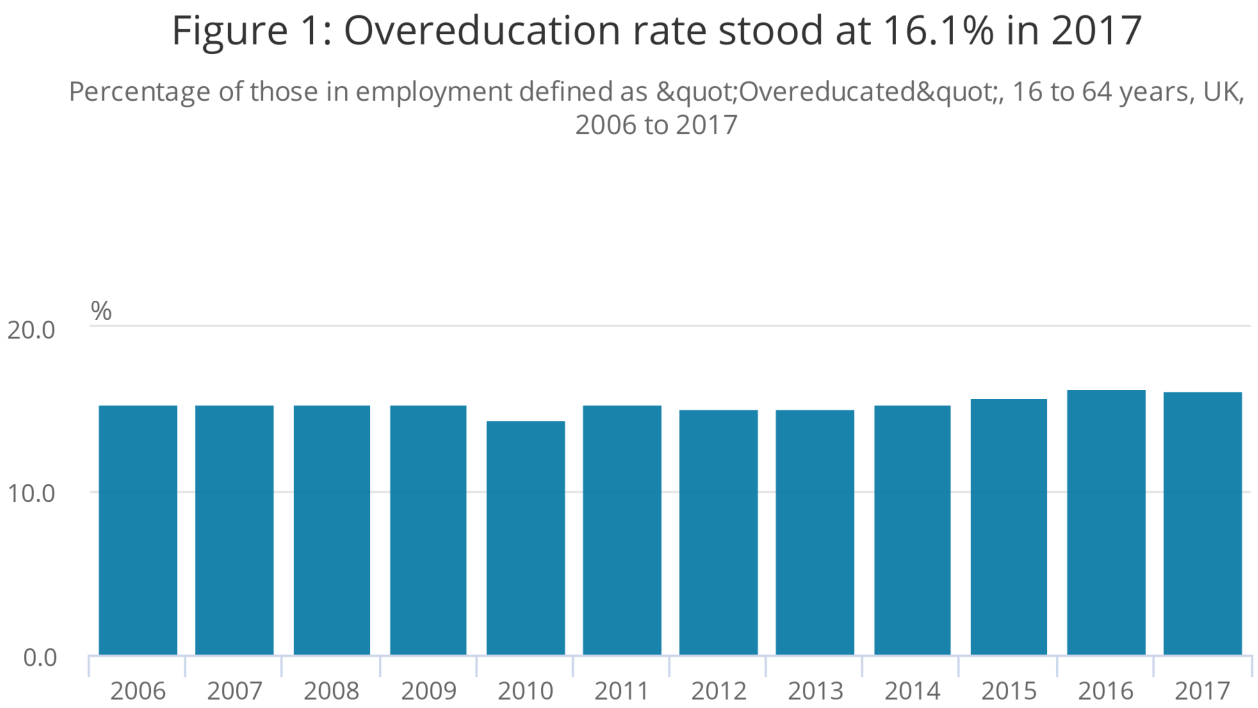
All in employment aged 16 to 64 years

Aggregate results show that in 2017, 68.4% of those in employment had a level of education close to the average of their job. Figure 1 presents percentage of those in employment who are classed as overeducated. From 2013, the overeducation rate began to rise reaching a peak of 16.3% in 2016.

This may be the result of the increase in the number of individuals attaining a first degree or equivalent. In fact, between 2013 and 2017 the total number of graduates in employment increased by 14.8%. The increase in overeducation could also mirror an increasing competition for higher skilled jobs and a surplus of candidates. From 2016 to 2017 the overeducation rate decreased slightly, by less than 0.2 percentage points, and in 2017 it stood at 16.1%. Over time, competition amongst graduates may rise the level of education required for the job, hence increasing the threshold. This may lead to a decrease in the number of overeducated employees.

Figure 1: Overeducation rate stood at 16.1% in 2017

Percentage of those in employment defined as "Overeducated", 16 to 64 years, UK, 2006 to 2017



Source: Annual Population Survey – Office for National Statistics

Notes:

1. The data for estimates prior to 2011 were collected on the previous SOC basis (SOC 2000) and have been mapped to an equivalent SOC 2010 basis. As a result there may be some inconsistencies with estimates before and after 2011.

Sex

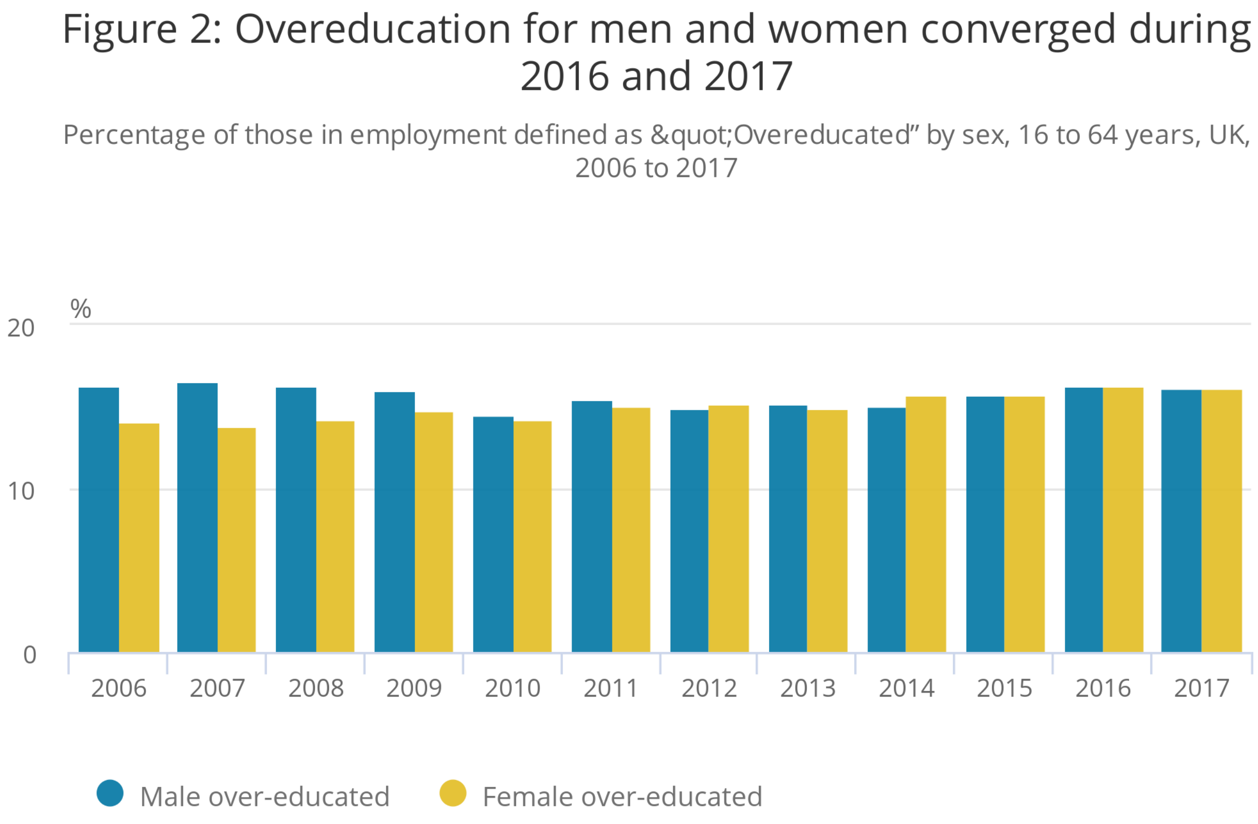
Empirical evidence on the relationship between overeducation and sex has been mixed, with a number of studies concluding that women have a higher overeducation risk than men (Baert and others, 2013; Betti and others, 2011; Ramos and Sanroma, 2013; Tani, 2012; Verhaest and Van der Velden, 2013) as well as those finding no differences between women and men (Blazquez and Budria, 2012; Chevalier, 2003; Chevalier and Lindley, 2009; Frei and Sousa-Poza, 2012). Very few studies indicate that there is higher incidence of overeducation for men (European Commission, 2012; Kiersztyn, 2013).

When we disaggregate our results by sex, we note that from 2006 to 2009 the rate of overeducated males was considerably higher than for females, but this gap started to narrow in 2010 due to an increasing number of women entering higher education (O'Leary and Sloane 2005, Green and Zhu 2010). Our data confirm this trend as from 2006 to 2017 the average education attainment for females increased more compared with males. Females had a slightly lower education attainment in 2006 but this trend was reversed and in 2017 the average education attainment was higher for females.

In 2016 and 2017 the rates for overeducated males and females converged as both sexes became more overeducated compared with previous periods (Figure 2). From 2011 female overeducation fluctuated but generally exhibited a much higher level compared with previous periods, the opposite is true for males.

Figure 2: Overeducation for men and women converged during 2016 and 2017

Percentage of those in employment defined as "Overeducated" by sex, 16 to 64 years, UK, 2006 to 2017



Source: Annual Population Survey – Office for National Statistics

Notes:

1. The data for estimates prior to 2011 were collected on the previous SOC basis (SOC 2000) and have been mapped to an equivalent SOC 2010 basis. As a result there may be some inconsistencies with estimates before and after 2011.

Age

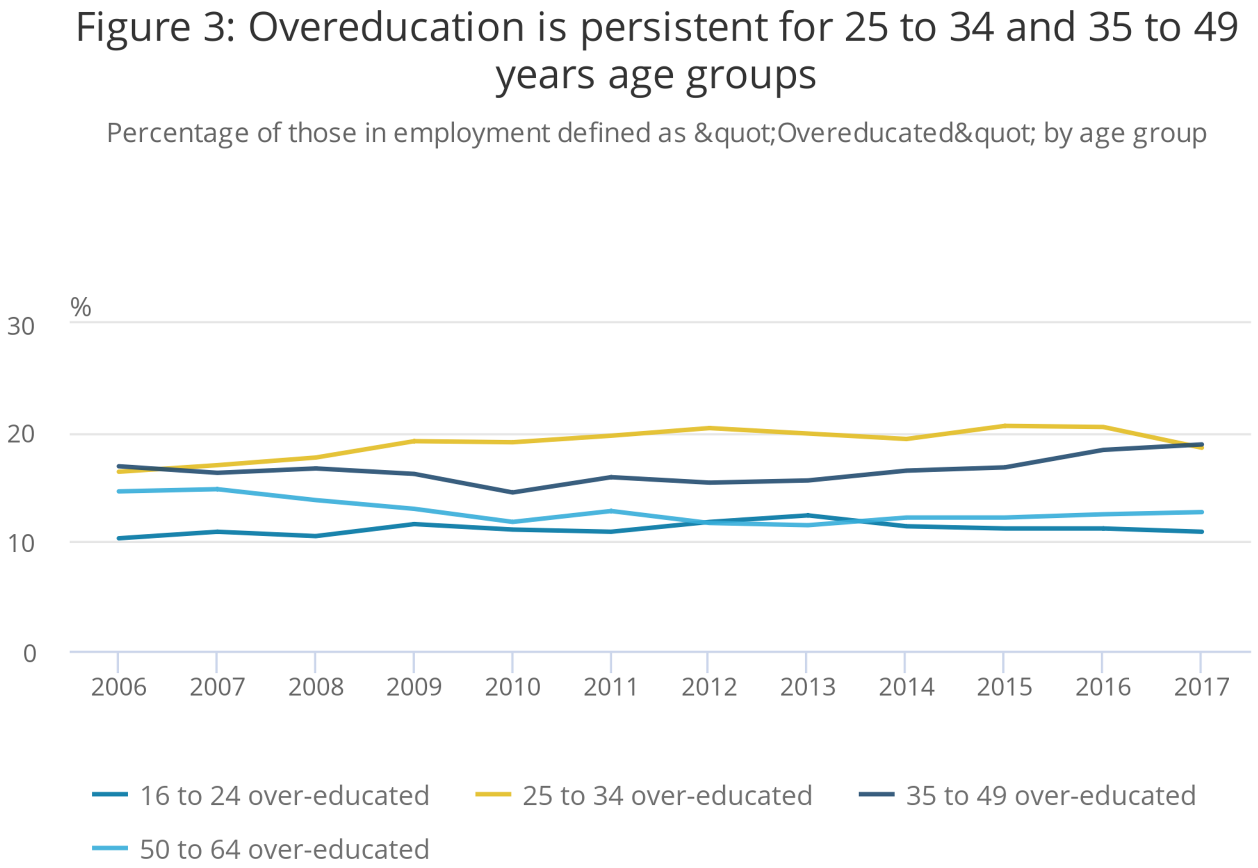
If overeducation was a temporary phenomenon, as predicted by the human capital and the career mobility explanations, we should observe a decline with age. However, the empirical evidence is quite mixed. Some studies emphasise that overeducation decreases with age (Jensen and others, 2010; Robst, 2008; Sutherland, 2012) or that the two have a U-shaped relationship (Tarvid, 2012), while some report that age is irrelevant (Chevalier and Lindley, 2009; Frei and Sousa-Poza, 2012; Kiersztyn, 2013).

Comparing the rate of overeducation for each age group, Figure 3 shows that those aged 25 to 34 years and 35 to 49 years experience the highest rate of overeducation, and the proportion of overeducated workers in the age group 35 to 49 years has increased from 2013 onwards. The finding of higher overeducation in 25 to 34 years age group is consistent with the presence of short-term labour market frictions. However, the high level of overeducation for the 35 to 49 years age group indicates a more persistent phenomenon, particularly as overeducation also features among older workers (50 to 64 years).

Those in employment aged 16 to 24 years experience the lowest rate of overeducation on average. This result should be interpreted with a caveat as the average obtained qualification level for this age group is lower compared with other age groups. For example, almost 70% of those in employment aged 16 to 24 years, hold either GCSE or A level or equivalent as their highest obtained level of education, whereas the corresponding figure for 25 to 34 years age group is 40%. This is an important consideration as education attainment and overeducation are positively correlated. In other words, people who hold GCSE or A level or equivalent education are less likely to be overeducated compared with, for example, graduates.

Figure 3: Overeducation is persistent for 25 to 34 and 35 to 49 years age groups

Percentage of those in employment defined as "Overeducated" by age group



Source: Annual Population Survey – Office for National Statistics

Notes:

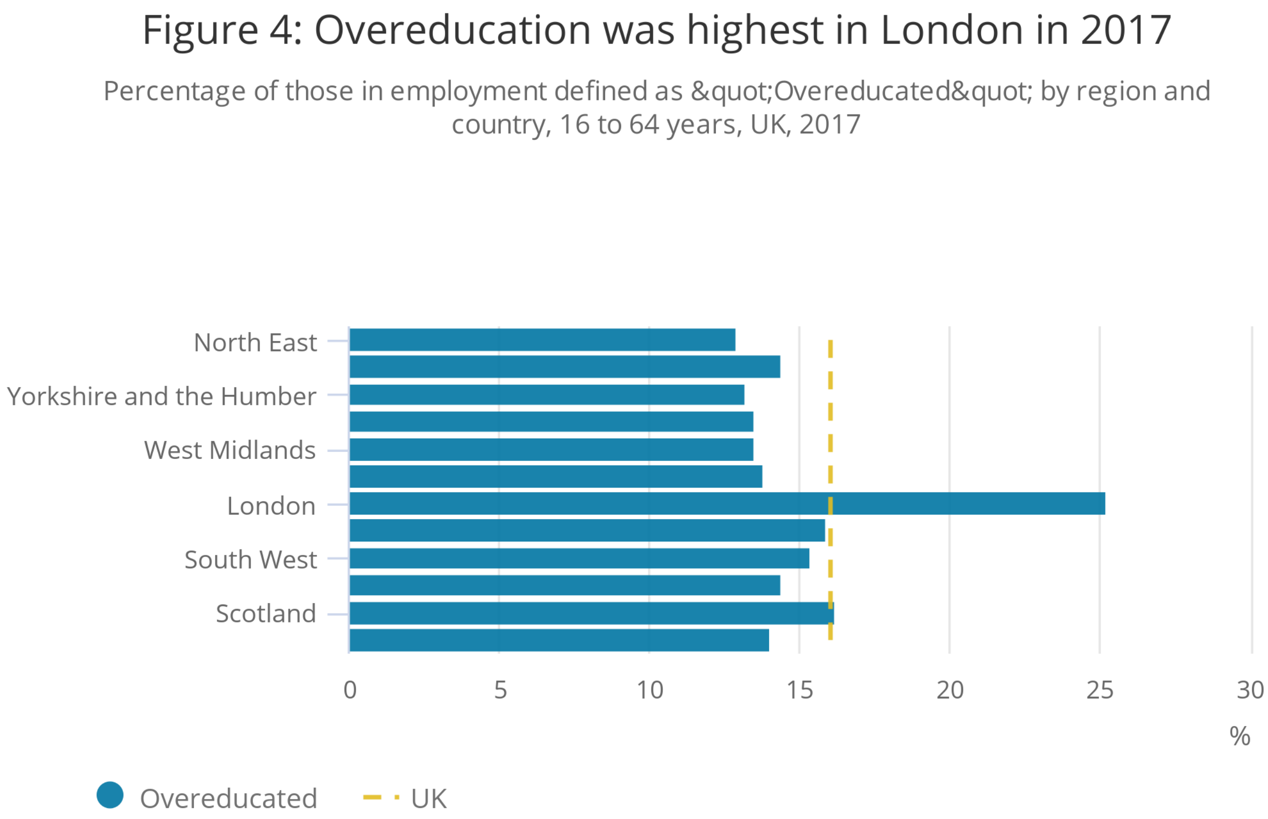
1. The data for estimates prior to 2011 were collected on the previous SOC basis (SOC 2000) and have been mapped to an equivalent SOC 2010 basis. As a result there may be some inconsistencies with estimates before and after 2011.

Region and country

Figure 4 shows that in 2017, London had the highest proportion of overeducated workers in the UK. Results for London are likely to be driven by the composition of the labour force, characterised by a relatively high proportion of immigrants who are typically overeducated. Many foreign nationals working in the UK come to the country to improve their English, hence they may be willing to take a lower-skilled job.

Figure 4: Overeducation was highest in London in 2017

Percentage of those in employment defined as "Overeducated" by region and country, 16 to 64 years, UK, 2017



Source: Annual Population Survey – Office for National Statistics

Notes:

1. Dashed line represents UK average.

Our data show that on average, non-UK born workers tend to be more overeducated compared with the UK-born. The non-UK born overeducated workers accounted for 15.2% of all workers living in London in 2017. It should be noted that the percentage of non-UK born overeducated workers was larger compared with the percentage of overeducated UK-born workers (10%).

Compared with the rest of the country, in 2017, London had the highest proportion of non-UK born matched and non-UK born overeducated and the lowest level of UK-born matched. For the other regions and countries, the average proportion of non-UK born overeducated workers was around 3%.

It should also be noted that our separate analysis shows that half of people living in London between July 2016 and June 2017, aged 21 to 64 years had a level of education above A level standard. This is relatively high compared to other regions and countries and especially compared to the North East where only 30% of people had a level of higher education above A level standard.

First degree subject

This sub-section presents analysis of overeducated graduates whose highest obtained qualification is first degree or equivalent. In 2017, the average overeducation rate for graduates with first degree or equivalent qualification was 30.9%. The overeducation rates for non-recent and recent graduates with first degree or equivalent were 29.2% and 38.6% respectively. This indicates a moderate improvement in the job to education match over time for these groups which is consistent with career mobility proposition.

According to career mobility argument some graduates may begin their careers in a job for which they are overqualified and this job may serve as a stepping stone to a better job in the future. Older graduates who are more likely to possess some pre-study work experience and who have been in their current jobs longer are on average less likely to be overeducated.

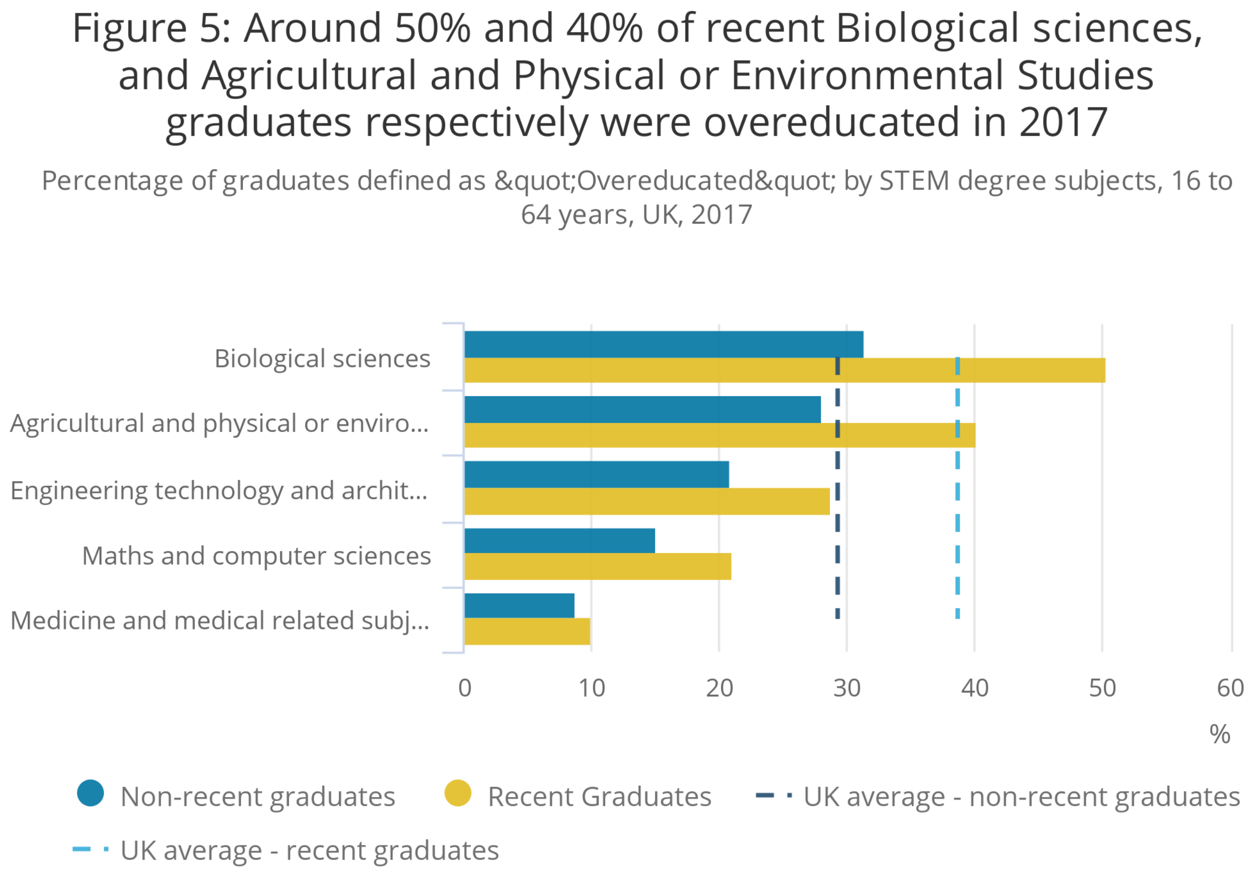
We conduct further analysis of overeducated graduates by graduation cohort. We note that 21.7% of graduates who completed their first degree or equivalent before 1992 were overeducated in 2017, whereas this figure is 23.4% and 24.8% for 1992 to 1999 and 2000 to 2006 cohorts respectively. The corresponding figure is 34.2% for those who graduated during or after 2007. Hence, the incidence of overeducation has increased over time.

Focusing solely on cohort-level overeducation rates is of limited use because of large variation in overeducation rates for graduates across major fields of study. For graduates with first degree or equivalent, the incidence of overeducation varies with respect to the subject studied but graduates from Science, Technology, Engineering and Mathematics (STEM) fields are relatively less likely to end up overeducated within the first five years of completing their degrees.

Figure 5 shows that amongst STEM subjects, the highest incidence of overeducation in 2017 was noted amongst graduates who completed Biological sciences and Agricultural and Physical or Environmental Studies. Around 50% and 40% of recent Biological sciences and Agricultural and Physical or Environmental Studies graduates respectively were overeducated in 2017.

Figure 5: Around 50% and 40% of recent Biological sciences, and Agricultural and Physical or Environmental Studies graduates respectively were overeducated in 2017

Percentage of graduates defined as "Overeducated" by STEM degree subjects, 16 to 64 years, UK, 2017



Source: Annual Population Survey – Office for National Statistics

Notes:

1. Dashed lines represents UK average.

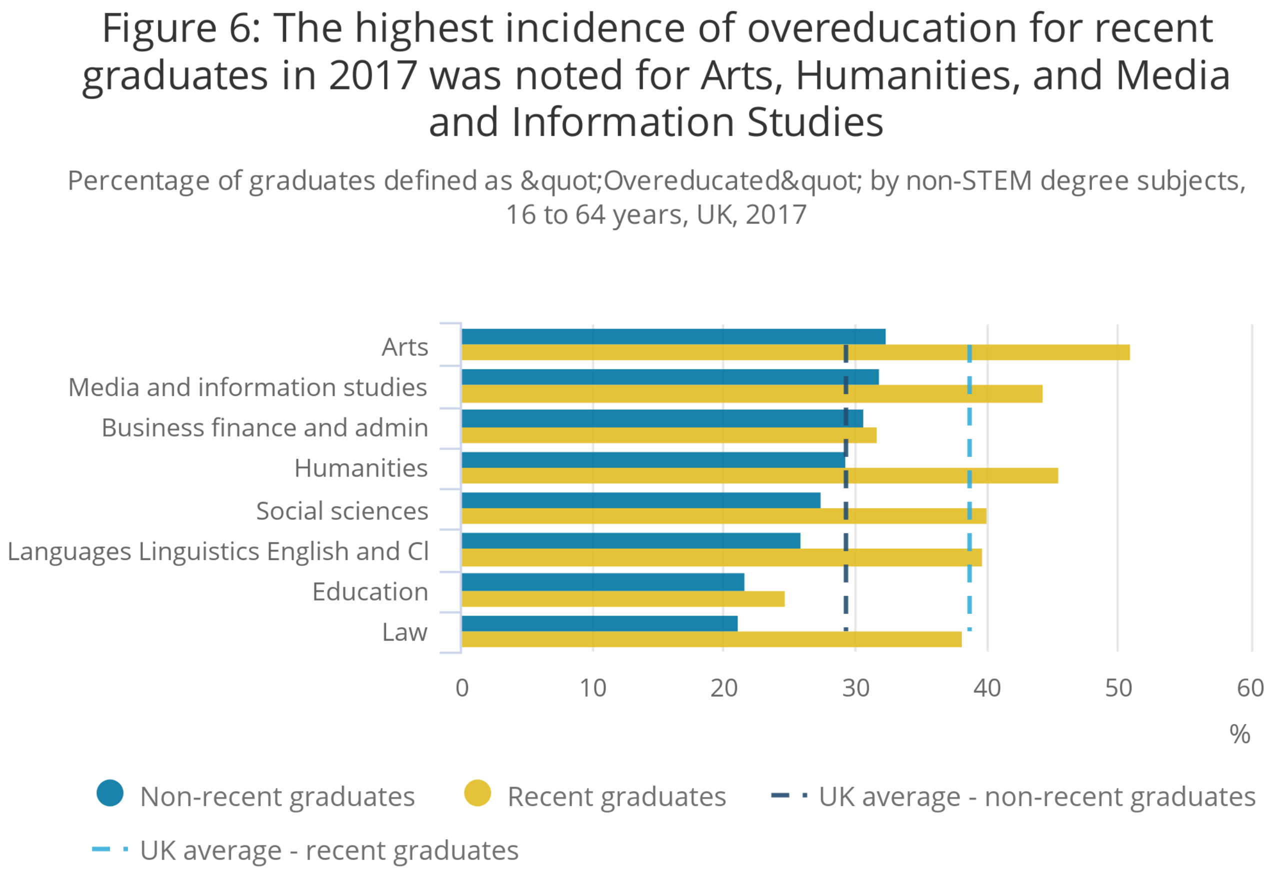
Figure 6 shows that in 2017 amongst recent graduates from non-STEM degree subjects the highest incidence of overeducation was noted for three groups namely: Arts; Humanities and Media and Information studies (51%, 45.5% and 44.4% of overeducated respectively). The four groups of non-recent overeducated graduates belonging to non-STEM degree subject namely Arts; Media and Information Studies; Business, Finance and Administration studies and Humanities had higher than average overeducation rate compared with non-recent graduates overall.

The relatively high rate of overeducation amongst recent Engineering, Technology and Architecture graduates is somewhat surprising. This is possibly due to labour markets for Engineering, Technology and Architecture favouring those with postgraduate qualification, which could result in recently qualified first degree or equivalent holders remaining in lower-skilled work while they attempt to secure employment related to their field of study. The lower rate of overeducation for these graduates after five years suggests that many were able to secure this type of employment or chose to secure skilled employment in other fields.

It should be noted that estimates for medicine and law graduates should be interpreted with caution as law and medicine require a first professional degree, which is normally acquired after a regular first (bachelor's) degree. For the purposes of our analysis which compares graduates with first (bachelor's) degree or equivalent, in this sub-section we exclude those who hold any qualification above that level, that is first professional degree or above in any subject.

Figure 6: The highest incidence of overeducation for recent graduates in 2017 was noted for Arts, Humanities, and Media and Information Studies

Percentage of graduates defined as "Overeducated" by non-STEM degree subjects, 16 to 64 years, UK, 2017



Source: Annual Population Survey – Office for National Statistics

Notes:

1. Dashed lines represents UK average.

Next, we aim to assess whether overeducated workers may be at a disadvantage compared to their matched counterparts. In particular, we aim to assess whether overeducation may be associated with lower earnings and whether any observed effect may differ for men and women and for recent graduates.

Notes for: Results-descriptive analysis

1. A graduate is defined as a person who is in employment, aged between 16 and 64 years, not enrolled on any educational course and who has a level of higher education of first degree or equivalent level standard. Following qualifications are defined as first degree or equivalent: (1) NVQ level 5 (2) Level 8 Diploma (3) Level 8 Certificate (4) Level 7 Diploma (5) Level 7 Certificate (6) Level 8 Award (7) First degree/foundation degree (8) Other degree.

4 . The relationship between wages and overeducation

To investigate the relationship between wages and overeducation, we estimate the earnings difference between overeducated and matched individuals while controlling for relevant individual and job characteristics. There is a large empirical literature on the impact of the education mismatch on productivity, generally captured through average hourly wages. This body of evidence draws upon the human capital theory, and on the assumption that wages equal marginal productivity in a competitive market.

Our indicators of required, over and deficit education are based on the distribution of actual educational attainments in each occupation defined at the three-digit SOC level and constructed by two age groups 16 to 35 years and 36 to 64 years. Our measure classifies as overeducated a worker whose education (years of schooling) deviates positively from the observed occupation average by more than one standard deviation, and as undereducated those with a negative deviation from the mean in excess of one standard deviation.

We also construct a variant of this procedure, replacing mean-centred bracket with a different measure of central location, the distribution mode. We use both measures (mean and mode) as robustness checks in our regression analysis in models 1 to 4 (Table 1). We control for various individual and job characteristics which may impact both the incidence of overeducation as well as wages. Full information can be found in Appendix 1.

Most of the empirical literature on education mismatch support the following two hypotheses:

- H1: Overeducated workers earn more than their co-workers who are matched but less than workers with the similar level of education in matched jobs; and
- H2: Under-educated workers earn less than their co-workers who are matched but more than similarly educated workers employed in lower level jobs.

Two main specifications have been used, where the first one represents extended versions of the Mincer (1974) equation:

$$\ln(w) = x\beta_1 + \beta_2 S^R + \beta_3 S^O + \beta_4 S^U + u_i$$

Where ln(w) is a natural log of hourly wages, x is a vector of workers' and job characteristics, S^R is the number of years of required schooling, S^O is the number of years of over-education and S^U is the number of years of deficit schooling (undereducation).

An alternative specification uses dummy variables to identify workers with different education level following Verdugo and Verdugo (1998):

$$\ln(w) = x\beta_1 + \beta_2 E + \beta_3 D^O + \beta_4 D^U + u_i$$

Where ln(w) is a natural log of hourly wages, E is the number of years of education for each worker, D^O and D^U are the dummy variables capturing whether the worker is over or under educated for his or her occupation. This specification compares overeducated and undereducated workers with those who are matched and have similar level of education.

