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ABSTRACT

The Anatomy of Job Polarisation in the UK[*]

This paper presents new evidence on the evolution of job polarisation over time and across skill groups in the UK between 1979 and 2012. The UK has experienced job polarisation in each of the last three decades, with growth in top jobs always exceeding that in bottom ones. Overall, top occupations have gained over 80% of the employment shares lost by middling occupations. The decline of middling occupations is entirely accounted for by non-graduates who have seen their relative numbers decrease and the distribution of their employment shift towards the bottom of the occupational skill distribution. The increase at the top is entirely accounted for by compositional changes, as a result of the increase in the number of graduates since the 1990s. Employment has not polarised for graduates, but has become less concentrated in top occupations, especially in the 2000s. The paper also documents that job polarisation has not been matched by wage polarisation across the occupational distribution in any decade and discusses how these new findings relate to the existing evidence for the US and to the prevailing technology-based explanation for job polarisation. Overall, the importance of occupational changes between skill groups and the performance of occupational wages over time cast doubts on the role of technology as the main driver of polarisation in the UK. In particular, the evidence suggests that supply-side changes are likely to be important factors in explaining why high-skill occupations continued to grow in the 2000s even as they stalled in the US.

JEL Classification: J21, J23, J24, O33

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1   Introduction

The share of low-paid low-skill jobs and that of high-pay high-skill jobs has increased relative to that of middling jobs in a number of developed countries (Autor 2014, Goos et al. 2014). Technological change and offshoring have been suggested as the main drivers of this polarisation of labour markets and studies comparing the explanatory power of the two generally conclude that the latter is more important (Acemoglu and Autor 2011, Autor and Dorn 2013, Goos et al. 2014, Michaels et al. 2014). The routine-biased technological change (RBTC) hypothesis proposes that technology reduces the relative demand of labour in mid-skill occupations due to the increasing ability of machines to perform easy-to-codify "routine" tasks which characterise these occupations.

In the simple version of the RBTC story whereby this inward shift of the labour demand curve is the dominant factor, middling occupations see both their employment share and relative wages decline. This fits well the evidence for the US in the 1990s, when both employment and wage growth polarised across the occupational skill distribution (Autor and Dorn 2013). Yet, the US did not experience job nor wage polarization in the 2000s, as employment growth became concentrated in low-skilled occupations and wage growth was monotonically increasing across the occupational skill distribution (Mishell et al. 2013, Autor 2014, Beaudry et al. *forthcoming*). In addition, polarisation in occupational wages has generally not been detected in other countries which have experienced employment polarisation, such as Germany (Dustman et al. 2009) and Canada (Green and Sand *forthcoming*). These puzzles have led recent contributions to stress that the relationship between technology and labour might be more complex than often assumed in the RBTC literature. For example, routine and non-routine tasks can be bundled together within the same occupations making it difficult to predict the impact of technology across occupations (Autor 2013, 2014). In addition, the heterogeneity of employment and wage patterns across countries and over time suggests that factors other than technology continue to play a significant role. For instance, Autor (2014) and Green and Sand (*forthcoming*) have emphasised how recent developments in occupational wages at the bottom of the distribution in the US and Canada respectively appear consistent with significant shifts in labour supply as well.

This paper provides new evidence on the evolution of occupational shares and wages in a technologically advanced country, the UK, which has experienced significant changes on the supply side of the labour market in recent decades. In their seminal contribution on the UK, Goos and Manning (2007) concluded that changes in the composition of the workforce could not explain job polarisation between 1979 and 1999[1]. The plots in Figure 1 raise the question as to whether this conclusion extends to the successive decade. From the mid-1990s onwards the shares of graduates and immigrants increased dramatically[2], boosted respectively by a large expansion in higher education places in the early 1990s[3][4] and the EU enlargement of 2004. In

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[1] Oesch (2013) offers an analysis similar to that of Goos and Manning (2007) for the period 1993-2008 and considers education-age cells focusing exclusively on the aggregate results for the compositional effects.

[2] The time-series for graduates appear to be affected by a discontinuity in the data in 1992, but exhibits a clear positive trend and further accelerates in the second half of the 1990s. Appendix B discusses this and other LFS data issues in more detail.

[3] In 1988 a significant reform to the age 16 school examinations was implemented with the introduction of GCSE's which switched from a norm-referenced evaluation system (in which relative performance is

addition, international evidence suggests that the 2000s might have been different also on the demand side, as the stalling of the growth of top jobs in the US and Canada has been interpreted as an indication that technology-driven demand for high-skill labour might have slowed down (Beaudry et al. *forthcoming*, Green and Sand *forthcoming*, Autor 2014).

Job polarisation in the UK has been already documented (Goos and Manning 2007, Bisello 2013, Holmes and Mayhew 2012, Akcomak et al. 2013, Oesch 2013), but, to the best of my knowledge, there is no evidence on how different skill and demographic groups have been affected and only limited evidence on changes in occupational wages which can help evaluate the potential drivers of the process[5]. The analysis by skill and demographic groups is important for two reasons. First, along with the evidence on wages, it is instrumental in assessing the role played in the polarisation process by changes in the composition of the workforce. Second, it is of interest per se, as it enhances our understanding of the specific challenges faced by different skill groups in an increasingly polarising labour market (Autor and Dorn 2009).

Faced with the same lack of credible sources of exogenous variation that permeates much of this literature[6], this paper presents a descriptive analysis that relies on three main logical building blocks commonly found in the literature. First, a shift-share analysis is used to highlight the contribution of changes within and between skill groups to job polarisation. This methodology has been widely used in related literature[7] and, crucially, is the one underlying Goos and Manning (2007)'s conclusion that supply side changes do not explain polarisation. More generally, the prevalence of within-skill group changes is often cited as evidence consistent with a pervasive effect of technology (Spitz-Oener 2006, Acemoglu and Autor 2011).

Secondly, the analysis looks at whether relative wages across the occupational skill distribution move in a way consistent with a shift in demand being the main driver of the observed changes, following the same logic underlying the analysis in Autor and Dorn (2013), Green and Sand (*forthcoming*), Mishel et al. (2013) and Autor (2014). Finally, in the discussion section, I relate the evidence presented in this paper for the UK to that available for the US, a natural benchmark given that the largest and arguably most influential fraction of the literature has focused on this country. This comparison also follows the logic that if the dominant driver of the process of polarisation is technological change, then one would expect to find broadly similar patterns within similarly-developed countries – a recurrent argument in the polarisation literature as well as in the earlier literature on skilled-biased technological change (see for example Card and Lemieux 2001, Dustman et al. 2009, Autor and Acemoglu 2011, Green and Sand *forthcoming*, Antonczyk et al. 2010).

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what matters and which effectively restricted the share that could obtain top marks) to one where in theory everybody could obtain the highest grades. See table 6 in http://www.parliament.uk/briefing-papers/SN04252.pdf which shows that the proportion of 16 year old pupils achieving five or more good grades had stalled around 25% in the years before 1988 and reached 37% in 1991, continuing to increase thereafter. This amounts to a very substantial increase in the size of the pool of potential university applicants.

[4]This was generated by changes in university financing and the conversion of former polytechnics into universities. See Blanden and Machin (2004) for a more detailed discussion.

[5] In his recent review of the UK literature, McIntosh (2013) reports that one unpublished study has looked at the evolution of wages by deciles of the occupational distribution finding no clear pattern in wage changes.

[6] Even strategies that exploit variations across local labour markets (as in Autor and Dorn 2013 and Autor et al. 2015) are unfeasible for the UK due to data limitations over the period considered here.

[7] See, for example, Autor et al. 1998 and Beaudry et al. *forthcoming.*

Compared to Goos and Manning (2007), this paper uses more than a decade of additional data and extends their analysis of changes in terms of age-gender-education cells to consider the role of immigrants[8] as well. The analysis goes beyond the aggregate compositional changes reported in Goos and Manning (2007) documenting for the first time changes in the occupational structure within different skill groups and highlighting their contribution to the overall process of job polarisation.

The paper makes a number of additional original contributions. In particular, it investigates the robustness of the finding of polarisation to (i) using occupational rankings based on education rather than wages and (ii) alternative ways of dealing with breaks in occupational coding over time. Both these aspects have been studied in the US but there is currently no evidence on either for the UK. The first point matters because wages are typically used as proxies for skills (Autor et al. 2006, Goos and Manning 2007) and it is therefore important that results hold when alternative skill rankings are used. The importance of the second point is highlighted by the recent finding (Mishel et al. 2013, Green and Sand 2013) that alternative ways of converting across occupational classifications affect the substantive findings for the US.

Finally, I document the extent to which compositional changes can account for the decline in routine employment and investigate the sensitivity of the results to the use of the alternative measures of routiness available in the literature (Autor 2013). This is an important exercise given the increasingly common practice of interpreting changes in routine employment as technology driven and of using routine task indexes as proxies for technology (Goos et al. 2014).

Overall, using methodologies closely related to those of previous literature, this paper concludes that changes in the occupational structure of the UK labour market over the past 30 years cannot be understood as being dominated by RBTC alone. In particular, the evidence strongly suggests that the increase in the share of graduates has contributed significantly to the main feature of the polarisation process in the UK, i.e. the substantial reallocation of employment from middling to top occupations. While in the US employment growth has gradually favoured low-skilled occupations, in the UK growth at the top has exceeded that at the bottom in each of the last three decades and overall top occupations have gained 80% of the employment shares lost by middling ones. There is no evidence of polarisation within skill groups. Non-graduates entirely account for the decline of middling occupations as their relative numbers have decreased and the distribution of their employment has shifted towards the bottom. Employment has not polarised for graduates and the increase in their relative numbers can account for the entire growth at the top since the 1990s. Compositional changes can account for most of the decline in routine employment across the occupational skill distribution, and ranking occupations by education rather than wage shows that it is the lowest educated occupations that lost most employment. There is no evidence of wage polarisation, but the weak performance of median wages in top occupations suggests that the role of supply-side changes might have been particularly important in the 2000s when employment growth in high skill occupations stalled in the US and Canada but continued in the UK.

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[8] Oesch (2013) also highlights the contribution of immigrants to the growth of employment at the bottom, but he does not assess the importance of this component versus other possible changes fuelling employment growth in low-paid jobs, such as the reallocation of employment of other skill groups.

The structure of the paper is as follows. Section 2 offers a brief review of the evidence on polarisation in the US. Section 3 describes the data used and Section 4 and 5 presents results on the evolution over time of polarisation and from the shift-share analysis respectively. Section 6 consider the role of routine occupations while Section 7 presents the evidence on changes in occupational wages before section 8 discusses the results in relation to those from the US literature and Section 9 concludes.

2   Evidence on job polarisation in the US

Autor et al (2006) first documented the polarisation of the US labour market in the 1990s with respect to both the occupational wage and education distribution. Most of the subsequent literature has then focused on wage rankings showing that polarisation has not unfolded evenly in the US labour market across the three decades. In the 1980s employment underwent a process of occupational upgrading, with higher growth in high-skill occupations, while the 1990s saw a polarisation pattern followed by a shift of employment shares towards the bottom until the onset of the Great Recession, when high-pay occupations began to regain some shares (Autor et al. 2006, Acemoglu and Autor 2011, Beaudry et al. *forthcoming*, Autor 2014). On the whole, however, employment growth has increasingly being biased towards low-wage occupations in the US (Autor 2014).

Job polarisation has affected different skill groups differentially in the US: between 1980 and 2005 the decline in routine employment was larger for non-college than for college workers. Among the college educated, employment shifted towards both ends of the distribution (with gains in better-paid jobs limited to young college workers), while employment of non-college workers shifted more towards the bottom (Autor and Dorn (2009)). Using aggregate data, Autor (2014) shows that the polarisation of graduate employment is to a large extent driven by the 1990s, while the 1980s were a decade of occupational downgrading, as were the 2000s until at least the onset of the Great Recession. Also, Beaudry et al. (*forthcoming*) show that the shift towards top occupations in young graduates' employment of the 1990s was reversed in the 2000s (even before the Great Recession) generating a downgrading pattern in employment changes similar to that found for young high-school graduates. Changes in employment for non-graduates, on the other hand, were polarised in each of the last three decades and predominantly characterised by a shift from routine to manual occupations (rather than abstract ones) in the 1990s and 2000s (Autor 2014).

Several studies have looked at the evolution of *occupational* wages both to evaluate their contribution to changes in overall wage inequality and to use their covariance with employment to assess the plausibility of demand-side explanations for changes in the occupational structure. For example, Autor and Dorn (2013) argue that the positive correlation between wage and employment changes in low-skill service occupations in the 1990s is consistent with the hypothesis that their growth was driven by increased demand generated by complementarity in consumption between services and goods, as the price of the latter fell as a result of routine-biased technological change[9]. However, the evidence on the covariance of occupational employment and wages does not all point in the same direction. Among routine occupations,

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[9] Autor and Dorn (2013) also present a detailed econometric analysis which exploits variation across local labour markets and find that service occupations grew more in areas were routine occupations declined the most – providing support for their hypothesis.

clerical occupations have seen their wages perform strongly even as their employment has been declining, presumably as a result of the spread of ICT. Among manual occupations, Mishel et al. (2013) report that wage growth in service occupations became very weak in the 2000s even as employment growth continued to accelerate. In his recent review of the latest developments of the literature, Autor (2014) highlights this as one of the puzzles confronting the RBTC hypothesis.

3   Data and occupational coding

I use four different datasets covering the period 1979-2012. Data on occupational shares and socio-demographic characteristics come from the Labour Force Survey which was carried out biannually from 1979 to 1983, then annually from 1984 to 1991, and finally quarterly from 1992 onwards. Between 1979 and 2012, the LFS uses four different occupational classifications (KOS, SOC90, SOC00, SOC10). I use probabilistic matching to bridge successive classifications and investigate the sensitivity of the conversion procedure to conditioning on different observable characteristics. To the extent that groups (for example, graduates vs non-graduates) grow over time at the different rates, different ways of reallocating them across occupations might affect the estimates of changes in the size of occupations over time[10]. Section 4 shows the results obtained converting across occupational classifications conditionally on education and unconditionally (as in Goos and Manning 2007) and the interested reader is referred to Appendix A (Section 12) for more details. In addition, Appendix B (Section 13) discusses the issues encountered in the LFS when measuring the share of graduates over time and the education of foreign-born workers.

