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Are UK Labour Markets Polarising?

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Craig Holmes and Ken Mayhew

SKOPE, University of Oxford

Editor's Foreword

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Abstract

In recent years, there has been a growing acceptance of two related phenomena: routinisation and polarisation. However, whilst existing evidence has shown what has happened to occupational structure in the UK, little has been done to look at the effects these processes have had on the resulting wage distributions. In particular, there has not been a full consideration of the implications of within-group effects, where new employees in growing occupations have different productive characteristics compared to existing employees. This paper uses a new method, proposed by Firpo, Fortin and Lemieux (2009), which allows for the decomposition of all distributional statistics into the composition and wage effects of individual explanatory variables, much like the well-know Blinder-Oaxaca decomposition of the mean. Using the Family Expenditure Survey between 1987 and 2001, our results demonstrate the importance of polarisation for the changing distribution of wages in the UK. First, there are effects from the composition of occupations, however, these are only really noticeable at the top of the wage distribution, and in many cases are smaller than the effects of deunionisation and the expansion of further and higher education. Second, there is evidence to suggest that within-group effects are important and may dominate other wage effects that could cause the ‘polarisation of wages’. The final distribution is one where top wages have grown more than middle wages, which in turn have grown more than bottom wages, leading to more inequality. However, routinisation and polarisation have played only a small part in these changes. Third, this methodology reveals a number of other interesting results. Declining gender pay gaps are observed at the bottom and middle of the distribution, but not at the top. Returns to experience have also increased in the middle and, particularly, at the top, suggesting the increasing value of on-the-job training, informal training and soft skills.

1 Introduction

In recent years, there has been a growing acceptance of two related phenomena: routinisation and polarisation. The routinisation hypothesis, attributed to Autor, Levy and Murnane (2003), is a refinement of the idea of skill-based technical change, where technological advancements increases the relative demand for skilled labour, which is complementary to increased utilisation of advanced technology. The routinisation hypothesis argues that technological advances, especially computer capital, provide a substitute for tasks with a clear set of regular instructions and so will decrease firms' need for labour to perform these tasks. At the same time, non-routine occupations may be complementary to computer capital and so firms will demand more labour to perform these occupations. Non-routine task-based jobs fall into two categories: skilled professional and managerial jobs, which are the most complementary to technical progress, and unskilled manual tasks or services (e.g. cleaning). The latter is not generally directly affected by technical change, but the impact of technology on other parts of the labour market is likely to lead to a rise of employment in these jobs.

Goos and Manning (2007) use this task categorisation to show that non-routine occupations tend to predominate at the top and bottom of the wage spectrum, with routine occupations somewhere between. This observation leads to the polarisation hypothesis, with increasing employment at high-paying and low-paying jobs and falling employment for middle-income jobs. Goos and Manning then look at changes in employment for occupations of varying quality, proxied by initial median wage in 1979. They find that there has been employment growth in wage deciles at both ends of the pay spectrum and declines in the middle deciles. Similar results are found by Autor, Katz and Kearney (2006) for the United States and Spitz-Oener (2006) for Germany.

If this is the case, then there may be significant changes in mobility over the past thirty years. An earlier paper (Holmes, 2010) looked at polarisation within a longitudinal dataset that could be used to analyse lifetime mobility patterns. It argued that while routinisation has certainly led to a decline in employment for many routine occupations and an increase in employment of non-routine occupations, it is not clear that an hourglass economy was the inevitable outcome. Underlying the critique is the implicit assumption made throughout this literature that the occupational wage structure has remained constant over the period of time being studied, so that initial median wage can be used as a proxy for position in the labour market across the entire time period. However, the wage structure of occupations could have transformed for a number of reasons.

The starting point for this paper is the belief that the existing methodology employed within the literature on polarisation is inadequate for demonstrating the extent of this phenomena and its eventual effect on wage distributions. The earlier paper derived wage distributions which showed little evidence that the middle is disappearing and that the top and bottom are growing. This paper looks to assess the changes more rigorously using econometric analysis of wage distributions derived from a more representative sample. The paper is set out as follows. Section two discusses relevant issues relating to wage distributions and inequality. Section three presents an econometric strategy for measuring polarisation in the wage distribution. Section four discusses the available data and presents descriptive statistics. Section five reports the results, and section six concludes.

2 Wage Distributions and Inequality

Any discussion of changing wage distributions over time will have implications for inequality – indeed changes in measures of inequality are convenient shorthand for describing the way a wage distribution is transforming. The UK, like many countries, has experienced an increase in wage inequality over the past 30 years. Prasad (2002) looks at the source of the increase in UK inequality, focusing on within-group and between-group inequality, where groups are occupations rather than regions or industries. He found that within-group inequality account for 75 per cent of the total. Moreover, the rising inequality of wages over time could be explained by (in order of importance): increased within-group variance; composition effects (i.e. moves into occupations with more between- and within-group inequality), and increased between-group variance. All three have implications for the process of routinisation and the analysis in this paper. First of all, the composition effects suggest that routinisation may be an important driver of inequality, as individuals move to occupations with more between-group inequality (i.e. to high wage and low wage non-routine jobs from middle wage routine jobs).

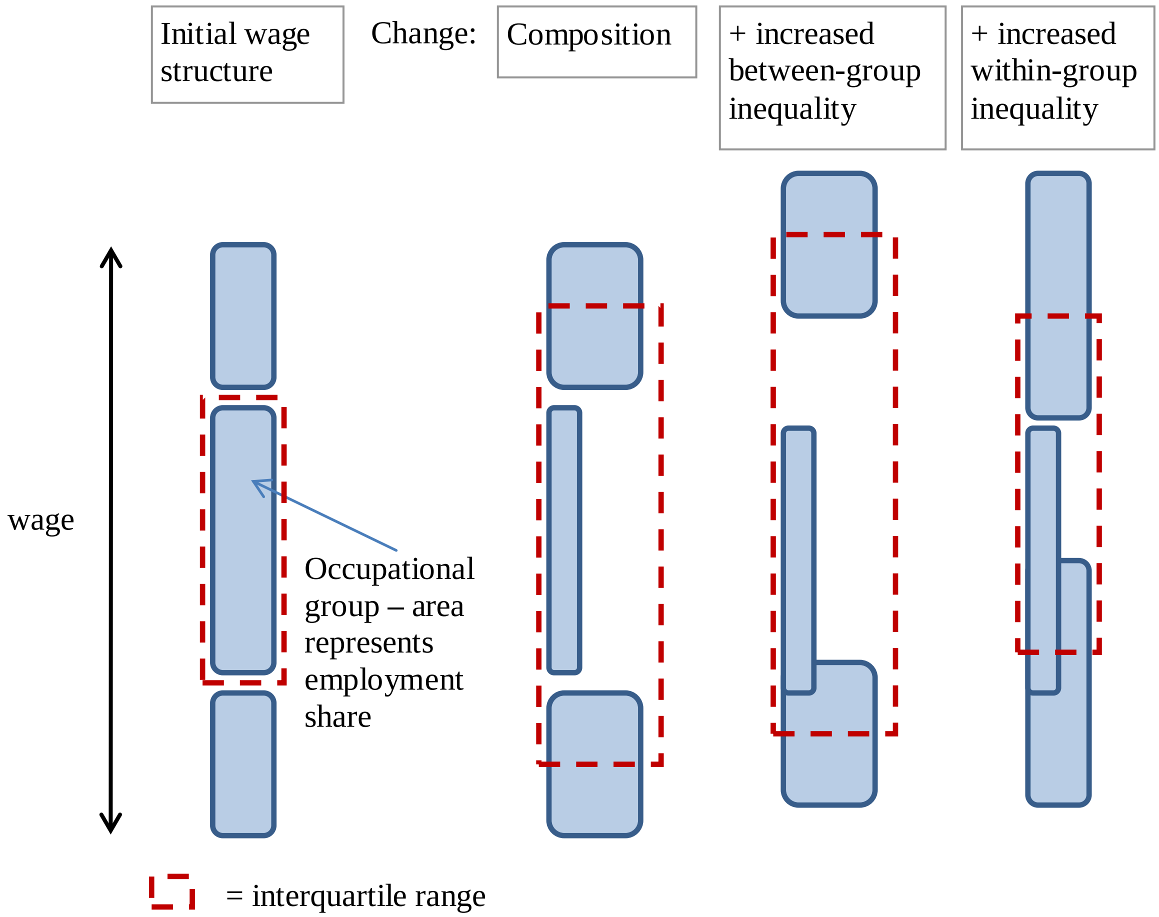
Increased between-group inequality may reflect one effect on wages that results from routinisation. In both the UK and the US, upper tail inequality – the ratio between the 90th percentile and median wages – has increased more markedly than lower tail inequality (see Machin and Van Reenen (2007) for a comparison of trends). Autor, Katz and Kearney (2006) link these patterns of wage growth and inequality changes to the polarisation hypothesis through a model where aggregate production is a function of high skill non-routine, routine and low-skill service labour, where routine labour is a perfect substitute with computer capital. Their model shows that as the price of computer capital falls, demand for the two non-routine occupations rises, as they are complements to computer capital in the production function. This leads to a wage increase of both, relative to routine labour. Thus, the top and middle move further apart, whilst the middle and bottom move closer together.