We also conduct quantile regression analysis for graduates where instead of considering the effect of overeducation on the mean wages, we look at 25th percentile, median and 75th percentile of wages. We aim to assess whether the effect of overeducation differs across different points of the pay distribution.

The analysis will be carried out for the whole sample and for a sub-sample of graduate workers. The latter will include controls for the degree subject and will distinguish between recent graduates (first degree completed within the past five years) and non-recent graduates.

Table 1: OLS regression, hourly wage estimation results, 2017

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5 (Female)**	**Model 6 (Male)**
Variables	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**
Obtained education	0.084***	0.076***				
	(0.003)	(0.003)				
Obtained education squared	-0.002***	-0.001***				
	(0.000)	(0.000)				
Overeducated dummy (mean)	-0.081***					
	(0.008)					
Undereducated dummy (mean)	0.058***					
	(0.008)					
Overeducated dummy (mode)		-0.033***				
		(0.007)				
Undereducated dummy (mode)		0.024***				
		(0.009)				
Required education years (mean)			0.100***		0.082***	0.111***
			(0.003)		(0.004)	(0.004)
Overeducation years (mean)			0.013***		0.010***	0.017***
			(0.002)		(0.002)	(0.002)
Undereducation years (mean)			-0.100***		-0.106***	-0.089***
			(0.006)		(0.008)	(0.009)
Required education years (mode)				0.031***		
				(0.001)		
Overeducation years (mode)				0.026***		
				(0.001)		
Undereducation years (mode)				-0.082***		
				(0.005)		
Constant	0.289***	0.396***	-0.299***	0.724***	0.058	-0.552***
	(0.051)	(0.051)	(0.057)	(0.047)	(0.082)	(0.081)
Observations	76,360	76,360	76,337	76,337	40,342	35,995
R-squared	0.432	0.430	0.433	0.424	0.412	0.426

Notes

1. Standard errors in parentheses. Back to table

2. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Back to table

Table 1 shows coefficient estimates based on the two specifications of the wage equations. As a robustness check, we use measures of educational mismatch based on the mean and on the mode years of required education in each occupation. The main findings can be summarised as the following.

Models 1 and 2 compare overeducated and undereducated employees with those who are matched to their jobs and have similar level of education. Both models predict a penalty for overeducation and a premium for undereducation. The penalty is larger when using a definition of educational mismatch based on the average (mean) years of education (8.1%) as opposed to a mode-based measure (3.3%). This means that the wage of an overeducated worker is between 3.3% and 8.1% lower compared to the wage of a worker with a similar level of education who is matched to the right occupation.

Models 3 and 4 compare overeducated and undereducated employees with their matched co-workers who may not have the same level of education. To correctly interpret the results, we express the total number of years of education (E) as a linear combination of required (E_r), over (E_o) and undereducation (E_u): $E = E_r + E_o – E_u$. The coefficient for required years of education is 0.100-implying that an additional year of required education increases wages by 10% – while the coefficient for surplus education is 0.013. Hence, although there is a positive return on wages for overeducated employees, the size of the coefficient indicates that for years of education beyond required a worker receives 8.7% wage penalty (0.100-0.013=0.087). When measuring education mismatch using the mode, returns on wages from an additional year of required education are lower than expected (0.031) and the corresponding coefficient for overeducation is 0.026. This means that education beyond what is required receives only 0.5% wage penalty. These results indicate that mode-based measures induce lower penalty for overeducation compared with mean-based measures.

Models 5 and 6 investigate the impact of overeducation on wages by estimating two separate models for female and male employees respectively. Given that the literature provides stronger support for the extended Mincer equation approach (Hartog 2000), we carry on with this specification in the rest of our analysis. Although the prevalence of overeducation is similar for women and men in 2017 (Figure 2), our estimates suggest that the diminishing return on wages is somewhat more pronounced for overeducated men than for women. Women receive 7.2% (0.082-0.010=0.072) lower return on wages for education beyond required level, whereas men receive 9.4% (0.111-0.017=0.094) lower return on wages for education beyond required level. However, women seem to receive higher penalty for undereducation. We should also note that the return on wages from the required education for men is higher compared to women as men earn 11.1% return on additional year of required education, whereas women earn 8.2%. This means that after controlling for individual and job characteristics, our results show that men receive higher returns on wages for required education.

Apart from education, some other individual characteristics feature prominent differences between the two sexes. The results for both individual and job controls are presented in Table 6, Appendix 2.

Evidently, the household context has different implications for men and women. Mothers earn less than childless females, whereas fathers do not suffer any fatherhood penalty. In fact, fatherhood has a significant and positive effect on wages. This is important to note because females' decisions and subsequently earnings may be to a greater extent (compared with males') driven by personal traits which we cannot observe in our data.

The estimators indicate that males' wages benefit from having dependent children. The results for men show that married men earn more than unmarried men and fathers earn more than childless men. By contrast, having dependent children lowers females' income. In other words, household characteristics that stimulate breadwinner role seem to induce wage premium only for men whereas women do not benefit.

We should also note that overeducation does not seem to make significant contribution to the gender wage gap. This is because, as shown in descriptive analysis, females are overeducated almost as often as males and given that overeducation is more severely penalised for men than for women.

Our findings indicate that a noticeable part of the wage gap may be attributed to women's labour market decisions as only males are granted breadwinner wage premiums, whereas women suffer wage reductions when they have dependent children.

In conclusion, although the overall returns on wages from investment in education are positive, overeducated employees earn lower wages than those with similar education who are matched to their jobs. In other words, there are positive but diminishing returns to overeducation. Undereducated workers earn more than similarly educated workers who are employed in lower-level jobs, but less than their co-workers whose level of education corresponds to that required in their occupation. These findings support hypotheses 1 and 2.

Graduates

In this sub-section, we aim to evaluate whether the impact of overeducation differs depending on the type of degree and whether younger (recent) graduates earn higher or lower wages compared to non-recent graduates (Table 2).

Table 2: OLS regression, hourly wage estimation results for graduates, 2017

	Model 7	Model 8	Model 9	Model 10	Model 11
Variables	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**
Required education	0.054***	0.054***	0.054***	0.053***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Overeducation	-0.014***	-0.018***	-0.022***	-0.018***	-0.017***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
Recent graduate	-0.005	-0.003	-0.005	-0.016	-0.005
	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)
STEM degree subject	0.021**	0.021**	0.021**	0.021**	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.064***	0.065***	0.064***	0.063***	0.064***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Female	0.018	0.017	0.014	0.019	0.017
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Tenure	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Overeducation*Tenure		0.000*			
		(0.000)			
Overeducation*Female			0.014***		
			(0.005)		
Overeducation*Recent graduate				0.012**	
				(0.005)	
Overeducation*STEM degree subject					0.011*
					(0.005)
Constant	-0.024	-0.027	-0.010	0.008	-0.024
	(0.141)	(0.141)	(0.141)	(0.142)	(0.141)
Observations	17,672	17,672	17,672	17,672	17,672
R-squared	0.403	0.403	0.403	0.403	0.403

Source: Annual Population Survey – Office for National Statistics

Notes

1. Robust standard errors in parentheses. Back to table
2. *** p<0.01, ** p<0.05, * p<0.1. Back to table

In all specifications, we find that overeducated graduates experience negative returns to overeducation, with an effect ranging between negative 0.014 and negative 0.022. There are no statistically significant differences in wages between recent and non-recent graduates, nor by gender. However, the type of degree does make a difference and all models predicts higher wages for workers with STEM degrees, compared to non-STEM. Other key findings include the following.

The wage penalty for graduates decreases the longer they stay with their employer, as both the coefficient on tenure and the interaction between tenure and overeducation are positive and statistically significant, although the latter effect is very small. This suggests that graduates may substitute education for the lack of previous work experience, accepting jobs requiring less education than they possess to acquire the necessary experience. It may also indicate that overeducation may not have negative effect on graduates' productivity as they gain more experience. Overall, increased tenure is rewarded by employers.

We investigate whether the negative returns on wages for overeducated graduates differ by sex. Our prior expectation was that negative returns on wages may be driven by the increasing number of overeducated female graduates. In contrast, we find that overeducated female graduates bear lower penalty (negative 0.008) compared with men (negative 0.022).

Another important question is whether recent graduates, that is those who graduated within the past five years, pay a higher penalty for overeducation compared to non-recent graduates. The intuition is partly driven by studies showing that managers are more inclined to hire more experienced as opposed to younger workers because the former are perceived as being more reliable and professional (Corgnet and others 2015). As a consequence, younger graduates are expected to suffer higher penalty for overeducation. However, we find that the negative effect of overeducation for non-recent graduates (negative 0.018) is nearly offset by the impact of overeducation for younger (recent) graduates (0.012). In other words, although recent overeducated graduates still have a negative return on wages, they earn around 1.2% more compared with non-recent overeducated graduates. Contrary to existing findings (Frenette (2004), Mavromaras and others (2010) and Carroll and Tani (2013)), recent graduates in the UK are penalized for their overeducation, although the penalty is lover compared to non-recent graduates. This suggests that recent graduates have specific skills or unobservable characteristics that are better valued in the labour market compared with non-recent graduates.

We look at the impact of overeducation by type of degree by including the interaction between a dummy indicating a degree in STEM subjects and overeducation. Results show that a degree in STEM subjects contributes towards reducing the penalty for overeducation from negative 0.017 (for non-STEM degrees) to negative 0.006.

An important information that is missing from our data is a direct measure of individuals' cognitive and non-cognitive skills (personality traits), both considered to be important for a successful labour market experience (Heckman and others 2006). Although education is generally used as a proxy for cognitive abilities, the fast expansion of the higher education in UK since the 1980s might have compromised quality for quantity (Chevalier and Lindley 2009).

This means that graduates may lack the adequate skills for the job despite having more education than required for their occupation (that is they might not be over-skilled). Empirical research using different proxies show that graduates with lower ability face a higher risk of overeducation (Barone and Ortiz 2011; Chevalier 2003; Lianos et al. 2004; Tarvid 2012; Verhaest and Omey 2010) and personality traits may be more important than ability in determining overeducation (Blazquez and Budria 2012; Tarvid 2013).

The nature of our data does not allow us to control for individuals' ability traits in regression analysis. However, if our results were affected by graduates' abilities we would expect the wage penalty on overeducation to be higher for low earners but much smaller or non-existent for higher earners. To test this proposition, we conduct a quantile regression analysis, which allows us to check how the impact of overeducation (and other controls) varies along the income distribution.

Table 3 shows that there are increasing returns to required education as we move up towards better paid jobs. An additional year of required education increases wages by 4% in the bottom quantile and by 6.1% in the top quantile. However, the penalty for overeducation changes marginally, from 1% to 1.1%. There is no wage difference between recent and non-recent graduates, while graduates with STEM degrees earn significantly higher wages only in the bottom half of the wage distribution. In higher-level occupations the type of degree does not significantly affect wages. This indicates that individuals in highly-paid jobs are endowed with additional unobserved skills, which are independent of the degree subject.

Table 3: Quantile regression, hourly wage estimation results for graduates, 2017

	Model 12	**Model 13**	**Model 14**
Variables	**q25**	**q50**	**q75**
Required education	0.040***	0.045***	0.061***
	(0.005)	(0.004)	(0.004)
Overeducation	-0.010***	-0.011***	-0.011***
	(0.002)	(0.003)	(0.003)
Recent graduate	-0.009	-0.013	-0.004
	(0.013)	(0.012)	(0.016)
STEM degree subject	0.016*	0.011**	0.007
	(0.008)	(0.005)	(0.006)
Age	0.047***	0.052***	0.065***
	(0.002)	(0.003)	(0.004)
Constant	0.291**	0.392***	0.156
	(0.124)	(0.123)	(0.117)
Observations	17,672	17,672	17,672

Source: Annual Population Survey – Office for National Statistics

Notes

1. Standard errors in parentheses. Back to table
2. *** p<0.01, ** p<0.05, * p<0.1. Back to table

Notes for: The relationship between wages and overeducation

1. Education mismatch refers to the difference between the worker's attained level of education and the education required on the job (Hartog 2000). If we define as E the number of years an employee has invested in education, Er the years of education required in an occupation, the mismatch arises when either E>Er, (overeducation), or E<Er (undereducation) (Cohn and Khan 1995).

2. The Mincer earnings function is a single-equation model that explains wage income as a function of schooling and experience, named after Jacob Mincer.

3. The dependent variable (hourly wages) is expressed in log form. If the distribution of a variable has a positive skew, taking a natural logarithm of the variable helps fitting the variable into a model. Also, when a change in the dependent variable is related with percentage change in an independent variable, or the other way around, the relationship is better modelled by taking the natural log of either or both variables.

4. We construct both mean and mode measures of education mismatch (over and under education) which we use in regression analysis (Models 1 to 4, Table 1). We describe our approach in more detail in Appendix 1.

5 . Conclusion

This article investigates the incidence of overeducation by sex, age and region and the incidence and persistence of overeducation for graduates by type of first degree. We also investigate the relationship between overeducation and wages for males and females and for recent and non-recent graduates.

We note that the incidence of overeducation does seem higher for certain age groups and in particular for those aged 25 to 34 years and 35 to 49 years. The relatively high incidence of overeducation for 35 to 49 years age group indicates that overeducation is a persistent phenomenon in the UK labour market. The incidence of overeducation is also higher in London compared with other UK regions and countries. It is higher for certain first degree subjects but it is generally lower for graduates with Science, Technology, Engineering and Mathematics (STEM) degrees, whereas the results for females and males in the most recent period (2017) do not seem to differ.

When we compare the relationship between overeducation and wages for men and women, we find that the wage penalty for overeducation is somewhat higher for men compared with women. Given that the incidence of overeducation does not differ between men and women and that men on average bear higher penalty for overeducation, we conclude that overeducation does not seem to contribute to the gender wage gap. Instead the gender wage gap may be attributed to women's labour market decisions and traditional gender roles as only males are granted breadwinner wage premiums, whereas women suffer wage reductions when they have dependent children.

In relation to graduates, we argue that overeducation would not be a concern if it was strictly a short-term phenomenon. However, our results show that a non-negligible number of graduates are still overeducated five years after completing their first degree (29.2%). With regards to the effect of overeducation on wages, recent (younger) overeducated graduates had a lower penalty on overeducation compared with older (non-recent) overeducated graduates. This finding indicates that younger graduates may have characteristics which are valued in the labour market. In addition, our analysis shows that earnings of overeducated STEM subject graduates contribute towards reducing the wage penalty for overeducation and almost offsetting it.

However, we do acknowledge that older (non-recent) graduates may have different characteristics compared with younger (recent) graduates in terms of abilities and/or motivation. In this respect our data has limitations as it does not allow us to capture these effects. Hence, we conduct quantile regression analysis under the assumption that if the wage penalty amongst graduates was related to lower ability, the penalty would be more prominent among the graduates who are lower earners. We find no support for lower ability argument as we observe no significant differences across the wage distribution for overeducated graduates.

However, we cannot rule out the possibility that for some graduates, overeducation and associated lower earnings may simply be a matter of choice and personality traits. In other words, some graduates may willingly refrain from maximizing their individual income due to hidden preferences (Frank, 1978). It follows that to fully depict the effect of overeducation on workers' productivity it is not sufficient to concentrate exclusively on earnings. Hence, we propose to extend our analysis to investigate the effect of overeducation on productivity directly, measured in terms of output per worker or total factor productivity.

Limitations

Our analysis investigates the relationship between overeducation and hourly wages. We acknowledge, however, that overeducation may be associated with some other individual or societal cost and/or benefits in addition to its effect on wages (Green and Henseke, 2016). These may relate to positive externalities such as lower crime rates and knowledge spill-overs or costs to the taxpayer, but the assessment of these is not within the scope of our present analysis.

Our data have several important limitations. To compute estimates of overeducation and conduct hourly wages analysis we use the Annual Population Survey (APS) (approximately 70,000 observations per year). Compared with the Labour Force Survey (LFS), the APS provides a larger sample. The APS is a sample survey and all estimates from it are subject to sampling variability. Sampling variability is dependent on several factors, including the size of the sample, the size of the estimate as a percentage of the population and the effect of the design of the sample on the variable of interest. Therefore, it is subject to a margin of uncertainty, as different samples provide different results.

In the LFS, earnings information is asked in the first and fifth wave and an hourly earnings variable is created using information on both pay and hours. Since the APS includes wave one and five from the LFS as well as regional boosts, the APS earnings question will be asked of all eligible employees. This is not calculated for those in self-employment. Gross hourly earnings data are known to be underestimated in the LFS or APS and this is principally because of proxy responses. To correct for this, our regression analysis includes a dummy control variable for proxy responses.

Hence, the Annual Survey of Hours and Earnings (ASHE) is the preferred source for earnings information. The ASHE is collected from the employer and as such the earnings information is thought to be more reliable as it is mainly provided with reference to company records. In contrast, the APS wages data is provided by the individual and it is subject to recall error, which is compounded when information is provided by proxy response.

It should be noted however, that the LFS and APS, unlike ASHE, allow us to investigate the relationship between overeducation and wages since both surveys contain sufficient information on wages as well as other individuals' characteristics such as the level of education.

Another important limitation of the data is that they do not have a sufficient panel element. The use of cross-section data in regression analysis makes it difficult to infer causality. This is because both education and overeducation are potentially endogenous. However, comparisons between males and females and between recent and non-recent graduates are made on the assumption that the sources of endogeneity and bias are similar across these categories and that therefore the differences in the estimates are informative.

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8 . References

Baert, S, Cockx, B, Verhaest, D (2013), Overeducation at the start of the career: stepping stone or trap? Lab. Econ. 25, pages 123 to 140.

Barone, C, Ortiz, L (2011). Overeducation among European University Graduates: a comparative analysis of its incidence and the importance of higher education differentiation. ‘Higher Education’, 61(3), pages 325 to 337.

Betti, G, D’Agostino,A, Neri, L. (2011), Educational mismatch of graduates: a multidimensional and fuzzy indicator. Soc. Indic. Res. 103(3), pages 465 to 480.

Blázquez, M, Budría, S. (2012), Overeducation dynamics and personality. Educ. Econ. 20(3), pages 260 to 283.
Carroll, D, Tani, M (2013). Over-education of recent higher education graduates: New Australian panel evidence. ‘Economics of Education Review’, 32, pages 207 to 218.

Chevalier, A (2003), Measuring over-education. Economica 70(279), pages 509 to 531 (2003).

Chevalier, A, Lindley, J (2009), Overeducation and the skills of UK graduates. J R Stat Soc: Series A (Statistics Society) 172(2), pages 307 to 337.

Cohn, E, Khan, S. P. (1995), The wage effects of overschooling revisited. ‘Labour Economics’, 2(1), pages 67 to 76.

Dang, A, Nguyen, N, Nguyen, L. (2017), The Wage Impacts of Over-education in Nine Major Occupation Groups in the UK: Propensity Matching Score Approach.

European Commission (2012), DG Employment, Social Affairs and Inclusion: Employment and social developments in Europe 2012. Tech. rep.

Forrest, R. (2015), Housing and family wealth, International Journal of Housing Policy, 15:4, pages 491 to 494.

Frei, C., Sousa-Poza, A.(2012), Overqualification: permanent or transitory? Appl. Econ. 44(14), pages 1837 to 1847.

Frenette, M. (2004). The overqualified Canadian graduate: the role of the academic program in the incidence, persistence, and economic returns to overqualification. ‘Economics of Education Review, 23’(1), pages 29 to 45.

Green, F (2016). Skills demand, training and skills mismatch: a review of key concepts, theory and evidence. ‘UK Foresight Future of Skills and Lifelong Learning Project’.

Green, F, Henseke, G. (2016), Should governments of OECD countries worry about graduate underemployment?. ‘Oxford Review of Economic Policy’, 32(4), pages 514 to 537.

Green, F, Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. ‘Oxford economic papers’, 62(4), pages 740 to 763.

Groot, W, and Van Den Brink, H. M. (2000). Overeducation in the labor market: a meta-analysis. ‘Economics of education review, 19’(2), pages 149 to 158.

Hartog, J (2000), Over-education and earnings: where are we, where should we go?. ‘Economics of education review, 19’(2), pages 131 to 147.

Heckman, J. J, Stixrud, J, Urzua, S (2006), The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. ‘Journal of Labor economics, 24’(3), pages 411 to 482.

ILO, (2014), Skills Mismatch in Europe.

Jensen, U, Gartner, H, Rässler, S(2010), Estimating German overqualification with stochastic earnings frontiers. AStA Adv. Stat. Anal. 94(1), pages 33 to 51.

Kiersztyn, A (2013), Stuck in a mismatch? The persistence of overeducation during twenty years of the post-communist transition in Poland. Econ. Educ. Rev. 32, pages 78 to 91.

Lianos, T. P, Asteriou, D, Agiomirgianakis, G. M (2004). Foreign university graduates in the Greek labour market: Employment, salaries and overeducation. ‘International Journal of Finance & Economics, 9’(2), pages 151 to 164.

Mavromaras, K, McGuinness, S, O'leary, N, Sloane, P, Fok, Y. K. (2010). The problem of overskilling in Australia and Britain. ‘The Manchester School, 78’(3), pages 219- to 241.

McGuinness, S (2006). Overeducation in the labour market. ‘Journal of economic surveys, 20’(3), pages 387 to 418.

McGowan, M A., and Andrews, D (2015). Labour market mismatch and labour productivity.

Mincer, J, 1974. Schooling, Experience, and Earnings. Columbia University Press, New York.

O’Leary, N. C, Sloane, P. J. (2005). The return to a university education in Great Britain. ‘National Institute Economic Review’, 193(1), pages 75 to 89.

Ramos, R, Sanromá, E (2013), Overeducation and local labour markets in Spain. Tijdschr. Econ. Soc. Ge. 104 (3), pages 278 to 291.

Robst, J (2008), Overeducation and college major: expanding the definition of mismatch between schooling and jobs. Manch. Sch. 76(4), pages 349 to 368.

Sutherland, J (2012), Qualifications mismatch and skills mismatch. Educ. Train. 54(7), pages 619 to 632. Tani, M (2012), Does immigration policy affect the education-occupation mismatch? Evidence from Australia. Australian Bull. Lab. 38(2), pages 111 to 140.

Tarvid, A (2012), Effects of the field of higher education on the prevalence of over-education in European countries. In: Kesner, J. (ed.) Education: Evaluation, Reform and Policy, pages 167 to 184. Athens Institute for Education and Research, Athens.

Tarvid, A (2013), Unobserved heterogeneity in overeducation models: Is personality more important than ability?. Procedia Economics and Finance, 5, pages 722 to 731.

Verdugo, R. R, and Verdugo, N. T (1989). The impact of surplus schooling on earnings: Some additional findings. ‘Journal of Human Resources’, pages 629 to 643.

Verhaest, D, Omey, E (2010), The determinants of overeducation: different measures, different outcomes?. ‘International Journal of Manpower, 31’(6), pages 608 to 625.

Verhaest, D, Van der Velden R (2013), Cross-country differences in graduate overeducation. Eur. Sociol. Rev. 29 (3), pages 642 to 653.

9 . Appendix 1

Method

Measures of micro-level education mismatch

The concept of overeducation (undereducation) means having more (less) education than required for the job, but uniquely accepted typology or measurement framework is lacking. Three different approaches exist (Table 4) with their own advantages and disadvantages. Moreover, different measures may lead to different results in terms of both estimating the prevalence of education mismatch as well as its relationship with wages.

The measurement of education mismatch has made use of both subjective and objective measures. All measures have some shortcomings and may be prone to a biased evaluation of the extent of over and under education. Common to all measures, the analysis starts with the evaluation of the level or years of education required in each occupation, usually following the three-digit Standard Industrial Occupation (SOC) codes. Levels or years of education above the required are defined as overeducation, while levels or years below are defined as undereducation. Objective measures can be divided into two sub-groups, namely normative and statistical.

Table 4: Measures of education mismatch

Measure	Description	Advantages	Disadvantages
Normative (objective)	Use a pre-determined mapping between the job and the required education level	Easily measurable	Assumes constant mappings over all jobs of a given occupation
		Objective	Costly to create and update mapping
Statistical (objective)	The are those with education level higher by some ad-hoc value than the mean or mode of the sample within a given occupation	Easily measurable	Assumes constant mappings over all jobs of a given occupation
		Objective	Sensitive to cohort effects
		Always up-to-date	Results depend on the level of aggregation of occupations
Self-assessment (subjective)	Respondents are asked about their perceptions of the extent their education or skills are used in their job	Always up-to-date	Subjective bias: respondents may overstate job requirements, inflate their status or reproduce actual hiring standards
		Corresponds with requirements in the individual firm	

Source: Authors' elaboration: (Hartog 2000)

Normative measure is based on experts' views, who specify the required level of education for the job titles in an occupational classification. One example is O*NET (Occupational Information Network), a unique, comprehensive database of worker competencies, job requirements, and resources. O*NET replaces the Dictionary of Occupational Titles (DOT) and it is the primary source of occupational information in the US.

The O*NET database contains a wide variety of worker and job oriented data categories as well as a rich set of variables that describe job and worker characteristics, including skill and educational requirements. The O*NET-SOC Occupation Taxonomy covers work performed in the US economy and defines the set of occupations for which data is collected. There is no dataset of this kind currently available in the UK.

Statistical measures are based on realized matches. Required education is computed using the mode or the mean level or years of education within each SOC classification. When using the mean, workers are classified as over or undereducated if their level of education is more or less than one standard deviation above their occupations' mean education level.

The statistical method assumes that the mean level of educational attainment represents the requirement for the occupation. It should be acknowledged, however, that educational attainment does not fully capture the skills required for each type of job for example experience, on-the-job training, non-exam based learning and some vocational qualifications. However, the approach does benefit from being measurable and generally comparable over time.

Subjective measures are derived from workers self-assessment via employees' surveys. These measures may be prone to measurement error due to respondents' subjectivity bias as respondents' may overstate job requirements or inflate their status within the company.

While previous meta studies of education mismatch literature by Groot and van den Brink (2000) and Rubb (2004) indicate the extent to which various definitions tend to identify different people as being either overeducated, undereducated or matched and generate different estimates of the incidence of and returns to overeducation; they provide no indication of which measure is closest to the true incidence or the extent to which any particular approach generates biased estimates. To a large extent, the level of correlation is likely to vary according to the dataset being used by researchers and the institutional or economic arrangements of the country in question.

The issue of empirical bias associated with the various definitions was addressed by Groot and van den Brink (2000) who conducted a cross-country meta-analysis of 25 studies, utilizing the various subjective and objective methodologies. The authors found that the standard deviation-based measure (statistical measure) tended to yield the lowest estimate of the incidence of overeducation.

The finding of a lower incidence under the standard deviation approach is not surprising, as the methodology requires education levels to be at least one standard deviation above the mean before overeducation is determined whilst the other approaches have no such requirement. In relation to the wage equation meta-analysis, the authors did not find any of the methodological approaches to significantly influence estimated returns.

A meta-analysis by Rubb (2004) found that neither the subjective nor occupational dictionary approaches (normative measure) yielded estimates of the overeducation wage effect that were significantly different from a measure based on the mean occupational level (statistical measure). Thus, one might conclude from such cross-country studies that whilst there are serious concerns relating to the low correlation between the various measures of overeducation the evidence would suggest that, in terms of estimating the returns to overeducation, the various approaches generate broadly consistent evidence. In section four we test this proposition and estimate the relationship between over and under education and wages using both mean and mode based measures of education mismatch.

Statistical method

We have previously published Analysis of the UK labour market-estimates of skills mismatch using measures of over and under education: 2015. In our previously published article as well as in our present analysis, we broadly follow ILO (2013, 2014) statistical approach. In our descriptive analysis we use highest qualification or trade apprenticeship as a proxy for educational attainment and job requirement, instead of years of full-time education.

When we estimate the relationship between hourly wages and education mismatch, we use years of education as a proxy for educational attainment and job requirement. This enables us to compare our results with other empirical studies which also assess the relationship between wages and education mismatch using years of education measure.

A range for the required level of education for a particular occupation is established by calculating the mean level of highest educational attainment within each three-digit SOC occupation group. The range is defined as being one standard deviation above and below the mean level of educational attainment. Each individual is then assigned a status based on whether their own level of education falls within or outside of this range for their particular occupation. Table 1 in our previous article gives an illustrated example of this. This method will, by construction, always result in a proportion of workers who can be classified as either:

- matched (individuals whose highest qualification falls within one standard deviation of the average level of educational attainment for their occupation)
- overeducated (individuals whose highest qualification is above one standard deviation of the average level of educational attainment for their occupation)
- undereducated (individuals whose highest qualification is below one standard deviation of the average level of educational attainment for their occupation)

All employees are compared to the average level of educational attainment for the occupation they are in. Aggregating these groups over all occupations gives an estimated matched, over and undereducated rate for the whole economy.

Our adopted methodology differs from the methodology applied in our previously published article as we incorporate several methodological changes and robustness checks. First, we use the Annual Population Survey (APS), whereas previous analysis uses the Labour Force Survey (LFS). Compared to the LFS, the APS provides a larger sample which increases the robustness of our results and enables us to conduct more granular analysis by region and type of degree.

Second, we should emphasise that the statistical method, by its construction, permits the average job requirement to increase across all occupations if participation in education and the average level of educational attainment in the population increases. The effect on the degree of matching across the whole economy is therefore dependent on the age composition of each occupational group and the distribution of older and younger workers across occupations.

For example, as older people leave the labour market – other things being equal – this will tend to increase the average job requirement level for the whole economy, and reduce the percentage of the labour market that are classified as undereducated. To address this issue we construct estimates of required education by three-level SOC separately for two age groups (i) 16 to 35 years and (ii) 36 to 64 years. However, we do acknowledge that this approach may not entirely eliminate the age driven cohort effect as our age bands are somewhat arbitrary.

Third, as a robustness check we construct four different estimates of education mismatch and compare these to an experts view (we use O*NET as a benchmark). We present the comparison between statistical measures and O*NET in Figure 7.

We construct four measures of education attainment using the LFS. Table 5 describes each of these four measures, their advantages and limitations.

Table 5: Statistical measures of education mismatch

Measure	Description	Advantages	Disadvantages
1.Mean level of educational attainment	The mean level of educational attainment is computed for each occupation at each given time period	Relatively easily measurable Changes over time to remain current and up to date	Susceptible to cohort bias
2. Mode level of educational attainment	The mode of the highest level of qualification is computed for each occupation at each given time period. In cases where there are two modes, we take the lower educational level	Less susceptible to cohort bias by taking the most frequent level of education	Not a continuous variable, can only take finite values Volatile time series
3.Mean years of education	Years of education is estimated by subtracting five years from the individuals' continuous years of full time education. The mean is then computed for each occupation at each given time period	Continuous variable measured in years	Will not capture the true years of education for those with a gap year in their education, nor will it capture the true years of education for those in part time education.
		Changes over time to remain current and up to date	Refers to years rather than type /level or other characteristics of education
4.Mode years of education	The mode years of education is computed for each occupation at each given time period. In cases where there are two modes, we take the lower value for the mode years of education	Less susceptible to cohort biases by taking the most frequent years of education	Difficult to establish a suitable threshold to classify matched individuals Will not capture the true years of education for those with a gap year in their education, nor will it capture the true years of education for those in part time education.