Because the LFS did not collect data on earnings until 1993, the wage data come from the panel dataset combining the New Earnings Survey (NES, 1979-2002) and its successor the Annual Survey of Hours and Earnings (ASHE), available from the UK Data Archive as NESPD. Wage information is provided by the employer and is therefore regarded as very reliable, but this dataset has no education variables and very limited information on workers' characteristics in general.

4   Employment polarisation over time

Figure 2 shows the changes in employment shares across occupations along the 1979 occupational wage distribution. Employment shares are computed from LFS data, while the occupation ranking is based on median wages from NESPD data. The figure on the left shows the percentage point change in employment share for each occupation, with markers proportional to the occupation employment share in 1979. The figure on the right shows a smooth line fitted non-parametrically through the points on the left, with each observation weighted by employment share in 1979. The solid black line is the fit for the employment changes obtained when the occupational conversion is done unconditionally, while the dotted line is the fit for the employment changes obtained with the conversion conditional on education. The two lines are

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[10] Recoding exercises conducted by the ONS have shown that the occupational distribution changes in different ways for the two genders for example. See "Changing to SOC2000 - Dual coding on the Labour Force Survey", Roeland Beerten, Laura
Rainford and Adrian Jones, Labour Market Trends, March 2001 at
http://www.ons.gov.uk/ons/rel/lms/labour-market-trends--discontinued-/volume-109--no--7/labour-market-trends.pdf

very similar, except for the fact, that, as expected, the conversion conditional on education shows a slightly higher growth for some of the top-paid occupations. On the whole, however, these differences do not affect the general conclusion: employment growth exhibits a polarised pattern between 1979 and 2012. In the remainder of the paper, I present only results obtained using the unconditional conversion method[11]. More generally, the polarisation result survives a number of robustness checks, including (i) ranking occupations by mean rather than median wages, (ii) using hours share rather than employment shares, (iii) using different base years for the occupational rankings, and (iv) occupational classifications other than SOC90.

Following Goos and Manning (2007), in Figure 3 occupations are grouped into employment-weighted deciles of the 1979 wage distribution. Only, the occupational deciles at the two extremes of the distribution gained shares between 1979 and 2012, with an overall shift of employment mostly directed towards high-skill occupations. The largest growth occurred in the 10th decile which more-than-doubled its relative size over this period.

Figure 4 plots the time series of the employment shares of the bottom (1st and 2nd deciles), middling (3rd to 8th deciles) and top (9th and 10th deciles) occupations normalised by their starting value in 1979. The dashed vertical lines indicate recession years[12], while the solid lines mark changes in occupational classifications in the LFS data. The UK experienced job polarisation in each of the last three decades, as middling occupations declined in a relatively steady manner between 1979 and 2012, losing about a third of their initial share. Job polarisation appears to be a long-term process not heavily affected by the business cycle[13]. Bottom occupations fluctuated above their initial share for most of the period and had grown by 10% by 2012. The share of top occupations grew by more than 80%, with more than half of that growth occurring in the first 13 years covered by the data[14].The pace of growth was then slower in the first half of the 1990s and accelerated again after 1997.

4.1 The role of occupational groups

Table 1 shows the contribution of each of the SOC90 major occupational groups to changes in the employment shares in the three segments of the occupational wage distribution. The bottom raw makes clear the magnitude of the shift of employment from the middle to the top: of the 19pp of employment share lost in middling occupations, 16pp have been gained by top occupations and only 3 by bottom ones.

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[11] Similarly, the polarisation result is not lost when the conversion of the native occupational classification to SOC90 is carried out conditionally on gender or age. In addition, a clear polarisation pattern is also observed in any period covered by the original occupational classification (i.e., before any conversion is implemented, for example between 2002 and 2011 using SOC00).

[12] The lines indicate, for each recession, the calendar year spanning he highest number of quarters with negative growth.

[13] In Appendix C (Section 14), I look at the recession periods more closely and find that they do account for a large fraction of the decline in middling occupations. However, the lack of quarterly data for two of the three recessions and the numerous changes occurring in the LFS in 1992 warrant caution in interpreting these results.

[14] I discuss the stark change in the slope of the series in 1992 in Appendix B (Section 12) and conclude data issues likely exaggerate the expansion of top occupations between 1991 and 1992, but the slowdown in their growth in the early 1990s is likely genuine as also found in other datasets. Most importantly perhaps, Figure 4 makes clear that the finding of polarisation (i.e. the decline in the share of middling occupations) holds in any time interval not straddling 1992.

Personal and protective services are the main drivers of growth at the bottom, as they almost doubled their share over 30 years. Within this group, the largest expansions are found in "health and related occupations" (which account for over half of the overall increase in service occupations), childcare, and catering occupations. Sales occupations also made a large contribution to the expansion of low-paid employment: the share of sales assistants and check-out operators increased by about 40% between 1979 and 2012. Craft and related occupations and other low skilled occupations (namely, cleaners and kitchen porters and hands) have instead lost shares. Table 2 shows that the growth of service occupations and the decline of craft occupations have been features of all three decades since 1980s. The growth of sales occupations, on the other hand, was concentrated in the 1980s and 1990s. Almost the entire (modest) growth in bottom occupations in the 2000s is due to service occupations.

The decline in middling occupations was driven by a sharp reduction in craft occupations[15] and plant and machine operatives, both of which lost over half of their shares for a combined total of more than 16% of overall employment. A significant but smaller contribution also came from clerical and secretarial occupations which lost about a quarter of their employment, but continued to account for the largest share of middling occupations in 2012 as they did in 1979. Over 80% of the decline in clerical occupations is due to the loss of "numerical clerks and cashiers" and "secretaries, personal assistants, typists, and word processor operators". Table 2 reveals that clerical occupations only started to lose employment shares in the 1990s and made a larger contribution than craft occupations to the decline of middling occupations in the 2000s. Overall, however, losses in clerical jobs do not explain more than a third of the total losses in middling jobs in any decade, with crafts and operatives always accounting for most of them.

4.2 Ranking occupations by education

Figure 5 shows that when occupations are ranked by mean education[16] rather than wage, the occupations in the first decile are the ones losing the largest shares and those at the top make the largest gains. Figure 5 uses the education ranking from the year 1993 because that is the first year with the original SOC90 classification in the LFS. When occupations are ranked by median wage in 1993 (Figure 6), a u-shaped pattern in occupational share changes emerges again, indicating that the difference between Figure 5 and the results presented earlier based on 1979 wages are not simple driven by differences in the reference years. Table 3 illustrates the differences between the wage and education rankings in 1993. Service and sales occupations drive the growth of employment in low-paid occupations, as we saw above, but most of their employment shares are then found in the middling deciles of the educational distribution. On the other hand, the fast declining group of plant and machine operatives is among the least

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[15] Over two thirds to the decline in craft occupations is accounted for by construction trades (including bricklayers, tillers, builders etc..) "Metal Machining, Fitting And Instrument Making Trades", "Metal Forming, Welding And Related Trades", and "Electrical and electronic trades".

[16] The rankings in Figure 5 are obtained using an average of an education categorical variable taken on 6 values. Education rankings are computed using native workers only. Similar results are obtained when occupations are ranked using the share of graduates, the share with at least high school education and the share with no qualifications. Moreover, the same results are obtained when the rankings (and the change in employment shares) are computed using 2-digit occupations with larger sample sizes. Finally, a clear upgrading pattern for the 1980s is also found when occupations are ranked using 1979 education and the original occupational classification for the LFS in that year. Similarly, if SOC00 and education from 2001 is used, one still sees an upgrading pattern for the 2000s.

educated, but enjoys relatively higher wages so that 68% of its 1993 employment is in the bottom two educational deciles but only 13% is in the bottom two wage deciles.

5 Employment polarisation and changes in the labour force: a shift share analysis.

This section presents the results of a shift-share analysis which decomposes changes in the employment share of each occupational decile as follows:

$$\Delta S_{ot} = \Sigma_g \Delta S_{gt} \omega_{og} + \Sigma_g \Delta \omega_{ogt} S_{gt} \tag{1}$$

Where ΔS_{ot} is the change in the employment share of decile o between t_0 and t_1; ΔS_{gt} is the change in the employment share of demographic group g and $\Delta \omega_{og}$ is the change in the share of group g employed in occupation decile o. Finally, ω_{og} is the average share of group g employed in decile o between t_0 and t_1 and S_{gt} is the average employment share of demographic group g over the same period. The first term on the RHS of equation (1) is the between component, i.e. the change in employment share accounted for by changes in the shares of different skill groups, holding constant the distribution of each skill group across the occupational deciles. The second term is the within-group component. i.e. the change in occupational share due to changes in the distribution of the skill groups across occupations, holding constant the relative size of the skill groups.

This methodology is closely linked to that used by Goos and Manning (2007) to support their conclusion that compositional changes do not explain polarisation in the UK. In this paper, I present the breakdown of the results by relevant skill groups to document how job opportunities have shifted for the different groups and whether job polarisation has occurred within each educational group – a fact often cited as evidence of a pervasive effect of technology (Spitz-Oener 2006, Acemoglu and Autor 2011).

5.1 Aggregate results

Figure 7 reports the results of the shift-share analysis using 48 skill groups defined by education-age-immigration-gender cells. In particular, I use 3 age groups (under 30, 31-50, and over 50) and 4 education groups: university or higher education qualification (for convenience I refer to this group as "*graduates*"); GCE (this the secondary education qualification required of students wanting to access University of education in the UK); GCSE and other qualifications; and no qualifications.

A clear message from the picture is that the changes in the composition of the workforce have led to a reallocation of employment shares towards top occupations, while changes in the allocation of skill groups across occupations have fuelled the relative growth of the bottom. It is the combination of these two forces that has led to the overall polarisation of the labour market between 1979 and 2012.

Table 4 compares the results of the shift-share analysis based on the 48 groups (as in Figure 7) with those obtained using either fewer or more cells. The stability of the relative size of the between and within-group components when one uses either just 4 education groups or as many as 400 skill cells is strongly suggestive that the key variable is education. For the remainder of the paper I focus on the results based on the 48 groups described above.

As shown in the top panel of Table 4 , occupations in the top two deciles grew by almost 16pp and this is entirely accounted for by compositional changes, reflecting the increase in the educational attainment of the workforce. The 19pp decline in middling occupations, on the other hand, is the result of two forces: compositional changes account for about a third of it (about 7pp)[17] while the shift of employment towards other occupations for the remaining two thirds (12pp). This reshuffling of skill groups across occupations has entirely been directed towards the bottom (as clearly visualised in Figure 7), and has only partially been offset by between-group changes, resulting in a net increase of 3.5pp at the bottom. The lower panels of Table 4 show that that the pattern of between and within skill group changes is similar in each of the three individual decades since 1979.

The next section presents the results of the shift-share analysis focusing on the two groups whose relative size has changed most dramatically in recent times, i.e. graduates and immigrants (Figure 1). Results by age groups and gender can be found in the Appendix (Section 14).

5.2   Results by education and immigration status

The breakdown by graduates vs. non-graduates[18] in columns 4 through 9 of Table 5 shows that the entire decline in middling occupations is accounted for by non-graduates. They contributed -28pp to the change in the employment share of middling occupations, over half of which is explained by the decline in their relative number (15.5pp). The compositional change has been the driving force in the decline of non-graduate employment since the 1990s, as indicated in the lower panels in Table 5.

Non-graduates have also seen a major shift in the distribution of their employment from middling to bottom occupations. Between 1979 and 2012, this shift has contributed to the loss of 12.7pp (column 9) in middling occupations which have been mostly reallocated to bottom occupations (11.6pp). Hence, in 2012 there were fewer non-graduates (relative to graduates) than in 1979 and they were much more concentrated in bottom occupations.

Graduates, on the other hand, have made monotonically increasing positive contributions to the growth of all three segments of the occupational distribution (column 4). The shift in graduate employment away from top occupations (column 6) is very small compared to the impact on aggregate employment of the large expansion in graduate numbers (column 5). For example, between 1979 and 2012 the increase in the share of graduates accounted for a 16.6pp growth in top occupations, while their reallocation towards lower occupations only subtracted 1.5pp. The within-group change among graduates has been negative in each decade at the top, while in the middle it is only negative (-0.2pp) in the most recent decade. As a result, the 2000s is the decade in which the shift of graduate employment towards the bottom is most pronounced.

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[17] Figure 7 shows that amongst the middling occupations (deciles 3 to 8), between-group changes have penalised occupations above but not below the median. In fact, the picture is suggestive that compositional changes may have led to upgrading from the very bottom towards the median, and then again from the occupational deciles just above the median towards the ones at the very top. This reflects the fact that over the period considered the number of workers with intermediate qualifications increased relative to those with none, but decreased relative to those with post-secondary qualifications.
[18] The figures are obtained as the sum of the between and within-group changes across those of the 48 groups used in the earlier analysis with a common education level.

The first row of Table 5 shows that graduates account for the growth in bottom occupations between 1979 and 2012. Although a higher proportion of non-graduates is found in bottom occupations in 2012 than in 1979, the reduction in the overall number of non-graduates means that overall fewer of them are found in these occupations as a fraction of all employees, as indicated by their net overall contribution of -0.4pp (column 7). Graduates have more-than-offset this decline through both between- and within-group changes. The lower panels of the table show that the contribution of graduates to the growth of bottom occupations only exceeded that of non-graduates in the 2000s.

The breakdown by immigration status (column 10 through 15) shows that the role played by foreign-born workers has increased over time. Most of the long-term results reported in the top panel of the table are driven by the results for the 2000s. Immigrants contributed to the growth of all three segments of the occupational distribution, with larger impacts at the two extremes hence sustaining the overall polarisation of the occupational distribution.

Over 30 years, the distribution of employment among immigrants has shifted towards the bottom (column 15). This is the result of a polarised pattern in the 1980s and 1990s, followed by a more pronounced downgrading one in the 2000s, as foreign-born workers lost shares at the top as well as in the middle.

The increase in the number of immigrants between 1979 and 2012 contributed to the growth of all occupational groups, but more so in top and middling occupations than bottom ones (column 14). This leads to the result that immigrants' largest contribution in absolute terms has occurred at the top, where they account for 3.8pp of the total 15.8pp increase in employment share (column 13).