Increased within-group variance suggests a secondary effect on observed wages as a result of routinisation, as displaced middle-skill routine workers move into non-routine occupations but earn a different wage to those traditionally employed in such occupations (for example, a lower wage in the high skill non-routine occupations, or a higher wage in the low skill service occupations). This could create a new type of middle-income occupation, as the displaced workers retain their overall relative position in the wage distribution, albeit in a different occupation.

Figure 1 represents the consequences of routinisation for each part of the decomposition described above. The initial wage structure has three occupational groups, corresponding to the high skill non-routine occupations, the middle skill routine occupations and the low skill service occupations. The first change is by the composition, as the non-routine occupations grow in employment share (represented by the area of each box). This is the effect suggested by Goos and Manning (2007). Second, the change in demand alters the relative wages of each occupation. This is the effect discussed by Autor, Katz and Kearney (2006). Finally, there is an increase in within-group inequality, which is this paper's contribution to the literature.

Figure 1 also demonstrates the idea that there is a new type of middling occupation (illustrated by the interquartile range). In the initial wage structure (strictly for expositional purposes) this just comprises the middle skill routine occupations. In the final wage structure, this comprises workers in all three occupational groups.

Figure 1: Decomposition of changes in the wage structure as a result of routinisation



3 Methodology

3.1 Issues

The aim of this paper is to look for evidence (or the absence of evidence) of polarisation in wage distributions and to assess its importance in shaping wage distributions over the past three decades. It is useful to clarify a particular point of definition. The term 'polarisation' is used in the literature to capture a number of related phenomena. Initially, it was used to mean the increased employment and labour demand for non-routine occupations, which occupy the outer parts of the wage spectrum (Goos and Manning, 2007). However, it has also been used in the literature to mean an observed change in wage growth patterns since the 1980s, i.e. increased inequality at the top and stable or even decreasing wage inequality at the bottom due to higher wage growth at the top and bottom of the labour market (Autor, Katz and Kearney 2006). The analysis in this paper stays closer to the initial contribution and uses the term polarisation to mean the growth in employment of high paying and low-paying jobs. Hence, polarisation is one factor which may explain changing wage distributions and increased wage inequality. Connected to this is the relative wage effects of routine and both kinds of non-routine occupations – in this paper, referred to separately from the employment composition effects.

Antonczyk, DeLeire and Fitzenberger (2010) similarly recognise the difference between these two effects, and so discuss polarisation of employment and polarisation of wages. They note that while the former applies to many developed countries such as the UK, the US and Germany, the latter is more of a special case for the US. However, the UK has exhibited similar patterns of wage growth over the past 30 years. One of the contributions of this paper will be to place the UK within this dichotomy.

The biggest problem is separating out the main effects that alter the shape of a wage distribution. Suppose there is, at any time t, a wage determination process captured by the relationship:

$$y_t = g_t(x) \qquad (1)$$

where x is a vector of observable variables which impact on the wage and g_t is a function which maps these variables into a single wage y. There are wage effects and compositional effects. Wage effects come through changes to the function g_t whilst composition effects come from changes in the joint distribution of x.

The relevant composition effects in this analysis are changes in employment by occupation – as suggested by the routinisation hypothesis – changes in educational attainment (especially through the expansion of higher education), increased female participation and union membership. The relevant wage effects are changing returns to schooling or qualifications, occupational premia through technological progress to non-routine occupations, changing patterns of discrimination and the weakening union premium. There may also be cohort effects and policy effects – for example, the national minimum wage was introduced in 1998 in the UK, which could have had substantial effects on the relative pay of lower-wage workers.

3.2 The econometric approach: an application of unconditional quantile regressions

There are numerous approaches to explaining changing wage distributions in the literature. The most common approach is via the use of some form of quantile regressions. In standard OLS regressions, the mean or expected value of a dependent variable is calculated, conditional on an array of explanatory variables. In the same way, quantile regressions estimate individual quantiles of the distribution of a dependent variable, conditional on an array of explanatory variables. Estimating this for all quantiles would describe exactly the conditional distribution of the dependent variable.

In this paper, we are interested in what Firpo, Fortin and Lemieux (2009) term unconditional quantile regressions – that is, the changes to the aggregate result of integrating each conditional quantile regression over the distribution of explanatory variables. As they point out, estimating the unconditional marginal effect of a given variable on quantiles is not as simple as it is for estimates of the mean, where the coefficients capture both the conditional and unconditional effect. As a result, there is no simple way of decomposing these changes in quantiles into the effects of an individual covariate.

In this paper, the methodology of Firpo, Fortin and Lemieux (2007, 2009) – henceforth FFL – is followed, which proposes one way to decompose changes in quantiles over time into coefficient and composition effects, much like the Blinder-Oaxaca decomposition of means. Most importantly, they propose a method for extracting the effect on individual covariates. There have been other attempts to do this (see, for example, Machado and Mata 2005); however, this approach appears more reliable as a way of estimating the individual composition effects, which are needed in an analysis of the effect of occupational structure on wage distributions. In this subsection, this methodology is set out. The next section presents the results and compares them to those found by Firpo, Fortin and Lemieux (2007) which applied the same methodology to male wages in the US between 1988 and 2005.

The process begins with two sets of wage data, which comprise the initial and final distribution. The first stage is to create the counterfactual wage distribution – that is, the final wage distribution that would have arisen if the wage determination process were identical to the initial period. For example, the returns to schooling may change over time as the demand for, and supply of, different skills or levels of education changes. The counterfactual distribution applies the initial returns to education to the final distribution of educational outcomes.

Assume there are N observations across the two time periods, where N_0 observations are from the initial time period, and N_1 are from the final distribution. There is an array of explanatory variables for each individual i called X_i, where $i = 1,...,N$. A dummy variable T captures group membership: $T_i = 1$ if the individual i is in the final distribution. Assume $Pr\ (T_i = 1) = p$. In each period, t, there is a wage determination process, captured by the function $g_t\ (X_i, e_i)$ where e_i is the error term. If Y_{it} is the wage of individual i in period t which results from this wage process, then the observed data Y_i can be defined.

$$Y_i = Y_{i0}\left(1 - T_i\right) + Y_{i1}T_i \qquad (2)$$

Equation (2) states that for each person in the sample, there is an initial wage and a final wage. However, we only observe the initial wage for people in the initial group, and the final wage for people in the final group.