Source: Office for National Statistics

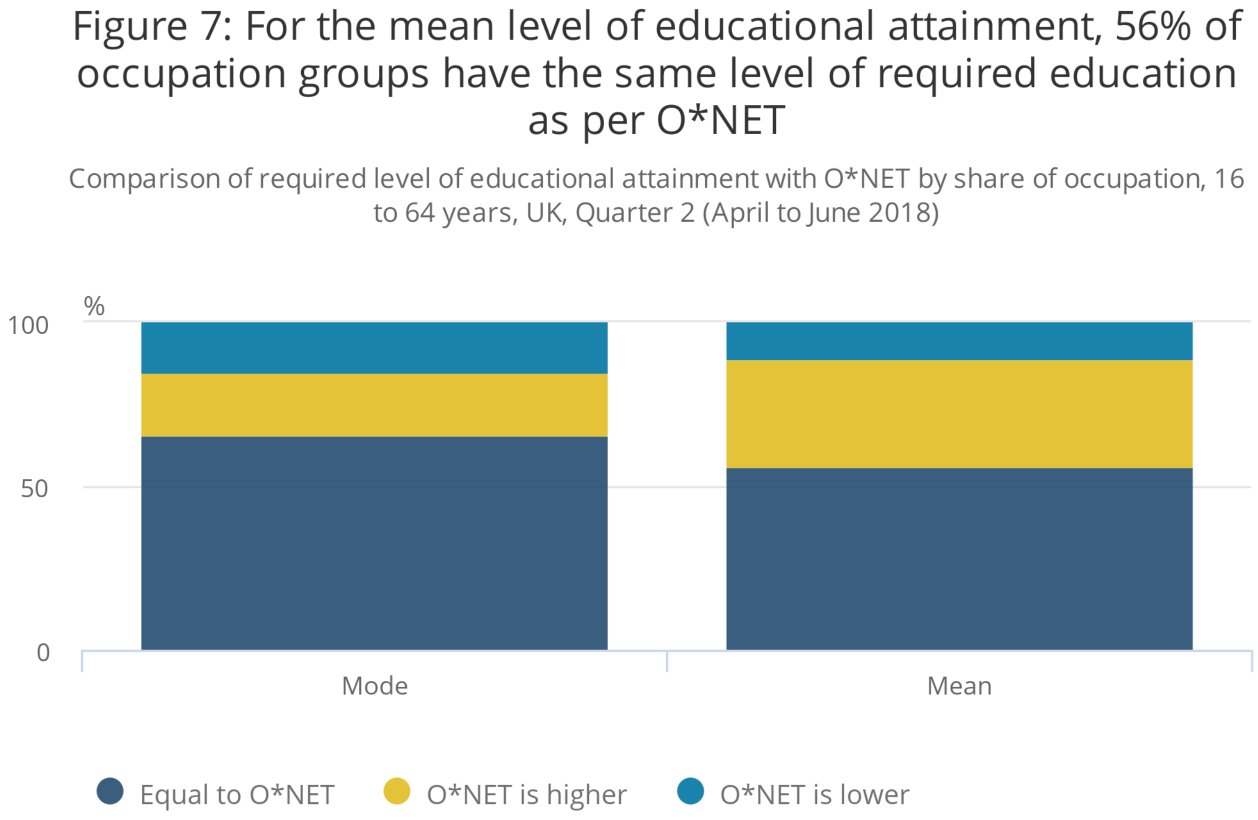
The O*NET category assignment data represents experts' insights into the required level of education for each occupation and it is not subject to cohort bias in the same way that our statistical measures are. Hence, O*NET provides a useful benchmark against which to compare our statistical measures. To conduct this comparison, we map each US SOC to a corresponding four-digit UK SOC, using a comprehensive US to UK SOC lookup.

After mapping all occupations to the LFS for the period April to June 2018, we compare the required level of education in O*NET to our measures (mean and the mode level of educational attainment for each occupation). The educational attainment data we drew from LFS do not always closely reflect the education assignment in the category system as depicted by experts view via O*NET. One major difference is that the category system such as O*NET reflects typical entry-level educational requirements, whereas LFS and APS data report the level of education attained by workers already in the occupation.

We thus observe that for the mode level of educational attainment approximately 66% of occupation groups on a four-level SOC have the same required level of education as per O*NET, whereas this was slightly lower for the mean level of education at 56% (Figure 7).

Figure 7: For the mean level of educational attainment, 56% of occupation groups have the same level of required education as per O*NET

Comparison of required level of educational attainment with O*NET by share of occupation, 16 to 64 years, UK, Quarter 2 (April to June 2018)



Source: Labour Force Survey – Office for National Statistics

Figure 7 also illustrates that there is a considerable share of occupations where category assignment (as per O*NET) shows higher level of education compared with our LFS mean and mode measures. This is slightly higher for the mean, whereby 22% of occupations require a higher level of education as per O*NET, compared with 19% for the mode. It is worth noting that US and UK qualifications are not directly comparable, hence, we have made slight adjustments to account for the fact that students finish high school at the age of 18 years under the US system.

There are several reasons why the educational attainment data may not match the category assignment. Examples are: underemployment, individual choice, and the trend of “upskilling,” in which the educational attainment of workers continues to rise over time. In some cases, the category assignment reflects a higher level of education than the attainment data show. This is because of changing entry requirements, individuals entering an occupation may need a higher level of formal education than those persons who are already working in it.

For example, automotive service technicians and mechanics entering the occupation may need a higher level of education compared to incumbents. Today's automotive engines and components have greater electronic and mechanical complexity, and prospective automotive service technicians and mechanics learn how to repair and maintain them while completing postsecondary education programs. The typical entry level education needed for this occupation is higher than in the past. By contrast, the educational attainment data are only a picture of the recent workforce and may not reflect typical requirements for new entrants to the occupation.

Despite the mode being reported as closer to the experts' view, in our descriptive analysis we chose to use the mean level of education attainment measure whilst making adjustments to mitigate the cohort bias as explained previously. This is because using the mode to produce aggregate matched and undereducated rates poses some limitations. First, with the mode measure we are unable to apply the standard deviation as a threshold from the mode. This would result in significantly lower matched rates of around 40%, therefore implying that 60% of workers are mismatched (either undereducated or overeducated).

Second, using the mode level of educational attainment results in a volatile time series. Given that the mode level of education is finite, a change in the mode would be staggered. For example, from 2012 to 2013 the mode level of educational attainment for a given occupation, may change from 5.0 to 4.0 which will result in volatile changes to the matched and mismatched rates making it more difficult to compare these rates over time.

In comparison with the mean where the level of educational attainment may change from, for example 5.4 to 4.8, the corresponding standard deviation change slightly, resulting in subtle changes in matched and mismatched rates. Therefore, using the mean level of educational attainment with a cohort adjustment allows us to construct a comparable time series while also addressing the cohort bias.

10 . Appendix 2

Regression analysis

In our regression analysis, we control for various individual and job characteristics which may impact both the incidence of overeducation as well as wages. These are: age and age squared (as the relationship between wages and age is non-linear), sex, marital status, number of dependent children, ethnicity, disability, type of employment contract (permanent versus temporary), full time or part time employment, region, occupational skill level, employer size, proxy for social status, immigration status, job tenure (a proxy for organisation specific experience) and survey proxy answers.

Individual factors such as gender, marital status and number of children, are likely to be important determinants of both hourly earnings and educational mismatch. For example, decisions regarding the family may affect individuals' chances of finding work related to their field of study, and this will affect their wages. Staying at home to raise children may require an individual to seek employment with a more flexible schedule, and this may involve foregoing the chance to work in a better paid job or indeed a job for which their qualification was intended.

The descriptive analysis in section three has shown a large regional variation in educational mismatch, implying that both the supply of and demand for skills differ across the UK regions and countries. The economic health and industrial composition of the region or country may largely determine the demand for particular skills and subsequently wages. Also, there is evidence that for certain groups such as married women, labour markets tend to be more geographically restricted. Hence the region or country is another important factor that we account for in our analysis.

Social status can also affect both wage levels and education mismatch (Forest, 2015), and it is usually proxied by the level of education of the father or mother. However, this information is missing in our dataset. We therefore make use of data on home ownership as related evidence shows that this is positively correlated with social status (Forest, 2015; Dang and others, 2017).

We also use the following interaction terms to reflect where the impact of one determinant of wages is affected by the level of another variable: sex multiplied by age, sex multiplied by marital status and sex multiplied by the number of dependent children. Here we acknowledge that females may experience more career interruptions than males due to marriage and having dependent children. Table 6 below is long version of Table 1. Table 6 presents coefficient estimates based on the two specifications of the wage equation discussed in section four with a full set of results for our individual and job control variables. The base control categories in Models 1 to 6 in Table 6 are: rented property; low job skill; London and agriculture.

Table 6: OLS Regression, hourly wage estimation results, 2017 (full model)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
					Female	**Male**
Variables	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**
Obtained education	0.084***	0.076***				
	(0.003)	(0.003)				
Obtained education squared	-0.002***	-0.001***				
	(0.000)	(0.000)				
Overeducated dummy (mean)	-0.081***					
	(0.008)					
Undereducated dummy (mean)	0.058***					
	(0.008)					
Age	0.041***	0.039***	0.049***	0.042***	0.044***	0.050***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of dependent children	0.008**	0.008***	0.010***	0.009***	-0.006*	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married	0.072***	0.073***	0.068***	0.072***	0.017***	0.060***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.007)
Female	0.027*	0.027*	0.016	0.026*		
	(0.015)	(0.015)	(0.015)	(0.015)		
White	0.054***	0.054***	0.049***	0.053***	0.023**	0.075***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)
UK born	0.058***	0.059***	0.022***	0.036***	0.033***	0.009
	(0.007)	(0.007)	(0.006)	(0.007)	(0.009)	(0.009)
Disability	-0.046***	-0.046***	-0.049***	-0.050***	-0.041***	-0.058***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.009)
Urban location	0.020*	0.021*	0.018	0.020*	0.037**	-0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.016)	(0.018)
Private sector	0.003	0.002	0.013**	0.003	-0.006	0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.009)
Full time	0.051***	0.052***	0.049***	0.052***	0.039***	0.089***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.011)
Permanent	0.063***	0.063***	0.065***	0.057***	0.035***	0.092***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.019)
Small firm	-0.131***	-0.132***	-0.128***	-0.134***	-0.092***	-0.165***

	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)
Proxy answer	-0.034***	-0.034***	-0.035***	-0.038***	-0.011*	-0.052***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)	(0.006)
Property owned outright	0.068***	0.069***	0.074***	0.081***	0.056***	0.090***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
Property bought with mortgage	0.132***	0.133***	0.134***	0.142***	0.108***	0.159***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Age*Female	-0.001***	-0.001***	-0.002***	-0.002***		
	(0.000)	(0.000)	(0.000)	(0.000)		
Married*Female	-0.059***	-0.060***	-0.057***	-0.057***		
	(0.009)	(0.009)	(0.009)	(0.009)		
Dependent children*Female	-0.016***	-0.015***	-0.015***	-0.015***		
	(0.004)	(0.004)	(0.004)	(0.004)		
High job skill	0.522***	0.542***	0.374***	0.551***	0.416***	0.353***
	(0.008)	(0.008)	(0.010)	(0.008)	(0.015)	(0.014)
Uppermiddle job skill	0.323***	0.333***	0.264***	0.348***	0.283***	0.262***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.010)
Lower middle job skill	0.119***	0.123***	0.104***	0.129***	0.099***	0.115***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
North East	-0.239***	-0.239***	-0.247***	-0.250***	-0.228***	-0.264***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.014)
North West	-0.222***	-0.222***	-0.229***	-0.229***	-0.218***	-0.240***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.013)
Merseyside	-0.197***	-0.196***	-0.208***	-0.209***	-0.202***	-0.214***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.016)	(0.017)
Yorkshire and Humber	-0.229***	-0.229***	-0.236***	-0.238***	-0.219***	-0.253***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)
East Midlands	-0.230***	-0.230***	-0.236***	-0.239***	-0.212***	-0.262***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.015)
West Midlands	-0.206***	-0.206***	-0.211***	-0.213***	-0.207***	-0.215***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.013)
East	-0.149***	-0.149***	-0.154***	-0.156***	-0.162***	-0.148***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.015)
South East	-0.120***	-0.120***	-0.125***	-0.124***	-0.135***	-0.115***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)
South West	-0.201***	-0.200***	-0.202***	-0.204***	-0.192***	-0.213***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.013)
West	-0.237***	-0.237***	-0.238***	-0.242***	-0.224***	-0.253***

	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.013)
Scotland	-0.195***	-0.195***	-0.197***	-0.203***	-0.180***	-0.216***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.013)	(0.014)
Northern Ireland	-0.252***	-0.251***	-0.248***	-0.254***	-0.226***	-0.272***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.017)	(0.018)
Tenure	0.008***	0.008***	0.008***	0.008***	0.009***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manufacturing	0.099***	0.099***	0.100***	0.102***	0.115***	0.080***
	(0.025)	(0.025)	(0.024)	(0.024)	(0.039)	(0.031)
Energy	0.215***	0.215***	0.212***	0.217***	0.223***	0.196***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.045)	(0.033)
Construction	0.121***	0.122***	0.137***	0.121***	0.157***	0.126***
	(0.026)	(0.026)	(0.025)	(0.025)	(0.042)	(0.032)
Hotels and restaurants	-0.025	-0.024	-0.025	-0.025	-0.030	-0.034
	(0.024)	(0.024)	(0.024)	(0.024)	(0.038)	(0.030)
Transport	0.167***	0.170***	0.160***	0.173***	0.180***	0.137***
	(0.025)	(0.025)	(0.024)	(0.025)	(0.039)	(0.031)
Finance	0.187***	0.192***	0.171***	0.200***	0.167***	0.155***
	(0.025)	(0.025)	(0.024)	(0.024)	(0.038)	(0.031)
Public services	0.017	0.020	0.002	0.026	-0.006	-0.000
	(0.024)	(0.024)	(0.024)	(0.024)	(0.038)	(0.031)
Other services	0.015	0.019	0.011	0.028	0.036	-0.035
	(0.026)	(0.026)	(0.026)	(0.026)	(0.039)	(0.034)
Overeducated dummy (mode)		-0.033***				
		(0.007)				
Undereducated dummy (mode)		0.024***				
		(0.009)				
Required education years (mean)			0.100***		0.082***	0.111***
			(0.003)		(0.004)	(0.004)
Overeducation years (mean)			0.013***		0.010***	0.017***
			(0.002)		(0.002)	(0.002)
Undereducation years (mean)			-0.100***		-0.106***	-0.089***
			(0.006)		(0.008)	(0.009)

Required education years (mode)				0.031***		
				(0.001)		
Overeducation tears (mode)				0.026***		
				(0.001)		
Undereducation years (mode)				-0.082***		
				(0.005)		
Constant	0.289***	0.396***	-0.299***	0.724***	0.058	-0.552***
	(0.051)	(0.051)	(0.057)	(0.047)	(0.082)	(0.081)
Observations	76,360	76,360	76,337	76,337	40,342	35,995
R-squared	0.432	0.430	0.433	0.424	0.412	0.426

Source: Annual Population Survey – Office for National Statistics

Notes

1. Standard errors in parentheses. Back to table
2. *** p<0.01, ** p<0.05, * p<0.1. Back to table

Table 7: OLS regression, hourly wage estimation results for graduates, 2017 (full model)

	Model 7	Model 8	Model 9	Model 10	Model 11
Variables	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**	**log_hourpay**
Required education	0.054***	0.054***	0.054***	0.053***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Overeducation	-0.014***	-0.018***	-0.022***	-0.018***	-0.017***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)
Recent graduate	-0.005	-0.003	-0.005	-0.016	-0.005
	(0.016)	(0.016)	(0.016)	(0.017)	(0.016)
STEM degree subject	0.021**	0.021**	0.021**	0.021**	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.064***	0.065***	0.064***	0.063***	0.064***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of dependent children	0.017**	0.017**	0.018**	0.018***	0.017**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Married	0.083***	0.084***	0.082***	0.082***	0.083***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Female	0.018	0.017	0.014	0.019	0.017
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
White	0.055***	0.055***	0.054***	0.055***	0.055***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
UK born	0.078***	0.077***	0.078***	0.077***	0.077***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Disability	-0.052***	-0.052***	-0.052***	-0.053***	-0.052***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Urban location	0.049**	0.048*	0.050**	0.050**	0.048*
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Private sector	0.047***	0.047***	0.047***	0.047***	0.048***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Full time	0.064***	0.064***	0.064***	0.064***	0.064***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Permanent	0.048**	0.048**	0.047**	0.047**	0.048**
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Small firm	-0.168***	-0.167***	-0.168***	-0.168***	-0.168***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Proxy answer	-0.018**	-0.018**	-0.019**	-0.018**	-0.018**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)

Property owned outright	0.046***	0.046***	0.046***	0.046***	0.046***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Property bought with mortgage	0.102***	0.102***	0.102***	0.102***	0.102***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age*Female	-0.001*	-0.001*	-0.002**	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married*Female	-0.056***	-0.056***	-0.054***	-0.056***	-0.056***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Dependent children*Female	-0.032***	-0.032***	-0.033***	-0.033***	-0.032***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
High job skill	0.401***	0.399***	0.399***	0.401***	0.398***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Uppermiddle job skill	0.315***	0.313***	0.314***	0.315***	0.312***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Lower middle job skill	0.137***	0.136***	0.135***	0.138***	0.136***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
North East	-0.278***	-0.278***	-0.278***	-0.278***	-0.278***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
North West	-0.273***	-0.273***	-0.272***	-0.273***	-0.273***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Merseyside	-0.229***	-0.229***	-0.229***	-0.229***	-0.229***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Yorkshire and Humber	-0.268***	-0.268***	-0.268***	-0.268***	-0.268***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
East Midlands	-0.267***	-0.267***	-0.267***	-0.267***	-0.267***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
West Midlands	-0.246***	-0.246***	-0.246***	-0.246***	-0.246***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
East	-0.161***	-0.161***	-0.161***	-0.161***	-0.161***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
South East	-0.147***	-0.147***	-0.147***	-0.147***	-0.147***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
South West	-0.256***	-0.256***	-0.255***	-0.255***	-0.255***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
West	-0.263***	-0.262***	-0.262***	-0.262***	-0.262***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)

Scotland	-0.244***	-0.243***	-0.244***	-0.244***	-0.244***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Northern Ireland	-0.284***	-0.284***	-0.283***	-0.283***	-0.284***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Tenure	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Tenure squared	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manufacturing	0.160**	0.159**	0.159**	0.160***	0.160**
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Energy	0.258***	0.257***	0.257***	0.259***	0.259***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
Construction	0.145**	0.144**	0.144**	0.146**	0.146**
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)
Hotels and restaurants	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Transport	0.154**	0.153**	0.154**	0.155**	0.154**
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Finance	0.188***	0.187***	0.187***	0.189***	0.188***
	(0.061)	(0.062)	(0.062)	(0.061)	(0.061)
Public services	0.007	0.006	0.007	0.008	0.007
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
Other services	-0.012	-0.013	-0.012	-0.011	-0.011
	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
Overeducation*Tenure		0.000*			
		(0.000)			
Overeducation*Female			0.014***		
			(0.005)		
Overeducation*Recent graduate				0.012**	
				(0.005)	
Overeducation*STEM degree subject					0.011*
					(0.005)
Constant	-0.024	-0.027	-0.010	0.008	-0.024
	(0.141)	(0.141)	(0.141)	(0.142)	(0.141)
Observations	17,672	17,672	17,672	17,672	17,672
R-squared	0.403	0.403	0.403	0.403	0.403

Source: Annual Population Survey – Office for National Statistics

Notes

1. Robust standard errors in parentheses. Back to table

2. *** p<0.01, ** p<0.05, * p<0.1. Back to table

Table 8: Quantile regression, hourly wage estimation results for graduates, 2017 (full model)

	Model 12	Model 13	Model 14
Variables	**q25**	**q50**	**q75**
Required education	0.040***	0.045***	0.061***
	(0.005)	(0.004)	(0.004)
Overeducation	-0.010***	-0.011***	-0.011***
	(0.002)	(0.003)	(0.003)
Recent graduate	-0.009	-0.013	-0.004
	(0.013)	(0.012)	(0.016)
STEM degree subject	0.016*	0.011**	0.007
	(0.008)	(0.005)	(0.006)
Age	0.047***	0.052***	0.065***
	(0.002)	(0.003)	(0.004)
Age squared	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Number of dependent children	0.016***	0.016**	0.029***
	(0.005)	(0.007)	(0.010)
Married	0.068***	0.076***	0.075***
	(0.014)	(0.014)	(0.017)
Female	0.047*	0.055***	0.108***
	(0.025)	(0.021)	(0.026)
White	0.042***	0.044***	0.061***
	(0.011)	(0.011)	(0.018)
UK born	0.080***	0.073***	0.067***
	(0.012)	(0.013)	(0.017)
Disability	-0.038***	-0.048***	-0.073***
	(0.011)	(0.009)	(0.011)
Urban location	0.021	0.028	0.024
	(0.020)	(0.021)	(0.021)
Private sector	0.011	0.046***	0.067***
	(0.010)	(0.009)	(0.013)
Full time	0.068***	0.063***	0.061***
	(0.009)	(0.008)	(0.013)
Permanent	0.062***	0.030**	-0.024
	(0.017)	(0.015)	(0.017)
Small firm	-0.118***	-0.107***	-0.105***
	(0.008)	(0.008)	(0.011)
Proxy answer	-0.015**	-0.025***	-0.004
	(0.007)	(0.007)	(0.011)

Property owned outright	0.037***	0.066***	0.086***
	(0.011)	(0.008)	(0.011)
Property bought with mortgage	0.099***	0.111***	0.122***
	(0.010)	(0.007)	(0.008)
Age*Female	-0.002***	-0.003***	-0.004***
	(0.000)	(0.001)	(0.001)
Married*Female	-0.033	-0.039**	-0.042*
	(0.021)	(0.017)	(0.024)
Dependent children*Female	-0.034***	-0.020*	-0.019
	(0.009)	(0.011)	(0.012)
High job skill	0.421***	0.460***	0.480***
	(0.020)	(0.017)	(0.019)
Uppermiddle job skill	0.299***	0.341***	0.388***
	(0.013)	(0.018)	(0.020)
Lower middle job skill	0.115***	0.124***	0.175***
	(0.013)	(0.018)	(0.020)
North East	-0.260***	-0.286***	-0.329***
	(0.016)	(0.018)	(0.020)
North West	-0.247***	-0.274***	-0.308***
	(0.014)	(0.016)	(0.020)
Merseyside	-0.226***	-0.223***	-0.304***
	(0.020)	(0.024)	(0.020)
Yorkshire and Humber	-0.264***	-0.268***	-0.318***
	(0.018)	(0.018)	(0.024)
East Midlands	-0.250***	-0.259***	-0.304***
	(0.011)	(0.015)	(0.021)
West Midlands	-0.235***	-0.233***	-0.303***
	(0.015)	(0.015)	(0.017)
East	-0.205***	-0.188***	-0.188***
	(0.015)	(0.022)	(0.027)
South East	-0.157***	-0.152***	-0.164***
	(0.012)	(0.016)	(0.017)
South West	-0.231***	-0.253***	-0.289***
	(0.018)	(0.016)	(0.022)
West	-0.250***	-0.274***	-0.321***
	(0.012)	(0.017)	(0.018)
Scotland	-0.211***	-0.234***	-0.284***
	(0.013)	(0.021)	(0.019)

Northern Ireland	-0.246***	-0.283***	-0.357***
	(0.030)	(0.022)	(0.023)
Tenure	0.013***	0.012***	0.008***
	(0.001)	(0.001)	(0.001)
Tenure squared	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Manufacturing	0.199***	0.105	0.036
	(0.056)	(0.073)	(0.056)
Energy	0.290***	0.202***	0.156***
	(0.060)	(0.076)	(0.051)
Construction	0.176***	0.091	0.003
	(0.061)	(0.070)	(0.053)
Hotels and restaurants	0.016	-0.074	-0.116**
	(0.059)	(0.071)	(0.054)
Transport	0.189***	0.097	0.039
	(0.064)	(0.063)	(0.054)
Finance	0.197***	0.117*	0.067
	(0.057)	(0.070)	(0.054)
Public services	0.068	-0.049	-0.151***
	(0.059)	(0.068)	(0.050)
Other services	0.018	-0.046	-0.100*
	(0.066)	(0.068)	(0.055)
Constant	0.291**	0.392***	0.156
	(0.124)	(0.123)	(0.117)
Observations	17,672	17,672	17,672

Source: Annual Population Survey – Office for National Statistics

Notes

1. Standard errors in parentheses. Back to table
2. *** p<0.01, ** p<0.05, * p<0.1. Back to table

Analysis of job changers and stayers

Composition and wage growth of job changers and stayers in the UK using Annual Survey of Hours and Earnings (ASHE) data. Data split by age, sex, contract, sector, skill, region and industry.

Contact:
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Release date:
29 April 2019

Next release:
18 July 2019

Correction

29 April 2019 14:55

A correction has been made to Figure 12: Earnings growth for job changers in London outpaced all other regions, Median growth of hourly earnings for job changers within regions, between 2017 and 2018, UK. This was due to a small error in the data used in the chart. You can see the original content in the superseded version. We apologise for any inconvenience.

10 September 2019 14:32

A correction has been made to the overall production figures in Section 12 and Figure 15 due to a small error in the summing up of the individual production industries. You can see the original content in the superseded version. We apologise for any inconvenience.

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1 . Main points

- Job stayers on average earn a higher hourly wage compared with those who change jobs; however, workers who switch jobs experience higher pay growth compared with those who do not.
- The relatively weak pickup in wage growth in recent years, despite record low unemployment, has been driven by job stayers – who represent most of the sample.
- Job changers moving between firms have higher pay growth than those moving within firms.
- Full-time job changers experienced higher earnings growth compared with job stayers, while part-time stayers and changers experienced similar growth to each other.
- Most job changers switch jobs within the same skill level and region.
- Job changers have more varied earnings growth across regions and industries than job stayers.
- On average, around 9% of people changed jobs each year between 2000 and 2018; this ranged from a post-recession low of around 5.7% in 2010 to a high of around 10.9% in both 2017 and 2018.

2 . Introduction

Analysis of workers who switch jobs and those who stay put is an important area of the labour market. Looking at the composition and pay growth for job changers is a good way to understand the strength or weakness in the labour market. For example, pay growth for job changers is more cyclical and quicker to react to the economic downturn than pay growth for job stayers, who are more closely tied to pay settlements that lag the cycle.

The extent of job switching can also signal how well the wage mechanism is working in the labour market or if labour supply is well informed of market conditions. More people switching jobs suggests an awareness of the labour market, reducing the likelihood of asymmetric information.

Pay growth of UK workers changing jobs voluntarily might be expected to be higher on average than that of workers who stay in their position, and so, workers changing jobs also puts upward pressure on wages. When workers changing jobs secure a pay rise, the average overall wage growth increases. Consequently, companies are pressured into paying higher wages to existing staff, as well as the new staff, to encourage them to stay in the job rather than change jobs. There will also be some workers who change jobs involuntarily due to redundancies.

There has been much focus on whether the Phillips Curve has flattened or shifted downwards, reflecting the relatively subdued pickup in wage growth, given the recent record low unemployment. This may be because the pay growth or job-to-job flows for job changers has been subdued compared with historical rates. Similarly, pay growth for those staying in the same job has remained subdued – which would need to increase to support a broader rise in labour cost pressures.

This article presents analysis using the Annual Survey of Hours and Earnings (ASHE) dataset[1] from 2000 to 2018. We examine the composition and hourly earnings[2] of job stayers and job changers. Individuals that stay in their job over two consecutive years are referred to as job stayers, and those who have changed jobs from one year to the other are referred to as job changers. This methodology differs from the methodology used in Employee earnings in the UK: 2018. For more detail on the differences, please see the methodology section of this article.

Notes for: Introduction

1. ASHE is an employer survey; hence we are unable to make inferences about whether job moves are voluntary or involuntary. However, we can observe whether pay has increased or decreased between two consecutive years. ASHE also does not cover the self-employed, who may have played a role in any structural and/or cyclical movements in flows and earnings.

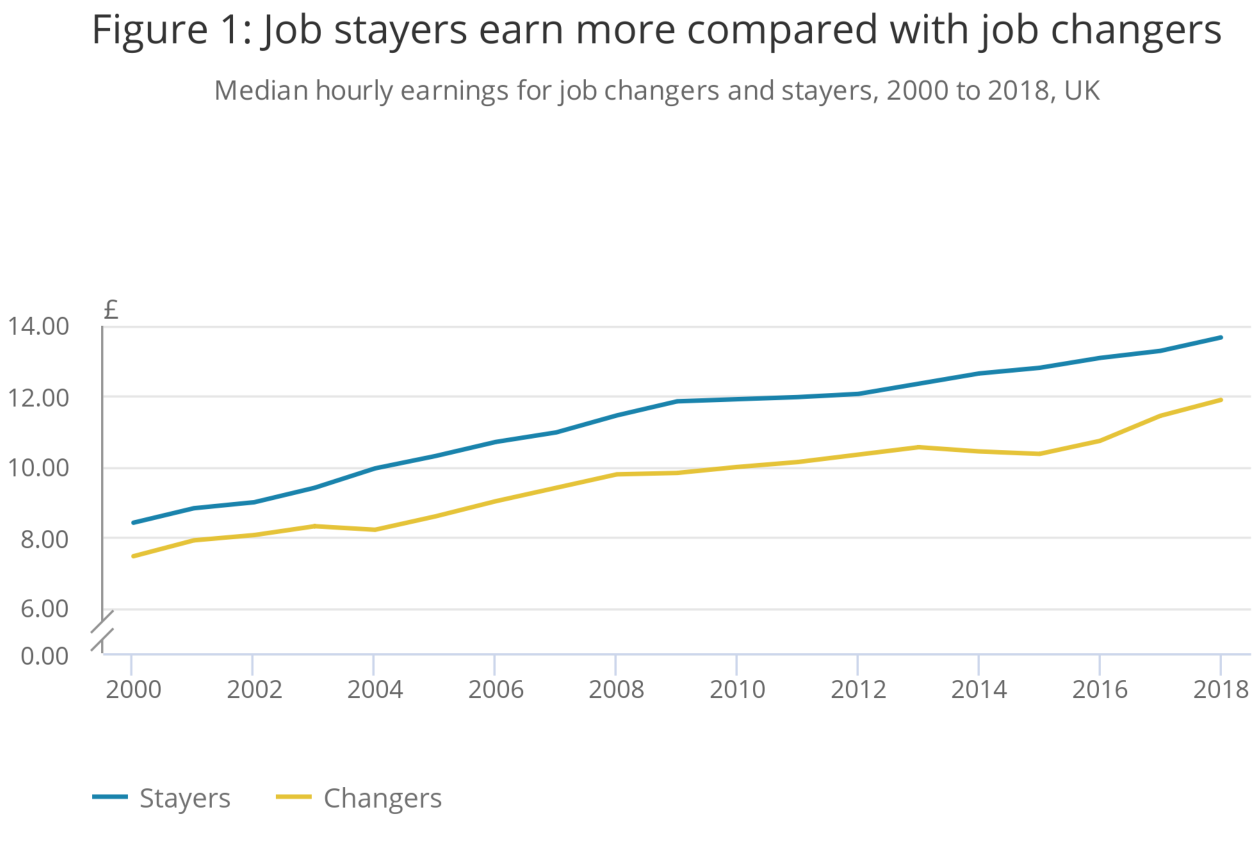
2. Hourly earnings is calculated as gross pay including incentive pay, overtime and shift premiums for the reference period, divided by the total paid hours worked during that period. This is because it reflects the actual gross pay of individuals, independent of the hours they work, enabling full comparisons to be made between groups in each time period. To capture the typical experience of earnings growth, median of hourly earnings growth is calculated. This is the rate of pay growth at the centre of the distribution of earnings growth.

3 . Job changers and stayers

Job stayers on average earn a higher hourly wage compared with individuals who change jobs, as shown in Figure 1. This may be partly due to the skills and experience they gain by staying in a job and the nature of their employment. In 2018, the median wage for job stayers was £13.67 compared with £11.90 for job changers.

Figure 1: Job stayers earn more compared with job changers

Median hourly earnings for job changers and stayers, 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

However, job changers experience higher pay growth compared with job stayers, as shown in Figure 2. This could either be due to workers on lower pay at the beginning of their careers switching jobs to achieve the level of pay of more established staff, or firms paying a higher wage to staff who have already been trained.

In 2018, the median of hourly earnings growth for job changers was 7.3% compared with 3.0% for job stayers. Earnings growth for job changers is more cyclical and quicker to react to the economic downturn than for job stayers, who are more closely tied to pay settlements that lag the cycle. Pay growth for job stayers in recent years has remained below the pre-downturn average.