However, it is at the bottom that they made the largest contribution relative to natives, as immigrants account for 4/5 of the 3.5pp net increase in employment shares in these low-pay occupations. The lower panels reveal that immigrants accounted for most of the growth in bottom occupations only in the 2000s.

In Appendix C (Section 14), I present a further breakdown of the results by education-immigration cells that clarifies two points. First, the growth at the bottom is not accounted for by the fact that highly educated foreigners end up in low pay occupations, as immigrants account for only 1.2pp of the 3.9pp graduate contribution to the growth in these occupations. Second, by far the largest positive contribution to growth of employment in low-pay occupations, has come from the reallocation of native non-graduates from middling to bottom occupations. In fact, this latter change alone almost entirely offsets the negative compositional change arising from their decline relative to graduates. As a result of this, it is graduates and immigrants that account for the net growth in bottom occupations, but the influx of these two latter groups alone would have not compensated the decline in bottom occupations induced by improvements in education over the past 30 years.

Things are different in the 2000s, when the share of natives employed in low-pay occupations declined for the first time and bottom occupations only grew due to the contribution of immigrants (columns 10 and 13, bottom panel, Table 5). Nevertheless, even in the most recent decade growth at the bottom is not explained by compositional changes only. The net contribution of improvements in education and increase in immigration is a negative 3.0pp (column 2, bottom panel, Table 5). This is more-than-offset by the positive 3.3pp change

stemming from the fact that all groups have increasingly been drawn to the bottom (column 3). What distinguishes the 2000s from the two earlier decades is that this reallocation of workers from the middle to the bottom affects graduates as well, as the comparison of columns 6 and 9 across the panels of Table 5 shows. Appendix C (Section 14) further clarifies that it is both native and immigrant graduates who have seen their employment shift towards the bottom in the last decade.

To summarise, the improvements in educational attainment have sustained the shift from middling to top occupations, while the reallocation of workers across occupations within skill groups has led to a substantial shift from the middle to the bottom. There is no clear indication of polarisation within skill groups. The decline in middling occupations is entirely accounted for by non-graduates who have both decreased in numbers and seen their employment become more concentrated at the bottom. In the 2000s the share of native workers employed in low-pay occupations declined for the first time and graduates (both natives and immigrants) also saw their employment shift towards the bottom.

6 Routine occupations vs non-routine occupations

This section investigates the role of routine occupations in accounting for changes in employment shares across the occupational distribution. I use different classifications of routine occupations based on all three main approaches described in Autor (2013). I provide a brief description each of them here with further details in Appendix D (Section 0).

The first approach simply uses occupations as proxies for job tasks, classifying 1-digit occupations based on the type of task that is perceived as typical of that occupation. Following the US classification by Acemoglu and Autor (2011)[19], I classify as routine the following groups: (i) clerical and secretarial occupations, (ii) craft and related occupations, (iii) sales occupations and (iv) plant and machine operatives.

The second approach measures the relative importance of different task dimensions (e.g. routine, abstract, manual) using standardised job descriptors that provide information on the tasks performed in each individual occupation. I use the "routine task index" (RTI) constructed by Autor and Dorn (2013) using the 1977 Dictionary of Occupational Titles (DOT) and then mapped to the European ISCO88 (2-digit) classification in Goos *et al.* (2014, Table 1, henceforth GMS).

The third approach uses job task information collected directly in the British Skill Survey (BSS) of 1997, 2001 and 2006. Respondents provide information on the importance of 36 different tasks in their job which can be used to construct an RTI index in the same fashion as Autor and Dorn (2013) as described in Appendix D (Section 0). In common with the previous one, this approach requires classifying the available tasks as either routine or non-routine. This is not a straightforward exercise. For example, Green (2012) points out that in Autor et al. (2003) (and hence Goos et al. 2014) "adds and subtract 2-digit number" is part of the GED Math score which is classified as a non-routine task, in spite of being an easily codifiable task. To minimise the role played by my own subjective judgement, I follow Akcomak et al. (2013) (henceforth AKR) who use a subset of the tasks split in groups intended to reflect those defined by the task measures in

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[19] This simple classification is used among others by Jaimovic and Siu (2012), Cortes et al. (2014) and Cortes (*forthcoming*).

Autor and Dorn (2013) and Goos et al (2014). Following the prevailing approach in the literature, I focus on a comparison of static routine measures (averaging across the task scores across the three waves of the BSS) but return to the importance of the within-occupation changes when discussing the results in Section **Error! Reference source not found.**.

No single classification is clearly superior to the others. Differences between them can arise for a number of reasons including (i) the fact that the underlying task information comes from different times and different countries and (ii) differences in the range of tasks covered in the original source and (iii) the classification of the available tasks in each source as routine or non-routine.

Table 6 shows the distribution of routine employment across the SOC90 major occupational groups based on these three classifications. For the two based on the RTI indexes, I consider both employment-weighted measures (i.e. the top employment-weighted third of occupations as in Autor and Dorn (2013)) and unweighted ones (i.e. occupations with an RTI larger than average) as indicated in the columns headings.

While clerical and secretarial occupations are consistently flagged as routine, there are notable differences across approaches for other occupational groups. Sales occupations, for example, are classified as routine by Acemoglu and Autor (2011), but less so under the weighted classifications based on the two RTI indexes. The proportion of craft and machine operative occupations classified as routine also differ between these two classifications. Most notably, perhaps, "other (low skill) occupations"[20] are classified as routine by the AKR index, but not by either of the other two approaches.

6.1 Results of the shift share analysis

Table 7 shows the results of the shift-share analysis for routine and non-routine occupations separately using three alternative classifications: the one based on the Acemoglu and Autor (2011) and the two using the top employment-weighted 30% occupations based on the GMS and AKR RTI indexes.

Routine occupations have declined relative to non-routine under all classifications. The comparison with the 1979 totals reported at the bottom of Table 6 indicates that the fall in routine-occupations is substantial as they have lost around 40% of their employment shares across classifications[21]. In panels A and C, most of the decline in routine occupations is accounted for by compositional changes[22]. In Panel B, within-group changes are more important, but the result is not robust to the use of the alternative classifications based on the same GMS RTI index. In all cases, routine occupations account for most of the decline in middling occupations and their contribution here is mostly from within-group changes.

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[20] This is a broad group including, among others, coal mine labourers, rail maintenance workers, refuse and salvage collectors, hospital, hotel and kitchen porters, lift and car park attendants, window cleaners and road sweepers, cleaners and domestics.

[21] In the more conservative classifications in panels B and C, some non-routine occupations also appear to have lost shares, but this result generally does not hold when the top employment-weighted 50% occupations by RTI are considered or when all occupations with an RTI above average are identified as routine.

[22] Results non reported here show, unsurprisingly, that this is entirely due to non-graduates.

Overall, therefore, in spite of the differences between the routine classifications seen in Table 6, one can draw some rather robust conclusions. First, routine occupations have declined relative to non-routine occupations and they account for most of the decline in middling occupations. Second, the overall decline in routine occupations is mostly accounted for by between-group changes, but the contribution to the decline in middling occupations is instead driven by within-group changes.

7 Changes in occupational wages

Table 8 reports changes in log median wages by SOC90 major occupational group and decade. The figures reported are the weighted average of the changes in the log median wages (from NESPD) at the 3-digit occupational level with weights equal to the 1979 employment shares (from LFS). One clear message from Table 8 is that the relative performance of wages of managers, professionals and technicians (who are very much concentrated in the highest segment of the occupational wage distribution – see Table 1) has deteriorated over time. The three top occupational groups enjoyed the strongest wage growth in the 1980s, but were outpaced by most other occupational groups in the most recent decade.

Among the low-pay occupations, total wage growth over 30 years was stronger for the groups that gained shares (personal services and sales occupations) than for those which lost shares (other occupations). This is consistent with the hypothesis that employment growth in these low-paid occupations has been demand-driven. However, the pattern is less clear when one looks at the individual decades. Wage growth for sales occupations declined relative to that in service occupations, as they began to lose shares in the 2000s (see Table 2), but wage growth in "other low-skill occupations" was similar to that in service occupations in that decade in spite of the continuing divergence in employment trends. Overall, these two low-pay occupational groups are the ones that exhibit the largest wage growth in the 2000s.

Clerical, craft, and operative occupations (groups 4,5, 8) are the groups disproportionally found in middling deciles and the ones which have had the largest losses of employment over the past 30 years, both in relative and absolute terms (see Table 1). Table 8 shows that only the wages of operatives have performed relatively badly, growing less than wages of all other groups over the whole period (but not in each single decade). Wages in clerical occupations, on the other hand, are among the fastest growing in every decade and over the whole period have undergone the largest growth among non-top occupations, at a level which is similar to that seen for wages of professional occupations. Wages of craft occupations have also performed similarly or even better than wages of other growing groups, such as service and sales occupations.

The pattern of wage changes found in Table 8 is reflected in Figure 8 which plots changes in log median wage within each decile of the 1979 occupational distribution. The figure also shows (measured on the RHS axis) changes in within-decile inequality as measured by the log of the ratio between the 90th and the 10th percentiles. There is no sign of polarisation in wage growth across deciles in any decade. The median decile exhibits the largest growth in the 1980s and 1990s and the second largest in the 2000s.

Reflecting the performance of wages among managers, professionals and technicians, wages in the top two deciles appear to deteriorate over time, especially relative the remaining deciles above the median. If in the 1980s top occupations experienced some of the largest gains in

median wages, in the 2000s they saw the smallest increase across the whole occupational distribution.

Inequality within occupational deciles has changed differentially across deciles over time as indicated by the plots in Figure 8. Inequality grew in every occupational decile in the 1980s with the largest increase in the median decile. In the 1990s, inequality declined in the first six deciles and grew slightly in the remaining four, with the strongest growth in the top decile. In the 2000s, inequality continued to decrease in the bottom two deciles, and grew the most in the median and in the top two deciles. Overall, therefore, inequality increased in all three decades in top occupations, while declined in the last two decades at the bottom.

8   Summary and discussion of main results

The evolution over time of job polarisation in the UK appears substantially different from that documented for the US in previous literature. In the US job polarisation only occurred in the 1990s and employment growth has progressively favoured bottom occupations since the 1980s culminating in the 2000s when low-paid occupations gained shares relative to all others (Autor 2014, Green and Sand *forthcoming,* Beaudry et al. *forthcoming*). By contrast, in the UK polarisation occurred in each of the last three decades with growth in high-skill occupations always exceeding that in low skill ones. Recent studies have disputed the exact timing of polarisation in the US using alternative ways of bridging breaks in the occupational coding (Green and Sand *forthcoming*, Mishel et al. 2013), but I show that the results for the UK are not sensitive to similar methodological issues. Overall, between 1979 and 2012, top occupations gained about 16 of the 19pp of employment shares lost by middling occupations.

Mishel et al. (2013) and Green and Sand (*forthcoming*) have argued that the occurrence of polarisation in the 1980s suggests the presence of a longer-term trend undermining the idea that the main driver of polarisation is a recent change in the nature of technological progress. Lending support to this objection, I document that in the UK the decline of middling occupations has unfolded steadily from the early 1980s driven in each decade by craft occupations and plant and machine operatives[23]. These occupational groups are known to have been declining in North America at least since the 1970s (Green and Sand *forthcoming*) if not earlier (Acemoglu and Autor 2011, Table 2). Acemoglu and Autor (2011, Table 6) find that this decline is explained mostly by changes within industries from the 1980s and argue that this is consistent with the RBTC hypothesis. However, Goos and Manning (2007, Table 7) and Goos et al. (2014, Table 1) show that the decline of comparable occupational groups (in the UK between 1979 and 1999 and in the EU-15 between 1993 and 2010 respectively) is mostly accounted for by between-industry changes. Departing from the common interpretation that sees the prevalence of within-industry changes as evidence in support of technological change, Goos et al. (2014) argue that routinisation can shift employment away from industries in which routine employment is used more intensively therefore generating between-industry changes in employment. The practical relevance of this mechanism relative to other potential drivers of structural change remains an open empirical question.

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[23] It is not entirely clear whether this steady rate of decline is compatible with the predictions of RBTC, since this hypothesis predicts that technology will reduce the routine-task intensity *within occupations* (Spitz-Oener 2006, Autor 2013) hence limiting the scope for substituibility over time.

The simple routine-biased technology story seems ill-equipped to explain why clerical occupations, which are flagged as routine under all the classifications I consider in this paper, have seen their wages increase at a pace similar to that of expanding professional occupations even as their employment share has slowly declined since the 1990s. A possible explanation for this finding (and the similar ones for the US and Canada reported in Green and Sand (*forthcoming)* and Autor and Dorn (2013)) is that, *within the same occupation*, technology substitutes workers in certain tasks but complements them in others. Autor (2014) argues that this complex relationship between technology and labour can help explain why job polarisation does not lead to wage polarisation in general, but the wider implications for labour market outcomes and workers' wellbeing of this more nuanced RBTC story have not yet been studied theoretically or empirically.

The differences highlighted in this paper between similarly developed countries such as the US and the UK suggest that factors other than (broadly similar) technological change might be at play. This point has been made already in related papers on Canada (Green and Sand *forthcoming*) and Germany (Antonczyk et al. 2010). The results of the shift-share analysis and the pattern in occupational wages indicate that the increase in the educational attainment of the workforce is likely to have contributed significantly to the most prominent feature of the polarisation process in the UK, i.e. the substantial reshuffling of employment from middling to top occupations. While the importance of immigrants has increased over time, they do not appear to have played a crucial role in reshaping the occupational structure of the UK labour market.

The shift-share analysis shows that the entire decline in middling occupations in the UK is accounted for by non-graduates. This is the result of both the decrease in their relative number and of their reallocation to different occupations, with the former – compositional –change prevailing in the 1990s and 2000s. Unlike in the US (Autor and Dorn 2009, Autor 2014), graduates have played no role in the decline of middling occupations, but the increase in their numbers accounts for the entire growth in the top ones from the 1990s – when their growth accelerated dramatically. Overall, changes in the relative size of skill groups account for about a third of the decline in middling occupations between 1979 and 2012 and for most of the decline in routine occupations across the whole distribution.

Importantly, when occupations are ranked by education rather than wages, it becomes clear that the occupations that have lost the largest employment shares are those with the lowest level of education. This is a result in stark contrast with that for the US where the wage and education rankings yield the same results (Autor et al. 2006).