The conditional distributions are found via a reweighting of the marginal distribution of Y, $F(y) = Pr\ (Y < y)$. It is possible to derive the conditional distributions of observed Y_0 and Y_1. For example:

$$F_0\left(y\right) = \Pr\left(Y_0 < y \mid T = 0\right) = \frac{\Pr\left(Y_0 < y \,\&\, T = 0\right)}{1 - p}$$
$$= E\left(\frac{\left(1 - T\right)I\left(Y < y\right)}{1 - p}\right)$$

$$
\begin{aligned}
F_1(y) &= \Pr(Y_1 < y \mid T = 1) = \frac{\Pr(Y_1 < y \,\&\, T = 1)}{p} \\
&= E\left(\frac{TI(Y < y)}{p}\right)
\end{aligned}
$$

where *I(Y<y)* is an indicator variable which takes the value 1 if $Y < y$.

In the same way the counterfactual distribution is called $F_C(y) = Pr(Y_0 < y|T_i = 1)$, which can be found by reweighting the data. The reweighting procedure for the counterfactual essentially takes the data of Y_0 for the group $T_i = 0$ then reweights it to take into account the different distribution of *X* in the two groups. To understand this, suppose people can be grouped together by their personal and productive characteristics. For each of these groups, there is an expected proportion for whom the value of Y_0 is less than a given wage y. Aggregating across all of these groups gives the probability that the entire sample's wage is less than the same wage *y*. As we have observed wages for the initial group only, these observations are reweighted by the ratio of observations of *x* in group 1 and group 0. Hence:

$$
\begin{aligned}
F_C(y) &= \Pr(Y_0 < y \mid T = 1) = \frac{\Pr(Y_0 < y \,\&\, T = 1)}{p} \\
&= E\left(\frac{(1-T)I(Y < y)}{p}\frac{p(X)}{1-p(X)}\right)
\end{aligned}
\tag{3}
$$

where $p(x) = Pr(T = 1|X = x)$. For example, if there are four people in the $T = 0$ group with a certain set of characteristics, where we expect two of those people to have a wage less than *y*, and if there are six people with the same characteristics in $T = 1$ group, then we would expect three of them to have a wage less than y. Thus, each observation in the $T = 0$ set where the individuals have these characteristics and their income is less than *y* is reweighted by 6/4 (or 1.5).

Equation (3) can be estimated using a logistical regression of *T* on the explanatory variables *X*. This derivation of the counterfactual distribution requires two assumptions: First, errors are independent of group (initial or final), given explanatory variables *X*.

Second, there is overlap in explanatory variables, so that observing any given set of explanatory variables does not imply membership to one group with certainty. This implies $0 < p(X) < 1$. Having derived the three distributions, distributional statistics can be broken down into wage and composition effects. Consider a given functional of interest, *v(F)*, which could be, for instance, the median or a given percentile of distribution F. FFL show that the decomposition of the change of a distributional statistics of a distribution *F*, *v(F)*, can be expressed:

$$\begin{aligned} \Delta v &= v(F_1) - v(F_C) + v(F_C) - v(F_0) \\ &= \Delta v_W + \Delta v_C \end{aligned} \tag{4}$$

where the subscripts on the distributions denote the final, counterfactual and initial distributions respectively, and Δv_W and Δv_C are terms for the wage and compositional effect.

The second contribution of FFL[1] is to divide these effects into the contributions made by individual covariates. There have been attempts in the literature to do this previously, however, existing methods are either restrictive (where the decomposition is limited to dummy variables) or potentially inaccurate. This method allows the breakdown of a distributional statistic into the contribution made by each explanatory variable, giving a linear equation which can be estimated. The approach proposed by FFL is as follows. Consider a given functional of interest, *v(F)*, which could be, for instance, the median or a given percentile of distribution *F(y)* with a corresponding density function *f(y)*. For this functional, it is possible to define an influence function, *IF(y)*, which measures the robustness of *v(F)* to a change in a single observation, *y*.

FFL use a re-centred version of the influence function, $RIF(y) = v(F) + IF(y)$, which has an expected value *v(F)*. Suppose *v(F)* is a quantile of the distribution *F*, denoted q_τ, where τ is the given cut-off – so $\tau = 0.5$ is the median. The RIF of this statistic for an observation *y* is defined as:

$$RIF(y; q_\tau) = q_\tau + \frac{\tau - I(y < q_\tau)}{f(q_\tau)}$$

[1] See Firpo, Fortin and Lemieux (2007) for a complete technical exposition of this summary.

As the RIF is the sum of the contribution of each observation to its robustness, then it is possible to estimate a conditional RIF regressed on the explanatory variables *X*. The statistic *v(F)* equals the expected value of the relevant conditional RIF. FFL then assume that the RIF can be approximated by a linear regression on the explanatory covariates for each of the three distribution (initial, counterfactual and final), leading to three sets of RIF regression coefficients for each statistic (γ_0, γ_C, and γ_1). They show that these coefficients can be used to decompose the wage and composition effects:

$$\Delta v_W = E(X \mid T=1)(\gamma_1 - \gamma_C) \tag{5}$$

$$\Delta v_C = E(X \mid T=1)\gamma_C - E(X \mid T=0)\gamma_0 \tag{6}$$

Moreover, if the conditional expectation of the RIFs is truly linear, rather than just as an approximation, then $\gamma_0 = \gamma_C$, which simplifies equation (6):

$$\Delta v_C = (E(X \mid T=1) - E(X \mid T=0))\gamma_0 \tag{7}$$

This now resembles the composition effect in the Blinder-Oaxaca decomposition of the mean. The approach taken in this paper is to decompose changes in certain distributional statistics over time into the contributions made by several explanatory variables, including education, age, experience and occupation. The distributional statistics that are relevant here are the median and quantiles at the top and bottom of the distribution.

4 Data

4.1 The dataset

The Family Expenditure Survey has collected data on households since 1957. It was designed to record household expenditure and income, and collects responses throughout the year to capture seasonal variations. The main purpose of the survey was to provide the weights for the United Kingdom Retail Price Index (RPI). It is a relatively small survey – the final survey, undertaken in 2000/1, contained over 6600 households (each household may have multiple respondents, although not all respondents are in the labour market). It was superseded in 2001 by the Expenditure and Food Survey. In terms of consistency of methodology and completeness of data, the Family Expenditure Survey (FES) is the most useful for constructing hourly wage distributions over the past 30 years. As noted above, the survey is a lot smaller than some of the larger alternatives – however, it provides detailed information on gross pay and hours worked. The larger Labour Force Survey only began providing wage data in 1994. The New Earnings Survey is an alternative; however, it does not have data on educational attainment and there are known problems with the sampling of low-income individuals.

Table 1: Employment share by socio-economic group

SEG group description	Employment shares, 1987	Employment shares, 2001
Employers and managers - large establishments	7.82%	10.68%
Professional: employees	4.73%	5.22%
Intermediate non-manual	11.09%	13.83%
Employers and managers - small establishments	5.21%	6.94%
Foremen & supervisors	9.61%	7.18%
Skilled manual	14.77%	10.10%
Junior non-manual	22.24%	21.62%
Farmers: employers & managers	0.31%	0.11%
Semi-skilled manual	10.62%	11.17%
Agricultural workers	1.28%	0.77%
Unskilled manual	6.27%	5.22%
Personal service	6.06%	6.82%

Source: FES, own calculations.