Figure 2: Job changers experience higher pay growth compared with job stayers

Median growth of hourly earnings for job changers and stayers, 2000 to 2018, UK

Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes:

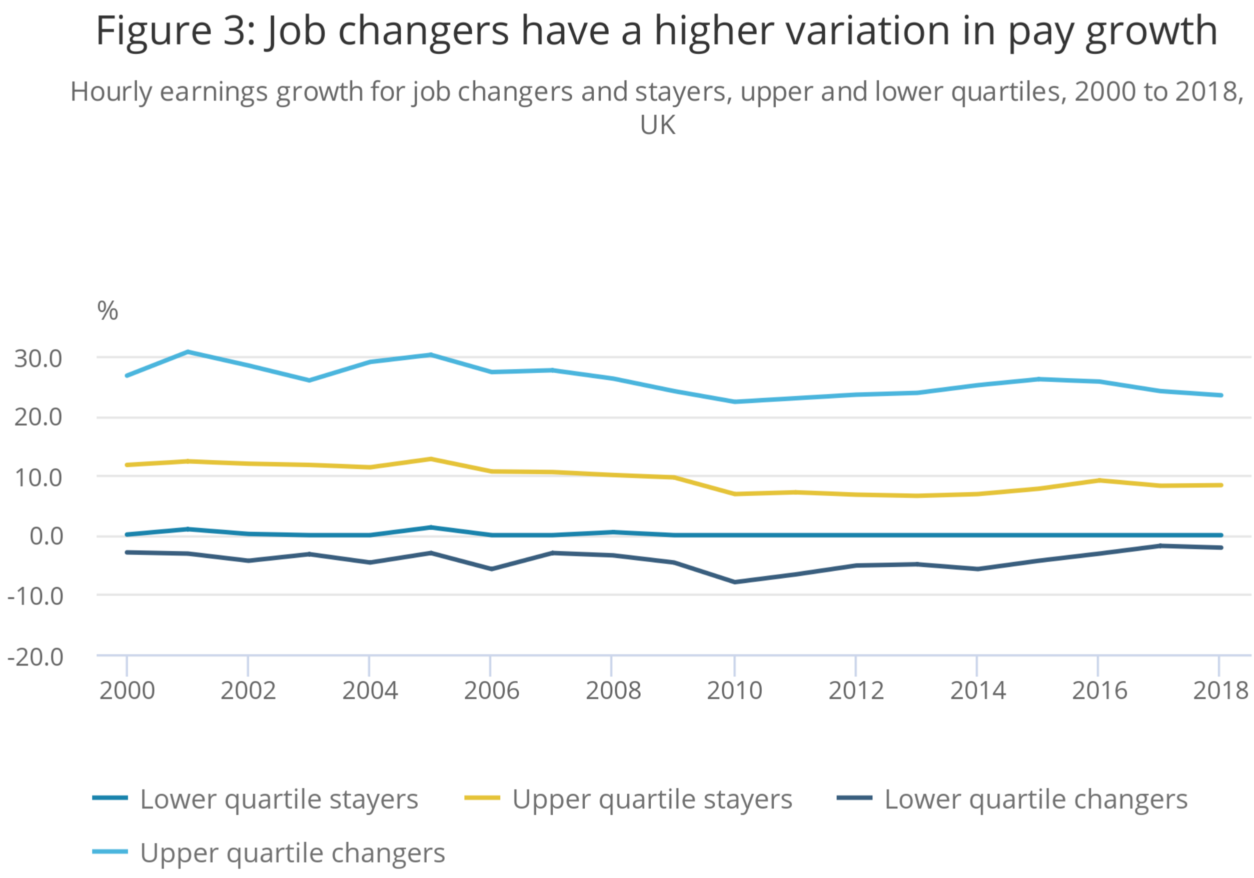
1. To capture the typical experience of earnings growth, median of hourly earnings growth is calculated. This is the rate of pay growth at the centre of the distribution of earnings growth. This is different from growth in median pay, which does not necessarily capture the changes in wages experienced by the majority of the continuously employed. This calculates how the pay at the centre of the distribution has changed between the periods. In other words, it shows how pay for the individual at the middle of the earnings distribution in one year compares with the pay for the individual at the middle of the earnings distribution a year later.

Although median earnings growth is a good summary measure of changing labour market conditions, it masks variation in experiences. As workers move between posts, or experience changes in their pay, the earnings of some individuals will rise in each period, while others will see their earnings fall.

To get a more detailed perspective of wage pressure, we also examine the hourly earnings growth at the lower and upper quartiles (Figure 3). Job stayers experience no hourly earnings growth at the lower quartile, and around 10% pay growth at the upper quartile across the series. Job changers, on the other hand, have a much greater variation in pay growth, with pay falling at the lower quartile, and around 25% growth at the upper quartile.

Figure 3: Job changers have a higher variation in pay growth

Hourly earnings growth for job changers and stayers, upper and lower quartiles, 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes:

1. Upper quartile is the 75th percentile and lower quartile is the 25th percentile.

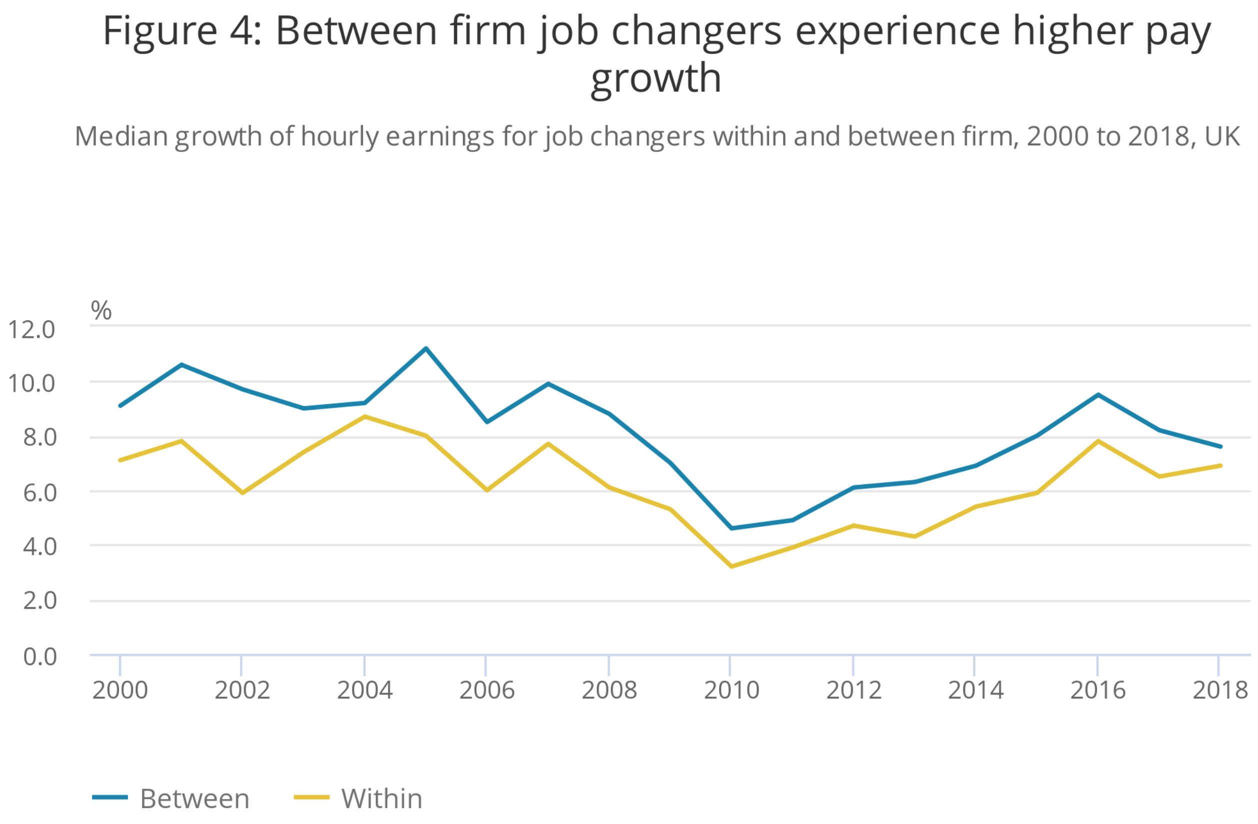
4 . “Within” and “between” firms

We construct a within and between firm variable to examine whether job changers can receive higher pay growth by staying in a similar job to the one they were previously in or not. Movement of workers “between” firms is defined as those workers who work in a different location compared with the year before, or have changed the industry they work in, or are in a different occupational category. In this sense, “between firm” is more a proxy for how different a job the workers are in compared with the previous year. “Within firm” will then be all the remaining individuals.

Of the job changers, those who moved within their own firm consistently received higher median earnings compared with those who moved between firms. The reverse is true for the growth of earnings; job changers between firms experience higher pay growth than within firm movers, as shown in Figure 4. This could be due to firms willing to pay more to acquire staff who have already been trained. Alternatively, it may reflect the higher risk premium workers attach to changing employer or that those who change industry or occupational category are generally doing so to move towards a post that is a better match for their skills. Only when a firm is willing to pay more than the existing firm (other things being similar), is a worker likely to switch between firms. In 2018, 75.4% of job changers moved between firms, while 24.6% moved within firms.

Figure 4: Between firm job changers experience higher pay growth

Median growth of hourly earnings for job changers within and between firm, 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

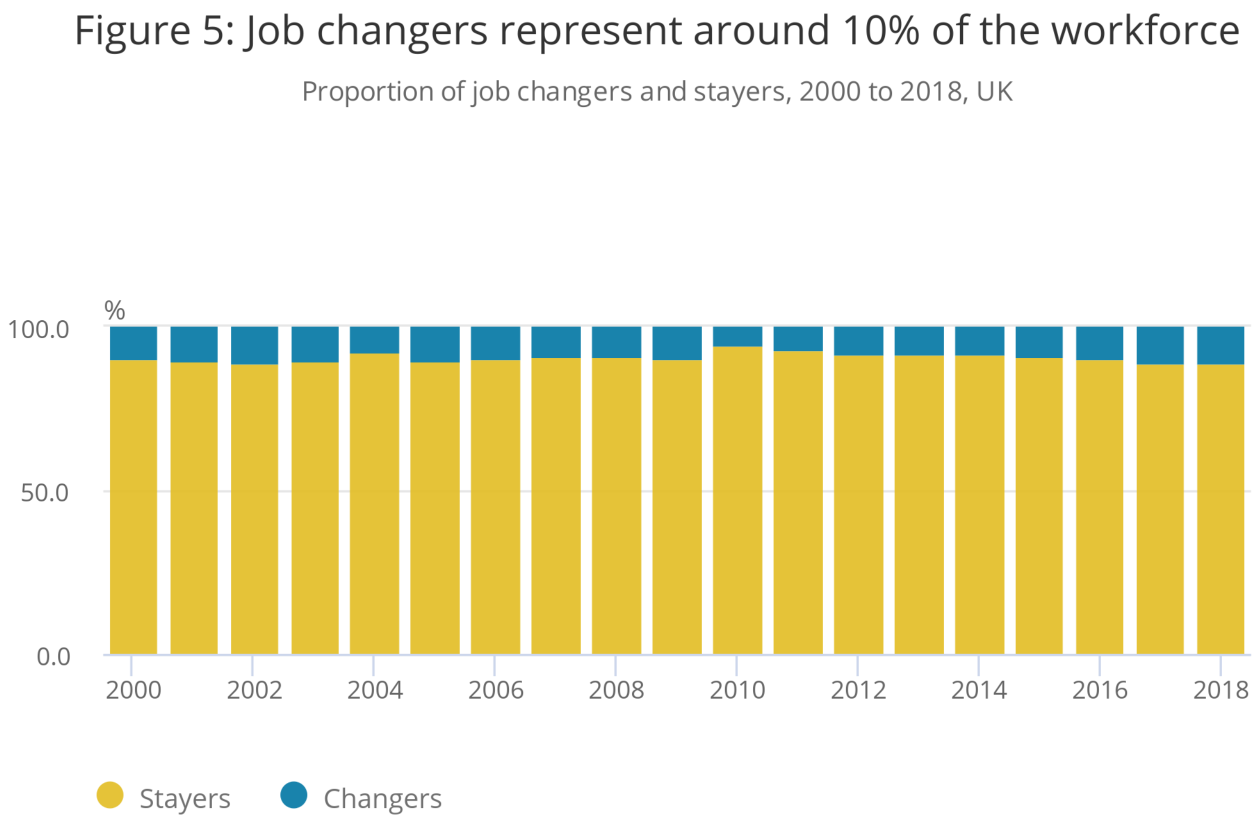
5 . Composition

Figure 5 shows that between 2000 and 2018 the proportion of people changing jobs has been, on average, 9.1% compared with 90.9% of people remaining in their jobs. This has varied over the years; in 2018 the proportion of job changers was around 10.9%. That was the same as the previous year, and the joint highest in the series. The percentage of workers changing jobs was the lowest in 2010, at around 5.7%, following the economic downturn. Although the economy started to recover from the downturn in 2009, fewer people moved jobs in 2010 than in all other years, possibly reflecting a risk-averse attitude of workers following the crisis. The labour market has since become more dynamic, with the proportion of people changing jobs increasing on average by 5.2 percentage points between 2010 and 2018 to around 10.9%. This coincides with:

- an unemployment decrease for the 16 years and over age group of 44.7%
- an employment increase for 16- to 64-year olds of 9.9%
- workforce jobs increasing by 11.0%

Figure 5: Job changers represent around 10% of the workforce

Proportion of job changers and stayers, 2000 to 2018, UK



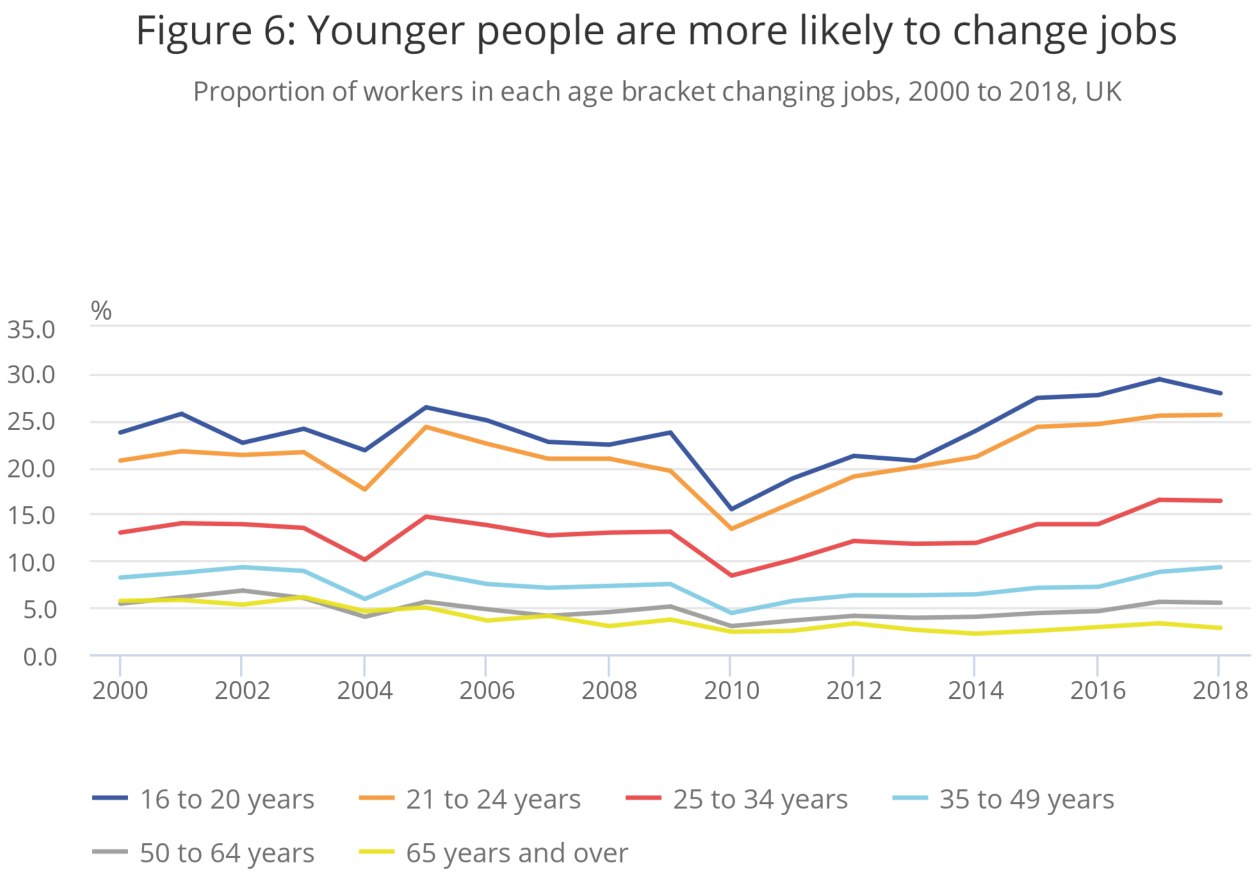
Source: Annual Survey of Hours and Earnings – Office for National Statistics

6 . Age

Data split by age show the starkest difference between changers, with people below the age of 35 years more likely to change jobs, as shown in Figure 6. This could be due to a greater proportion of younger workers in part-time, unstable or temporary jobs. From 2017 to 2018, 51% of 16-to-20-year-old job changers switched jobs from a part-time job to another part-time job.

Figure 6: Younger people are more likely to change jobs

Proportion of workers in each age bracket changing jobs, 2000 to 2018, UK



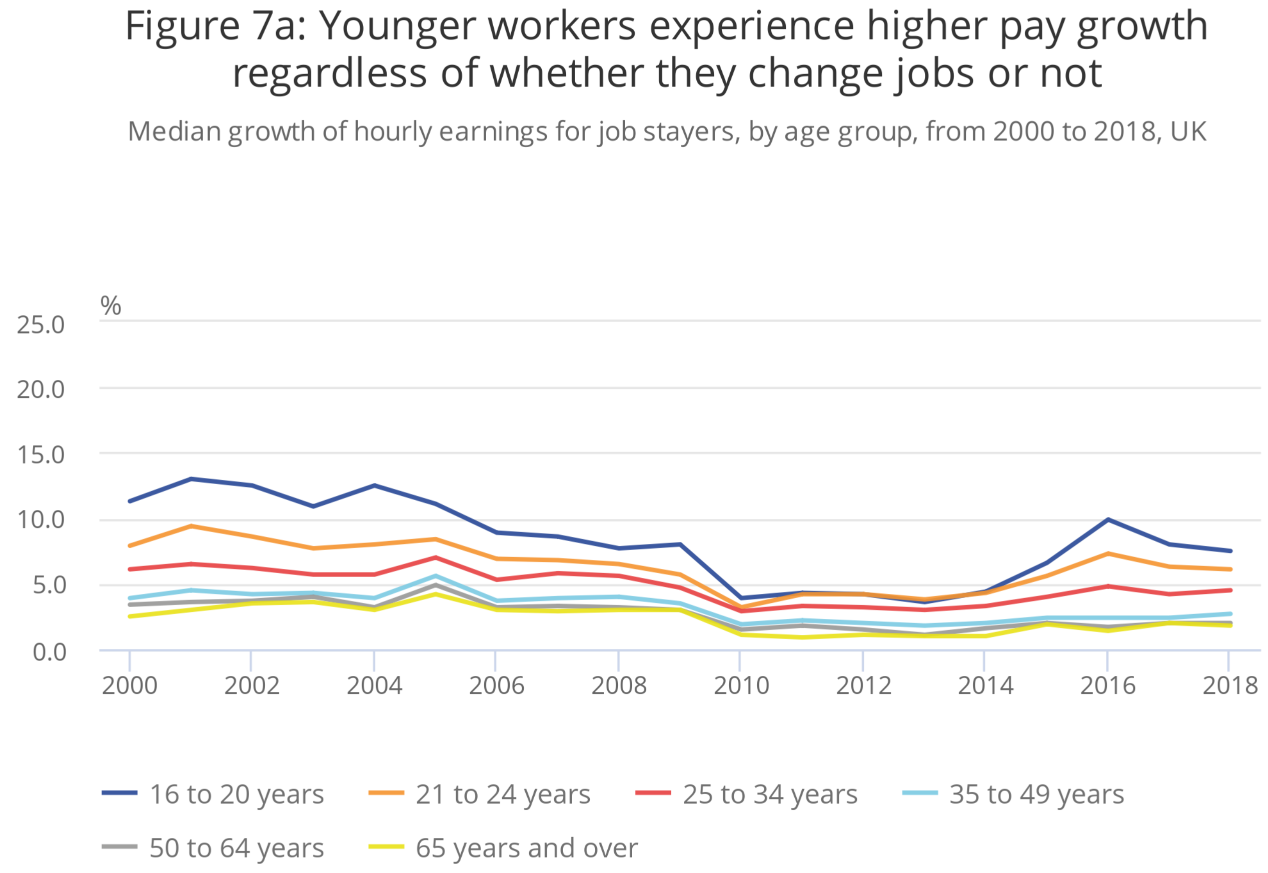
Source: Annual Survey of Hours and Earnings – Office for National Statistics

Figures 7a and 7b display the median earnings growth of job stayers and changers by age. Earnings typically reflect career progression, with younger workers earning less than the older workers. Hence, younger workers experience higher pay growth regardless of whether they change jobs or not. Since 2010, growth in earnings for people aged 35 years and older has been subdued, with those not changing jobs experiencing a median hourly earnings growth between 0.9% and 3.0% per year, while those who changed jobs received between 0.0% and 6.5%.

The uptick in earnings growth in 2016 for younger job stayers (aged less than 25 years), coincides with the introduction of the national living wage. Although the living wage was not applicable to these workers, there is some evidence for upward pressure on their wages.

Figure 7a: Younger workers experience higher pay growth regardless of whether they change jobs or not

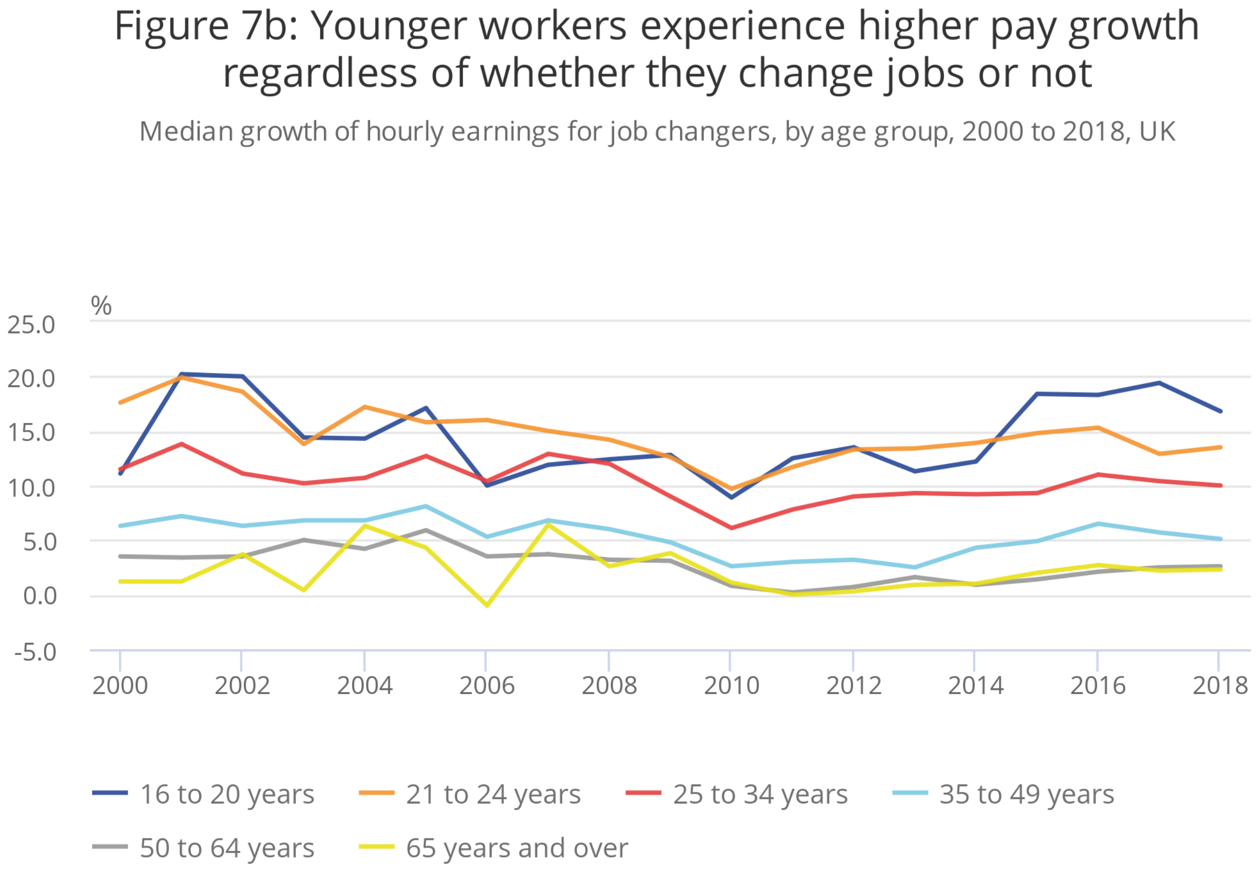
Median growth of hourly earnings for job stayers, by age group, from 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Figure 7b: Younger workers experience higher pay growth regardless of whether they change jobs or not

Median growth of hourly earnings for job changers, by age group, 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

7 . Sex

For both men and women, those who stayed in the same job earned more than their counterparts who changed jobs across the time series. In 2018, the median of hourly earnings including overtime for female job changers was around £11, while for female job stayers it was around £12. On the other hand, male job changers earned a median wage around £13, while male job stayers earned around £15. In 2018, 45.5% of the total sample were male stayers and 43.5% were female stayers.

As depicted in Figure 8, earnings growth for job stayers is very similar for both sexes and is lower than earnings growth for job changers. In 2018, the median earnings growth for male job changers was 8.6% while for male job stayers it was 3.0%. In the same year, the median earnings growth for female job changers was 6.5% compared with 2.9% for female job stayers.

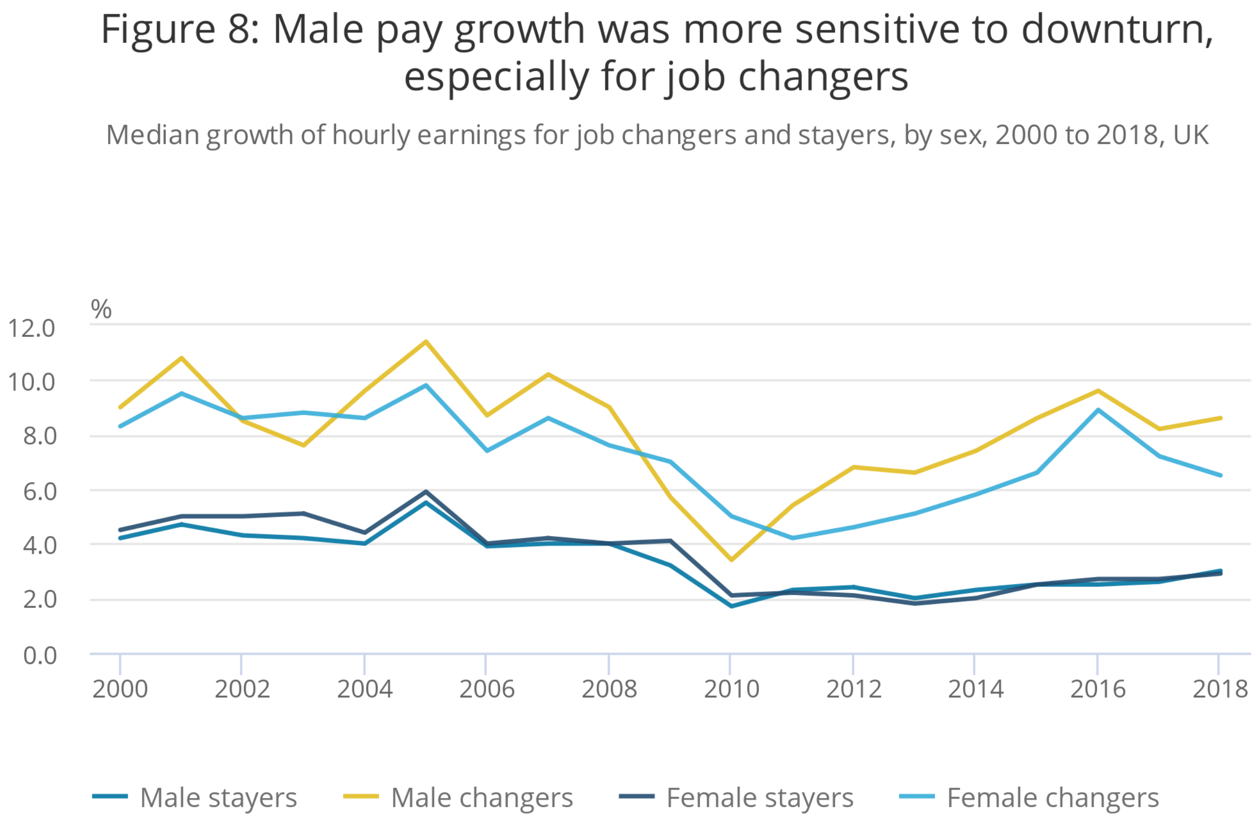
Women and men, on average, get similar pay growth if they stay in the same job. But women experience a lower earnings growth compared with men when they change job. This may be due to more women changing jobs from part-time to part-time, compared with men.

Earnings growth for men was more sensitive to the 2008 to 2009 economic downturn, compared with women. This is especially pronounced for the job changers but can also be seen for the job stayers. This may be because more men are in full-time contracts and wage growth for full-time changers was affected by the downturn more. The slowdown in median earnings growth for male job changers during the downturn was immediate and sharp, while the female job changers experienced a slower recovery.

In 2018, both men and women experienced earnings growth below their pre-downturn average. This is especially pronounced for job stayers.

Figure 8: Male pay growth was more sensitive to downturn, especially for job changers

Median growth of hourly earnings for job changers and stayers, by sex, 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

8 . Contract type

In 2018, around 75.4% of employees worked full-time and 24.6% worked part-time. Of the full-time workers, 88.9% stayed in the same job as the year before, while 89.6% of part-time workers stayed in the same job as the year before.

Full-time job changers had higher median earnings growth than job stayers. Their earnings growth was more strongly affected by the 2008 economic downturn. However, it remained above stayers' growth. Fewer full-time workers changed jobs during this period. In 2007, 8.6% of full-time workers changed jobs, compared with 5.4% in 2010.

On the other hand, median wage growth for part-time stayers and changers is similar, except for 2016 when the changers experienced stronger growth. This coincides with the introduction of the living wage, which resulted in greater upward pressure on part-time changers' wage but also some pressure on the part-time stayers' wage. Before 2016, part-time changers experienced wage growth similar to both part-time and full-time stayers. These workers experienced a protracted slowdown in earnings growth following the economic downturn, with median earnings growth remaining flat for four years after 2010 at about 2.4%.