The changes in occupational wages do not exhibit any clear sign of polarisation. This is in line with results from other countries that have experienced job polarisation but not wage polarisation (such as Canada – Green and Sand (forthcoming) – and Germany – Dustman et al. (2009) Antonczyk et al. (2010), Kampelmann and Rycx (2011)). A distinctive result for the UK, is that, as top occupations continued to expand, growth in their median wages deteriorated over time relative to other occupations leading to the result that in the 2000s high skill occupations saw the lowest median wage growth across the whole distribution (while within-occupation inequality continued to increase).

These results indicate that increase in the share of graduates might help explain why the UK continued to see growth in top occupations in the 2000s when the evidence from the US suggests that technology-driven demand for cognitive skills slowed down (Beaudry et al. *forthcoming*). I also find that in the last decade the employment structure of graduates in the UK shifted towards the bottom, consistently with the evidence for the US in Beaudry et al (*forthcoming*) who link it to the slowdown in demand for cognitive skills[24].

Clearly, this descriptive evidence does not rule out an important role for technological change. Some of the growth in the supply of graduates might have been an endogenous response to changes in demand. A causal analysis of the precise mechanisms at play is impeded by the lack of credible sources of exogenous variation which indeed permeates this literature more generally. In fact, changes in the supply of graduates are typically treated as exogenous in related literature, in part because of the time and cost involved in acquiring additional education when demand changes (Autor 2014, Card and Lemieux 2001**).** There are, in addition, good reasons to doubt that the surge in the share of graduates in the UK is endogenous. In fact, the US, arguably the technology leader, did not experience a comparable expansion in the share of graduates over the same period (Acemoglu and Autor 2011) and, as already discussed, even saw a slow-down in the demand for high-skill occupations in the 2000s (Beaudry et al. *forthcoming*), while the share of graduates continued to increase in the UK (Figure 1). Between 1988 and 1996, participation in higher education in the UK increased by 93% and only by 15% in the US (OECD 2007). This was in large part a stepwise change following the reforms of the late 1980s and early 1990s which led to a sharp increase in the proportion of young people remaining in education after the age of 16 and greatly increased the availability of university places (Bolton 2012, Blanden and Machin 2004, Walker and Zhu 2008, Devereux and Fan 2011)[25]. The evolution of the graduate wage premium is also consistent with an increase in the importance of changes in supply over time, as after a sharp increase in the 1980s, its pace of growth greatly slowed down in the 1990s and 2000s (Machin 2011)[26].

The employment growth at the bottom end of the occupational skill distribution has occurred *in spite of* the substantial increase in educational attainment. While immigrants account for a substantial fraction of *net* growth in these occupations (mostly in the 2000s), by far the most significant change offsetting the downward pressure arising from the increase in education is the reallocation of native workers with intermediate qualifications from middling occupations into "service occupations", most notably health, childcare and catering occupations. Wage growth for these occupations was robust over the past 30 years and the highest across all occupational groups in the 2000s. In the US, service occupations also drove the growth of low-

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[24] This finding is in line with those of the literature on over-education (Green and Zhu 2010), but I note that the changes in the allocation of graduates across occupations account for a small fraction of the overall changes observed in the labour market.

[25] More specifically, following a reform of the age 16 examination system in 1988, the share of 17 year old in education climbed from under 30% in 1988 to more than 50% in 1993 greatly expanding the pool of potential university applicants in subsequent years. This change and the expansion in the number of university places available from the early 1990s also led to a sharp increase in the participation rate in higher education which rose from 19.3% in 1990 to 33% in 2000. See (Bolton 2012) http://www.parliament.uk/briefing-papers/SN04252.pdf

[26] Walker and Zhu (2008) argue that the supply of graduates outstripped demand in the 1990s but an increase in the demand for unobserved skills prevented the gross graduate premium from falling.

pay employment since the 1990s, but, unlike the UK, their wages have declined relative to those of higher-skill occupations in the 2000s (Mishel et al. 2013, Autor 2014).

Explaining the increase in both employment and wages in service occupations in the US in the 1990s, Autor and Dorn (2013) show evidence consistent with a model in which the complementarity in consumption between goods (produced by mid-skilled workers) and services (produced by the low-skilled) drive demand for services up as technological change drives the price of goods down. Another demand-based explanation for the growth of service occupations emphasises instead the role of increased demand from high skill workers who substitute home production with market services as increasing returns to skills raise the opportunity cost of their time (Ragusa and Mazzolari 2013).

The UK evidence is at least broadly consistent with these demand-based hypothesis. In addition, two UK-specific factors might have helped sustain wage growth in low-skilled service occupations in the 2000s. The first is the introduction of the UK national minimum wage in 1999 and its subsequent increases at a pace faster than average earnings for much of the subsequent decade (LPC 2014). The second is again the increase in the educational attainment of the workforce, which has shifted labour supply away from these occupations. Consistent with this interpretation, I find that as the relative supply of low-skilled declined, graduate employment shifted slightly towards low skill occupations in the most recent decade even as overall employment growth continued to be driven by high-skill occupations.

Overall, while it is clear that compositional changes alone cannot explain the entire polarisation of the UK labour market, the evidence clearly points to the fact that the increase in the share of graduates has contributed significantly to the distinctive feature of the polarisation process in the UK compared to the US, i.e. the reallocation of employment from middling to top occupations. This adds to a recent but growing body of evidence that suggests that the relationship between technology and labour is more nuanced than suggested by the RBTC hypothesis and that developments in modern labour markets are not entirely dominated by technological change.

9   Conclusions

This paper presents new evidence on the evolution of job polarisation over time and across skill groups in the UK since 1979. The main feature of the polarisation process in the UK over the past 30 years has been a substantial reallocation of employment from middling to top occupations – which has occurred in each of the last three decades. This is very different from the pattern documented in previous literature for the US, where employment growth gradually shifted towards low-pay occupations culminating in the 2000s when these latter saw the largest growth across the occupational skill distribution.

The decline of middling occupations is entirely accounted for by non-graduates who have seen their relative numbers decrease and the distribution of their employment shift towards the bottom of the occupational skill distribution. The increase in the share of graduates, on the other hand, can account for the entire growth at the top since the 1990s. The weak performance of median wages in top occupations suggests that the role of supply-side changes might have been particularly important in the 2000s, when employment growth in high skill occupations stalled in the US and Canada.

On the whole, using methodologies closely related to those of previous literature, this paper concludes that changes in the occupational structure of the UK labour market over the past 30 years cannot understood as being dominated by RBTC alone. Far from suggesting that technology does not matter, this evidence highlights that much remains to be understood on its complex relationship with labour, especially if predictions on the quality and quantity of future jobs are to be made.

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10 Tables

Table 1 - Contributions of major occupaitonal groups to employment changes in different segments of the occupational wage distribution, 1979-2012.

SOC90 Major Occupational Groups	Bottom		Middle		Top		All		
	1979 share	2012-1979 (pp change)	1979 share	2012-1979 (pp change)	1979 share	2012-1979 (pp change)	1979 share	2012-1979 (pp change)	% change
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 Managers and Administrators	0.28	0.04	2.27	**0.98**	5.55	**9.14**	8.10	10.16	125.4
2 Professional	-	-	0.52	0.58	6.77	**4.07**	7.29	4.65	63.9
3 Associate professional and technical	-	-	2.68	**2.80**	3.26	3.37	5.94	6.17	103.8
4 Clerical and secretarial	1.10	-0.07	17.76	-4.72	-	-	18.86	-4.79	-25.4
5 Craft and related	2.08	-1.35	16.39	-9.78	0.45	-0.23	18.92	-11.36	-60.0
6 Personal and protective services	6.07	**5.83**	0.97	0.50	0.65	0.24	7.68	6.57	85.6
7 Sales	4.89	**1.95**	0.36	-0.28	1.64	-0.20	6.90	1.47	21.3
8 Plant and machine operatives	1.67	-1.04	12.54	-6.60	0.60	-0.34	14.80	-7.98	-53.9
9 Other occupations	7.02	-2.34	4.49	-2.56	-	-	11.51	-4.90	-42.6
Total	23.10	3.02	57.99	-19.07	18.91	16.05	100	0	

Cells highlighted in grey are the lowest two values in the columns, figures in bold are the highest two.

Table 2 - Contributions of major occupational groups to changes in employment shares in the bottom and middle deciles of the occupational distribution by decade, 1979-2012.

SOC90 Major Occupational Groups	Bottom Occupations				Middling Occupations			
	1979-1989	*1989-1999*	*1999-2009*	*Total*	*1979-1989*	*1989-1999*	*1999-2009*	*Total*
1 Managers and Administrators	0.03	-0.17	**0.14**	0.00	0.44	0.14	**0.32**	**0.90**
2 Professional	-	-	-	-	0.26	0.12	0.27	0.66
3 Associate professional and technical	-	-	-	-	**1.05**	**0.81**	**0.76**	**2.62**
4 Clerical and secretarial	-0.09	0.03	-0.05	-0.11	0.65	-2.47	-2.07	-3.89
5 Craft and related	-0.54	-0.36	-0.44	-1.34	-4.32	-3.26	-1.56	-9.14
6 Personal and protective services	1.45	**1.92**	**1.83**	**5.19**	0.10	**0.30**	0.17	0.57
7 Sales	1.21	**0.69**	-0.24	**1.66**	-0.10	-0.10	-0.04	-0.24
8 Plant and machine operatives	-0.59	-0.23	-0.36	-1.18	-2.80	-1.19	-2.15	-6.14
9 Other occupations (a)	-0.33	-1.63	-0.50	-2.47	-1.44	-0.47	-0.59	-2.50

Cells highlighted in grey are the lowest two values in the columns, figures in bold are the highest two.

a: include farm workers, coal mine labourers, rail and road construction and maintanenance workers, porters, cleaners, windows cleaner.

Table 3 - Distribution of major occupational groups across the wage and educational distribution based on the year 1993

	Bottom		Middle		Top		Total
	Wage	*Education*	*Wage*	*Education*	*Wage*	*Education*	
1 Managers and Administrators	0.20	-	4.14	9.81	9.14	3.67	13.49
2 Professional	0.16	-	1.15	0.64	8.90	9.58	10.21
3 Associate professional and technical	0.06	-	7.11	2.89	2.26	6.54	9.43
4 Clerical and secretarial	0.66	-	16.83	17.50	-	0.06	17.50
5 Craft and related	1.62	1.60	9.65	9.76	0.09	-	11.36
6 Personal and protective services	6.56	2.52	3.10	7.82	0.74	-	10.40
7 Sales	6.41	-	1.90	8.31	-	-	8.31
8 Plant and machine operatives	1.29	6.94	8.96	3.31	-	-	10.25
9 Other occupations	6.65	8.60	2.40	0.46	-	-	9.05
Total	23.61	19.66	55.25	60.50	21.13	19.84	

Wage distribution based on median wage of 3-digit occupations in 1993. Education distribution based on mean education.

Table 4- Shift-share decomposition of changes in occupational shares (pp) by different set of groups.

	Total[d]	Education only 4 groups[a]		Education, age, gender, immigration 48 groups[b]		Education, age, gender, immigration, geography 400 groups[c]	
		Between	*Within*	*Between*	*Within*	*Between*	*Within*
1979-2012							
Bottom	3.5	-10.2	13.8	-8.9	12.4	-8.9	12.4
Middle	-19.3	-6.2	-13.1	-7.2	-12.0	-7.5	-11.8
Top	15.7	16.4	-0.7	16.2	-0.4	16.3	-0.6
1979-1989							
Bottom	0.9	-3.6	4.4	-2.2	3.1	-2.3	3.1
Middle	-5.9	-0.3	-5.6	-1.3	-4.5	-1.5	-4.4
Top	5.0	3.9	1.1	3.6	1.4	3.8	1.2
1989-1999							
Bottom	1.0	-4.2	5.3	-4.2	5.2	-4.5	5.5
Middle	-6.6	-1.9	-4.7	-2.4	-4.2	-2.2	-4.4
Top	5.6	6.1	-0.6	6.6	-1.1	6.7	-1.2
1999-2009							
Bottom	0.3	-2.8	3.2	-3.0	3.3	-2.5	2.9
Middle	-4.9	-1.5	-3.3	-1.4	-3.5	-1.5	-3.4
Top	4.5	4.4	0.2	4.3	0.2	4.0	0.5

a: 4 education groups (Higher+Further education, A-Level, O-Level+other, None).

b: 4 education groups, 3 age groups (<30, 31-50, >50), 2 genders, 2 immigrant status.

c: 4 education groups, 5 age groups (<25, 26-35, 36-45, 46-55, >55), 2 genders, 2 immigrant status, 5 geographies (North, Midlands&EastAnglia, London, South, Scotland+Wales+NI)

d: the between and the within components do not always sum up to the totals due to rounding.

Table 5 - Contributions of skill groups to changes in employment shares (pp) across the occupational distribution. Results from a shift-share analysis.

	All			Graduates			Non-Graduates			Natives			Immigrants		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
1979-2012	*Total*	*Between*	*Within*	*Total*	*Between*	*Within*	*Total*	*Between*	*Within*	*Total*	*Between*	*Within*	*Total*	*Between*	*Within*
Bottom	3.5	-8.9	12.4	3.9	3.1	0.8	-0.4	-12.0	11.6	0.6	-10.1	10.7	2.9	1.2	1.7
Middle	-19.3	-7.2	-12.0	9.0	8.3	0.7	-28.3	-15.5	-12.7	-20.6	-10.3	-10.4	1.4	3.0	-1.7
Top	15.8	16.2	-0.4	15.0	16.6	-1.5	0.7	-0.4	1.2	11.9	12.3	-0.4	3.8	3.9	0.0
1979-1989															
Bottom	0.9	-2.2	3.1	0.3	0.4	0.0	0.5	-2.6	3.1	0.6	-2.2	2.8	0.3	0.0	0.3
Middle	-5.9	-1.3	-4.5	1.2	1.1	0.1	-7.1	-2.4	-4.6	-5.5	-1.5	-4.0	-0.4	0.1	-0.6
Top	5.0	3.6	1.4	2.4	2.5	-0.1	2.6	1.1	1.5	4.4	3.2	1.2	0.6	0.4	0.3
1989-1999															
Bottom	1.0	-4.2	5.2	0.3	0.7	-0.4	0.7	-4.9	5.6	0.9	-4.1	5.0	0.1	-0.1	0.3
Middle	-6.6	-2.4	-4.2	3.6	2.9	0.7	-10.2	-5.4	-4.8	-6.4	-2.7	-3.7	-0.2	0.3	-0.5
Top	5.6	6.6	-1.1	6.2	6.4	-0.3	-0.6	0.2	-0.8	4.6	6.0	-1.3	0.9	0.7	0.2
1999-2009															
Bottom	0.3	-3.0	3.3	1.8	0.7	1.1	-1.5	-3.7	2.2	-1.6	-4.2	2.6	1.9	1.2	0.7
Middle	-4.9	-1.4	-3.5	2.6	2.7	-0.2	-7.5	-4.1	-3.3	-6.6	-3.2	-3.3	1.7	1.8	-0.2
Top	4.6	4.3	0.2	4.5	5.4	-0.9	0.1	-1.0	1.1	3.0	2.3	0.7	1.6	2.1	-0.5

The table reports the total by education groups from the shift-share analysis with 48 skill groups. Immigrants are defined as foreign-born workers.