The initial and final wage distributions will be taken from the 1987 and 2001 surveys, with the latter adjusted for RPI inflation. The 1987 wave was the first to have a useful coding of occupations. While the FES does not use the older KOS and more recent SOC codes for recording occupations, since 1987 it has recorded socio-economic groups (SEG). Although these are broad groups, and may mask some variation between different occupations, Table 1 shows that they capture the expected patterns of employment growth, in that those that have been most adversely affected between 1987 and 2001 are skilled and unskilled manual labour, forepersons and junior non-manual workers. This fits with the routinisation hypothesis, given the routine tasks these occupations generally are engaged in. Interesting, semi-skilled labour has grown in employment share whilst skilled and unskilled have shrunk – under a comparison with the later NS-SEC categories, which replaced SEG, more semi-skilled manual occupations are deemed semi-routine rather than routine, compared to both skilled and unskilled manual labour. Skilled manual labour, conversely, falls into two categories under NS-SEC – routine manual and higher technical occupations.

Another reason for treating semi-skilled workers as non-routine, low paid occupations can also be seen in the transition matrix in Table A1, which takes data from the National Child Development Survey, a cohort study which began in 1958. Occupational transitions between 1981 and 2004 are presented using SEG classifications. For reasons of career advancement, it would be expected, in the absence of routinisation, to see individuals moving to higher paying occupations over time, especially between occupations that are similar. The percentage of semi-skilled workers moving to either of the other two manual occupations is much lower than those moving in the opposite direction. Due to career advancement, this would not be expected between skilled and semi-skilled manual occupations at least – this suggests that some displaced skilled workers were forced to take lower paying non-routine work, in line with the routinisation hypothesis.

At the same time, Table 1 also shows that high skill non-routine occupations, such as professional occupations, managerial occupations and intermediate non-manual occupations (which include supervisory positions, higher technical positions and middle-management), have all grown in employment share, as have low skill service occupations. Again, this fits with the routinisation hypothesis. In the econometric model, dummies for the following occupational groups are included:

Occupation group	**Socio-economic group**
MANAGER	Employers and managers – large and small, farmers
PROFESSIONAL	Professional: employees
INTERMEDIATE	Intermediate non-manual
ADMIN	Junior non-manual
MANUAL ROUTINE	Skilled and unskilled manual, foremen and supervisors
SERVICE	Personal service
MANUAL NON-ROUTINE	Semi-skilled manual

These could be grouped together as three occupational categories (as in the model Autor, Katz and Kearney), with the top three combining as abstract occupations (high skill, non-routine occupations), the bottom two as low skill non-routine manual and service occupations, and the middle two as routine occupations. However, there are sufficient observations in each group to use a more detailed decomposition of occupations. In particular, the division between managerial and professional occupations makes sense – the latter tends to require certain qualifications for entry, so increased demand cannot be met by supply in the same way.

As well as occupational codes, variables for schooling, work experience, union membership and gender are also included in the model of wage determination. The FES records the age when the individual finished full-time education, rather than the length of schooling or the qualification level reached. In the literature – see, for example, Gosling, Machin and Meghir (2000) – the usual method is to assume that individuals finish school at the expected age for each level of attainment. Therefore, we can create dummies for each level of education as follows:

Level of attainment dummy variable	**Age finished full time education**
DEGREE	Over 20
POST COMP	18-20
HIGH SCHOOL	16-17
NO QUALS	Below 16

There is some variation in the minimum school leaving, which might mean that the dummy measures above may be changing in terms of what they are measuring. For example, prior to 1972, the minimum school leaving age was 15, whilst after 1972 the minimum school leaving age was raised to 16. After 1972, there would be a number of individuals who would have left at 15 had they the choice, but remained in education for another year. Providing that marketable skill is not solely the result of schooling (i.e. there is an unobservable innate ability component) and assuming that the 15 year old drop outs were of a low ability, then the HIGH SCHOOL dummy captures different sets of individuals depending on the cohort. In the analysis below, both specifications are reported.

Individuals report union subscription fees as one of the deductions from their gross income. A dummy for union membership is included if this contribution is greater than zero. Sex is included as a dummy which takes the value of one if the individual is female. Unfortunately, the FES does not have any data on racial background. Finally, experience is calculated as the individual's age minus their full-time education leaving age.

4.2 Descriptive statistics

Table 2 presents the mean values of the explanatory variables used. They show expected patterns of change in the labour market. The expansion in higher education and higher staying-on rates after compulsory education are captured by the dataset, with the number of workers with a degree increasing from 9.7 per cent to 16.7 per cent. The occupational changes are identical to those in Table 1, except some categories have been summed together. The two other compositional changes are increased female participation and declining union membership. Female workers account for 50.1 per cent of employment in the 2001 sample, up from 46.4 per cent. Union membership has fallen from 29.0 per cent to 14.9 per cent over the time period.

These statistics can be compared with national trends to assess whether this sample is representative. Brook (2002) reports union density for British employees between 1991 and 2001, which fell from 37.5 per cent to 28.8 per cent. Hence, our measure of union membership underreports actual membership. This makes sense given that it is an indirect measure of individuals who deduct subscription fees from their net pay. Workers may pay membership fees in other ways, and patterns of payment method may change over time. This issue was discussed in Bell and Pitt (1998), who conclude that the measure is reliable and that any bias should be small.

Data from the Labour Force Survey shows that women accounted for 41.3 per cent of all employment in 1987 and 45.8 per cent in 2001. However, restricting employment to just employees changes this to 47.2 per cent in 1987 and 49.4 per cent in 2001. Our dataset does not include the self-employed (due to missing data on hours), which may have significantly more male employment than female employment. Thus, we consider our dataset representative of the UK labour force for employees.

Table 2: Mean values of explanatory variables

Variable	2001	1987
DEGREE	0.1672	0.0974
POST COMP	0.1687	0.1090
HIGH SCHOOL	0.4438	0.4143
NO QUALS	0.1835	0.3586
MANAGER	0.1759	0.1311
PROFESSIONAL	0.0523	0.0475
INTERMEDIATE	0.1684	0.1478
ADMIN	0.2153	0.2238
SERVICE	0.0681	0.0611
MANUAL ROUTINE	0.1965	0.2630
MANUAL NON ROUTINE	0.1113	0.1070
UNION	0.1486	0.2903
SEX	0.5005	0.4643
EXP	21.87	20.87
N	6332	7596

Source: FES, own calculations.

Finally, UK Census data from 1991 and 2001 can be used to estimate changes in educational attainment over the time period. The 1991 Census records degrees, higher degrees and diplomas by all those over 18 years old, whilst the 2001 Census records Level 1-5 qualifications for 16-74 year olds, where Level 4 and 5 contain degrees, as well as other higher vocational qualifications. Hence, the share of the population with a higher qualification is measured as 13.4 per cent in 1991 and 19.6 per cent in 2001. This suggests that the degree measured based on full-time education leaving age reasonably records the pattern on growth in education. The lower percentages could be explained by two factors. First, the Census measure includes a number of Level 4 qualifications which could, potentially, be completed before age 21, so the leaving-age measure would not include them. Second, many higher qualifications may be achieved after the completion of full-time education. The leaving-age measure would also not capture these individuals.

5 Results

5.1 The counter-factual distribution

In order to calculate equation (3), we need to estimate *p(X)*, the probability an observation in the final distribution given the observable variables. To find this, a logistic regression of a dummy variable for time (which takes the value of one if the data was recorded in 2001, and zero if the data was recorded in 1987) was performed on the explanatory variables. Table 3 presents the results of this estimation, using the qualification dummies model. The schooling past school leaving age model is estimated separately, but not reported here.