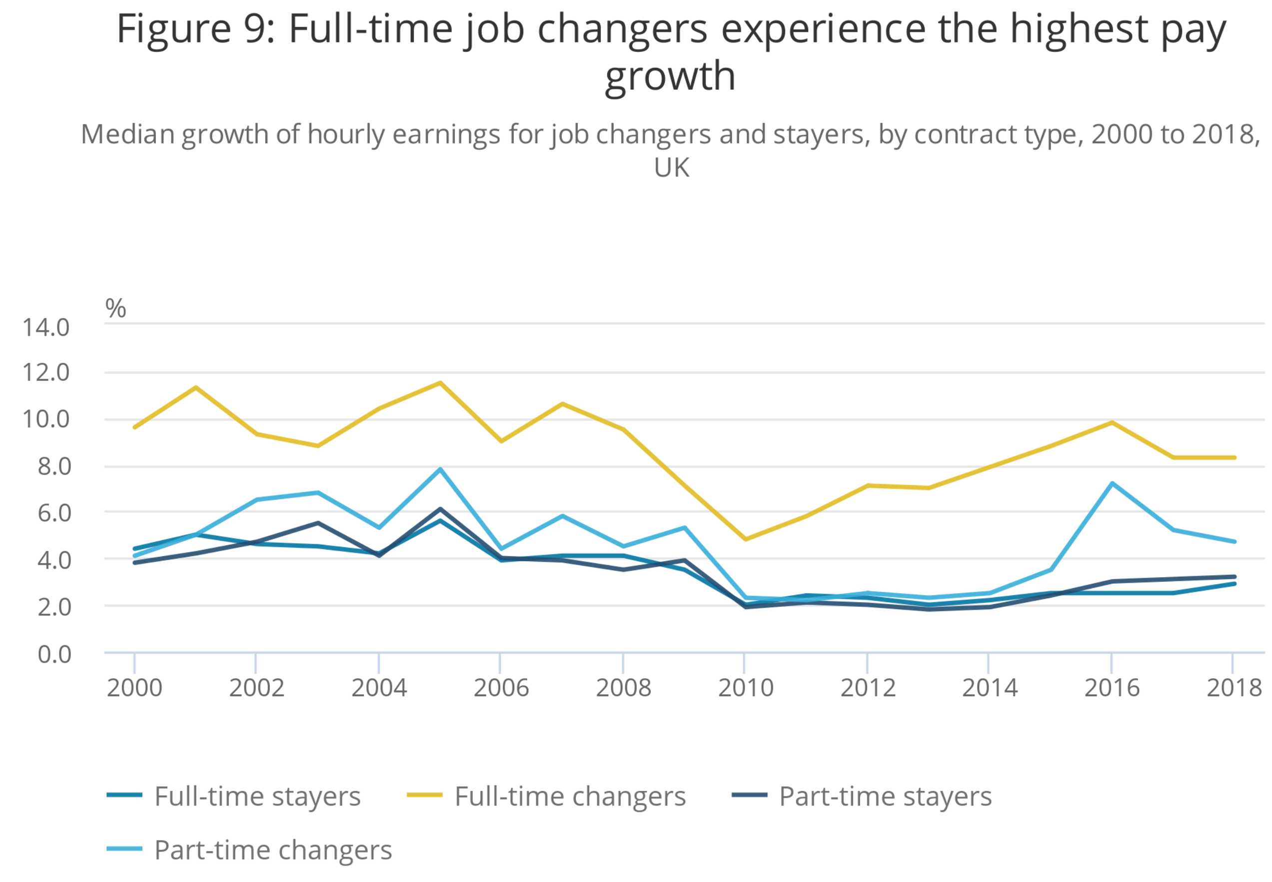
Of the part-time changers, around 32.0% moved from a full-time job in 2017 to a part-time job in 2018, experiencing a wage growth of 4.7%. Of the full-time changers, around 17.2% moved from a part-time job in 2017 to a full-time job in 2018, experiencing a wage growth of 8.5%. Thus, there was a higher proportion of people moving from full-time to part-time in 2018, which if involuntary, reflects an increase in underemployment.

Please note:

The above paragraph was updated for clarity on 2 May 2019.

Figure 9: Full-time job changers experience the highest pay growth

Median growth of hourly earnings for job changers and stayers, by contract type, 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes:

1. Full-time defined as employees working more than 30 paid hours per week (or 25 or more for the teaching professions).

9 . Sector

In 2018, 28.5% of people worked in the public sector and 71.5% worked in the private sector. Of the people who worked in the public sector, 91.6% stayed in the same job as the previous year, while 88.5% of the people who worked in the private sector stayed in the same job as the previous year.

Figure 10 shows that pay growth is observed to be higher for job changers compared with job stayers for both the public and private sectors. Private sector job changers were more strongly affected by the 2008 economic downturn than stayers. However, their earnings growth remained above that of the stayers. Since the downturn, private sector changers have more or less recovered their earnings growth. Whereas for the stayers, while the earnings growth has started increasing, it remains below the pre-downturn trend.

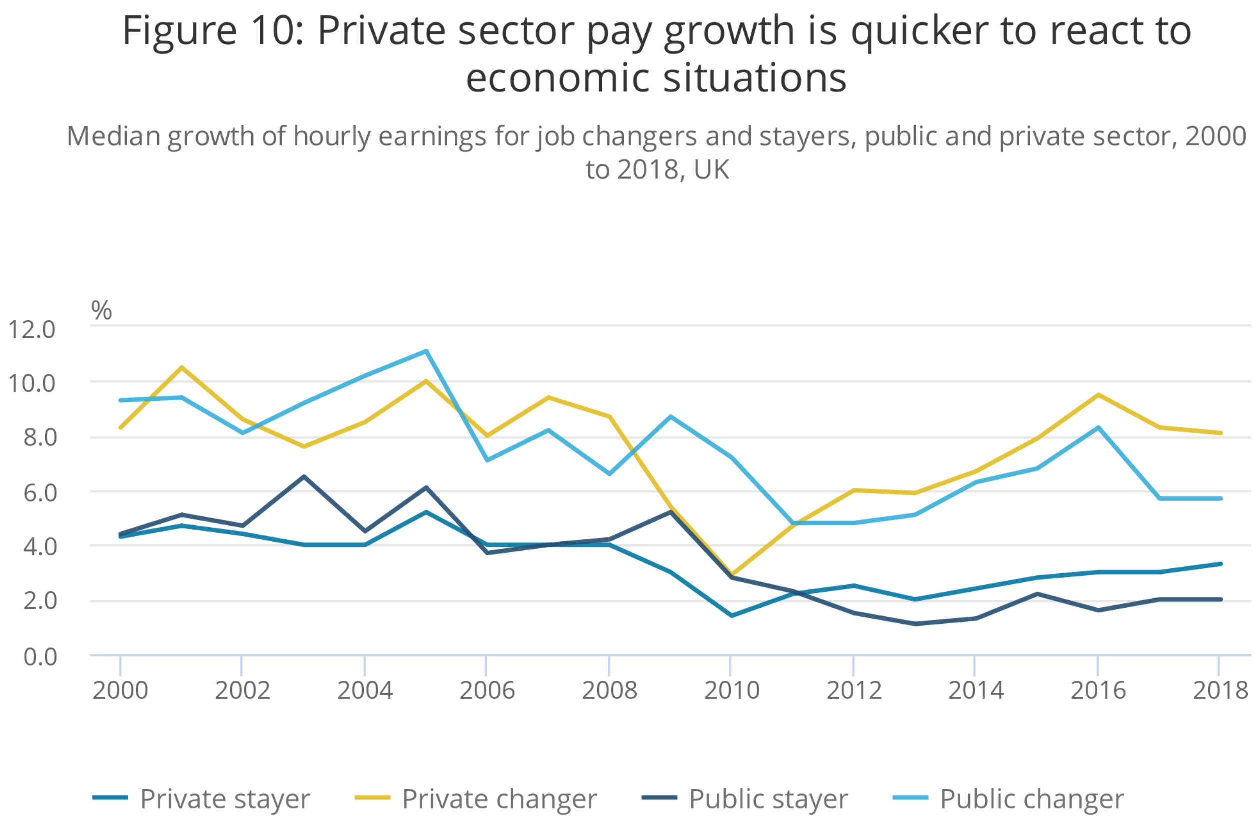
On the other hand, both public sector changers and stayers experienced a slowing in earnings growth during the downturn, although changers experienced a faster recovery than stayers. Both types of public sector workers are still receiving earnings growth below the pre-downturn trend, which may be a result of the government budget cuts following the economic downturn.

Both changers and stayers in the private sector were affected by the economic downturn a year earlier than the public sector. The private sector experienced a sharp slowdown in earnings growth in a shorter time and the public sector had an extended slowdown in earnings growth.

Of the job changers, in 2018, 75.4% of workers changed jobs from the year before within the public sector, while 94.8% changed jobs within the private sector. Of those who moved jobs, around 24.6% of workers moved from a private-sector job in 2017 to a public-sector job in 2018, while 5.2% of workers moved from a public-sector job to a private-sector job in the same period.

Figure 10: Private sector pay growth is quicker to react to economic situations

Median growth of hourly earnings for job changers and stayers, public and private sector, 2000 to 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes:

1. For consistency over time, employees of those banks classified to the public sector since 2008 have been treated as if they were in the private sector.

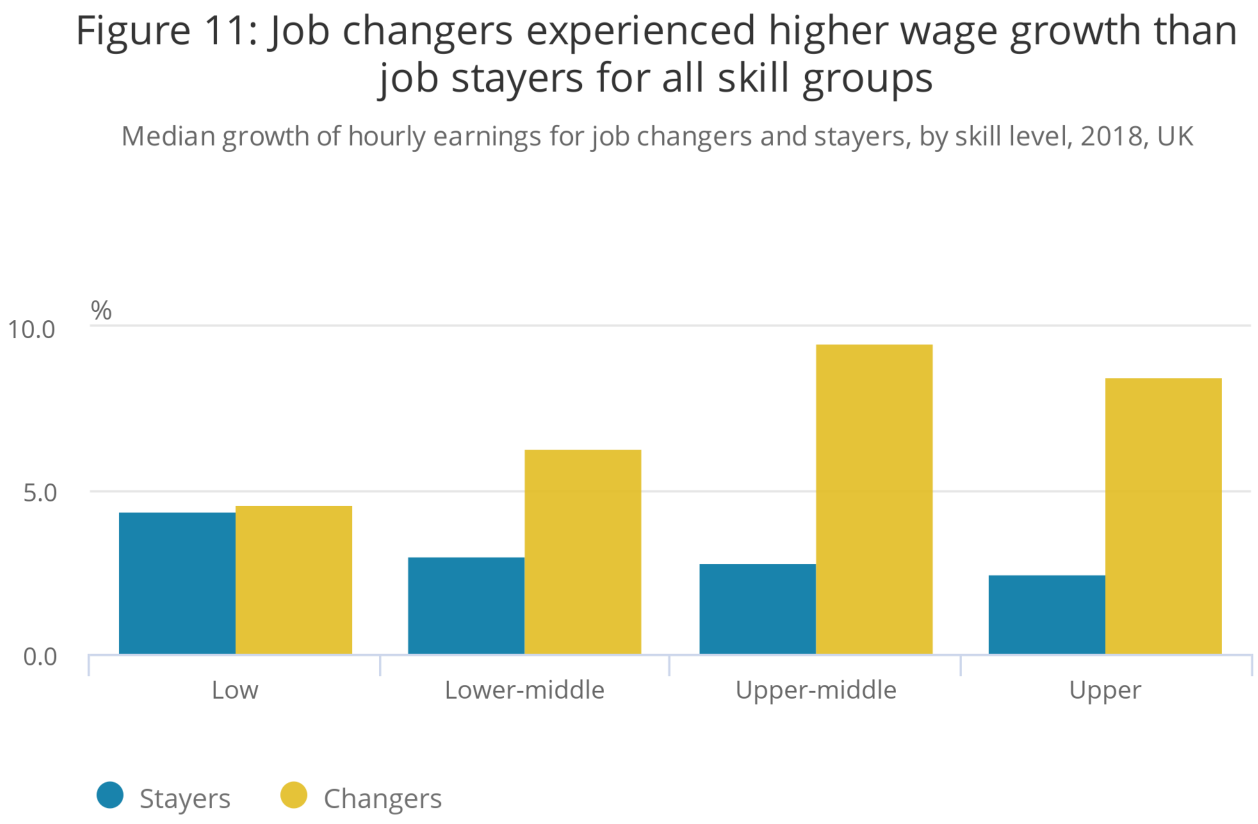
10 . Skill group

We use the Standard Occupational Classification (SOC) to create four skill levels. In 2018, job changers experienced higher median earnings growth than job stayers for all skill groups. While the job stayers experienced slowing wage growth with increasing skill level, job changers generally experienced increasing wage growth with increasing skill level (except the upper-skilled workers whose wage growth was less than that of the upper-middle-skilled workers).

The declining wage growth for job stayers as skill level increases could be due to a greater proportion of lower-skilled workers receiving wages close to the National Living Wage. Such workers have experienced higher pay growth in recent years compared with workers on a higher hourly wage. For example, the 4.4% pay rise of low-skilled job stayers corresponds to the 4.4% pay rise from the National Living Wage increasing from £7.50 an hour in 2017 to £7.83 an hour in 2018. Job changers, on the other hand, can receive higher wage growths by switching jobs, especially at higher-skill levels.

Figure 11: Job changers experienced higher wage growth than job stayers for all skill groups

Median growth of hourly earnings for job changers and stayers, by skill level, 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Looking at the composition of job moves we see that, on average, lower-skilled occupations have more workers changing jobs. In 2018, 12.1% of low-skilled people changed jobs, while 11.3% of lower-middle, 11.2% of upper-middle, and 9.9% of upper-skilled workers changed jobs.

Table 1 shows the movement of workers between skills for job changers between 2017 and 2018. Most of the workers that changed jobs moved to jobs at the same skill level, represented by the diagonal. The upper triangle of the table represents movement of workers to higher-skill levels than the previous year, while the lower triangle represents movement of workers to jobs at skill levels lower than the previous year. Aside from those changing jobs at the same skill level, most move up or down one skill level only. This suggests that while there may be some skill mismatch in the UK labour market, most workers are changing jobs within the same skill level.

Table 1: Most job changers moved jobs within the same skill level
Proportion of job changer flows by skill level, from 2017 to 2018, UK

	2018			
2017	**Low**	**Lower-middle**	**Upper-middle**	**Upper**
Low	62.1	13.5	8.7	2.9
Lower-middle	28.4	72.8	25.3	14.1
Upper-middle	7.2	8.0	55.1	11.7
Upper	2.2	5.7	10.9	71.2

Source: Annual Survey of Hours and Earnings – Office for National Statistics

11 . Region

Regional differences in movement of job changers is an indicator of labour mobility. To examine this, we look at the 12 NUTS1 areas of the UK[1]. Of all the regions, Northern Ireland and East had the highest proportion of job changers (11.8%), while North East had the lowest (8.3%) in 2018. In the same year in London, around 11.1% of workers changed jobs from the previous year.

Of the job changers, most workers changed jobs within the same region, which may imply that labour is not mobile between regions. This could potentially lead to mismatch between workers and jobs in that workers are not closely located to jobs that match their skillset.

The East Midlands had the lowest proportion of job changers within the same region in 2018 at 74.5%, followed by London at 74.8%. Of London workers, 9.1% came from the South East, whereas 7.3% of workers in the East had moved from London, and 8.2% of workers in the South East had switched from London.

In the same year, Northern Ireland had the highest proportion of within-region job moves at 95.4%. The presence of the Irish Sea may explain why workers in Northern Ireland are less mobile.

Table 2: Most workers changed jobs within the same region
Proportion of job changes within and between regions, from 2017 to 2018, UK

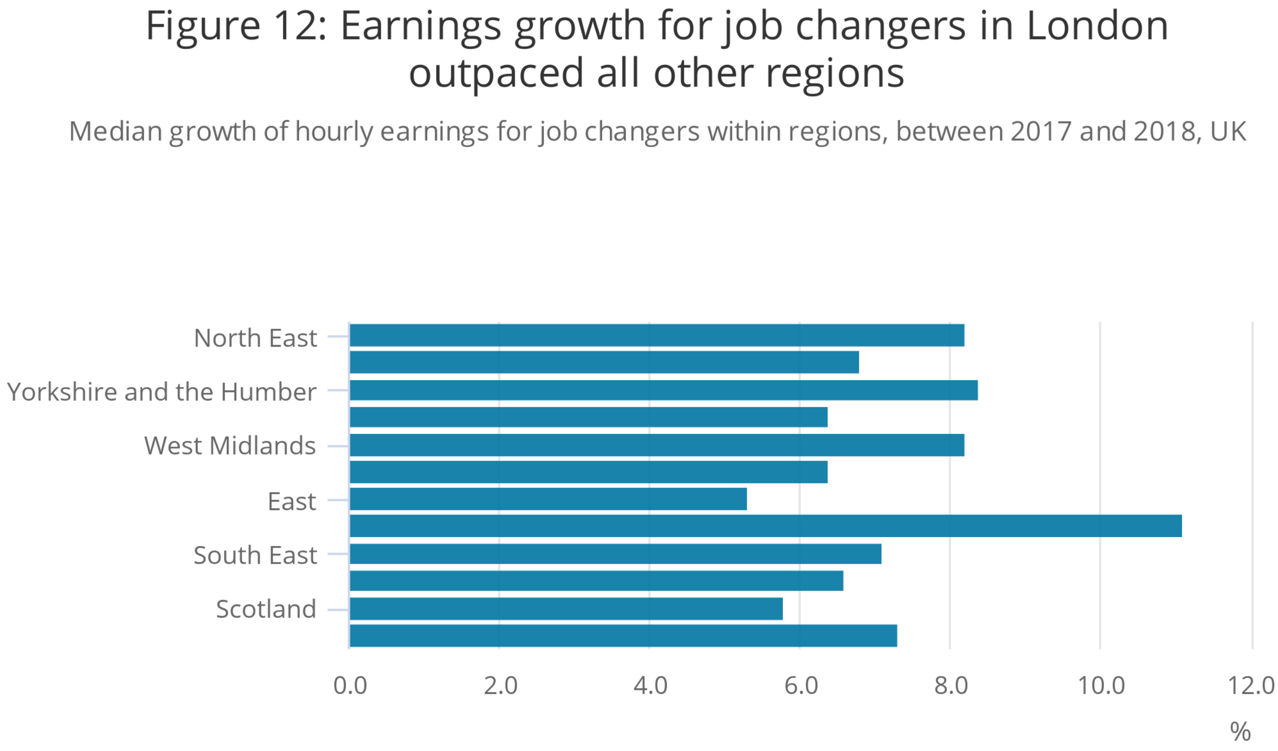
	2018											
2017	**North East**	**North West**	**Yorkshire and the Humber**	**East Midlands**	**West Midlands**	**South West**	**East**	**London**	**South East**	**Wales**	**Scotland**	**Northern Ireland**
North East	82.0	0.7	2.3	0.4	0.3	0.6	0.6	1.0	0.6	0.0	0.7	0.2
North West	2.8	83.8	2.8	2.2	3.2	1.1	1.0	2.1	1.3	4.4	0.7	0.7
Yorkshire and the Humber	3.0	2.4	80.5	5.1	0.7	1.0	1.0	1.9	1.3	0.4	0.9	0.3
East Midlands	1.0	1.4	3.9	74.5	4.8	1.4	2.4	1.8	1.6	1.4	0.9	0.0
West Midlands	1.2	2.4	2.1	5.0	77.4	3.1	1.7	1.7	2.2	2.2	1.2	0.2
South West	1.9	1.5	1.3	1.5	1.9	81.9	1.2	1.6	2.6	3.3	0.6	0.5
East	0.4	1.7	2.4	6.0	2.9	2.1	77.8	4.2	3.3	1.5	0.8	0.9
London	2.3	1.6	1.9	1.2	3.2	2.2	7.3	74.8	8.2	2.1	1.6	0.6
South East	4.3	2.2	1.8	3.1	3.0	5.3	5.4	9.1	76.7	1.8	1.0	0.8
Wales	0.0	0.6	0.1	0.4	1.0	0.9	0.5	0.6	1.0	82.9	0.2	0.2
Scotland	0.8	1.2	0.7	0.4	1.2	0.4	0.9	0.9	1.0	0.0	91.3	0.2
Northern Ireland	0.3	0.5	0.1	0.1	0.4	0.1	0.2	0.2	0.3	0.0	0.0	95.4

Source: Annual Survey of Hours and Earnings – Office for National Statistics

Job changer wage growth outpaced that of job stayers for all regions, following the aggregate trend. Figure 12 plots the median hourly earnings growth within the regions for job changers between 2017 and 2018 (growth for the diagonal in Table 2). It shows that workers changing jobs within London experienced the highest earnings growth at about 11.1%. This is 2.7 percentage points higher than Yorkshire and The Humber, which has the second-highest earnings growth for job changers.

Figure 12: Earnings growth for job changers in London outpaced all other regions

Median growth of hourly earnings for job changers within regions, between 2017 and 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

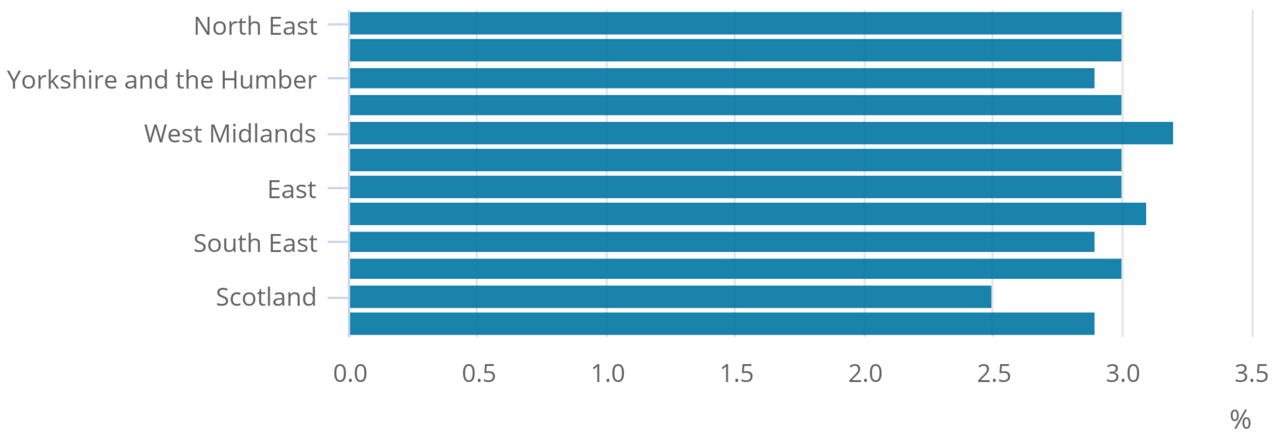
Figure 13 reports median earnings growth of stayers for all regions in 2018. In contrast to changers, earnings growth by region in 2018 for job stayers was less varied, with West Midlands experiencing the highest growth (3.2%) and Scotland the lowest (2.5%).

Figure 13: Job stayers in all regions experienced a slower growth between 2.5% and 3.2%

Median growth of hourly earnings for job stayers within regions, between 2017 and 2018, UK

Figure 13: Job stayers in all regions experienced a slower growth between 2.5% and 3.2%

Median growth of hourly earnings for job stayers within regions, between 2017 and 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes for: Region

1. To examine geographical differences, we look at Nomenclature of Territorial Units for Statistics level 1 (NUTS1 level). This breaks our data down by nine English regions, plus three other countries of the UK (Scotland, Wales, Northern Ireland). These are work areas and not where the people reside.

12 . Industry

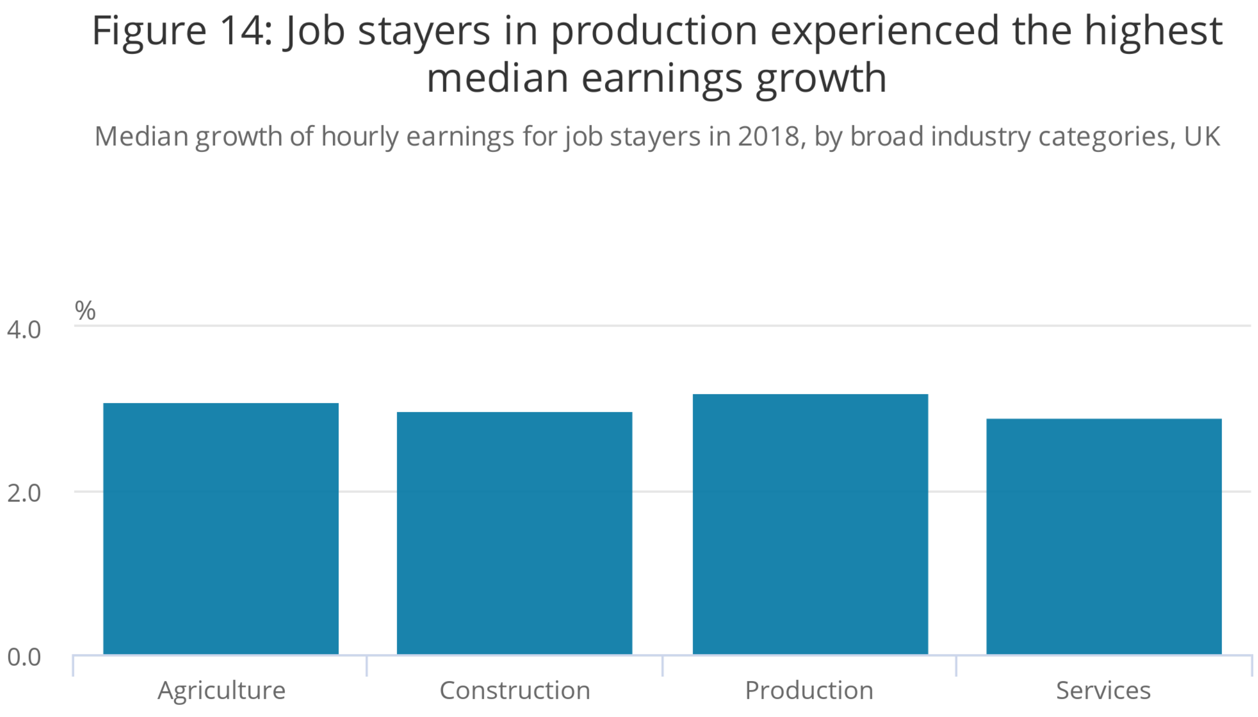
To examine differences in industry, we look at four broad industry categories: agriculture, production, construction and services, using the [Standard Industrial Classification](https://www.ons.gov.uk).

In 2018, 83.8% of all workers worked in service industries, of which 88.7% stayed in the same job. Similarly, 11.9% of individuals worked in the production industry in 2018, and of these 91.5% stayed in the same job as the year before. The corresponding figures for 2018 in construction and agriculture are 3.5% in construction, of which 88.9% stayed in the same job, and 0.5% in agriculture, of which 90.2% stayed in the same job as the year before.

Job stayers in the production industries experienced the highest pay growth in 2018 at 3.2%, followed by agriculture at 3.1%, construction at 3.0% and services at 2.9%.

Figure 14: Job stayers in production experienced the highest median earnings growth

Median growth of hourly earnings for job stayers in 2018, by broad industry categories, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes:

1. Broad industry categories are as follows:

i. Agriculture: A

ii. Production: B to E

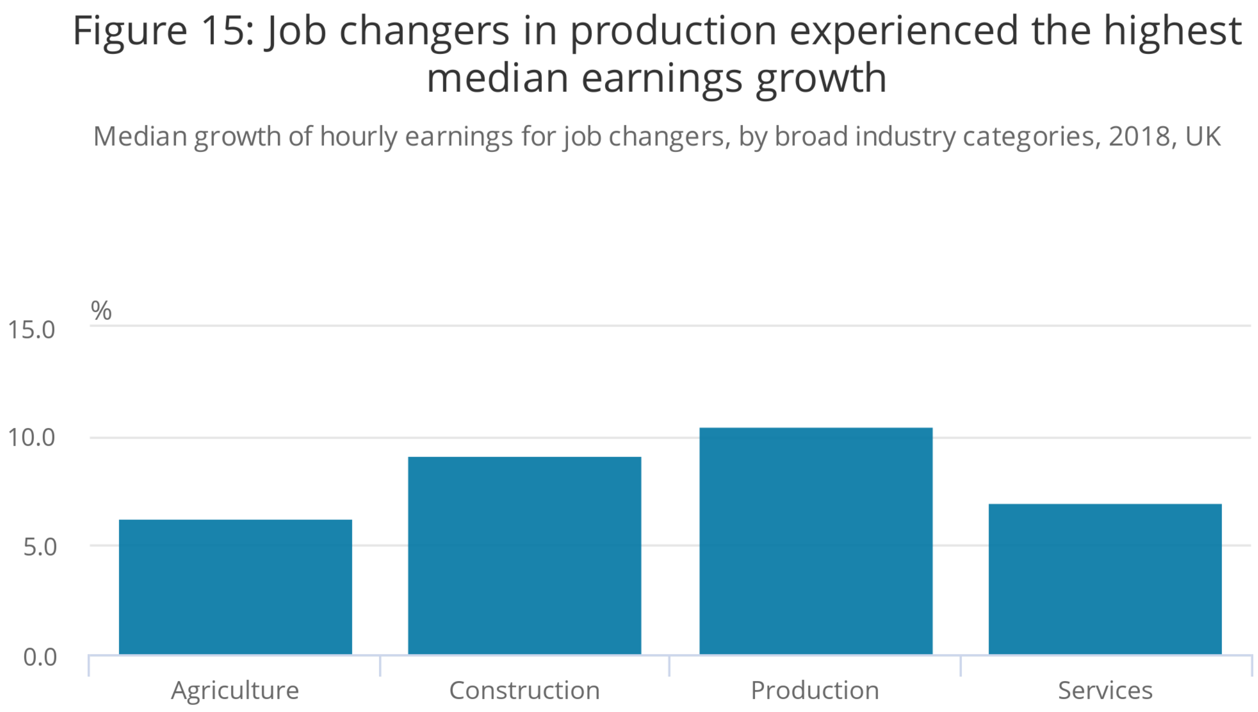
iii. Construction: F

iv. Services: G to S

Job changers also experienced the highest earnings growth in the production industries (10.5%). However, this was followed by construction (9.1%), services (7.0%) and agriculture (6.3%). The median earnings growth for job changers was greater than that of job stayers across all broad industries in 2018.

Figure 15: Job changers in production experienced the highest median earnings growth

Median growth of hourly earnings for job changers, by broad industry categories, 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes:

1. Broad industry categories are as follows:

i. Agriculture: A

ii. Production: B to E

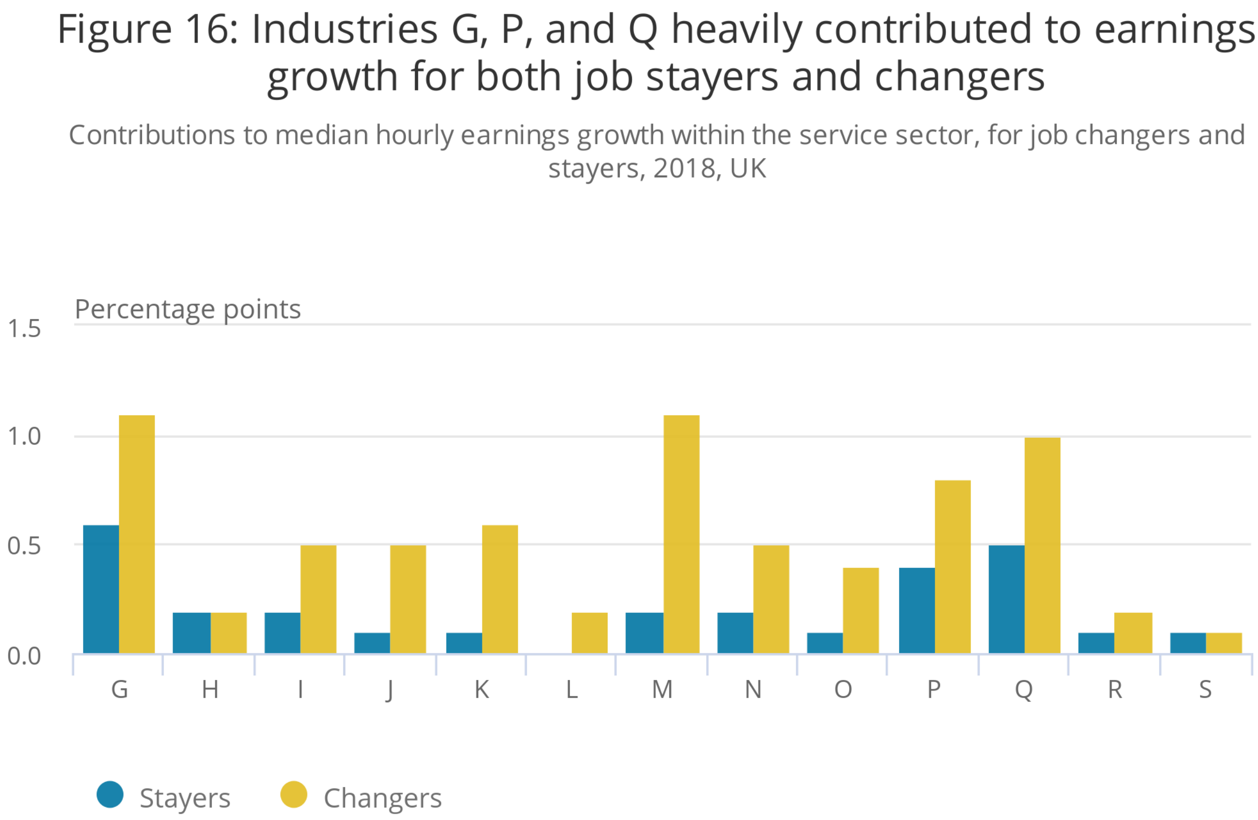
iii. Construction: F

iv. Services: G to S

Within the largest broad industry, services, the earnings growth of both job stayers and changers was driven by different industry categories. For both stayers and changers, industries G (Wholesale, retail, repair of motor vehicles), P (Education), and Q (Human, health and social activities) heavily contributed to earnings growth. For job changers, industry M (Professional, scientific and technical activities) was also a big driver of earnings growth. Figure 16 illustrates the magnitude of these contributions to the service sector earnings growth for job stayers and changers.