Table 6 -**Distribution of routine employment across 1-digit occupations (SOC90) based on alternative classifications.**

SOC90 Major Occupational Group	*1979 Total Employment Share*	*Routine employment share in 1979 based on alternative classifications:*						
		AA 2011	**GMS 2014** (a)			**AKR 2013**		
			Top 30%, employment weighted	Top 50%, employment weighted	RTI above unweighted average	Top 30%, employment weighted	Top 50%, employment weighted	RTI above unweighted average
1 Managers and Administrators	8.10	0.00	0.00	0.00	0.00	0.00	0.20	0.20
2 Professional	7.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3 Associate professional and technical	5.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4 Clerical and secretarial	18.86	18.86	18.78	18.78	18.78	15.59	15.59	18.78
5 Craft and related	18.92	18.92	4.20	13.84	13.84	0.14	9.28	18.92
6 Personal and protective services	7.68	0.00	0.00	0.00	0.83	0.83	0.83	0.83
7 Sales	6.90	6.90	0.48	4.89	5.23	0.34	0.34	5.23
8 Plant and machine operatives	14.80	14.80	6.38	9.46	9.46	12.83	14.58	14.65
9 Other occupations	11.51	0.00	0.56	4.24	9.47	10.35	10.46	10.46
Total share(b)	**100**	**59**	**30**	**51**	**58**	**40**	**51**	**69**

The details on each classification are provided in Section 0. AA: Acemoglu and Autor (2011). GMS: Goos et al. (2014). AKR: Akcomak et al. (2013).

(a): the RTI index of GMS is only available for 21 ISCO88 codes and therefore does not cover all occupations used in the analysis of this paper.

(b): the totals might not correspond to the column headings because ISCO88 2-digit codes correspond to large occupations making the running sum of employment by occupations a discrete rather than continuous variable.

Table 7 - Shift-share decomposition of changes in occupational shares (pp) by type of occupations using alternative routine classifications, 1979-2012.

	Non routine Occupations			Routine Occupations		
	Total	*Between*	*Within*	*Total*	*Between*	*Within*
(A) Routine classification based on Acemoglu and Autor (2011)						
Bottom	4.2	-4.6	8.8	-0.7	-4.3	3.6
MIddle	2.6	1.6	1.0	-21.8	-8.8	-13.0
Top	16.6	16.3	0.3	-0.8	-0.1	-0.7
All				**-23.4**	**-13.2**	**-10.1**
(B) Routine classification based on RTI index from Goos et al. (2014) – top 30%						
Bottom	6.1	-6.9	12.9	-1.6	-1.1	-0.4
MIddle	-7.9	-2.9	-4.9	-11.5	-1.4	-10.1
Top	14.9	12.3	2.6	0.0	0.0	0.0
All				**-12.7**	**-3.4**	**-9.3**
(C) Routine classification based on RTI index from Akcomack et al. (2013) – top 30%[a]						
Bottom	6.5	-4.2	10.7	-3.0	-4.7	1.7
MIddle	-6.7	-1.5	-5.1	-12.6	-5.7	-6.9
Top	15.9	16.2	-0.3	-0.1	0.0	-0.1
All				**-15.7**	**-10.5**	**-5.3**

Results from a shift-share analysis with 48 groups: 4 education groups, 3 age groups, gender, immigration status. Details on the routine classifications are provided in Section XX and Appendix D. The discrepancies between the totals in Panel B and the other two panels is due to the fact that the RTI index from Goos et al. (2014) is only available for 21 ISCO 88 codes.

(a): due to the size of the underlying occupations, the actual initial share of routine occupations here is 40% as shown in Table 6.

Table 8 - Average changes in log median wages of major occupational groups by decade, 1979-2999.

	1979-1989	*1989-1999*	*1999-2009*	*Total*
1 Managers and Administrators	0.33	0.24	0.10	0.67
2 Professional	0.32	0.19	0.13	0.64
3 Associate professional and technical	0.43	0.11	0.16	0.71
4 Clerical and secretarial	0.31	0.15	0.18	0.64
5 Craft and related	0.25	0.16	0.19	0.60
6 Personal and protective services	0.26	0.14	0.21	0.61
7 Sales	0.27	0.15	0.13	0.55
8 Plant and machine operatives	0.21	0.10	0.17	0.49
9 Other occupations (a)	0.20	0.08	0.22	0.51

Changes computed as the weighted average of the change in log median wage in each decade with weights equal to the employmetn share in 1979.

a: include farm workers, coal mine labourers, rail and road construction and maintenance workers, porters, cleaners, windows cleaner.

11 Figures

Figure 1 - Changes in shares of skill and demoographic groups between 1979 and 2012

No data points in 1980 and 1982 (and 1983, 1992 for education only).
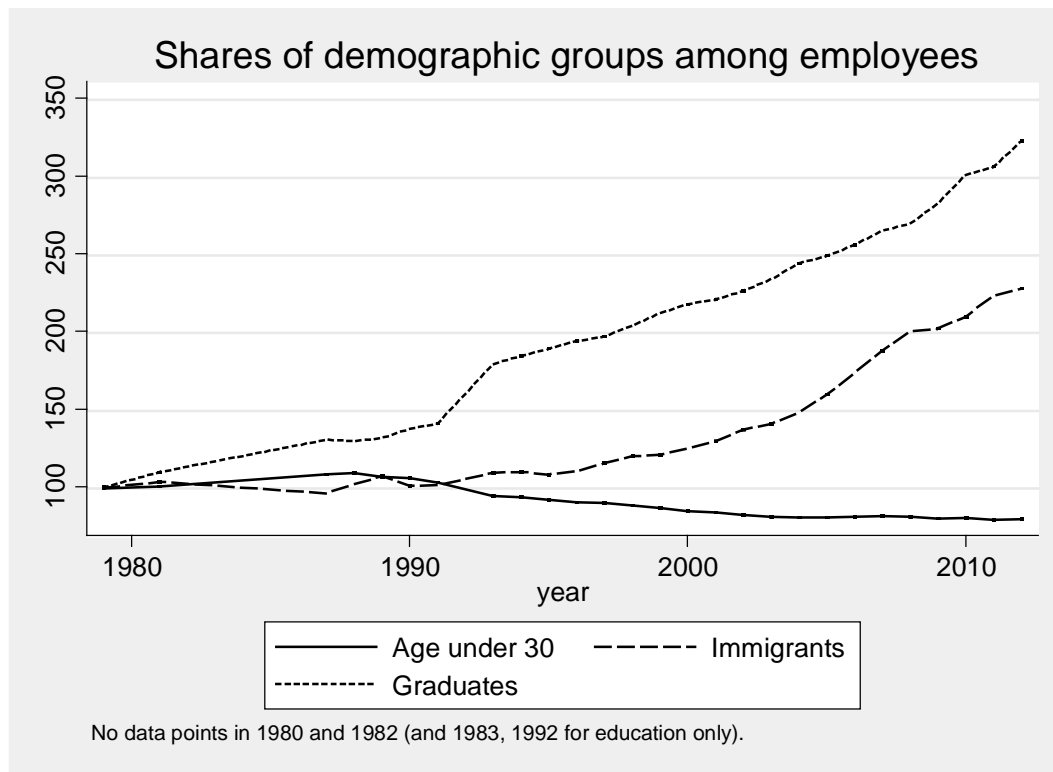
Figure 2 - Smoothed changes in occupational shares across the 1979 occupational wage distribution, 1979-2012.

Changes in employment shares, 1979-2012

Occupational classification: SOC90.
Occupation ranking based on wages from NESPD 1979.
Employment shares computed from LFS data.

Smoothed fit from kernel local cubic regressions obtained using STATA's lpoly command.
Observations weighted by employment share in 1979.
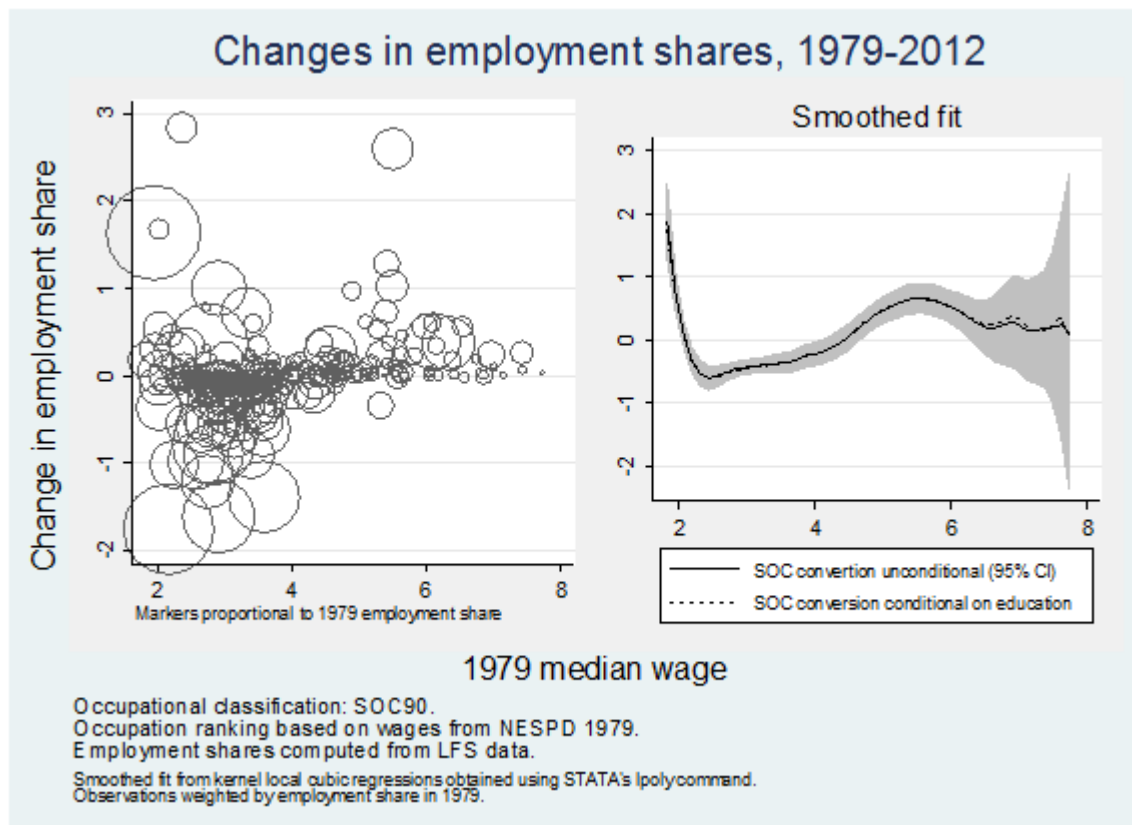
Figure 3 - Changes in employment shares by occupational deciles, 1979-2012.

Changes in employment shares, 1979-2012

Occupation ranking based on median wage (293 3-digit soc90 codes, NESPD 1979)
Occupation shares computed from LFS data, occupation classification converted (v) to soc90.

Figure 4 - Occupational shares by group of 1979 deciles.

Share of employment by group of 1979 deciles
Occupations ranked by median wage
All employees

Legend:
- Bottom (1 2)
- Middle (3/8)
- Top (9 10)

Solid vertical lines indicate SOC changes
Dashed vertical lines indicate recession years
Deciles based on NESPD 1979, shares from LFS data.
Occupational classification: soc90

Figure 5 - Decadal changes in employment shares by deciles of the 1993 education distribution.

Changes in employment shares by decade

1979-89   1989-99   1999-09

Occupation ranking based on mean education (314 3-digit soc90 codes, LFS 1993)
Occupation shares computed from LFS data, occupation classification converted (v) to soc90.
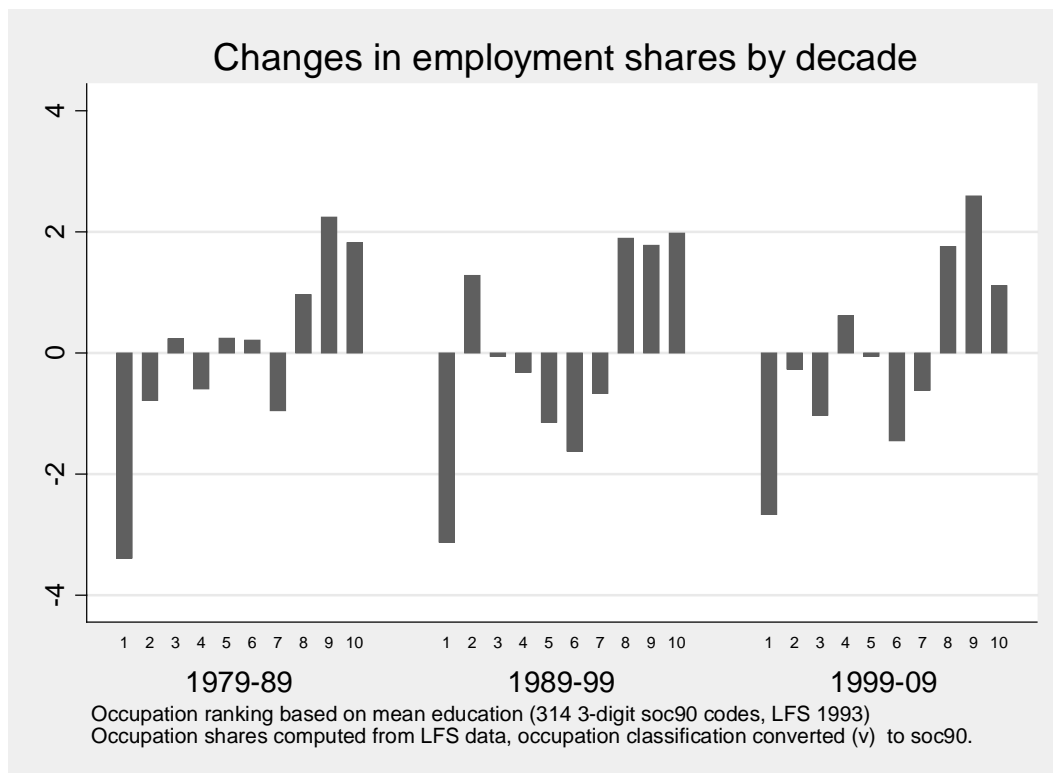
Figure 6 - Decadal changes in employment shares by deciles of the 1993 wage distribution.