Table 3: Logistic regression for estimation of counterfactual distribution

		TIME (1=2000, 0 = 1986)	
Demographics	UNION	-0.8258	***
		(0.045)	
	SEX	0.1148	***
		(0.040)	
	EXPERIENCE	0.0357	***
		(0.001)	
Education	DEGREE	0.6627	***
		(0.062)	
	POSTCOMP	0.4731	***
		(0.056)	
	NO QUALS	-1.2831	***
		(0.052)	
Occupations	MANAGERIAL	0.0963	
		(0.064)	
	PROFESSIONAL	-0.2289	**
		(0.093)	
	ADMIN	0.0235	
		(0.059)	
	SERVICE	0.2557	***
		(0.084)	
	MANUAL ROUTINE	0.1624	***
		(0.062)	
	MANUAL NON ROUTINE	0.5034	***
		(0.072)	
	CONSTANT	-0.7493	***
		(0.065)	
	N	= 13928	
	Log likelihood	= -8858.6	

Notes: Reference group – non-union male, high school qualifications, intermediate occupation. *** = 1% significance, **=5% significance.

The reference group are non-union males with high school qualifications in intermediate occupations. Encouragingly for the specification presented above, the variable MANAGERIAL is insignificant for predicting time period. In the model, intermediate occupations – the reference occupation – and managerial occupations form two of the three non-routine high wage occupational groups, with professional occupations generally requiring certain qualifications for entry. The lack of statistical significance on the MANAGERIAL variable in the above suggests that the two occupations have moved together, as is predicted by a simple three-occupation group model with broad non-routine and routine occupations. The lack of significance on the ADMIN variable is less expected, as employment in administrative occupations declined over the time period. This is likely the result of controlling for education.

Table 4: Decomposition of wage and composition effects across major percentiles

	$v(F_1)$	$v(F_c)$	$v(F_0)$	Δv_W	Δv_C
0.05	0.5488	0.4224	0.4055	0.1263	0.0169
0.10	0.7441	0.6650	0.6419	0.0791	0.0231
0.15	0.8497	0.7577	0.7401	0.0920	0.0176
0.20	0.9462	0.8431	0.8232	0.1031	0.0199
0.25	1.0320	0.9163	0.8959	0.1157	0.0204
0.30	1.1078	0.9985	0.9634	0.1093	0.0351
0.35	1.1814	1.0756	1.0403	0.1057	0.0353
0.40	1.2583	1.1394	1.1039	0.1189	0.0356
0.45	1.3282	1.2132	1.1716	0.1150	0.0416
0.50	1.3973	1.2865	1.2349	0.1108	0.0516
0.55	1.4686	1.3690	1.3021	0.0996	0.0669
0.60	1.5445	1.4558	1.3766	0.0887	0.0793
0.65	1.6312	1.5413	1.4491	0.0899	0.0922
0.70	1.7158	1.6320	1.5267	0.0838	0.1053
0.75	1.8163	1.7313	1.6124	0.0850	0.1189
0.80	1.9226	1.8326	1.7120	0.0901	0.1206
0.85	2.0382	1.9538	1.8264	0.0844	0.1274
0.90	2.1813	2.0964	1.9706	0.0848	0.1258
0.95	2.4178	2.3026	2.1688	0.1152	0.1338

Source: FES, own calculations

Table 4 summarises the changes in the percentiles in the sample, decomposed as in equation (4). As wages are in logarithmic form, the differences are approximately equal to the percentage change of each percentile. For example, the 10th percentile has increased by approximately 7.9 per cent due to wage effects and 2.3 per cent due to composition effects. Figure 2 graphs these distributions. It shows that composition effects are much more important at the top of the distribution, whereas any changes at the bottom of the distribution appear to be mainly driven by wage effects.

Figure 2: Initial, counterfactual and final distributions, FES 1987-2001

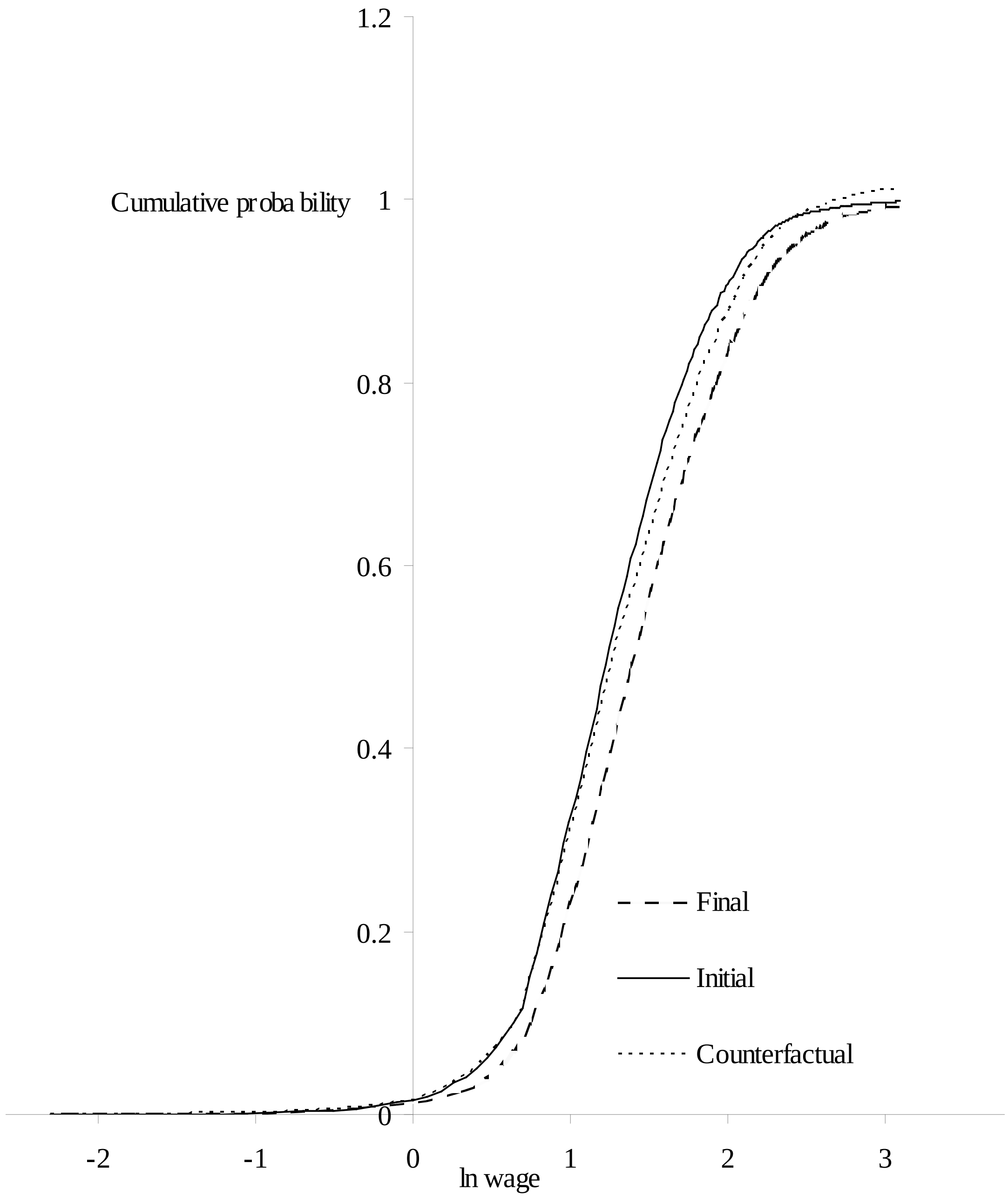


Table 5: Individual contributions to wage and composition effects for selected percentiles