Figure 16: Industries G, P, and Q heavily contributed to earnings growth for both job stayers and changers

Contributions to median hourly earnings growth within the service sector, for job changers and stayers, 2018, UK



Source: Annual Survey of Hours and Earnings – Office for National Statistics

Notes:

1. Industry categories are defined as follows:

G: Wholesale, retail, repair of motor vehicles

H: Transportation and storage

I: Accommodation and food services

J: Information and communication

K: Financial and insurance

L: Real estate

M: Professional, scientific and technical activities

N: Administrative and support activities

O: Public administration and defence

P: Education

Q: Human, health and social activities

R: Arts, entertainment and recreation

S: Other service activities

13 . Conclusion

In this article we present descriptive analysis of the flow of labour in the economy. Specifically, we have compared the wage growth of job stayers and job changers. We have also examined those changers who moved “within” and “between” firms.

Job stayers on average earn a higher hourly wage compared with individuals who move jobs. However, workers who switch jobs see higher pay growth compared with those who do not. Job changers moving between firms have higher pay growth than those moving within firms. This could be due to firms’ willingness to pay a higher wage to acquire already trained staff. This would then put upward pressure on the pay of existing staff. This is illustrated by the within-firm job changers’ wage growth, which is higher than that of job stayers.

Job changers also tend to be lower skilled (12.1% of low-skilled workers in 2018 compared with 9.9% of upper-skilled workers in the same year) and more concentrated in the private sector (11.5% in 2018 compared with 8.4% in the public sector in the same year). Slightly more women changed jobs in 2018 (11.4%) than men (10.4%).

Flow of labour in the economy is a broad area. Further research could seek to identify more wide-ranging reasons that influence workers staying or changing jobs, and the extent to which there are barriers to do so. Some workers may be keen to change jobs but cannot do so due to, for instance, lack of infrastructure, information asymmetries or employers being a local monopsony. Hence such workers forgo a growth in earnings that they could have otherwise achieved. On the other hand, there may be some workers who want to stay in their jobs but are forced to move (involuntary redundancy, such as a firm closure) and friction in the labour market may lead to people accepting new jobs at a lower wage than previously available.

14 . Authors

Amina Syed, Matthew Eddolls and Piotr Pawelek

15 . About the data

The analysis is carried out using the Annual Survey of Hours and Earnings (ASHE) micro dataset. All estimates for 2018 are provisional and relate to the reference date 16 April 2018. Data from the 2017 survey have been subject to small revisions since the provisional estimates were published on 26 October 2017. For the analysis, the following notes apply:

1. Employees on adult rates, pay unaffected by absence.
2. Jobs that are not their main occupation are dropped for individuals with more than one job.
3. Full-time defined as employees working more than 30 paid hours per week (or 25 or more for the teaching professions).
4. Skills are defined by the Standard Occupational Classification 2010.
5. Industry is defined by the Standard Industrial Classification 2007.
6. Regions are at NUTS1 level (Nomenclature of Units for Territorial Statistics). This breaks our data down by nine English regions, plus three countries of the UK. These are work regions and not where the people live.
7. A guide to interpreting ASHE estimates addresses common questions about the data.
8. Further information about ASHE can be found in quality and methodology on our guidance and methodology page and in the Quality and Methodology Information (QMI) report.

16 . Methodology

We match those individuals who were in the Annual Survey of hours and Earnings (ASHE) sample in two consecutive years and drop the rest to create a continuously employed ASHE dataset. We can then compare the earnings growth between t and t-1 years using the hourly earnings growth variable.

ASHE has a variable “sjd” that identifies people who were in the same job as the year before or not. We use this variable to define job stayers; those who are in the same job as the previous year (sjd=1), and job changers; those who are not in the same job as the previous year (sjd=2).

This is different from the Employee earnings in the UK: 2018 bulletin, which compares earnings growth between all employees and those in the same job who were continuously employed in two time periods.

For the analysis, the following notes apply:

1. All earnings analysis is conducted using hourly earnings, which are derived using gross pay including incentive pay, overtime and shift premiums for the reference period, divided by the total paid hours worked during the reference period.

2. To capture the typical experience of earnings growth, median of hourly earnings growth is calculated. This is the rate of pay growth at the centre of the distribution of earnings growth. This is different from growth in median pay, which does not necessarily capture the changes in wages experienced by the majority of the continuously employed. This calculates how the pay at the centre of the distribution has changed between the periods. In other words, it shows how pay for the individual at the middle of the earnings distribution in one year compares with the pay for the individual at the middle of the earnings distribution a year later.

3. There are no weights available for longitudinal ASHE, hence job weights are used.

4. ASHE methodology is not specifically designed to model earnings growth for employees over time.

5. Movement of workers "between" firms is defined as those workers who are either in a different area of work compared with the year before, or they have changed the industry they work in, or are in a different occupational category. All others are defined as "within firm" changers.

Compendium

Contributions to earnings growth in the UK: 2018

Composition of earnings growth, based on contributors using the Annual Survey of Hours and Earnings; basic pay, variable pay and hours. Broken down by sex, sector, region and country.

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9. Quality and methodology

1 . Main points

- The growth of mean weekly earnings near the median was 2.6% in the year to April 2018, up from 2.1% in the previous year, with weekly nominal pay (excluding bonuses and overtime) as the main driver.

- Earnings growth for males is more dependent on variable factors, such as hours worked, bonuses and overtime.

- The difference between earnings growth near the upper quartile for the public sector compared with the private sector is closed through higher contributions from variable elements of pay (bonuses and overtime).

- Across regions and countries in 2018, Yorkshire and The Humber faced the largest contributions to the growth of mean weekly earnings near the median from nominal pay excluding bonuses and overtime at 3.3%.

2 . Introduction

In recent years, the labour market has shown signs of continued tightening as the unemployment rate has fallen to historical lows while the employment rate has continued to increase.

In such labour market conditions we would expect to see higher earnings growth, as there are fewer unemployed people competing for each vacancy. As such, this would be expected to add upward pressure to wages with employers expected to pay higher wages to attract labour. Despite the tightness that has been observed in the labour market of late, there has been a wage puzzle in the UK labour market as this tightness has not so far shown up in a sustained increase in wage inflation.

The latest Annual Survey of Hours and Earnings estimates show that median gross nominal weekly earnings rose by 3.5% in the year to April 2018, up from 2.1% in the previous year. This article describes the growth in mean nominal weekly earnings in recent years for particular portions of the distribution of earnings growth. This is distinct from the growth of the median of the wage distribution given in the headline Annual Survey of Hours and Earnings (ASHE) statistics[1]. Earnings growth here is broken down into underlying contributions in two ways. Firstly, it is broken down by type of earnings:

- basic pay: Nominal paid weekly wages or salary

- variable pay: Overtime pay, Incentive pay (bonuses), shift pay, and other variable pay types

Secondly, it is compared with the growth in paid weekly hours worked.

Growth in mean weekly earnings at the median was 2.6% in the year to April 2018, up from 2.1% in the previous year. This is the highest rate since late 2008 (Figure 1), although this is still somewhat subdued compared with pre-recession rates.

This article builds upon analysis used in the May 2015 Economic review that aims to uncover how the sources of earnings growth change across the distribution. It also uses its methodology to enable comparison of contributors to earnings growth.

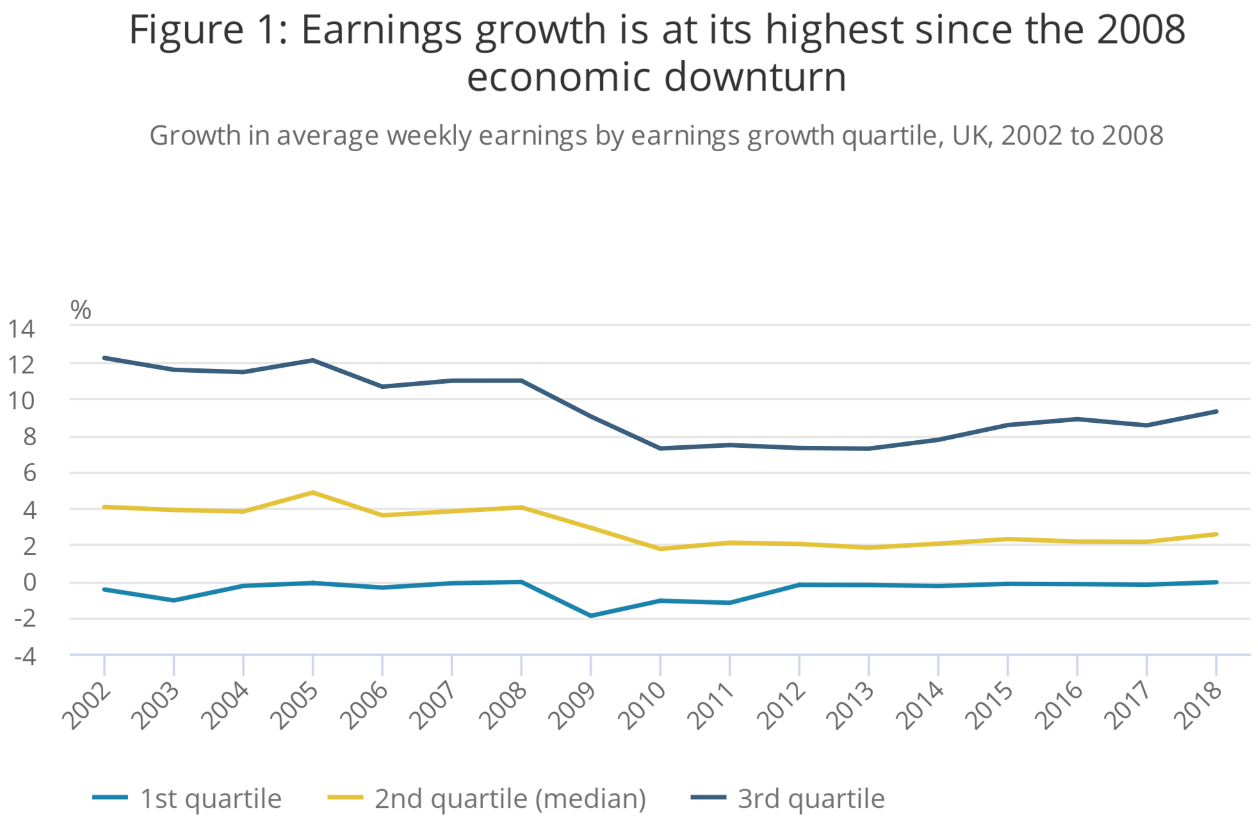
To provide breakdowns of contributions, the distribution of the growth of weekly earnings has been divided by 20-quantiles (ventiles). The growth of mean earnings for the 5th, 10th, and 15th ventile groups have been used to estimate the first, second (median) and third quartiles, respectively. This process enables contributions to be estimated at each quartile and represents 5% of the population, rather than just a single individual observation for each quartile. This method helps retain representation, as three different variables are being analysed and negates the skewed compositional effect that would occur by using a single observation of one variable.

To differentiate them from standard estimates of the quartiles of the growth rates this article uses the terms “growth of mean weekly earnings at the quartile” and “growth of mean weekly earnings at the median."

The growth of mean earnings constructed for these three groups can then be broken down into contributions from basic pay and variable pay by constructing those statistics for the same groups. Similarly, we can compare against growth in hours for each of those groups.

Figure 1: Earnings growth is at its highest since the 2008 economic downturn

Growth in average weekly earnings by earnings growth quartile, UK, 2002 to 2008



Source: Office for National Statistics - Annual Survey of Hours and Earnings

Notes:

1. 2018 data are provisional.

Figure 1 shows that earnings growth at the first quartile has been flat for around 20 years. Possible explanations for this are that there is an over-supply of low-skilled workers or that productivity has been weak especially in low-skilled sectors. This has been addressed before in a recent distributional analysis of ASHE.

In contrast, the growth of mean earnings at the third quartile was 9.3% in the year to April 2018. This is its highest since 2008, picking up from 8.5% in the previous year. Other analysis in this release suggests that the those with highest earnings growth are moving between jobs. As these employees are more active in the labour market, low unemployment is likely to be pushing up wages.

Figure 1 suggests that nominal weekly earnings growth has still not recovered to the pre-downturn rates for the majority of workers, whilst those in the bottom quartile have returned to the flat growth seen since the turn of the millennium. The following section looks at the contributions to weekly earnings growth from basic pay, variable pay and hours. And the remainder of this article examines how those contributions differ across, sex, sector, and regions and country

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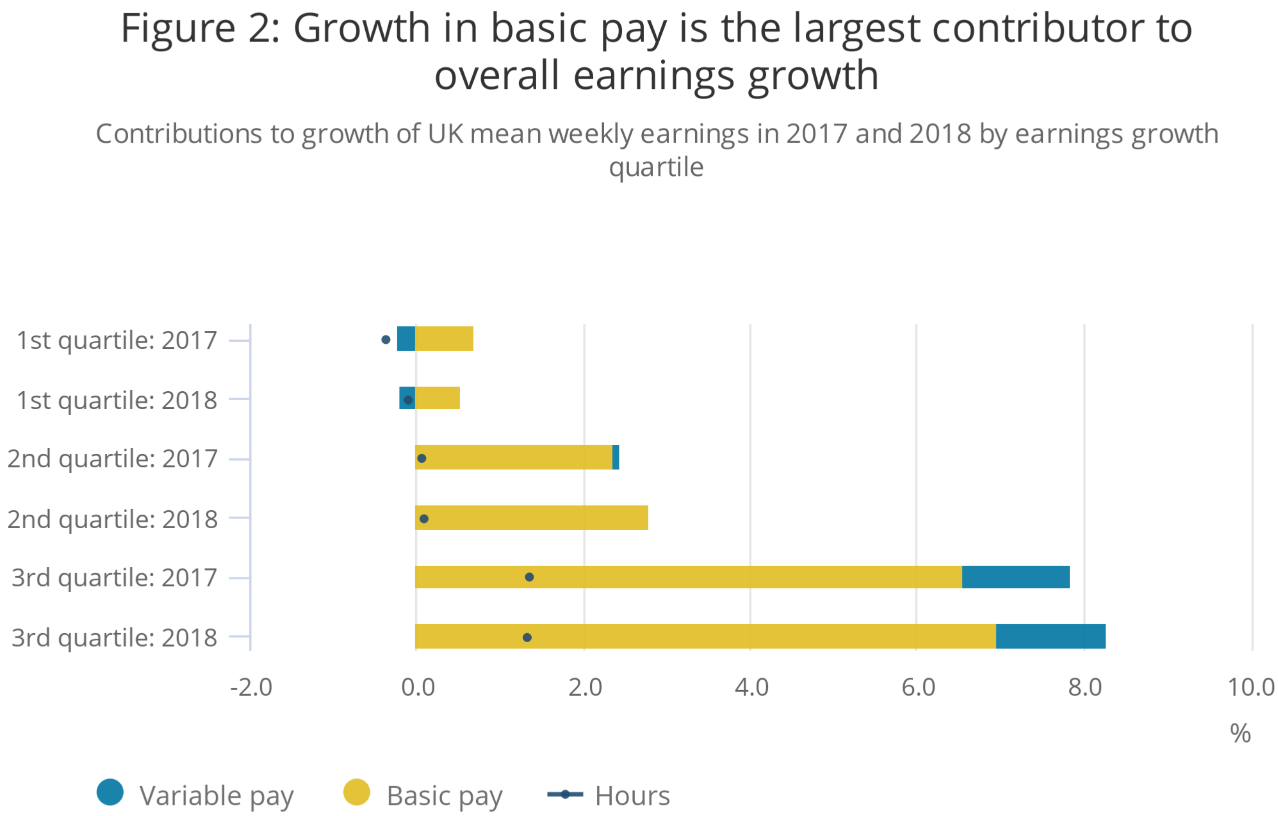
3 . Contributions to growth in weekly earnings

Figure 2: Growth in basic pay is the largest contributor to overall earnings growth

Contributions to growth of UK mean weekly earnings in 2017 and 2018 by earnings growth quartile



Source: Office for National Statistics - Annual Survey of Hours and Earnings

Notes:

1. 2018 data are provisional.

2. The chart shows the growth of mean weekly earnings for selected portions of the earnings growth distribution.

3. The sum of the contributions split may differ from total wage growth. Decomposing growth rates by components never fully sums to its totals due to statistical interaction terms.

In 2018, the growth in mean weekly earnings at the median was 2.9%, up from 2.5% in the previous year and its highest since 2008. The breakdown of weekly earnings growth shown in Figure 2 demonstrates that basic pay acts as the primary contributor for the median increase in weekly earnings.

Variable pay played a more prominent role in earnings growth at either ends of the earnings growth distribution. For example, at the first quartile the contribution to growth from variable pay was negative 0.2% , while the contribution from basic pay remains positive at 0.5%. The third quartile exhibits larger contributions from all elements, whilst remaining dominated by basic pay at 7.0% . Variable pay contributes 1.3%. Hours increased by 1.3% for this group, however, so a higher average rate of pay was not the only driver of the increase in earnings.

Changes in the growth rates of average weekly earnings between 2017 and 2018 have been driven primarily by basic pay rather than variable pay at all three quartiles.

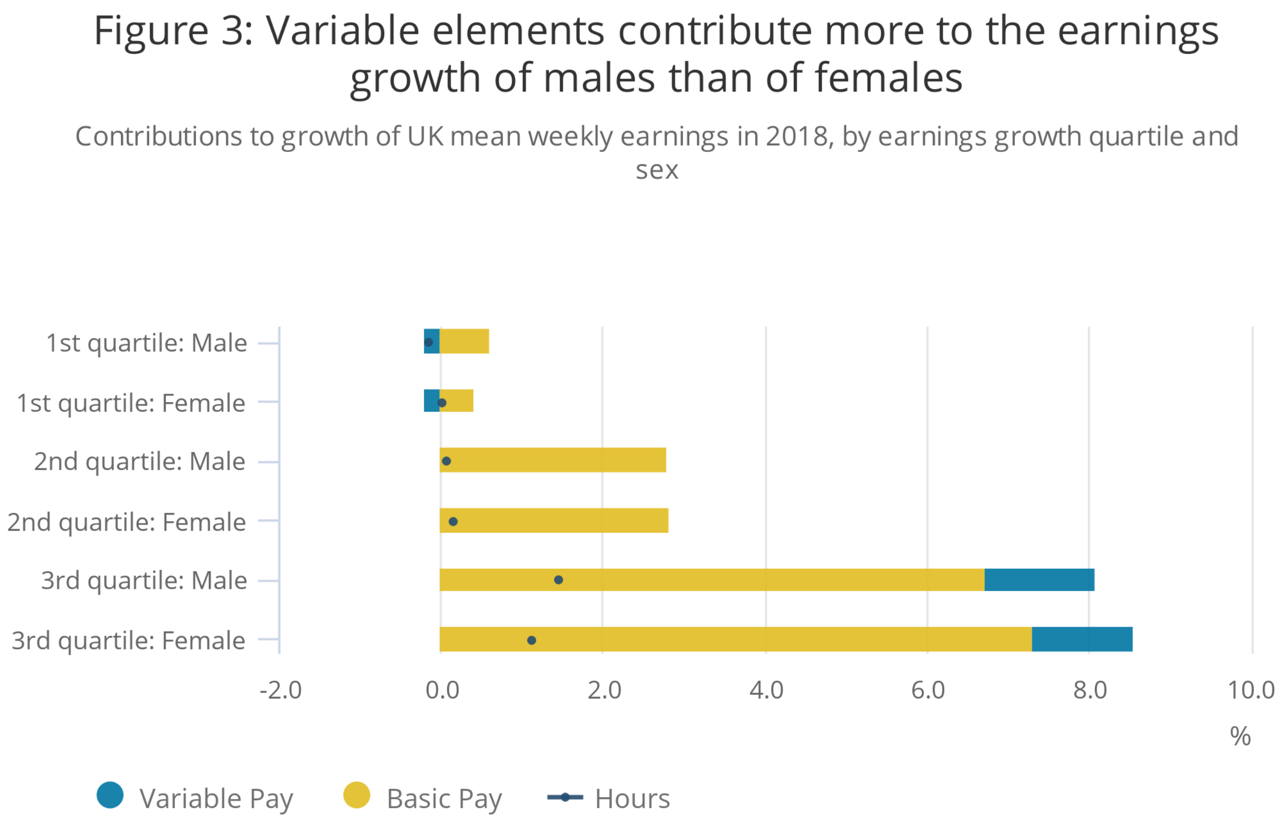
It might be that for those on higher wages, there is a strong income effect. As wages rise beyond a certain point, employees may then choose to work fewer hours and retain the same income, substituting income for leisure time. In other words, at a certain high wage level, employees will use additional income to reduce hours and increase leisure. As this analysis focuses on earnings growth and not income groups, it is not known for sure what income groups the wage growth quartiles represent.

4 . Contributions to growth in weekly earnings by sex

Previous analysis of the gender pay gap found it to have fallen to 8.6% among full-time employees. This is defined as the difference in average hourly earnings between men and women. This only looks at descriptive analysis, as factors have not been controlled to allow for like-for-like comparisons. Figure 3 shows that mean weekly earnings at the median for males increased by 2.8% in the year to April 2018, compared with 2.9% for females.

Figure 3: Variable elements contribute more to the earnings growth of males than of females

Contributions to growth of UK mean weekly earnings in 2018, by earnings growth quartile and sex



Source: Office for National Statistics - Annual Survey of Hours and Earnings

Notes:

1. 2018 data are provisional.

2. The chart shows the growth of mean weekly earnings for selected portions of the earnings growth distribution.

3. The sum of the contributions split may differ from total wage growth. Decomposing growth rates by components never fully sums to its totals due to statistical interaction terms.

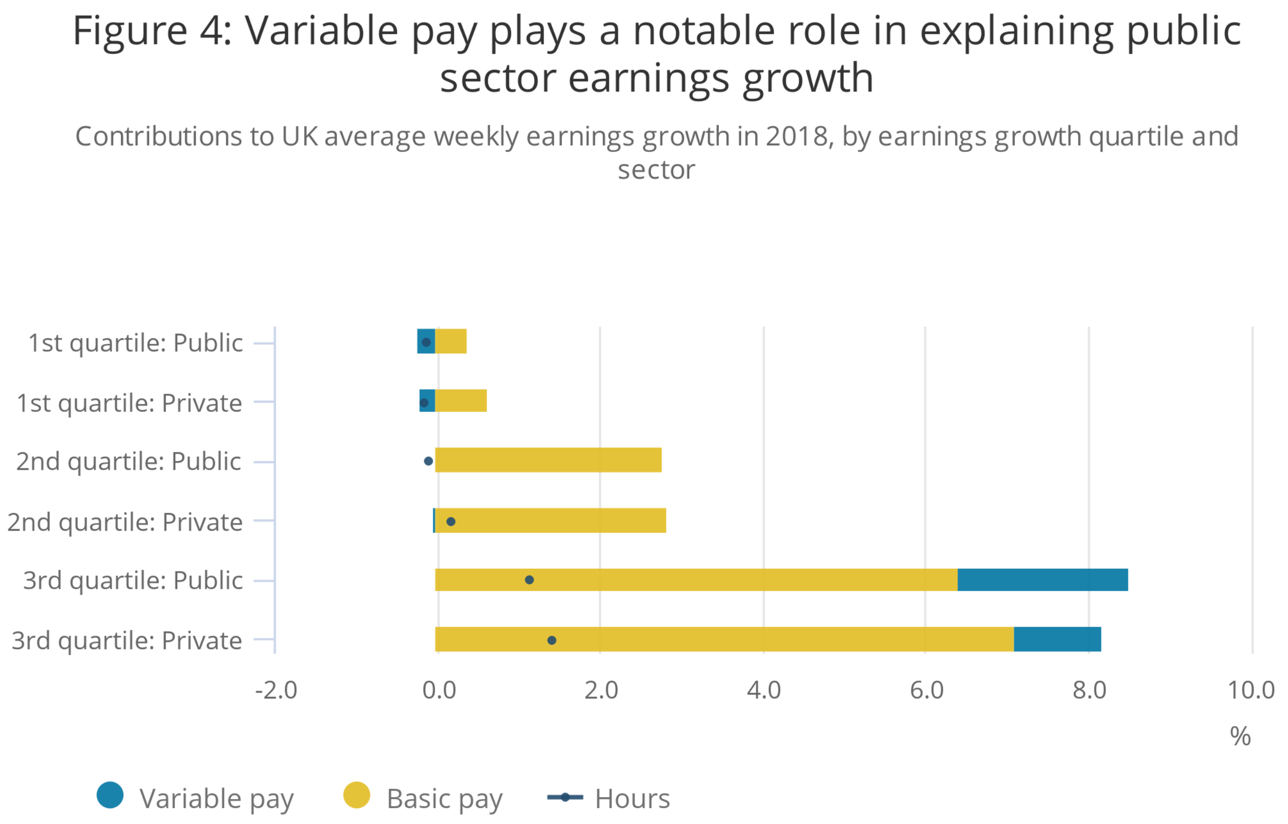
The basic pay contribution to earnings growth is higher for females at the median and third quartile. At the median, basic pay makes up almost the total earnings growth, and in 2018, females experienced marginally higher earnings growth at 2.9%. The only place where hours play a negative role in earnings growth is for males at the first quartile, where a reduction in hours worked is holding back earnings.

5 . Contributions to growth in weekly earnings by sector

Wages traditionally differ between the public and private sectors, with public sector wages being restricted by the pay freeze since 2010. Variable pay may also be more prevalent in the private sector if bonuses and overtime pay are more common than in the public sector. It should be noted that this analysis focuses on contributions to earnings growth and not contributions to earnings levels.

Figure 4: Variable pay plays a notable role in explaining public sector earnings growth

Contributions to UK average weekly earnings growth in 2018, by earnings growth quartile and sector



Source: Office for National Statistics - Annual Survey of Hours and Earnings

Notes:

1. 2018 data are provisional.

2. The chart shows the growth of mean weekly earnings for selected portions of the earnings growth distribution.

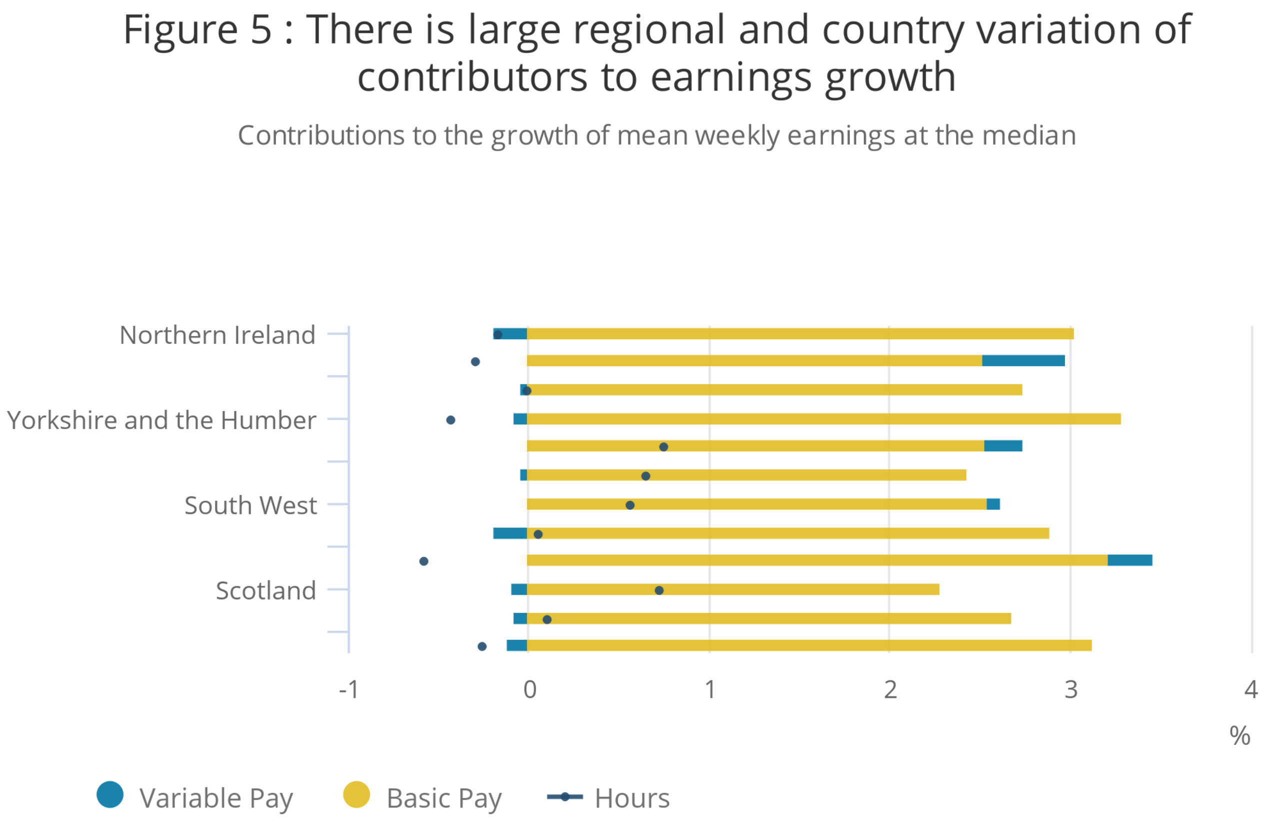
3. The sum of the contributions split may differ from total wage growth. Decomposing growth rates by components never fully sums to its totals due to statistical interaction terms.

At the lower quartiles, first and second, the contributions from basic pay lead to the marginally higher growth in mean weekly earnings for the private sector in comparison with the public sector; with contributions at the median of 2.9% and 2.7%, respectively. The public sector shows a far larger contribution to earnings growth from variable pay, suggesting more growth in performance-related pay or overtime pay, for those experiencing the highest pay growth. Compared with the private sector, one possible explanation is that the public sector wage constraint has affected basic pay and employees may have opted to work overtime to increase their earnings (paid as variable pay).

6 . Contributions to growth in weekly earnings by region and country

Figure 5 : There is large regional and country variation of contributors to earnings growth

Contributions to the growth of mean weekly earnings at the median



Source: Office for National Statistics - Annual Survey of Hours and Earnings

Notes:

1. 2018 data are provisional.
2. The chart shows the growth of mean weekly earnings for the portions of the earnings growth distribution proximate to the median.
3. The sum of the contributions split may differ from total wage growth. Decomposing growth rates by components never fully sums to its totals due to statistical interaction terms.

This regional and country breakdown looks at the growth at the median for each region and country for the year leading up to April 2018, and what can be seen is that all three elements are noticeably different.

There is a high degree of variation between regions and countries. London, and the South East have visibly different contributions to earnings growth from hours, at negative 0.3% and 0.1%, respectively. Hours play a negative role in London but a positive one in the South East.