Changes in employment shares by decade

1979-89   1989-99   1999-09

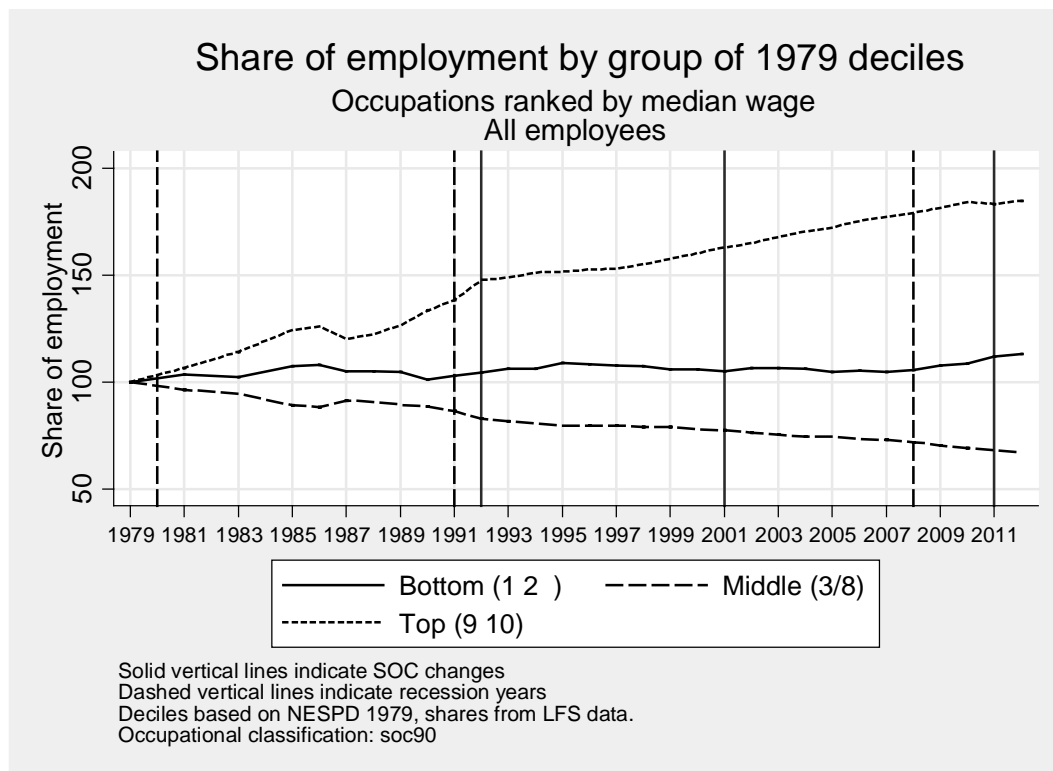Occupation ranking based on median wage (310 3-digit soc90 codes, NES 1993)
Occupation shares computed from LFS data, occupation classification converted (v) to soc90.
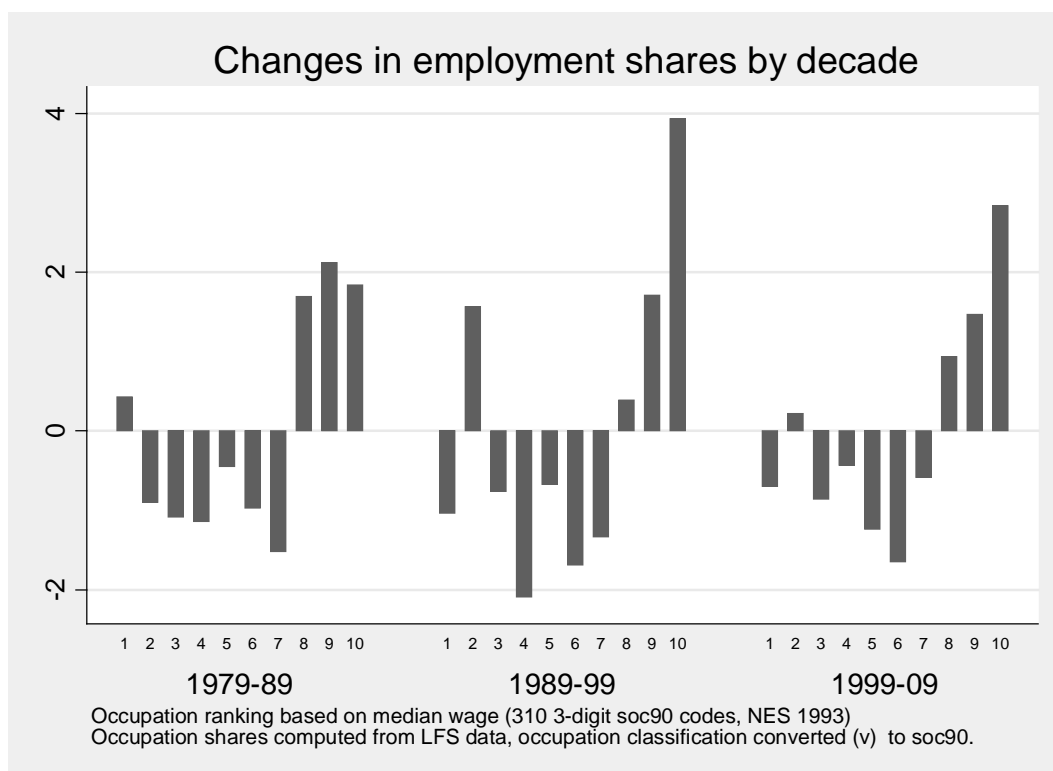
Figure 7 - Shift-share decomposition of changes in employment shares of 1979 occupational deciles.

Shift-share decomposition of changes in employment shares of occupational deciles
1979-2012

Between: change in employment share due to changes in demographic composition.
Within: change in employment share due to changes in occupational shares within demographic groups.
48 groups: 4 by education, 3 by age, 2 by immigration, 2 by gender.
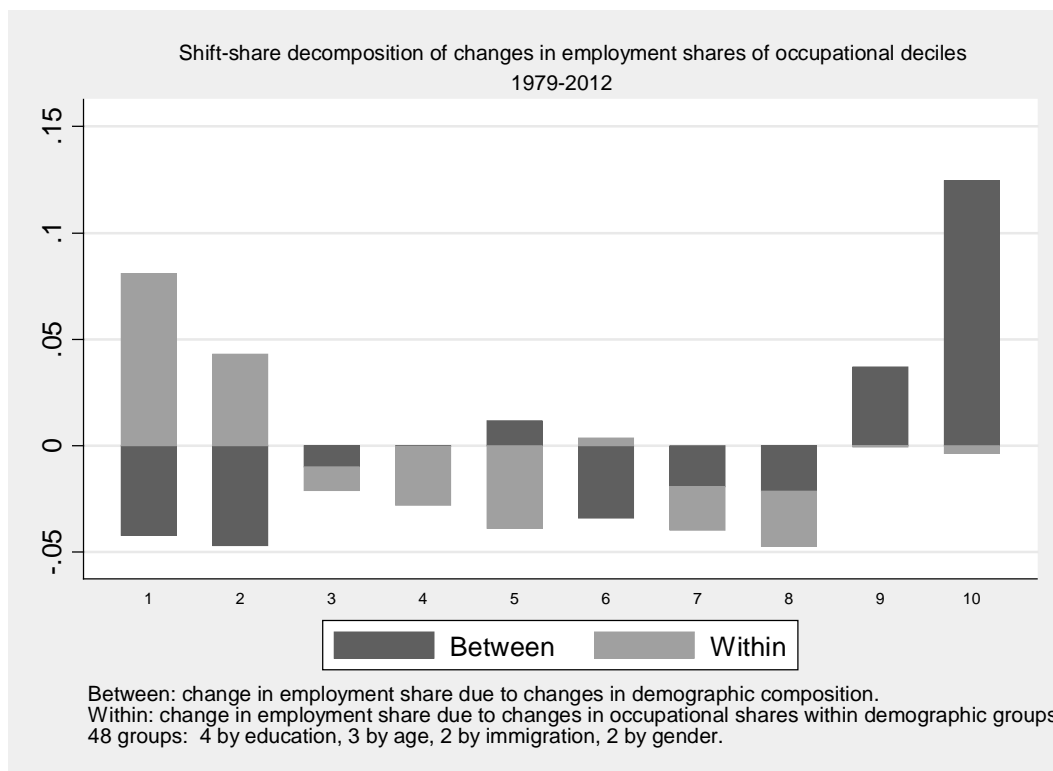
Figure 8 - Changes in hourly median wages and inequality by occupational decile and decade

Changes in hourly median wages and inequality by occupational deciles

Change in log(median)   — — — — Change in log(90/10) (RHS axis)

Wage data from NESPD, deflated using CPI (1987 base)
Occupational deciles based on 1979 NESPD, using SOC90.
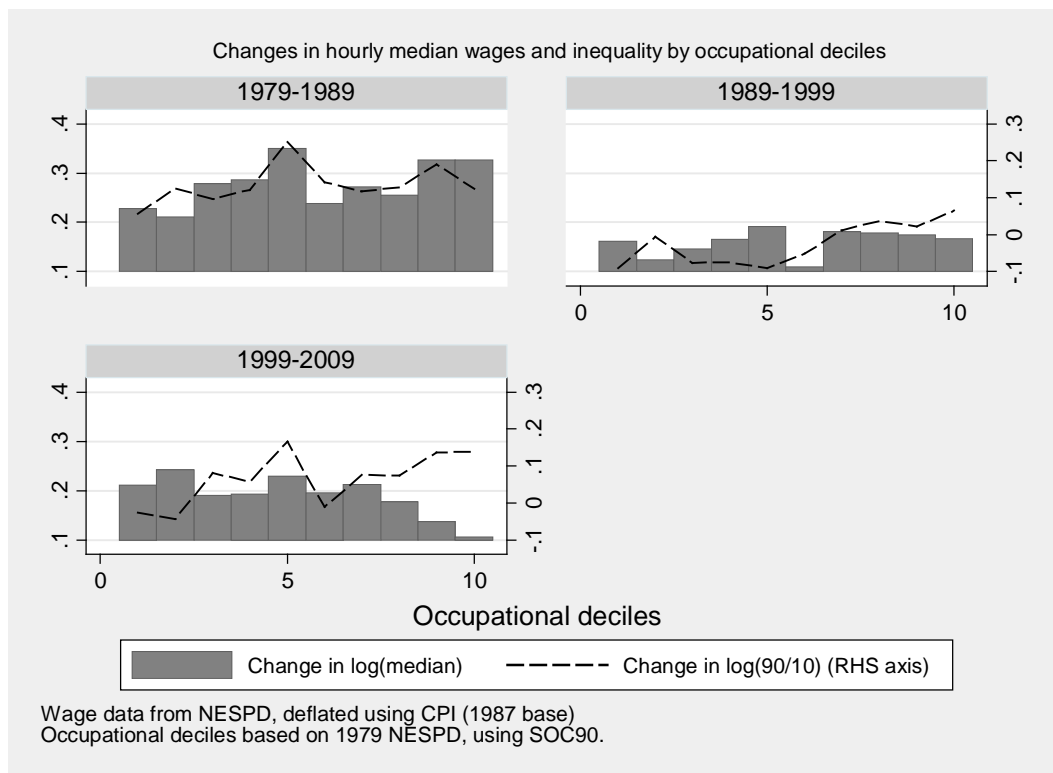
12 Appendix A : bridging occupational classifications

Between 1979 and 2012 the LFS used four different occupational classifications. After the Key list of Occupations for Statistical purposes (KOS) between 1979 and 1991, the 1990 Standard Occupational Classification (SOC90) was adopted in 1992, and its successors SOC00 and SOC10 were introduced in 2001 and 2011 respectively. In addition, the NESPD data for 1979-1989 come with a different version of the KOS system. For ease of reference, throughout the paper I will refer to the KOS classification of the early LFS data as SOC80, and to that from the NESPD data as SOC70. Moreover, the occupational classification in which a dataset is originally coded in will be referred to as the "native" occupational classification.

The study of occupational changes over time requires a method to bridge the different occupational classifications. In general, there is no 1-to-1 correspondence even between successive classifications as one (origin) occupation can be split into several (destination) occupations. The ONS (2002) reports that the agreement between any two SOC in dual-coded datasets is always less than 80% even at the 1-digit level.

The availability of a dual-coded dataset offers a way to bridge two classifications by providing estimates of the proportions of a given origin occupation which "move" to different destination occupations. With this information at hand, one can then randomly allocate individuals from a given origin occupation to a set of destination occupations, replicating the empirical distribution observed in the dual-coded dataset[29]. This is the method used by Goos and Manning (2007) in their study of polarisation between 1979 and 1999, to convert the occupational coding in the early editions of the LFS (which I refer to as SOC80) to SOC90.