Education dummies model

	10th percentile		Median		90th percentile	
	Composition	Wage	Composition	Wage	Composition	Wage
UNION	-0.0352	-0.0003	-0.0354	-0.0032	0.0002†	-0.0061
DEGREE	0.0170	0.0071	0.0246	-0.0046	0.0435	0.0239
POST COMP	0.0084	0.0117	0.0106	-0.0046	0.0125	0.0066
NO QUALS	0.0012†	0.0035‡	0.0190	-0.0006	0.0320	-0.0108
SEX	-0.0052	0.0294	-0.0131	0.0574	-0.0081	-0.0186
MANAGER	-0.0013†	0.0128‡	0.0009†	0.0203	0.0230	0.0137
PROFESSIONAL	-0.0002†	0.0012‡	0.0001†	0.0070	0.0026	0.0092
ADMIN	0.0012	0.0013	0.0028	0.0118	0.0011	0.0064
SERVICE	-0.0030	-0.0043	-0.0042	0.0069	-0.0013	-0.0005
MANUAL ROUTINE	0.0107	0.0239	0.0239	0.0143	0.0154	-0.0042
MANUAL NON ROUTINE	-0.0012	0.0106	-0.0024	0.0174	-0.0011	0.0018
EXP	0.0078	0.0030	0.0065	0.0343	0.0100	0.1008
CONST	0.0000	0.0026	0.0000	-0.0326	0.0000	-0.0301
Total	0.0001	0.1026	0.0333	0.1237	0.1298	0.0921

Years past school leaving model

	10th percentile		Median		90th percentile	
	Composition	Wage	Composition	Wage	Composition	Wage
UNION	-0.0321	-0.0029	-0.0344	-0.0038	0.0007†	-0.0085
YEARS ED	0.0154	-0.0137	0.0268	-0.0242	0.0496	0.0069
SEX	-0.0058	0.0272	-0.0136	0.0963	-0.0084	-0.0368
MANAGER	-0.0020†	0.0086‡	0.0003†	0.0196[0]	0.0226	0.0224
PROFESSIONAL	-0.0003†	0.0016‡	-0.0001†	0.0077[0]	0.0024	0.0108
ADMIN	0.0008	-0.0076	0.0027	-0.0120	0.0010	-0.0114
SERVICE	-0.0027	-0.0041	-0.0042	-0.0022	-0.0011	-0.0045
MANUAL ROUTINE	0.0104	0.0010	0.0243	-0.0064	0.0140	-0.0215
MANUAL NON ROUTINE	-0.0012	0.0018	-0.0024	0.0022	-0.0010	-0.0092
EXP	0.0066	-0.0451	0.0036	-0.0024	0.0057	0.0584
CONST	0.0000	0.1558	0.0000	0.0891	0.0000	0.1271
Total	-0.0110	0.1224	0.0031	0.1638	0.0854	0.1337

Notes: Reference group in RIF regressions, non-union male with high school education in an intermediate occupation. All effects are significant at 1% level, except where marked:

†Individual composition effect not significant – RIF coefficient for initial distribution not significant at 10% level

‡ Individual wage effect not significant – RIF coefficient on counterfactual and final distribution not significant at 10% level

[0] RIF coefficient on counterfactual no significant at 10% level, but coefficient on final distribution is significant.

5.2 Individual contributions

The focus is on the 10th, 50th and 90th percentiles to describe what is happening to the wage distribution. The nine RIF regressions are calculated (one for each of these three statistics in the initial, counterfactual and final distributions), which give the set of coefficients on the explanatory variables. Combining these and the expected values of each of the covariates as described in equations (5) and (7) give the individual contributions of each to the wage and composition effects.

Table 5 presents the individual contributions for both models of educational attainment[2]. This table should be interpreted with care - these are the actual contributions to the change in each percentile, rather than the coefficients from the RIF regression. Note also that a positive composition effect for a single variable does not mean that variable has a positive effect of wages, but rather that given the change in composition of that variable (positive or negative) over the time period, the result has been a positive effect on the percentile in question.

5.2.1 Unions and sex

The composition effect for UNION on the 10th percentile is negative – that is, the change in union membership reduced the 10th percentile by 3.5 per cent, all other things equal. The coefficient from the RIF regression is positive, however, which says that greater union membership increases the wage of low earners. The negative contribution comes from the change in membership rate, which has declined. Unions have a similarly large effect on the earnings of middle-income workers. The decomposition shows that this occurs through membership – the wage effects, corresponding to the union premium, have remained relatively constant over the time period. The union effects for the highest earners are not significant.

Sex has impacted on the wage distribution in two key ways. First, increased female participation, holding the initial wage structure constant, has a negative effect on wages. This makes sense, given there was a gender pay gap in 1987. The regressions show that increased female participation has affected all parts of the wage distribution, meaning that women are increasingly participating at all income levels, with the largest

[2] In the analysis below, the focus is on the first educational dummies model – see section 5.3 for details on how the alternative model is less well specified. The overall effects are similar in most cases.

effects observed in middle-income occupations. Wage effects, through a declining gender pay gap, outweigh the composition effects for low and middle earners. Second, at the top end there is evidence that women are doing relatively less well compared to their male counterparts, with the pay gap widening over the period.

5.2.2 Education and training

The remainder of the model explains changing distributions through the effect of (i) skills and qualifications, and (ii) occupations and the type of tasks they involve. Large wage effects are observed for the experience variable. Experience could be a proxy for skills developed informally, especially soft skills such as leadership, decision-making, problem solving and teamwork, as well as those developed through on-the-job training. For high earners, the return to experience has increased wages by approximately 10 per cent. Not surprisingly, this effect is much smaller for low earners, where soft skills are less important.

Table 5 shows that the expansion of higher education has a positive effect on wages at all income levels. Even for low earners, the larger number of graduates has increased 10th percentile wages by 1.7 per cent. The effect is even greater for higher earners, as would be expected. Moreover, there have been increasing returns to degrees (over high school qualifications) for both low earners and higher earners (but curiously, not middle-income earners). Similarly, higher staying-on rates after compulsory education have increased earnings across all income levels, however, there are only sizeable increases in returns to that education for lowest earners.

5.2.3 Occupations

Finally, the paper turns to the occupation specific variables. Increasing polarisation of employment into low wage and high wage non-routine occupations away from middle income routine occupations and holding the wage structure constant should increase the wage at the higher percentile, decrease it at the lower percentile and have an ambiguous (but presumably smaller) effect in the middle. From the results, it can be seen that total wage growth at the bottom because of changing occupational structure is 0.7 per cent, 1.9 per cent for median incomes and 3.0 per cent for higher wage earners.

The increase in employment share in managerial occupations has a large positive effect for the highest earners. This is predicable, as under the initial wage structure managers were the highest wage occupations. This is essentially the kind of composition effect Goos and Manning identify, with more workers in high wage jobs pushing the top end of the distribution away from the middle and bottom. Increased employment in professional occupations has had only a small effect on high earners despite the increase in professional employment share, possibly, because it has coincided with the expansion of graduates qualified to fill these jobs, so any wage effects from increased professionalisation may be captured within the DEGREE composition effect.

What is noticeable is that occupational composition has had limited effect on the low end of the wage spectrum in the way predicted by the polarisation hypothesis. The signs on SERVICE, MANUAL ROUTINE, MANUAL NON-ROUTINE and ADMIN are as expected. As these effects are all relative to the reference group and holding the wage structure constant, an occupation with a lower average wage than intermediate occupations that is growing will have a negative effect on wages, whilst an occupation with a lower average wage than intermediate occupations that is shrinking will have a positive effect on wages. However, the increased employment in service and non-routine manual occupations does not have the large effects that managerial occupations have at the top, leading to the positive, rather than the negative, total effect of occupational structure. Given that managerial and professional occupations are not a significant driver of wages at the bottom end of the distribution, this suggests that it is the growth in intermediate occupations which has had the largest occupational composition effect for low earners, rather than the growth of service or non-manual routine occupations. One problem with this analysis is that intermediate occupations may be too broad a group, containing both higher technical occupations and some lower skill occupations that are closer to service occupations and occupy the lower part of the wage distribution. Therefore, the positive occupational composition effect may be biased by the contribution of the higher wages of the higher technical occupation to the average intermediate occupation's wage.