In Scotland hours play a larger role than in Wales with contributions to earnings growth at 0.7% and negative 0.3%, respectively. However, these two countries experience similar basic pay contributions, at 2.2% and 2.5% , respectively.

Yorkshire and The Humber had the highest contribution from basic pay at 3.3%. around 0.2% higher than London. Wales faced the highest positive contribution from variable pay across regions and countries at 0.5%. The West Midlands faced the highest positive contribution from hours across regions and countries at 0.7%.

7 . Conclusion

The relatively stagnant nature of the first quartile of growth in weekly earnings apparent in Figure 1, can be seen in Figure 2 to be due to contributions from variable pay and hours. Where downward pricing of basic pay may be sticky, employers may seek to offset this and minimise cost constraints through fewer demanded hours and lower incentive pay as opposed to cutting staff. A reduction of hours and variable pay, is what has been to some extent holding back the earnings growth of the employees that have had negative or 0% earnings growth.

At the upper ends of the growth distribution, females face higher contributions from basic pay in comparison with males. Growth in earnings for males is slightly more reliant on variable factors (variable pay and hours) than for females. Despite evident differences in the make-up, total values of growth for all quartiles remain notably similar between males and females. Looking at how these trends fare when controlling for industry would be appropriate.

One conclusion that can be drawn from this analysis is that earnings growth as a whole is not being driven by increased working time and variable pay due to a flexible labour market and the growth of the “gig economy”, as is sometimes assumed. Basic pay remains the most important contributor.

Across all splits in contributions to growth, even in regions and countries where growth is smaller, the common theme shows basic pay as the majority driver in average weekly earnings growth. Growth near the median is almost exclusively dominated by this variable. Basic pay here consequently proves the strongest indicator for average growth in an employee’s weekly earnings growth. Higher basic pay could be the result of promotions or job changes, a theme picked up elsewhere in this publication.

8 . Authors

Henry Moore and Samuel Olokesusi, Office for National Statistics.

9 . Quality and methodology

This nominal analysis focuses on the most recent ASHE data [Employee earnings in the UK: 2018](#).

The Annual Survey of Hours and Earnings (ASHE) is based on a 1% sample of employee jobs taken from HM Revenue and Customs Pay As You Earn (PAYE) records. Information on earnings and hours is obtained from employers and treated confidentially. ASHE does not cover the self-employed or employees not paid during the reference period.

An analysis of the variation in the levels of earnings provides useful insight into distributional outcomes in the UK. By necessity, this work focuses on employees who reported being in employment in consecutive periods – which permits the calculation of earnings growth rates.

The analysis uses weekly pay as the variable of interest. This variable includes basic pay (normal weekly rate of pay) and variable pay (incentive pay (bonuses), overtime payments and other variable pay). It reflects the actual gross earnings of UK employees, independent of the number of hours worked. Pensions and benefits in kind are excluded from this analysis.

This analysis uses a standard filter – employees on adult rates of pay whose earnings have not been affected by absence.

All employees aged 16 years and over – with no upper age limit – are included in the analysis. This analysis is to show wage changes for the median (second quartile) as well as the first and third quartile from this range.

Growth rates illustrate the earnings change on the year. For example, the 2018 growth rate corresponds to the growth employees experienced between their April 2017 and 2018 earnings. Note that the ASHE methodology is not specifically designed to model earnings growth for employees over time.

Caution should be taken when drawing conclusions from comparisons across the time series because ASHE estimates were subject to discontinuities in 2006 and 2011.

Throughout this analysis, filters have been applied to the ASHE dataset, they are: sex, public or private sector, Nomenclature of Territorial Units for Statistics: NUTS 1 regions and countries.

Contributions to earnings analysis using Annual Survey of Hours and Earnings (ASHE) provisional 2018 data and previous ASHE datasets.

Compendium

Long-term trends in UK employment: 1861 to 2018

Examines the long-term trends in UK employment and provides the historical and legislative context behind some of the trends. Includes analysis by various components, such as industrial sector, sex, full-time and part-time employment, private and public sector employment, as well as employee and self-employed.

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1 . Main points

- The highest employment rates recorded were in the years 1872, 1943 and 2018, at 76% of the working age population; the lowest rate was 61% recorded in 1932, during the Great Depression.

- The labour market participation of women increased over time to reach a record high of 74.2% in 2018; the increase was driven by change in social norms and employment and equality legislation, and structural change in the economy.

- Patterns of employment have changed over time: manufacturing employment declined drastically from the 1960s onwards, and services sector employment increased significantly over the same period.

- Private and public sector employment have both shown upward trends, though the private sector remains the dominant employer; the decline in public sector employment during the 1980s and 1990s was due largely to privatisation of the economy affecting public corporations.

- Self-employment increased at a faster rate from 1979 onwards, to reach the record high of 15% of total employment in 2016.

2 . Introduction

The labour market plays an important role in allocating workers to jobs. It also affects the distribution of earnings and therefore income. Understanding the labour market is important for understanding economic and social changes. The study of long-term employment dynamics will therefore help put current trends into their historical perspective.

This article takes as its background the major changes in the laws and institutions that were introduced between 1860 and 2018 (see Annex 1). The data used for the analysis are mainly from the Bank of England's [Millennium of Macroeconomic Data]. Other long-term economic data are being catalogued as part of the Economic Statistics Centre of Excellence (for more information, see the [data inventory report (PDF, 1.36MB)]).

3 . Legislative changes

The 19th and 20th centuries saw significant changes in many aspects of legislation that in turn contributed to significant shifts in the labour market. The interplay of these changes is complex and beyond the scope of this article, but a more detailed summary of these changes can be found in Annex 1. However, the most important changes can be summarised as follows:

- the 19th century saw changes to education policy and the legalisation of trades unions

- the early 20th century brought with it the beginning of the modern welfare state and widening of educational opportunities

- the immediate post-war period witnessed the establishment of an expanded welfare state

- the later-half of the 20th century saw the passing of significant legislation to tackle gender and racial discrimination and disadvantage

- more recently, times have seen the introduction of the National Minimum Wage and National Living Wage, in addition to policies to promote flexible working

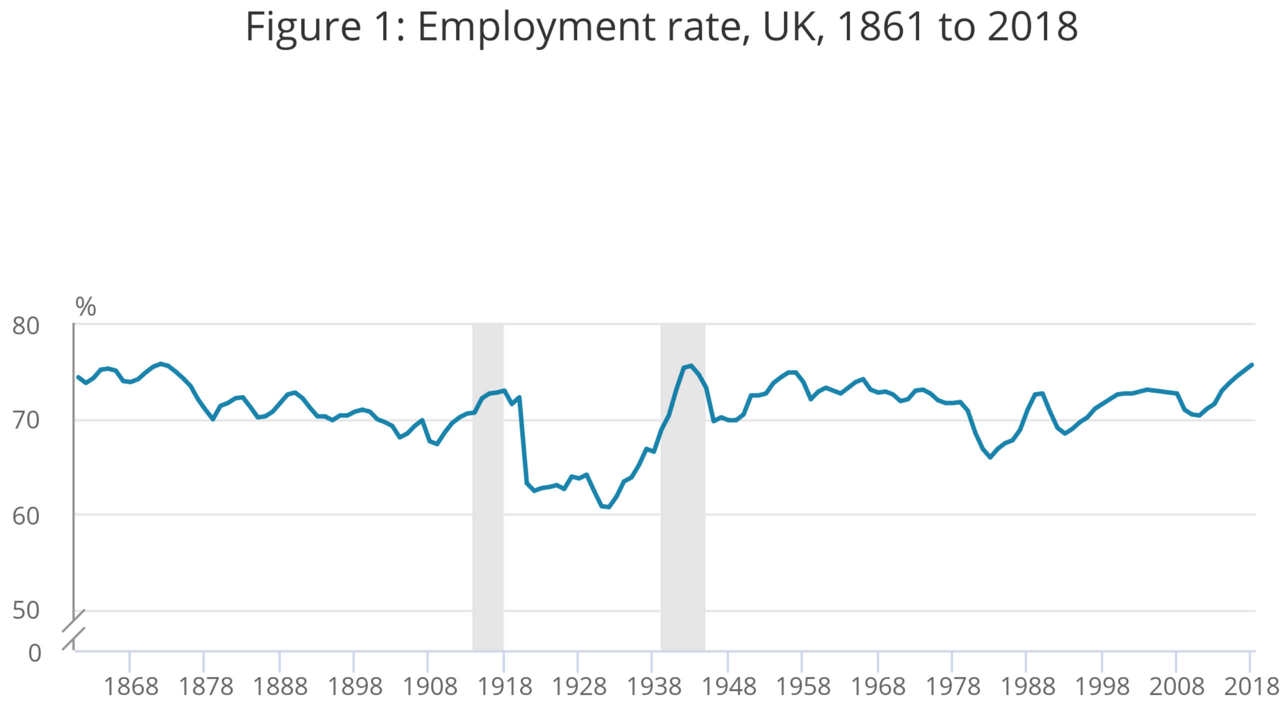
Alongside the legislative reforms have been huge changes in society, many connected with gender. Ideas of gender roles have shifted dramatically and while issues such as the gender pay gap remain, the situation for today's workforce is significantly different compared with the past.

It is against this backdrop of a changed legislative and social environment that the changes in the labour market should be considered.

4 . Trends of the employment rate

Figure 1 shows the employment rate since 1861[1]. The employment rate is, in the long run, affected by developments in educational attainment and wider economic policy. Because of the sensitivity of the employment rate to business cycles, its movement clearly indicates the periods of economic booms and busts. What is striking in Figure 1 is the high increase in employment during World War 1 and World War 2.

Figure 1: Employment rate, UK, 1861 to 2018



Source: Bank of England - A Millennium of Macroeconomic Data

Notes:

1. Although the long-term employment data plotted in Figure 1 are continuous, they do not come from a single source. The series are a composite of several data sources as explained in Annex 2. Further discussion of how the series were derived and the underlying assumptions and processes are contained in the Millennium of Macroeconomic Data.

The highest employment rates recorded were in the years 1872, 1943 and 2018, at 76% of the working age population. During the inter-war years (1919 to 1938), the employment rate averaged 64%, in part reflecting a much more subdued economic outlook. Between 1946 and 1970, the average employment rate was 73%. The lowest rates were during the Great Depression, where it reached a low of 61%, followed by the early 1980s recession at 66%.

Notes for: Trends of the employment level and rate

1. The Millennium of Macroeconomic Data has two series of employment: one measuring the employment of people aged 16 years and over, and another measuring the employment of people aged 16 to 64 years. We use the 16 years and over series because it accounts for changes in the labour market over time. The employment rate, in line with the international conventions, is based on the age group 16 to 64 years and measures the extent to which available labour resources are used (employed). It is calculated as a ratio of the number of people aged 16 to 64 years who are employed to the working age population.

5 . The evolution of sectoral distribution of employment

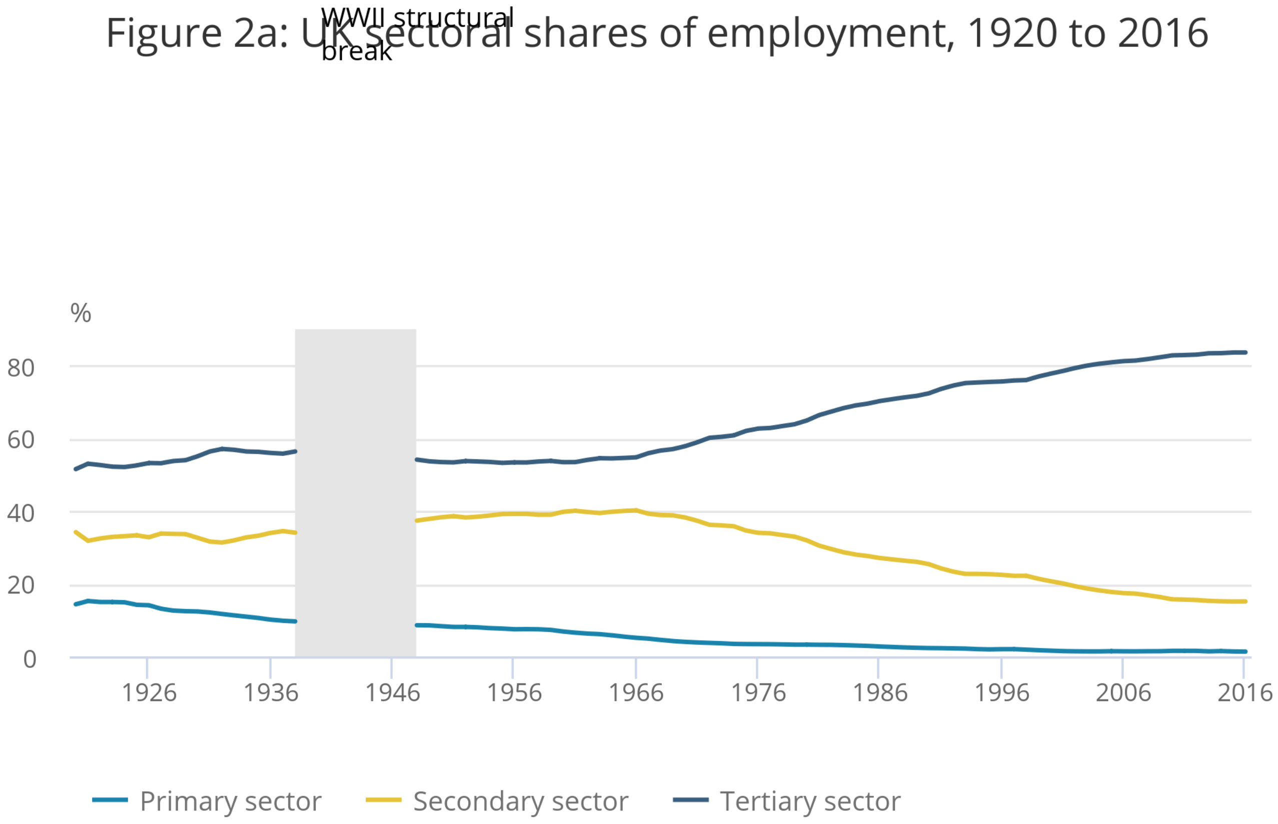
This section presents an examination of the sectoral distribution of employment over time. The sectors of the economy are categorised into the following three sectors[1]:

- primary (primarily agriculture and mining)
- secondary (primarily manufacturing and construction)
- tertiary (services)

The sum of employment in the three categories produces the total employment in the economy. So, the shares of employment sum up to one (or 100%).

Figure 2a shows the employment shares of the three sector categories over time. It shows that since 1920, the largest proportion of workers were employed in the tertiary sector, followed by the secondary and primary sectors respectively.

Figure 2a: UK sectoral shares of employment, 1920 to 2016



Source: Bank of England - A Millennium of Macroeconomic Data

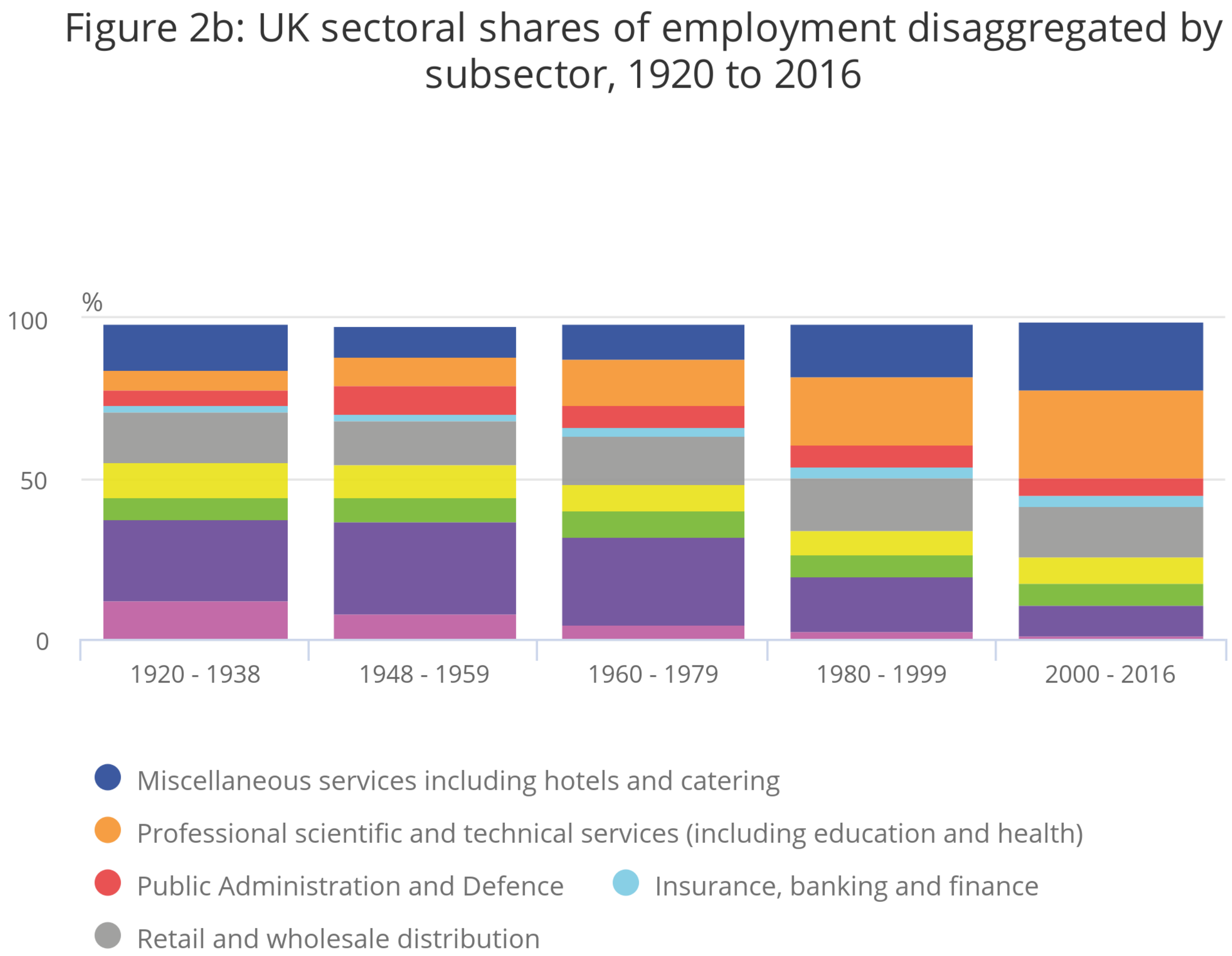
Notes:

1. A structural break was included for the period 1939 to 1947 as data were not available.

The primary sector share of employment decreased consistently over time, from 14.3% in 1920 to 1.3% in 2016. Secondary and tertiary sector employment shares were 34.2% and 51.5% in 1920, respectively. From 1966 onwards, the tertiary sector share of employment increased significantly to reach 83.6% of total employment in 2016. Over the same period, the secondary sector share of employment decreased to reach 15.1% of total employment in 2016. These changes show how the UK economy evolved to become more services-sector driven.

A more detailed representation of the UK's sectoral shares of employment can be shown by a disaggregation into its various subcategories. This helps us to understand the main driving factors behind the trends in primary, secondary and tertiary sectors. Figure 2b shows the employment shares disaggregated into 11 subsectors over time.

Figure 2b: UK sectoral shares of employment disaggregated by subsector, 1920 to 2016



Source: Bank of England - A Millennium of Macroeconomic Data

Notes:

1. In the diagram, agriculture, forestry and fishing, and mining and quarrying have been combined to form the "primary sectors". The gas, electricity and water sector is very small relative to other sectors and has been suppressed.

The manufacturing sector drove the overall decline in secondary sector employment shares, decreasing from an average of 25% during the inter-war years to an average of 9.5% between 2000 and 2016. The growth in the tertiary sector share of employment was driven mainly by growth in the following two subsectors:

- professional, scientific and technical services including education and health, from an average of 13.8% between 1960 and 1979, to 27.2% between 2000 and 2016
- miscellaneous services, including hotels and catering, from an average of 10.9% between 1960 and 1979, to an average of 21.23% between 2000 and 2016

Notes for: The evolution of sectoral distribution of employment

1. The primary sector consists of the following sub-sectors: agriculture, fisheries and forestry, and mining and quarrying; the secondary sector consists of manufacturing, construction and gas, electricity and water; and the tertiary or services sector is made up of transport, storage information and communication, retail and wholesale distribution, insurance, banking and finance, public administration and defence, professional, scientific and technical services (including education and health), and miscellaneous services, including hotels and catering.

6 . Women’s labour market participation

The employment patterns of women in the UK have changed significantly. For instance, according to the 1911 Census, about 28% of all women in England and Wales worked in domestic service.

Women’s employment changed significantly during the two world wars, and they played vital roles in war-related industries like the production of ammunition. While 23.6% of women were employed in 1914 (Anitha and Pearson, 2013), this increased to 36% in 1918. At the peak of World War 2, up to 90% of single women aged 18 to 40 years were engaged in national service activities. Therefore, the world wars transformed the structure of the labour market, creating opportunities for women in sectors that were formerly dominated by male employment.

Outside periods of war, women’s position in the labour market was more marginal. A combination of explicit rules and social norms meant that women faced limited opportunities to work, and where work was available it was often less well paid.

Since World War 2, the position of women in the labour market has changed radically. Industrial changes, incremental improvements in legislation and shifting social attitudes have all contributed to a significant increase in female participation in the labour market. Table 1 shows the number of women aged 16 years and over who were engaged in economic activity between 1951 and 2018 (in 10-year averages). It shows that female economic activity increased by nearly 2.5 times over the period 1951 to 2018.

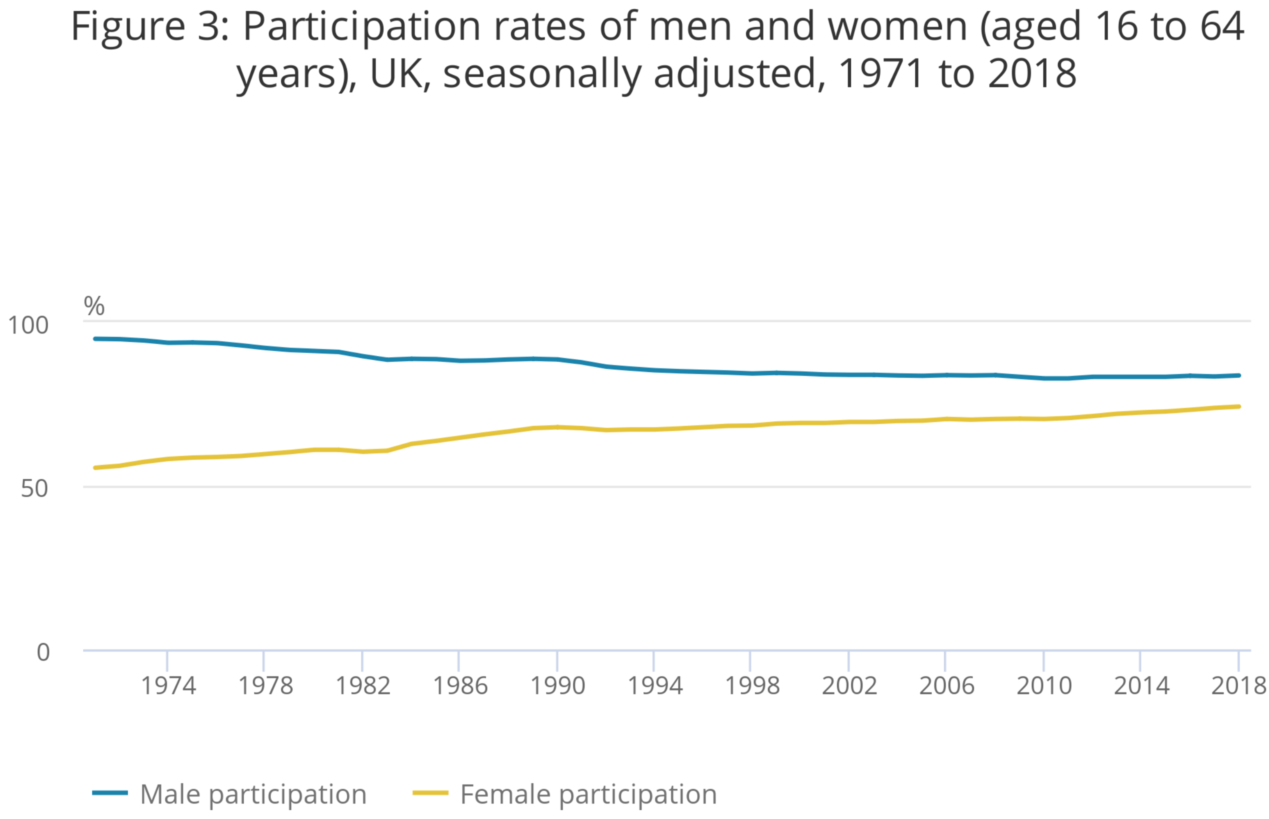
Table 1: Number of economically active women over time, UK, 1951 to 2018

Period	Number economically active women
1951 to 1960	6.91 million
1961 to 1970	8.35 million
1971 to 1980	10.12 million
1981 to 1990	11.7 million
1991 to 2000	12.72 million
2001 to 2010	13.99 million
2011 to 2018	15.35 million

Source: Anitha and Pearson (2013) and Office for National Statistics - Labour Force Survey

We can learn more about women’s labour market participation by comparing female and male participation rates over time. Figure 3 shows a comparison of the participation rates between 1971 and 2018. The participation of women increased steadily over time, from 55.5% in 1972 to 74.2% in 2018. Although male participation remained higher, it fell from a high of 94.9% in 1971 to 83.7% in 2018.

Figure 3: Participation rates of men and women (aged 16 to 64 years), UK, seasonally adjusted, 1971 to 2018



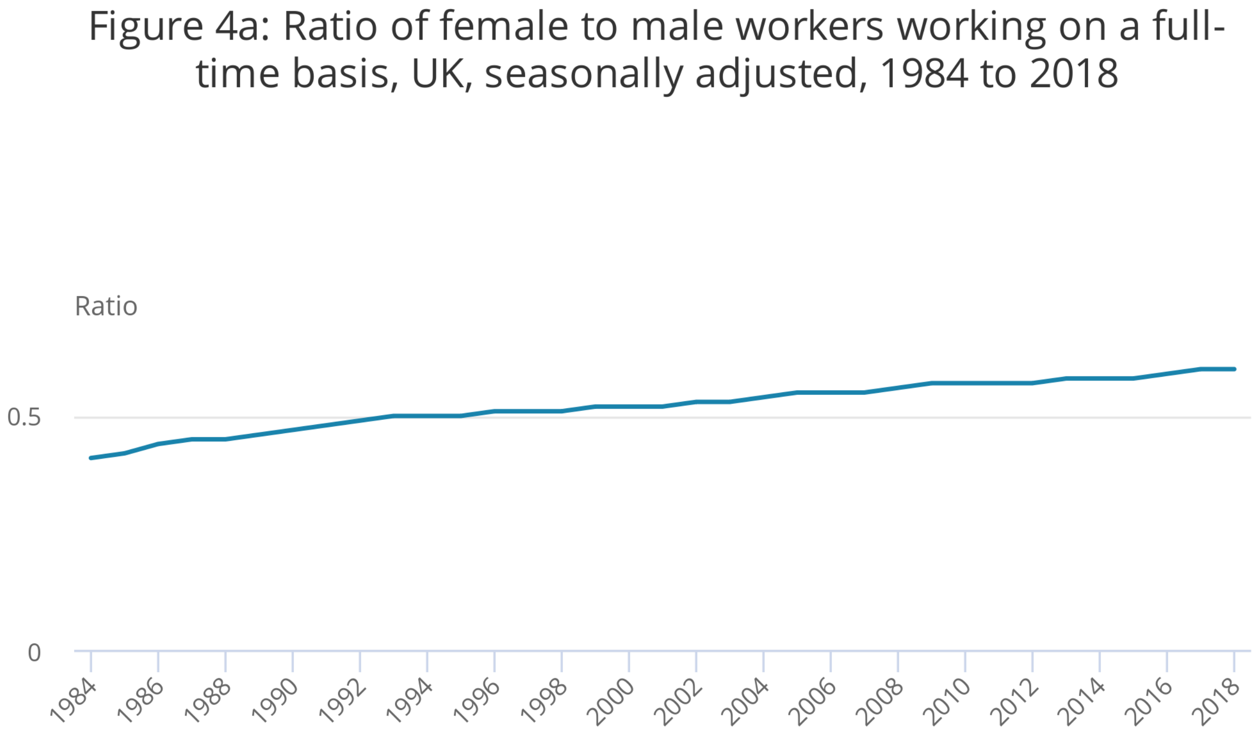
Source: Bank of England - A Millennium of Macroeconomic Data

Figure 3 shows that the gap between female and male participation rates has been declining since the 1970s, driven by the increase in the number of women joining the labour force. The lowest ever gap of 9.5 percentage points occurred in 2018.

7 . Full-time and part-time working (1984 to 2018)

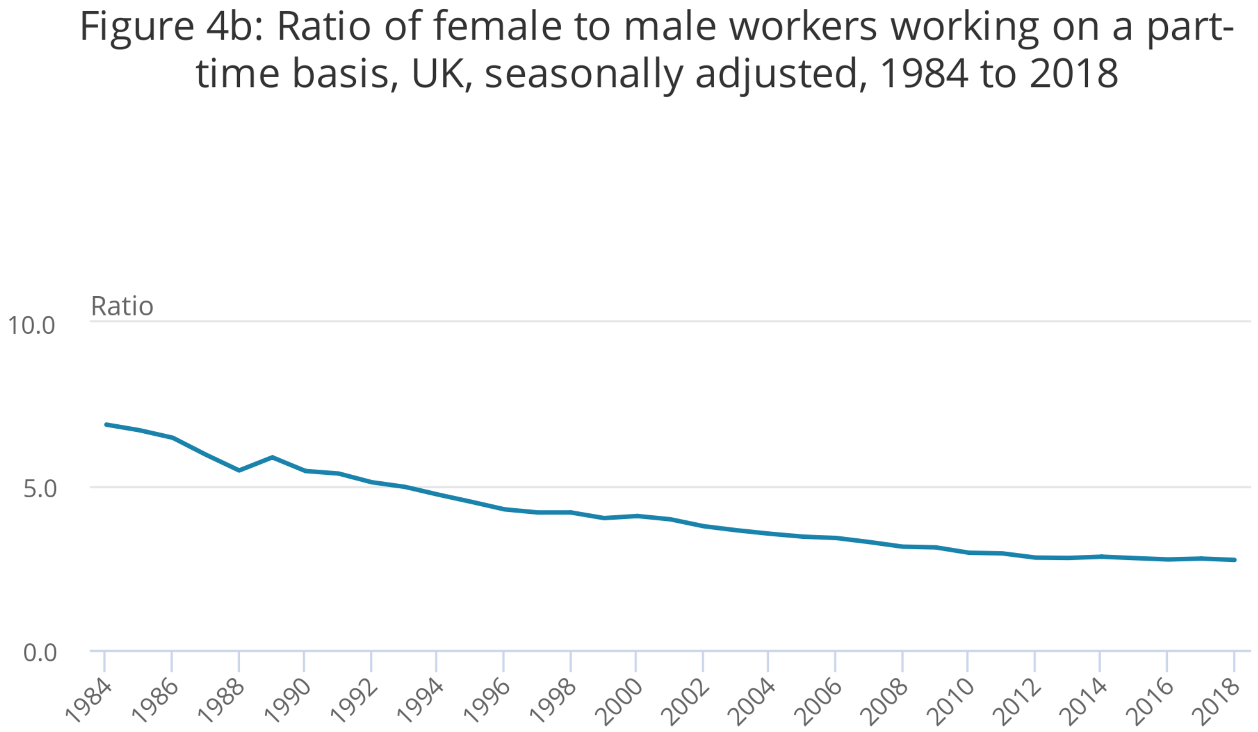
People in employment are often categorised based on whether they work on a part-time or full-time basis. The data for these series disaggregated by sex are available from 1984 and are illustrated in Figures 4a and 4b. Figure 4a shows the ratio of female to male full-time workers and shows an upward trend. This was driven by the growing number of women in full-time employment. The annual average growth rate of female full-time employment between 1984 and 2018 was 1.4%, while that of men was 0.3% over the same period. Between 2012 and 2018, female full-time employment grew by an average 2.1% per annum.