A potential limitation of this approach is that it assumes that the splitting of the origin occupation into the destination occupations is random. Intuition suggests that this is unlikely to be the case since individuals with the same origin occupation are reclassified precisely because they are thought to be doing different jobs and are therefore likely to differ in some respect. For example, it is reasonable that individuals with different skills and education levels will have different probabilities of being assigned to different destination occupations. This can potentially lead to systematic errors in the measurement of occupational shares and their changes if the different demographic groups within an origin occupation grow at different rates. The problem is that the growth of the fastest growing group will be assigned to all the destination occupations in proportions that reflect the demographic composition of the origin occupation in the dual-coded dataset. This will certainly result in an underestimate of the growth in the number of people employed in the destination occupation which actually receive a higher proportion of the fastest growing group, once the non-randomness of the occupational splitting is taken into account. Depending on a number of other factors, including the growth rate of other occupations and demographic groups, this can lead to either over or under estimation of employment shares over time.

For example, suppose that having a university degree is a variable that plays a significant role in the reallocation of individuals between two occupational classifications. It is reasonable that on average graduates within any origin occupation are more likely to be recoded as working in

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[29] Or equivalently, compute the size of the destination occupation as a weighted average of the different origin occupations which "contributes" to it.

higher-paid destination occupations than non-graduates. As it is well known, the population of graduates in the UK greatly expanded over the past thirty years and in particular in the 1990's. If one applies an unconditional conversion between the two classifications over this time period, this is likely to result in an underestimate of the share of workers employed in higher-paid occupations since too much of the growth of the graduate population is attributed to lower-paid occupations.

I compared the results using the unconditional conversion method of Goos and Manning (2007) with the three sets of results obtained conditioning the occupational conversion on gender, age and education. I found that the conditional conversion methods do, as expected, effectively reallocate some of the employment growth between occupations – but this takes place among occupations which are close on the wage distribution leaving substantively unaltered the main conclusion that the UK labour market has polarised over the past thirty years. In light of this, the paper only presents the results obtained using the unconditional conversion method.

[Details on dual-coded datasets used for the conversion to be added].

13 Appendix B : Problems with LFS data

13.1 Assessing the reliability of the LFS time series around the 1992 discontinuity

Over the period 1979-2012, the LFS changes occupational coding three times. The time-series in Figure 4 show that the only point in time where this might matter is 1992, when SOC90 was adopted. However, in the same year the LFS changed in other significant ways. This appendix reflects on the relevance of such changes for the analysis of this paper.

I begin by considering the possible role of breaks in occupational coding in shaping the peculiar pattern in the share of top occupations in the late 1980s and early 1990s. Figure 4 shows that growth in occupations in the highest 2 deciles strongly accelerated in the second half of the 1980s and then abruptly slowed down in the early 1990s. As noted in the paper, this means that more than half of the total increase in top occupations over the 30-year period considered occurred in the first 13 years. The fundamental concern is whether this patter is driven by changes in occupational coding.

To address this issue one would ideally require a dataset with a consistent occupational coding straddling 1992. In the absence of such a dataset, this section compares several different time-series for top occupations. Some of these series are obtained from NESPD/NES data (rather than LFS) and offer consistent occupation coding for at least part of the period of interest, while others are computed using LFS data, but use a different wage rankings which does not require converting across occupational classifications.

 As a reminder, the time-series in Figure 4 are all computed using LFS data, with the original occupational classifications from outside the interval 1992-2001 converted to SOC90. Occupations are ranked and split into deciles based on 1979 wages from NESPD data, which are also converted to SOC90.

The first series considered in this section uses a consistent native occupational coding for all the 1980's. The series is obtained from NESPD data for 1979-1990, using the original occupational

coding of that dataset which I label for convenience "SOC70". The occupational wage rankings are computed from the same dataset in 1979. This is therefore a different occupational classification (and a different occupational wage rankings) from Figure 4.

The second series is obtained from NES data for the period 1990-2001 using the original (unconverted) classification occupation SOC90 for the whole period. The occupational wage ranking is the same as for the series in Figure 4 (1979 NESPD data converted to SOC90). This series straddles the year of the LFS occupation change (1992) maintaining the same original classification, and therefore provides further insights on the behaviour of the series around 1992 net of any conversion issues.

Unfortunately, no dataset offers the possibility of obtaining a wage ranking for the occupations as originally classified in the LFS in the 1980's[30]. It is however possible to rank occupations by the mean education level instead. To avoid further complications, such education rankings are computed for each year only in the original occupational classification of each dataset. This leads to two additional time-series which are useful for the purpose of this section.

The first one comes from LFS data for 1979-1991 and uses the original occupational classification available in those years (KOS, which for convenience I label SOC80) ranking occupations by mean education in 1979. This series therefore uses the same data as the original plot in Figure 4, but with an unconverted occupational classification and a different ranking of occupations.

The second series based on education rankings spans 1979-2001 and uses LFS data in SOC90 (converted from SOC80 for the portion before 1992) and, unlike the other series so far, uses a ranking (based on mean education) from 1993.

Figure 9 plots all of these series, including the original series from Figure 4. The left panel shows the series obtained grouping occupations by the wage ranking (which for all series is based on 1979), while the right panel draws the two series based on education rankings (which in one case refer to 1979 and in the other to 1993).

Net of the relatively small differences that one would expect given the underlying differences between these series, the plots seems to convey a broadly consistent message regarding the behaviour of top occupations in the late 1980's and early 1990's.

In particular, in the left panel, we see that both the NESPD and NES series (with their unconverted occupational classification) show steeper slopes in the late 80's than they do in years immediately before (NESPD) or after (NES). Similarly, the plots in the right panel based on education rankings also show sustained growth in the late 80's regardless of whether the series is obtained after converting the occupational classification.

Overall, therefore, the graph is reassuring that the behaviour of the time-series for top occupations is not driven by issues related to occupational coding. Most importantly, strong growth in top occupations is seen in the late 1980s using LFS data even when one uses a ranking based on education and the native occupational classification for those years and the data from NES and NESPD (in their respective native occupational classifications) also show a deceleration in the growth of top occupations around 1992.

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[30] The LFS does not contain wage information till 1993.

Nevertheless, Figure 9 makes clear that there is a discontinuity in the LFS series in 1991. Figure 1 shows that in the same year a significant discontinuity is also found in the time-series for the share of graduate employees. In particular, between 1991 and 1992 the share of graduates jumps up by 19% (from 17.6% to 21%), while the average annual growth is around 2% between 1988 and 1991 and around 3% between 1992 and 2012. This discontinuity is not explained by any apparent changes in the coding of the education question in the LFS, nor can be accounted for by changes in the occupational classification. These findings suggest that the changes in the sampling frame of LFS implemented when the survey became quarterly in 1992 might have led to an increase in the estimate of the share of high-skill and high-pay workers.

The dataset documentation mentions three major differences between the pre- and post- 1992 LFS, as the new quarterly survey took on a panel design, introduced an unclustered sample of addresses for the whole of Great Britain, and added people living in NHS accommodation and students in halls of residence to the sample. It is not immediately obvious why any of these changes would generate the discontinuities that we see in the data.

The concern is of course whether these discontinuities are important for the substantive conclusions of the paper. In particular, one might worry that the finding of job polarisation in the 1990s (defined as 1989-1999 in the paper) might be driven by such discontinuities. However, Figure 4 shows that there is still a clear polarisation pattern in employment growth if 1992 is taken as the starting year for the 1990s – in fact there is a slight acceleration in the growth of top occupations and decline of middling occupations in the second half of the 1990s.

Another worry might be that the discontinuity in the series for graduates might affect the conclusions of the shift-share analysis at least for the 1990s (1989-1999) as it might exaggerate the role of between-skill-groups changes. However, the main substantive conclusions on the relative importance of within vs between- group changes across the occupational distribution remains unaltered when the shift-share analysis is carried out for the period 1992-2002 (and 2002-2012).
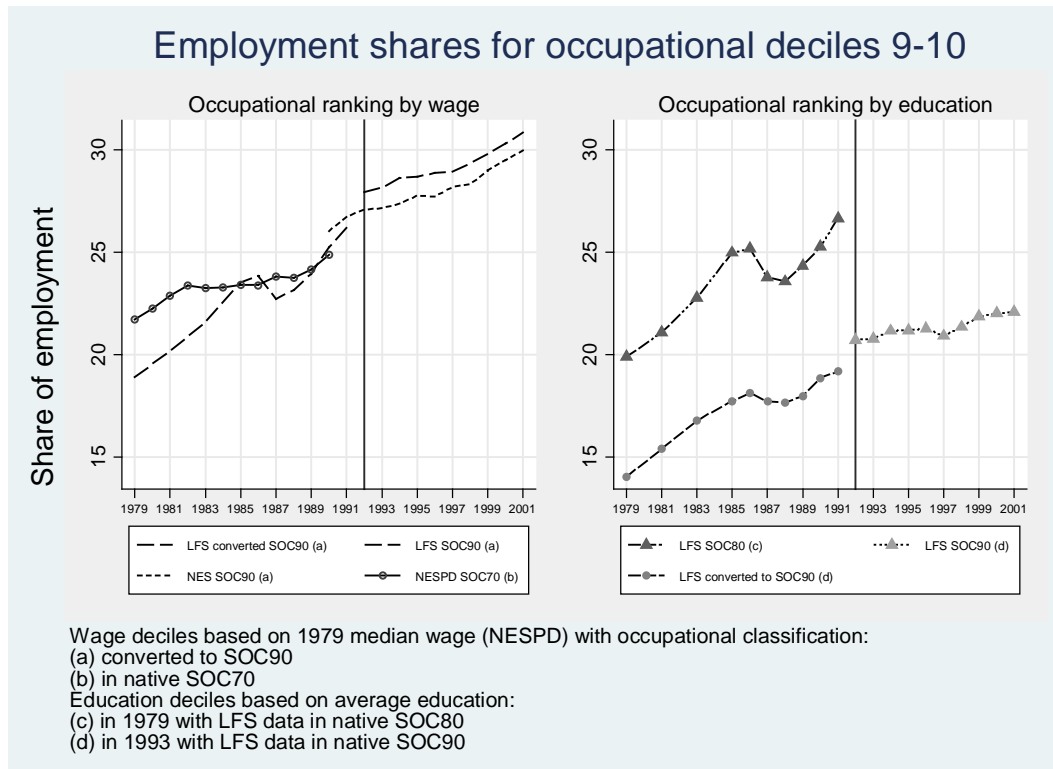
13.2 The education variable for immigrants

A large fraction of university-level qualifications awarded by foreign institutions were coded as "other qualifications" in the LFS until recently. The correction of this issue in 2011 led to an increase of 8-9% foreign-born workers with university education and a corresponding decline in those with "other" qualifications compared to the previous year. This problem likely resulted in underestimate of the growth in the number of graduates in the period of strong immigration growth post 1998 and accounts for the sharp increase in graduates seen in 2011 in Figure 1. However, I found that the main results of the analysis in terms of the relative contributions of different education groups in each decade hold when one consider only the native workers (who are not affected by this misclassification problem). In addition, the results for the long difference between 1979 and 2012 are unlikely to be affected by this issue in a significant way since immigration became quantitatively important only in the late 1990s and the classification problem was rectified in 2011. The paper presents results for the analysis by education groups pooling together natives and immigrants, while a further breakdown by education and immigration status can be found in Appendix C (Section 14).

I did consider the option of defining skill levels using "age left education" as others have done before. However, as acknowledged in the literature, such variable ignores differences in the

education systems across countries. In addition, exploratory tabulations revealed a significant degree of variation in "age left education" within groups with the same qualification levels. These two facts indicated that using this alternative classification would likely introduce further noise in the analysis and has led to the decision not to pursue this approach.

Figure 9 - Comparison of different time series for top occupations around the occupation coding break of 1992

Employment shares for occupational deciles 9-10

Wage deciles based on 1979 median wage (NESPD) with occupational classification:
(a) converted to SOC90
(b) in native SOC70
Education deciles based on average education:
(c) in 1979 with LFS data in native SOC80
(d) in 1993 with LFS data in native SOC90

14 Appendix C: further results.

14.1 Polarisation and recessions

Table 9 focuses on the contributions of the three recessions to the changes in employment shares of different parts of the occupational distribution. Because quarterly data are only available from 1992 onwards I continue to use annual data here. Each of the three recessions lasted four quarters spanning over two calendar years. For the 1990q3-1991q3 and 2008q2-2009q2 contractions, the recession period is defined as the three-year window beginning the calendar year before the start of the recession and ending the calendar year after the end of it (1989-1992 and 2007-2010 respectively for the two recessions). For the 1980q1-1981q1 recession, the longer interval 1979-1983 was taken since LFS data are not available for 1982. It should also be noted that 1979, the initial year of observation, also contains two (non-

consecutive) quarters of negative growth (1979q1 and 1979q3) and that the last quarter of 2010 also saw negative growth.

Overall, the three recessions account for about 30% of the period considered and for a higher proportion of the overall change in employment shares (see the last column of Table 9). Half of the 19pp decline in the share of middling occupations and of the 16pp increase in the share of top occupations occurred during recessions. In addition, the annualised decline in middling occupations was larger during each of the three recessions than over the entire 1979-2012 period, with the strongest acceleration occurring in the recession of the early 1990s. However, these estimates are likely to be biased positively by the aforementioned discontinuity in the LFS time-series in 1992 (see Appendix B - Section 12). In addition, Figure 4 makes clear that the acceleration in the decline of middling occupations (and, even more clearly, in the growth of top occupations) had begun at least in 1988, well before the onset of the recession.