Holding the wage structure constant, the Goos and Manning polarisation of employment effect is found within these wage distributions. That said, the decomposition shows that compared to other changes (such as union membership, gender composition and educational distributions), these effects are small and in some cases dominated by effects acting in the opposite direction.

The wage decomposition for occupations gives a number of interesting insights into the way the relative wages of the different occupational groups have changed and then affected the final wage distribution. They offer some support for the idea that there is a new form of middling occupations. First, managers and professional occupations have a sizeable wage effect on the middle earners but no composition effect, suggesting that these occupations have only been an important determinant of middle-income earners wages in recent years. These could be explained by managerial or professional occupation categories expanding over a wider wage range than before as they grow in employment share, so that now there are many more middle-income managers than 20 years ago.

Second, the wage effect for manual routine occupations is positive despite being in decline. The Autor, Katz and Kearney form of the polarisation hypothesis would suggest that, in the absence of any innate ability effect, the relative wage of manual routine and intermediate occupations would decrease, rather than increase. Including abilities, as they do, makes this result ambiguous – the relative wage of non-routine occupations per effective unit of labour input may increase, but the individuals moving to these occupations may differ in abilities. A possible interpretation of these results is that the types of individuals who move from manual to intermediate non-manual occupations are those who are less skilled or able in their former job. So, for example, a highly skilled tradesman may have much more to lose by shifting to a non-manual job, whereas a less able individual may not. Those left behind in the declining occupations will have a higher observed wage, on average, whereas the growing occupation will have a lower observed wage, on average, with increasingly large negative wage effects to these occupations lower down the distribution. These within-group effects were emphasised in section two. Autor and Dorn (2009) suggest that those leaving declining occupations are the older individuals who have developed greater specific skills in those occupations, whilst younger workers find it less costly to move occupation, or, with an eye on future employment prospects, do not enter these occupations at all. These results could potentially support this idea. Again, this suggests that there is a new sort of middling occupation.

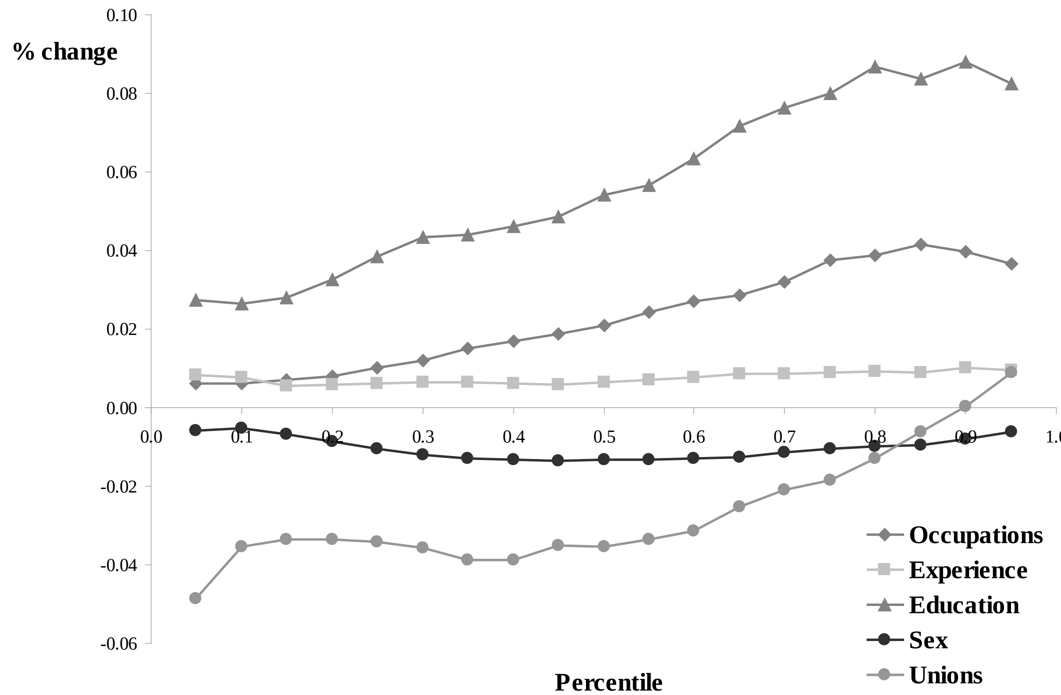
From these results, the Autor, Katz and Kearney effect, where low wages grow faster than middle incomes due to changing demands for different occupations, is not supported by the wage decomposition: 10th percentile incomes increase by 4.6 per cent whilst median incomes increase by 7.8 per cent over the time period due solely to changing occupational wage premia. This supports the conclusion of Antonczyk, DeLeire and Fitzenberger (2010), that ‘polarisation of wages’ is a US-only phenomenon.

The problem of arbitrarily choosing a reference group in a Blinder-Oaxaca for wage effect decompositions of the mean is widely acknowledged, and Firpo, Fortin and Lemieux extend this to their decomposition. As a result, it should be noted that there may be problems interpreting the wage effects beyond what has been done here; the magnitude of various wage effects depends on the choice of the reference or base group, with some effects concealed within the constant term. This makes comparisons of contributions difficult. However, it is valid to look at the signs of effects, their significance and total wage effects across the distribution, as none of these depend on the choice of reference group.

5.2.4 Comparison

This section has focused on three specific percentiles to broadly describe the experiences of individuals at the bottom, middle and top of the wage distribution. Figure 3 shows the decomposition of the composition effect across all percentiles, showing that the three selected percentiles were typical of surrounding points in the distribution in terms of their magnitude and trends across the distribution. A similar representation for the wage effect decomposition is not presented, for the reasons mentioned above – part of the wage effect of any category of variable is concealed within the constant term. For example, the narrowing gender pay gap in the lower percentiles may reflect female wages getting higher or male wages getting lower. Whichever it is determines the overall effect of gender on the wage distribution. However, the contribution on the FEMALE variable is relative to a notional MALE variable, which is included within the constant term.

Figure 3: Decomposition of composition effect across all percentiles, 1987-2001



5.3 Misspecification tests

Firpo, Fortin and Lemieux (2007) note that the decomposition offers a first order approximation of the composition effect, using the assumption that the RIF regression is linear in the explanatory variables. To see whether this assumption creates misspecification errors, the difference between the predicted and actual composition effects are considered. If the model is truly linear, the predicted composition effect in (7) should equal the actual difference between the initial and counterfactual distributions.

Table 6 shows the error in the total composition and wage effects for the three deciles calculated above. The table first shows that the model using years past school leaving age is more misspecified than the educational dummies model, where the errors are relatively small, compared to the magnitude of some of the other effects. This is likely because the effect of schooling is not linear – the RIF regression coefficients on the DEGREE variable are much larger than on other levels, suggesting some non-linearity in the relationship. By focusing on just the education dummies model, and computing RIF regressions and composition effects for each vigintile (5th percentile, 10th percentile etc.), then the specification errors across the entire distribution can be observed. This is shown in Figure 3.

Encouragingly, the errors across the entire distribution appear uncorrelated with percentile or actual change. There is an obvious negative bias (all errors are positive), which suggests some misspecification, however, these errors are small enough, relative to other individual components of the decomposition, to argue that misspecification is not an important problem in this analysis.