Figure 4a: Ratio of female to male workers working on a full-time basis, UK, seasonally adjusted, 1984 to 2018



Source: Office for National Statistics - Labour Force Survey

Figure 4b: Ratio of female to male workers working on a part-time basis, UK, seasonally adjusted, 1984 to 2018



Source: Office for National Statistics - Labour Force Survey

Figure 4b shows the ratio of female to male part-time workers and shows a downward trend over time. Although the number of women working on a part-time basis increased over time, the annual average growth between 1984 and 2018 (1.1%) was lower than that of men working on a part-time basis over the same period (3.9%). The different growth rates caused the ratio to decline over time. However, total part-time employment had an upward trend over the whole period.

The share of full-time employment taken by women has increased over time from 29.0% in 1984 to 37.6% in 2018. Legislative and cultural change are likely to be factors here, just as they contributed to overall rises in employment.

Historically, women have dominated part-time employment. In 1984, they accounted for 87.3% of part-time workers. While still in the majority, that proportion fell to 73.3% in 2018. Several factors explain the fall, including:

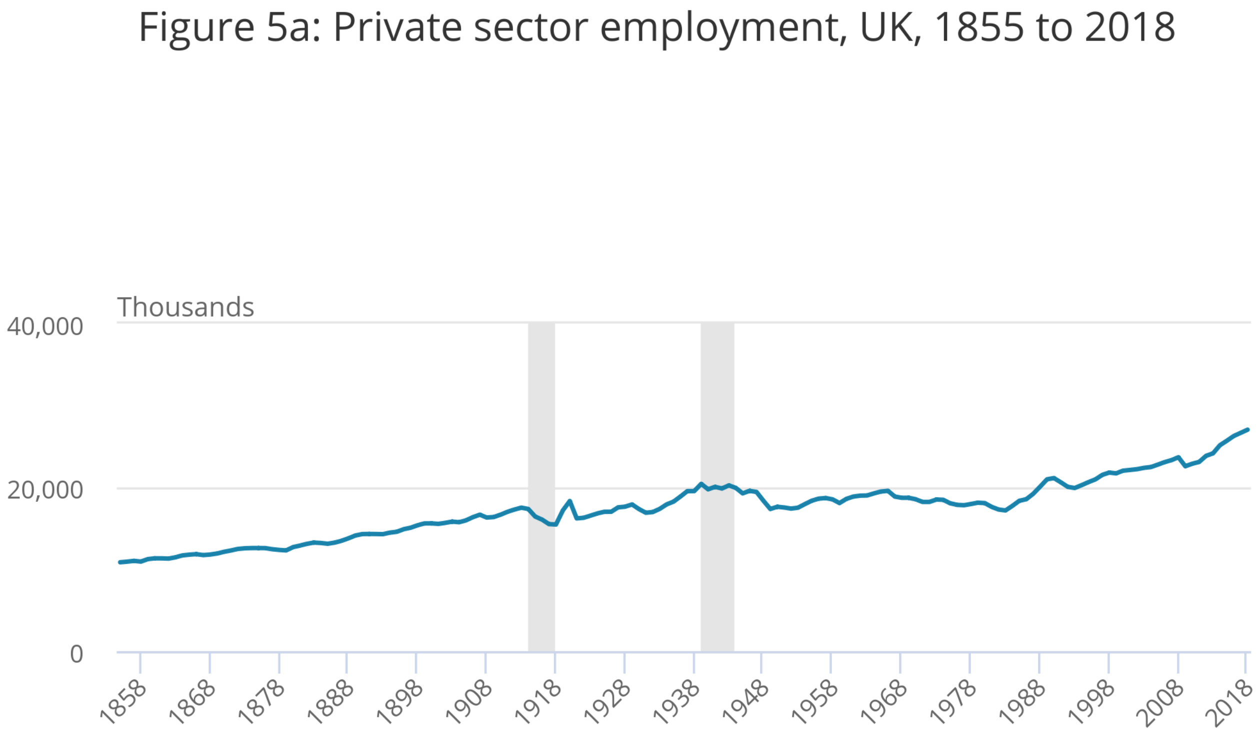
- a rise in the age of women having their first child
- an increase in the population (and especially that of younger women in the workforce)
- the introduction of childcare vouchers and other legislative changes that facilitate mothers' working on a full-time basis

8 . Public and private sector employment

Employment can also be categorised as private or public sector employment. Figures 5a and 5b show the private and public sector employment levels over the period 1855 to 2018 respectively. The figures show that workers have predominantly been employed in the private sector.

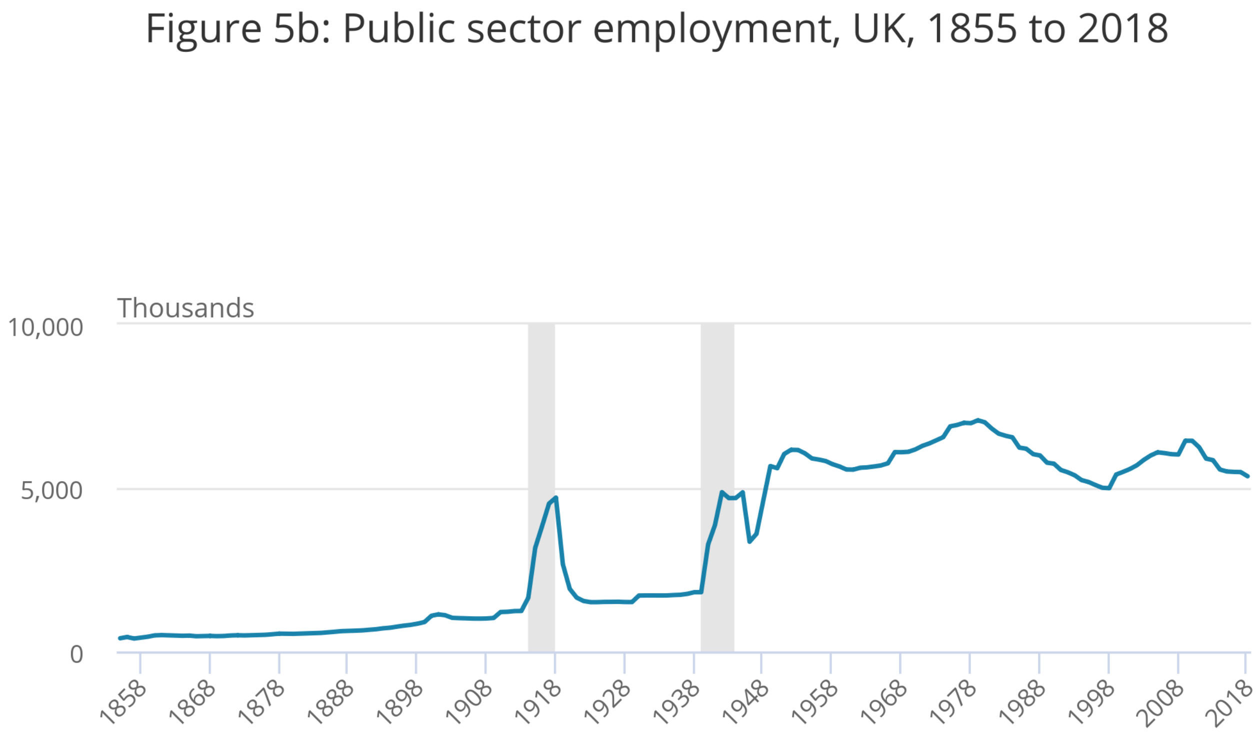
In 1855, private sector employment amounted to 10.9 million workers. In that year, private sector employment constituted 96% of all employment. By 2018, it reached its highest level of 27 million, making up 83.5% of all employment. Between 1983 and 2018, the private sector experienced significant growth, increasing by 57.4%.

Figure 5a: Private sector employment, UK, 1855 to 2018



Source: Bank of England - A Millennium of Macroeconomic Data

Figure 5b: Public sector employment, UK, 1855 to 2018



Source: Bank of England - A Millennium of Macroeconomic Data

Both private and public sector employment show upward trends. Public sector employment growth was due to the general expansion of central and local government. For example, there was significant employment growth during the world wars, and later in line with the evolution of the welfare state.

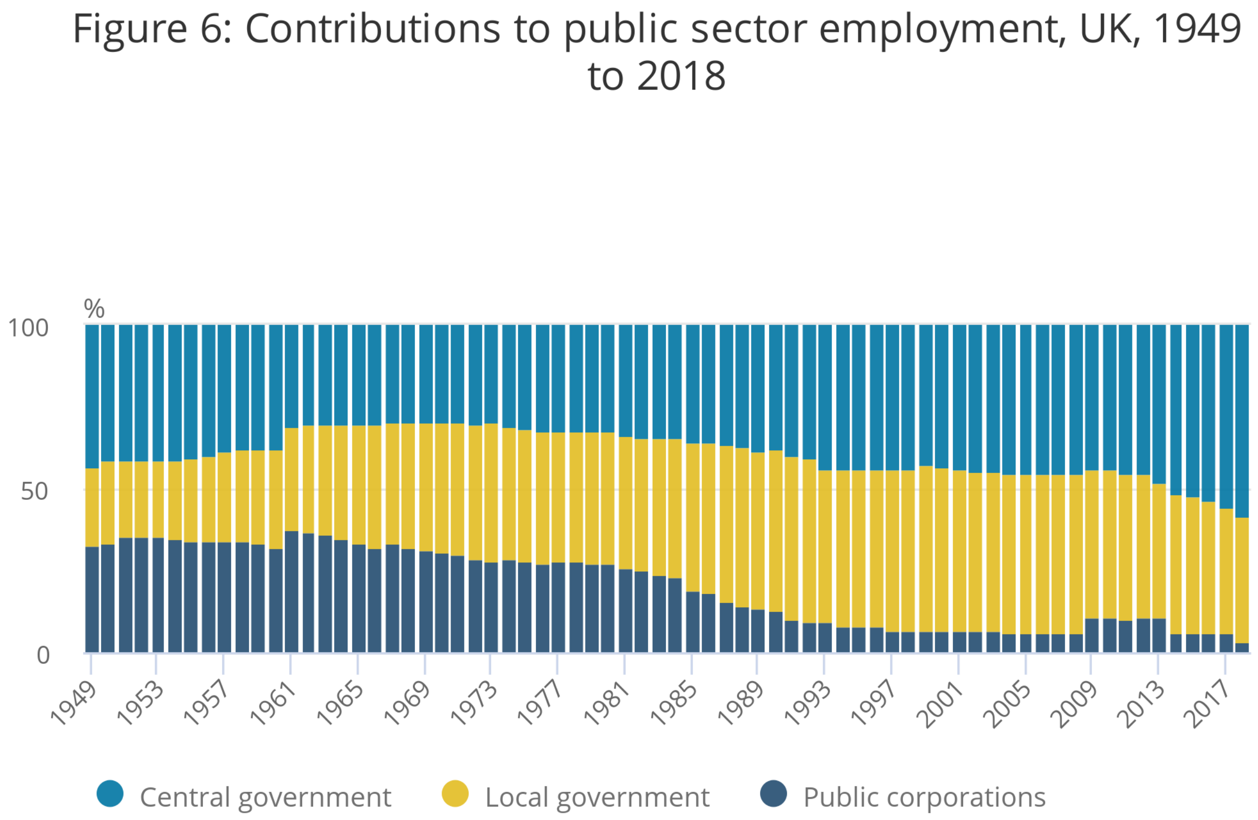
Comparing private and public sector employment trends indicates that, in general, the two tended to move in opposite directions. In some cases, this was the direct result of changes in policy. For example, public sector employment increased significantly after World War 2, partly because of the nationalisation of some entities in the economy, including railways, coal mining, public utilities and heavy industry, and this was mirrored by a substantial decline in private sector employment. By 1979, public sector employment had reached its highest level of 7.07 million, representing 28.1% of total employment.

In the 1980s, policy moved in the opposite direction with the privatisation of some industries. This coincided with a reduction of public sector employment to levels comparable with the 1950s. The following two decades saw public sector employment decline significantly, reaching 4.99 million by 1998. The share of public sector employment also reduced to 18.6% of total employment.

Although public sector employment increased during the 2000s until the economic downturn of 2008 to 2009, it decreased again in the period after the downturn, when austerity measures were put into effect to tackle the budget deficit. As of 2018, 5.36 million people were employed by the public sector, representing 16.5% of total employment. Similar figures were observed shortly after World War 2.

We can disaggregate public sector employment to illustrate its changing structure over time. Figure 6 shows the contribution of those employed in central government, local government and public corporations to public sector employment between 1949 and 2018.

Figure 6: Contributions to public sector employment, UK, 1949 to 2018



Source: Bank of England - A Millennium of Macroeconomic Data

Figure 6 shows that, since 1949, the composition of public sector employment has changed significantly. Public corporations' contribution to public sector employment decreased, while the contribution of central government increased. The contribution of local government increased until 2000. Since then, it has been on a downward trend.

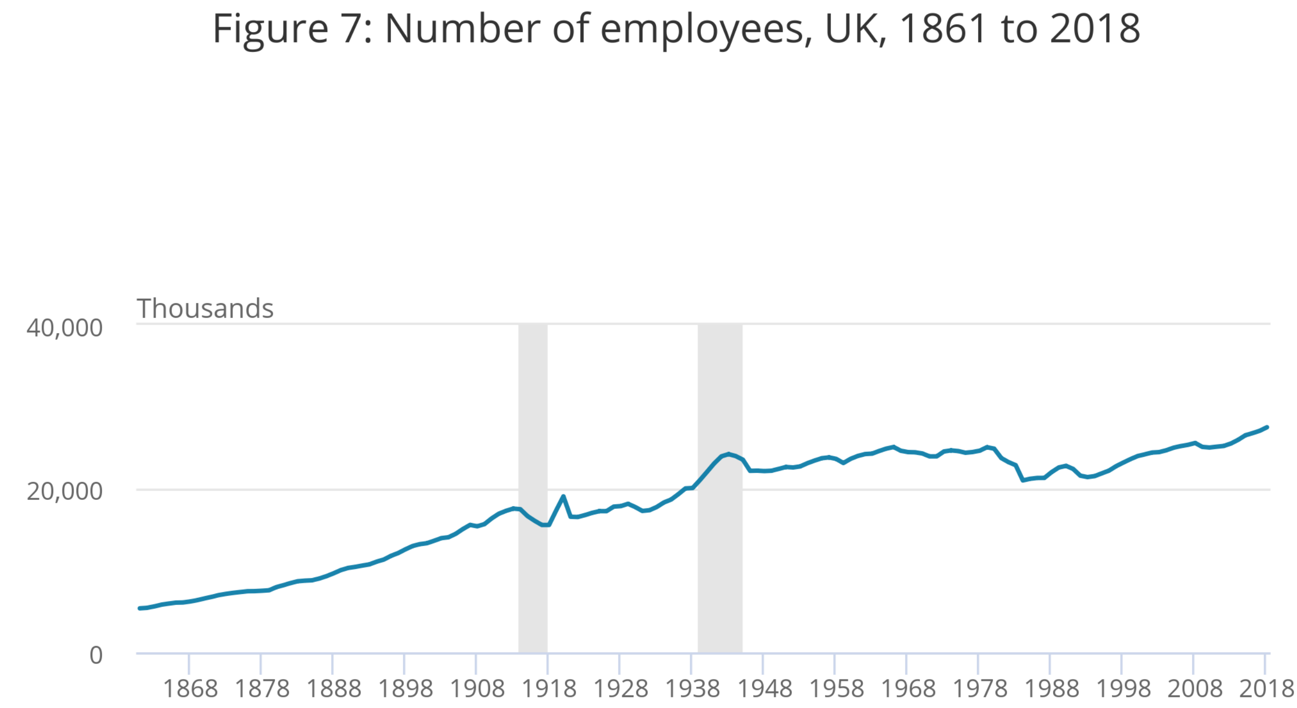
Between 1979 and 1998, the contribution of public corporations to public sector employment decreased from 27.7% to 7.1%. This indicates that the fall in public sector employment from the 1980s onwards was driven largely by reductions in employment by public corporations.

9 . Employees and self-employed workers

The final categorisation we will explore in this article is the split between employees and self-employed workers [1]. The choice of working arrangement has implications for both the earnings and work-life balance of an individual. In general, employees have higher job security and earn more than self-employed workers. Self-employed workers often have greater working flexibility. Self-employment can also allow people who would otherwise be inactive to enter or remain in the labour force. For instance, some older workers may prefer to join self-employment than to retire.

Figure 7 shows the trend of employees between 1862 and 2018 [2]. It shows that the number of employees had an upward trend, and the short-term changes were sensitive to business cycles. The growth in the number of employees was strong between 1861 and 1916. The growth during the inter-war years was interrupted by the decreases in employee level shortly after World War 1, as well as during the Great Depression.

Figure 7: Number of employees, UK, 1861 to 2018

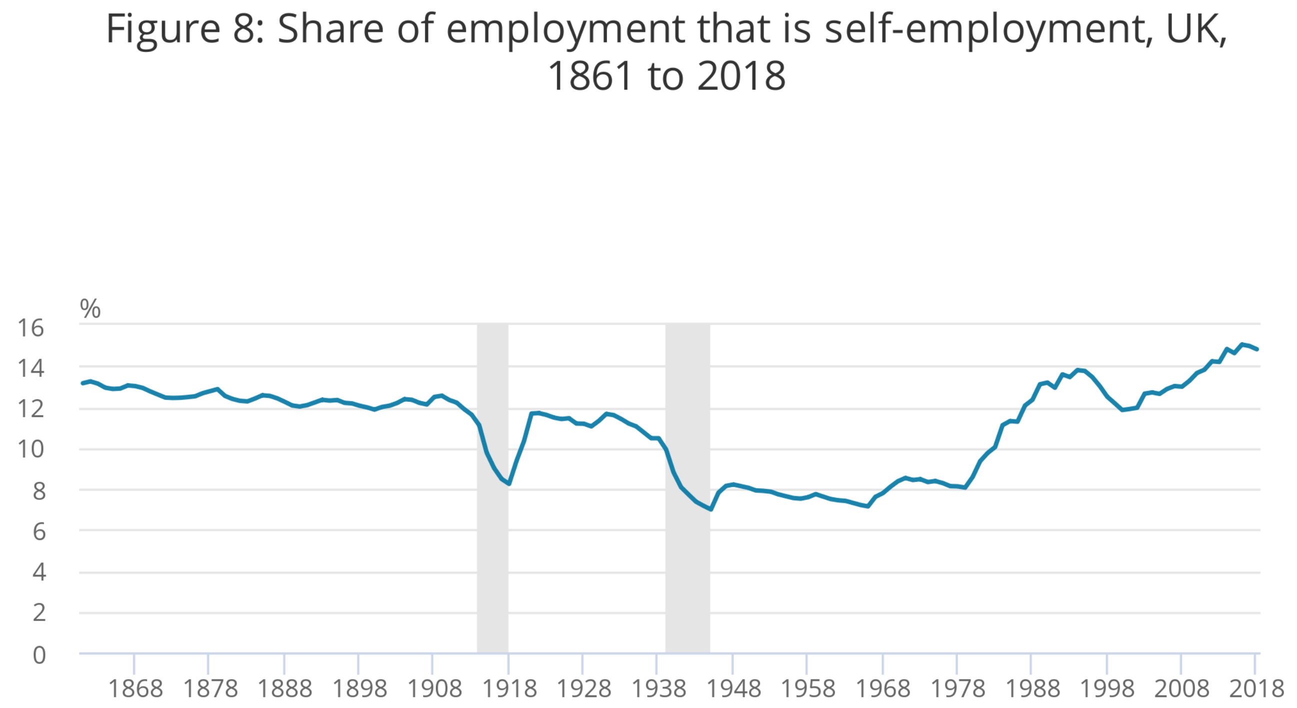


Source: Bank of England - A Millennium of Macroeconomic Data

Over the period 1946 to 1980, the number of employees increased at a moderate rate. Between 1980 and 1984, there was a sharp decline in the number of employees, and this coincided with the economic downturn experienced in the early 1980s. Since then, the number of employees has shown an upward trend, reaching a peak of 27.49 million in 2018.

Figure 8 shows the rate of self-employment between 1861 and 2018, that is, the proportion of total employment that is self-employed. It is worth mentioning that self-employment is not a modern concept; there has been a reasonable share of self-employment in the economy since records began in the mid-19th century.

Figure 8: Share of employment that is self-employment, UK, 1861 to 2018



Source: Bank of England - A Millennium of Macroeconomic Data

Figure 8 shows the rate of self-employment was relatively flat between 1861 and the early years of the 20th century. It decreased during the world wars, and by 1945 had reached its lowest rate of 7%. It increased strongly between 1966 and 1994, and reached its highest rate of 15% in 2016. The increase in the rate of self-employment can partly be attributed to technological changes. For example, in recent years the rise of the "gig economy" has been based on new technology platforms that have made it easier for people to become self-employed. This also has the consequence of allowing for greater employment flexibility and less labour market rigidity, leading to self-employment becoming a more attractive alternative form of employment for some than in the past.

Notes for: Employed and self-employed workers

1. This classification excludes unpaid family workers and people on government-supported training and employment programmes.

2. Using data from the Bank of England's [Millennium of Macroeconomic Data] gathered from the original sources of Feinstein (1972, 1989, 1990), "Economic trends" annual supplement addition (1997), and Office for National Statistics' Workforce jobs measures, we are able to track employee and self-employment back to 1861. Self-employment levels were already provided in these data. Applying a similar method, we were able to calculate employee levels. We use the standard framework to define our disaggregation in line with the International Labour Organisation (ILO).

10 . Implications and conclusions

The analysis of the long-term trend of employment provides insights into the evolution of employment. At a headline level, employment rates today are not that different to those seen around 150 years ago. But in other respects, there have been notable events and changes:

- employment has been sensitive to economic shocks and other events; periods of war increased employment, while economic downturns such as the Great Depression saw significant falls in the share of people in work
- the sectoral composition of employment has changed radically, especially in the last 50 years or so, with manufacturing employment falling from around 25% to about 10% today; employment in the services sector now stands at over 80%
- the employment patterns for women have changed significantly, as a combination of industrial change, legislation and shifting cultural attitudes have given women more opportunities; the gap between male and female participation rates has fallen by nearly three-quarters in the last 50 years
- although most part-time workers are women, the gender split of part-time working has changed significantly since records began; this has been driven by both increasing numbers of men working part-time and more women working full-time
- the number and share of workers in the public sector has increased many times in the last 150 years; most recently, the changes in public sector employment have been driven by changes in the welfare state and government policy on public ownership
- 'the share of' self-employment today is only a little above that seen 150 years ago, though it reached a low in the immediate post-war period

These trends and developments have been the cumulative result of changes in technology, industrial structure, legislation and social change. In that respect, the employment trends we describe have shown the changing socio-economic history of the UK.

11 . References

Airth-Kindree AVM (1987), ‘Munitionettes: British women in munitions during the First World War’, Verlag: University of Tulsa

Anitha S and Pearson R (2013), ‘Striking Women’, Lincoln: University of Lincoln

Benjamin D and Levis K (1979), ‘Searching for an Explanation of Unemployment in Interwar Britain,’ Journal of Political Economy, volume 87, pages 441 to 478

Bowden S and Higgins DM (2004), ‘British industry in the interwar years’ in: Floud R and Johnson P (eds), The Cambridge Economic History of Modern Britain, volume 2: Economic Maturity, Cambridge, Cambridge University Press, pages 374 to 402

Broadberry S (1986), ‘Aggregate Supply in Interwar Britain,’ Economic Journal, volume 96, pages 467 to 481

Broadberry S and Crafts NFR (1990a), ‘The Impact of the Depression of the 1930s on the Productive Potential of the United Kingdom’, European Economic Review, volume 34, pages 599 to 607

Clarke P (1996), 'Hope and Glory: Britain 1900-1990', London: Penguin

Denman, James and McDonald, Paul (1996) 'Unemployment statistics from 1881 to the present day: Special Feature (PDF, 2.8MB)', Labour Market Statistics Group, Central Statistical Office

Eichengreen B (2002), 'The British economy between the Wars (PDF, 285.4KB)', University of California, Berkeley

Goetz SJ, Fleming DA and Rupasingha A (2012), 'The Economic Impacts of Self-Employment,' Journal of Agricultural and Applied Economics, Southern Agricultural Economics Association, volume 44, issue 3, pages 1 to 7

McKinlay A and Zeitlin J (1989), 'The Meaning of Managerial Prerogative: Industrial Relations and the Organisation of Work in British Engineering, 1880-1939,' in: Harvey C and Turner J (eds), Labour and Business in Modern Britain, London: Cass, pages 32 to 47

Undy R (2012), 'Trade union organisation 1945 to 1995', Britain at Work, London: TUC Collections

12 . Annex 1: Main changes to the UK's employment institutions and laws since 1860

Table 2: Changes to the UK's employment institutions and laws since 1860

Law	Description
Trade Union Act, 1871	Trade Unions were legalised for the first time.
Factory Act, 1878	Prohibited work for children under 10 years of age in all trades.
Trade Disputes Act, 1906	Protected Trade Unions from being sued for damages during strike action.
The Old Age Pensions Act, 1908	Provided a State Pension for retired workers.
National Insurance Act, 1911	A levy was introduced to mobilise resources to give a benefit to people if they were unable to work.
Education Act, 1944	Protected female teachers from being dismissed upon marriage.
National Insurance Act, 1946	Laid the foundation of the welfare state and provided comprehensive benefits. Introduced an all-inclusive National Insurance scheme covering all male and female workers aged 15 years and over, including part-time workers. It provided for compulsory contributions for unemployment, sickness, maternity and widows' benefits. It also provided for old age pensions from employers and employees, and instituted a comprehensive state health service, effective in 1948.
The National Assistance Act, 1948	It provided financial assistance for the unemployed and those who had not paid enough contributions into the National Insurance scheme. It also provided for the elderly who had not been paying into the National Insurance scheme during their lives, and established standardised minimal living conditions for the unemployed.
Factories Act, 1961	Consolidated much legislation on workplace health, safety and welfare in Great Britain.
Contracts of Employment Act, 1963	Introduced the right for workers to be given a contract of employment, and entitlement to a minimum statutory termination notice.
National Insurance Act, 1965	Consolidated the National Insurance Acts 1946 to 1964.
Redundancy Payments Act, 1965	Workers were given the right to a severance pay when they were made redundant after a qualifying work period.
Race Relations Act, 1965	Criminalised discrimination in education and employment based on race.
Equal Pay Act, 1970 (effective 1975)	Legislated equal pay for men and women performing similar jobs.
Industrial Relations Act, 1971	Introduced compensation for unfair dismissal.
1972	UK's ascension to the European Union.
Trade Union and Labour Relations Act, 1974	Introduced rules on the functions of trade unions, their legal status and immunity when they take strike action in furtherance of a trade dispute.
Health and Safety at Work Act, 1974	Defined the central authority and structure for the regulation and enforcement of workplace health, safety and welfare.
Sex Discrimination Act, 1975	Criminalised discrimination in work, education or training based on sex or marital status.
Transfer of Undertakings (Protection of Employment) Regulations, 1981	Protected employees' terms and conditions when a business or part of one, was transferred to a new employer.
The Equal Pay (Amendment) Act, 1985	Sought to ensure that women and men were paid the same for work of equal value.
1990	For the first time, married women were taxed separately from their husbands (that is, independent taxation of women).
Employment Act, 1990	Made all forms of closed shop union activity illegal.

Trade Union and Labour Relations (Consolidation) Act, 1992	Defined trade union rights and responsibilities, provided a collective bargaining framework and protected striking workers.
Disability Discrimination Act, 1995	Protected disabled people in employment and in respect to access to services.
Pensions Act, 1995	Phased in the equalisation of State Pension ages for men and women over a 10-year period.
Employment Rights Act, 1996	Collated existing laws on individual employment rights.
Protection from Harassment Act, 1997	Gave protection from harassment, stalking and other forms of persistent conduct that may cause alarm and distress.
Data Protection Act, 1998	Governed the protection of personal data in the country.
Working Time Regulations, 1998	Introduced the right to paid holidays per year (20 days), breaks from work, and limits to excessively long working hours.
National Minimum Wage Act, 1998	Introduced a National Minimum Wage at £3.60 per hour (for people aged 21 years and over).
Human Rights Act, 1998	Incorporated the rights contained in the European Convention of Human Rights into UK law.
Maternity and Parental Leave Regulations, 1999	Guaranteed maternity leave for 52 weeks in total.
The Sex Discrimination (Gender Reassignment) Regulations, 1999	Prohibited employers from discriminating against transgender people.
Part-Time Workers (Prevention of Less Favourable Treatment) Regulations, 2000	Obliged employers to give part-time workers treatment that is comparable to that offered to people on full-time contracts doing the same jobs.
Fixed Term Workers (Prevention of Less Favourable Treatment) Regulations, 2002	Obliged employers to give people on fixed-term contracts comparable treatment to that given to people on permanent contracts doing the same jobs.
Paternity and Adoption Leave Regulations, 2002	Guaranteed fathers two weeks' leave at the statutory rate of pay after the birth or adoption of a child.
Employment Equality (Sextual Orientation) Regulations, 2003	Introduced protection against discrimination based on (actual or perceived) sexual orientation.
Employment Act, 2003	Introduced the right to flexible working for parents with young and disabled children.
Employment Equality (Religious or Belief) Regulations, 2003	Protected against unlawful discrimination on grounds of religion or belief.
Employment Equality (Age) Regulations, 2006	Protected against unlawful discrimination on grounds of age.
Working Time (Amendment) Regulations, 2007	Increased the statutory minimum annual leave entitlement to 28 days.
Pensions Act, 2008	Came into effect incrementally from 2012 onwards. Introduced the right to automatic enrolment into a basic occupational pension scheme.
Equality Act, 2010	Collated existing anti-discrimination legislation.
Additional Paternity Leave Regulations, 2010	Allowed women to transfer up to 26 weeks of their maternity leave to their partners.

Shared Parental Leave Regulations, 2014	Enabled eligible mothers, fathers, partners and adopters to choose how to share time off work after a child is born or placed for adoption.
Deduction from Wages (Limitation) Regulations, 2014	Limited the period over which claimants can seek to recover deductions from wages to a maximum of two years.
Modern Slavery Act, 2015	Introduced to tackle modern slavery by consolidating the offences relating to human trafficking and slavery.

13 . Annex 2: Description of the main data source

The Bank of England's Millennium of Macroeconomic Data spreadsheet is large and contains a broad set of macroeconomic and financial data stretching back to the 13th century. The underlying data were produced by Steve Broadberry, Bruce Campbell, Alex Klein, Mark Overton and Bas van Leeuwen (2015), and are included as a standalone section of the database. Although the data do not represent official Bank of England data or National Statistics and are considered as "work-in-progress", they are the most comprehensive historical series available. The data are also the Bank of England's contribution to the Economic Statistics Centre of Excellence (ESCoE) project on developing historical national accounts statistics.

The Bank of England spreadsheet is organised into annual, quarterly, monthly and weekly sections. The continuous time series for the main macroeconomic and financial aggregates link various historical components together using several assumptions. The annual series, of which we use, are based on separate and more reliable sources than higher frequency series and cover a wider range of data.

For employment data, the ultimate source prior to the Labour Force Survey (LFS) is the census but some of the data (from 1900 to 1953) were obtained from a secondary source (Feinstein (1972): National Income and Expenditure 1855 to 1965). For the period 1871 to 1900, the data were obtained by interpolating the census data for England and Wales, Scotland and Ireland separately (assuming a constant growth rate for each decade) and then adding them up. For the period 1953 onwards, Office for National Statistics data were used. This article makes use of labour market data from 1860 onwards because it is from that date that complete series exist for the main employment variables.

The Bank of England's Millennium of Macroeconomic Data spreadsheet does not have disaggregated data for all the variables we examine in this study. Such data are available from the 1970s, and for some variables, from the 1990s, from the Office for National Statistics. We use these data to illustrate how the labour market has changed over the past 40 years.