Table 6: Actual and predicted changes to selected distributional statistics

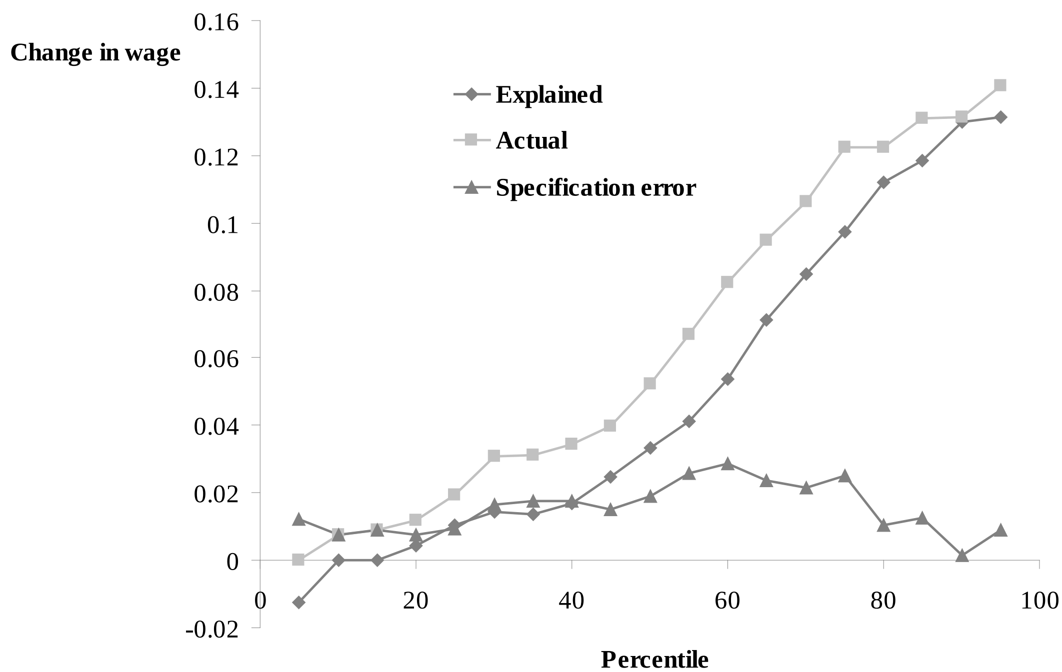
Education dummies model

	Composition			Wage		
Percentile	Predicted	Actual	Difference	Predicted	Actual	Difference
10	0.0001	0.0077	0.0076	0.1026	0.0945	-0.0081
50	0.0333	0.0524	0.0191	0.1237	0.1099	-0.0138
90	0.1298	0.1314	0.0016	0.0921	0.0793	-0.0128

Year past school leaving model

	Composition			Wage		
Percentile	Predicted	Actual	Difference	Predicted	Actual	Difference
10	-0.0110	0.0077	0.0187	0.1224	0.0945	-0.0279
50	0.0031	0.0524	0.0493	0.1638	0.1099	-0.0539
90	0.0854	0.1314	0.0460	0.1337	0.0793	-0.0544

Figure 4: Specification error across all percentiles



6 Conclusion

Between 1987 and 2001, wage distributions have changed due to a wide range of factors. This paper has attempted to quantify these changes. One factor that has been put forward in recent years is that the labour market is polarising as employment in high wage and low wage non-routine occupations has grown at the expense of middling routine occupations, leading to an 'hourglass' economy.

By breaking down changing wage distributions into individual composition and wage effects, it has been possible to see the relative importance of each factor. First, there is some evidence of polarising employment in the distributions, particularly at the top of the distribution, where there are positive wage effects arising from the increase in employment in high skill non-routine occupations such as managerial occupations, professional occupations and the decline in manual routine occupations. Similarly, there are small, negative effects to wages resulting from the increase in employment share by non-routine manual and service occupations at the bottom end of the distribution. These are the polarisation effects emphasised by Goos and Manning (2007).

Second, the results also suggest that if the UK labour market has polarised, it is in employment only, with limited evidence that low wages have grown faster than middle wages. One interpretation of this result has been highlighted – that productive abilities of labour supply determines observed wages as well as relative demands. These within-group effects have been omitted from the literature in the past. We would suggest that, in the UK, these effects dominate the wage polarisation effect suggested by Autor, Katz and Kearney (2006).

Third, and perhaps most importantly, these effects are just one of a number of factors which have changed wage distributions over the time period. Declining union membership and decreasing gender pay gaps make, overall, much larger contributions to the resulting wage distribution, particularly at the bottom and middle of the distribution. Moreover, the role of education, experience and general or transferable skills generally make a larger contribution to changes than the occupational composition and the specific skills they produce. Both the expansion of higher education and increased staying-on rates after compulsory education have had positive effects at all parts of the distribution, as have increased returns to those qualifications across the distribution.

The most obvious comparison for this work is in Firpo, Fortin and Lemieux (2007), who apply the methodology used in this paper to the wage distributions of US males between 1988 and 2005. They focus on measures of inequality more than on individual percentiles; however, it is possible to draw some parallels. Their main conclusion is that institutional factors, such as union membership, and educational attainment have had a much stronger impact on distributions than occupations or industries. Moreover, once education is controlled for, changing wages to non-routine and routine occupations has only had a modest effect on the distribution. On these points, our results agree.

This paper offers the first attempt, as far as we are aware, to apply this novel methodology to UK data. It provides a much more rigorous evaluation of the importance of the polarisation phenomena than existing methodologies, which overly rely on a strong assumption that wage structures have essentially remained constant, by looking directly at the resulting wage distributions. By doing so, it can be seen that it is just one factor amongst many that shapes the wage distribution of the UK and, moreover, there are numerous effects on wages not discussed previously, which explain why even after routinisation, the majority of jobs continue to fall in the middle of the distribution.

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Table A1: Transition matrix between SEG categories, 1981 to 2004

SEG, 1981	Description	SEG, 2004											
		1	**2**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**13**	**15**
1	employers and managers: large establishments	**23.1%**	15.4%	3.8%	40.4%	7.7%	1.9%	3.8%	0.0%	1.9%	1.9%	0.0%	0.0%
2	employers and managers: small establishments	15.9%	**22.7%**	2.7%	27.3%	9.1%	5.5%	3.6%	5.9%	6.4%	0.5%	0.0%	0.5%
4	professionals: employees	23.4%	13.9%	**32.3%**	24.7%	1.9%	0.6%	1.9%	0.0%	1.3%	0.0%	0.0%	0.0%
5	intermediate non-manual	15.7%	7.9%	4.2%	**50.2%**	11.8%	5.6%	1.6%	0.7%	1.4%	0.5%	0.1%	0.3%
6	junior non-manual	9.0%	8.7%	3.3%	31.3%	**30.5%**	8.0%	1.8%	1.5%	4.8%	1.2%	0.0%	0.0%
7	personal service	7.5%	7.1%	3.4%	22.0%	16.4%	**24.3%**	4.9%	0.7%	8.2%	4.1%	0.0%	1.5%
8	foremen & supervisors	11.8%	14.7%	4.1%	13.1%	5.7%	2.4%	**20.8%**	19.2%	6.9%	0.8%	0.4%	0.0%
9	skilled manual	7.3%	10.0%	3.4%	15.2%	5.2%	2.0%	17.3%	**26.9%**	10.3%	2.3%	0.1%	0.1%
10	semi-skilled manual	7.8%	8.0%	1.6%	14.7%	14.1%	6.2%	10.0%	9.4%	**21.5%**	6.4%	0.0%	0.4%
11	unskilled manual	7.7%	6.9%	1.5%	17.7%	9.2%	4.6%	10.8%	19.2%	13.1%	**9.2%**	0.0%	0.0%
13	farmers: employers & managers	0.0%	12.5%	0.0%	12.5%	0.0%	0.0%	0.0%	12.5%	0.0%	0.0%	**50.0%**	12.5%
15	agricultural workers	1.6%	14.3%	4.8%	7.9%	7.9%	1.6%	12.7%	14.3%	12.7%	4.8%	4.8%	**12.7%**

Source: NCDS, own calculations