Table 9 - Contribution of recession periods to changes in occupational shares

	Percentage point change in share of total employment				Ratio over 1979-2012 change			
	1979-2012	1979-1983	1989-1992	2007-2010	1979-1983	1989-1992	2007-2010	Total recessions
	(a)	**(b)**	**(c)**	**(d)**	**(e)** (b/a)	**(f)** (c/a)	**(g)** (d/a)	**(h)** (e+f+g)
Bottom (deciles 1-2)	3.02	0.51	-0.14	0.94	0.17	-0.04	0.31	0.44
Annualised change	*0.09*	*0.13*	*-0.05*	*0.31*	*1.40*	*-0.49*	*3.43*	
Middle (deciles 3-8)	-19.07	-3.18	-3.87	-2.27	0.17	0.20	0.12	0.49
Annualised change	*-0.58*	*-0.79*	*-1.29*	*-0.76*	*1.38*	*2.23*	*1.31*	
Top (deciles 9-10)	16.05	2.67	4.01	1.33	0.17	0.25	0.08	0.50
Annualised change	*0.49*	*0.67*	*1.34*	*0.44*	*1.37*	*2.75*	*0.91*	

14.2 Shift-share: breakdown by age and gender

Table 10 reports the results of the shift-share analysis by age groups between 1979 and 2012. The increase in the size of older age groups (31-50 and over 50) explains most of the growth at the top, reflecting that these workers are more specialised in higher occupations. Interestingly, across all age groups the within-group changes appear polarised and skewed towards the bottom. It is however the under-30 who made the largest contribution to the growth of bottom occupations. Although not shown here, this pattern is observed in each of the three decades considered. Over the entire period 1979-2012, the youngest age group accounts for the entire 3.5pp increase at the bottom. This is not the result of mere compositional changes as it is driven by a large within-group change (+7.3pp). In other words, younger people from across all skill groups have increasingly been drawn to the bottom. The under-30s also account for 2/3 of the decline in middling occupations (12pp of the total 19pp) both through between- and within-group changes. The only positive sign found for middling occupations is for the between-group change for the over-50s (+1.1pp). This older group, however, has also seen its employment shift away from middling occupations as indicated by the negative within-group change (-1.6pp), leading to a small negative contribution to the overall change in the share of middling occupations.

The lower panel of Table 10 shows that both genders have contributed to the polarisation of the labour market. Men account for most of the growth in bottom occupations (3.2pp out of 3.5pp), while women for most of the growth at the top (10.2pp out of 15.8pp).

Between-group changes have contributed to the decline at the bottom and the growth at the top for both genders. As for middling occupations, compositional changes have had different effects between the two genders: among men they made a negative contribution, while among women their contribution was positive[31]. For both genders the within-group changes have been polarised and for both, on the whole, employment has shifted towards the bottom. In fact, between 1979 and 2012, the within-group contribution to the growth of bottom occupations by the two genders was the same (6.2pp, see Table 10). Men, however, have also moved away from top occupations (-1.7pp) while more women have reached the highest-paying occupations from across the skill groups (+1.3pp). Similar patterns are found in the results by decade, which are not reported here.

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[31] This is likely due to the stronger growth of education attainment among women than men.

Table 10 -Contributions of demographic groups to changes in employment shares (pp) across the occupational distribution between 1979 and 2012. Results from a shift-share analysys.

	Total	Between	Within
Bottom			
Under 30	3.5	-3.8	7.3
31-50	-1.0	-4.4	3.4
Over 50	1.0	-0.7	1.7
Middle			
Under 30	-12.1	-5.7	-6.5
31-50	-6.6	-2.7	-3.9
Over 50	-0.5	1.1	-1.6
Top			
Under 30	1.6	2.4	-0.8
31-50	9.6	9.0	0.5
Over 50	4.6	4.7	-0.1
Bottom			
Men	3.2	-3.0	6.2
Women	0.3	-5.9	6.2
Middle			
Men	-15.8	-11.3	-4.5
Women	-3.5	4.0	-7.5
Top			
Men	5.6	7.3	-1.7
Women	10.2	8.9	1.3

Totals by demographic groups from the shift-share analysis with 48 skill groups.
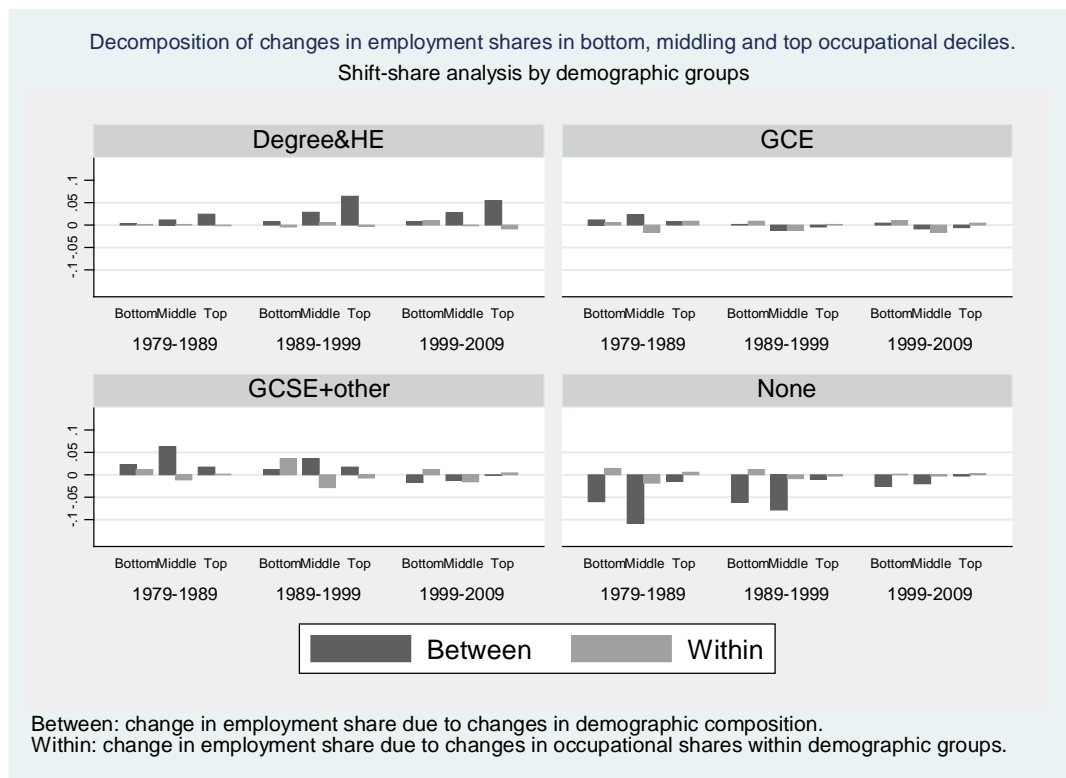
14.3 Shift-share: breakdown by education+immigration

Table 11 - Contributions of skill groups to changes in employment shares (pp) across the occupational distribution. Results broken **down by education and immigration status.**

	Natives						Immigrants					
	Graduates			Non-graduates			Graduates			Non-graduates		
1979-2012	*Total*	*Between*	*Within*	*Total*	*Between*	*Within*	*Total*	*Between*	*Within*	*Total*	*Between*	*Within*
Bottom	2.7	2.2	0.5	-2.1	-12.3	10.2	1.2	0.9	0.3	1.7	0.3	1.4
Middle	7.0	5.9	1.1	-27.6	-16.2	-11.4	2.0	2.3	-0.3	-0.6	0.7	-1.3
Top	11.5	13.1	-1.6	0.4	-0.8	1.2	3.5	3.4	0.1	0.3	0.4	-0.1
1979-1989												
Bottom	0.3	0.3	0.0	0.3	-2.5	2.8	0.0	0.1	0.0	0.2	-0.1	0.3
Middle	1.1	0.9	0.1	-6.5	-2.4	-4.1	0.1	0.2	-0.1	-0.5	0.0	-0.5
Top	2.1	2.3	-0.1	2.2	0.9	1.3	0.3	0.2	0.1	0.3	0.2	0.2
1989-1999												
Bottom	0.3	0.7	-0.3	0.5	-4.7	5.3	0.0	0.1	-0.1	0.1	-0.2	0.3
Middle	3.4	2.7	0.7	-9.8	-5.4	-4.4	0.2	0.3	-0.1	-0.4	0.0	-0.4
Top	5.5	5.9	-0.4	-0.9	0.0	-0.9	0.6	0.5	0.1	0.3	0.2	0.1
1999-2009												
Bottom	1.3	0.5	0.8	-2.9	-4.6	1.8	0.5	0.3	0.2	1.4	0.9	0.4
Middle	1.7	1.9	-0.2	-8.3	-5.2	-3.1	0.8	0.8	0.0	0.9	1.1	-0.2
Top	3.2	3.8	-0.6	-0.2	-1.5	1.3	1.3	1.6	-0.3	0.3	0.5	-0.2

The table reports the total by education groups from the shift-share analysis with 48 skill groups.

Figure 10- Shift-share decomposition of employment shares in bottom, middling and top occupational deciles. Results by educational groups and by decade.

Between: change in employment share due to changes in demographic composition.
Within: change in employment share due to changes in occupational shares within demographic groups.

15 Appendix D: measuring routine occupations

In the spirit of Autor (2013)'s recommendation to use "off the shelf" measures of the routine task intensity of different occupations, I use three different classifications of routine occupations available in the literature.

The first one is based on Acemoglu and Autor (2011) (henceforth AA) and makes use of occupational categories directly rather than resorting to measures at the task level. AA group the US Census and CPS occupations as follow:

1) Non-routine cognitive: managerial, professional and technical occupations.
2) Routine cognitive: sales, clerical and administrative support occupations.
3) Routine manual tasks: production and operative occupations.
4) Non-routine manual tasks: service occupations.

These occupational groups map easily into the 1-digit SOC90 occupational codes. The coarse level of the occupation categories means that jobs that differ substantially from the perspective of their potential for automation are grouped together. For example, sales occupations will include both check-out operators – who are increasingly substituted by machines – and sellers expected to persuade customers to buy a product or service – a task that Autor et al. (2003) classify as non-routine.

The second classification is based on the Routine Task Intensity index provided in Table 1 of Goos et al. (2014). As their appendix explain, this uses the five original task measures from Autor et al. (2003) based on the US Dictionary of Occupational Titles from 1977 (see Appendix A.2 in Autor et al. 2003). They collapse the original five task measures into three task aggregates: the Manual task measure corresponds to the DOT variable for "eye-hand-foot coordination"; the Routine task measure is an average of "set limits, tolerances and standards" and "finger dexterity"; the Abstract task measure is the average of "direction control and planning" and "GED Math" – which measures mathematical and formal reasoning requirements. Appendix 1 in Autor et al. (2003) provides more details on these variables and offer some examples of tasks falling into each of these groups. While these indicators have been widely used in the literature, they are not exempt from criticism. For example, Green (2012) points out that in Autor et al. (2003) (and hence Goos et al. 2014) "adds and subtract 2-digit number" is part of the GED Math score which is classified as a non-routine task, in spite of being an easily codifiable task.

Because the variables in Autor et al. (2003) are available for US Census occupational codes, Goos et al (2014) have to implement several occupational conversions to be able to use them with ISCO88 codes: they convert the Census occupations into US SOC codes, then US SOC Codes into ISCO08 and finally ISCO08 into ISCO88 codes. Their paper reports the RTI index for 21 2-digit ISCO88 occupational codes.

Finally, I split occupations into routine vs non-routine depending on the level of their RTI index, using both employment-weighted and unweighted measures. For example, I classify as routine occupations the (employment-weighted) third with the highest RTI (as in Autor and Dorn 2013), or any occupation with an RTI higher than the unweighted average.

The third classification used in this paper uses task data from three waves of the British Skill Survey (1996, 2001, 2007). BSS contains 36 questions on activities workers perform on their

job. Respondents are asked "We are interested in finding out what activities your job involves and how important these are" and they can rate the importance of each of the activities on a 5-point scale ranging from "essential" to "not at all important/not applicable". As pointed out in Green (2012), it is not obvious how to split this long list into routine vs non-routine, i.e. more or less easy to automate. Table 12 reports the full list of tasks available and the classification adopted in Akcomak et al. (2013) which effectively leaves out the majority of tasks available.

I build a Routine Task Intensity index at the level of 2-digit ISCO88 codes to maximise comparability with Goos et al. (2014)[32]. The RTI index is built following Autor and Dorn (2013) through the following steps:

1) I compute the occupation-level average score for each individual task over the three years (1997, 2001, 2006).
2) I divide the tasks into three groups: routine, service, cognitive (as in Table 12). For each occupation, I compute a score for each of these three groups of tasks.
3) Then for each occupation I compute a routine task intensity index as: ln(routine)-(ln(service)+ln(cognitive)).
4) This is then standardised across occupations (i.e. I substract the mean and divide by the standard deviation).
5) I then identify the "routine occupations" based on the level of their RTI index, using both employment-weighted and unweighted measures, as explained above for the indicator based on the RTI index provided by Goos et al. (2014).

The problem of classifying tasks (rather than occupations) as routine is one that affects both the approach based on the DOT definitions and the BSS data. The issue is further complicated by the fact that the range of tasks that can be automated changes over time as technology evolves and/or becomes more widespread. Arguably, for example, the task of "persuading/selling" might appear more easily subject to automation today than at the time of Autor et al. (2003) as indicated by the ever-more frequent use of automatically generated marketing messages based on online behaviour or spending habits traced by electronic payment systems.

A related issue, discussed in Autor (2013), is the mounting evidence that the task content of occupations changes over time, perhaps partly as a consequence of technological change. Akcomak et al. (2013) show substantial change in routine-intensity within occupations in the UK using BSS data. Hence differences in classifications based on task information from the late 1970s (such as the RTI index from Goos et al. 2014) and from the 1990s (such as the RTI index based on the BSS data) can reflect differences in changes in tasks within occupations. Following the prevailing approach in the literature, I focus on a comparison of static routine measures but return to the importance of the within-occupation changes when discussing the results.

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[32] ISCO88 codes are available in the BSS in 2001 and 2006. For 1997, I convert SOC90 (3 digit) ISCO88 (4 digits using the crosswalk available here: www.cf.ac.uk/socsi/CAMSI/occunits/uksoc90toisco88v1.sps.

15.1 Tables and figures

Table 12 - Classification of tasks from the British Skills Surveys into Routine and Non-routine (service or cognitive)

	Task description	Classification according to AKR 2013
1	Paying close attention to detail	-
2	Dealing with people	service
3	Instruct, training or teaching people	cognitive
4	Making speeches or presentations	cognitive
5	Persuading or influencing	-
6	Selling a product or service	service
7	Counselling, advising or caring for customers	-
8	Working with a team of people	-
9	Listening carefully to colleagues	service
10	Physical Strength	-
11	Physical stamina	-
12	Skill and accuracy in using your hands or fingers	-
13	Knowledge of how to use or operate tools	-
14	Knowledge of particular products/services	service
15	Specialist knowledge or understanding	service
16	Knowledge of how your organisation works	-
17	Using a computer	-
18	Spotting problems or faults	routine
19	Working out causes of problems	-
20	Thinking of solutions to problems	cognitive
21	Analyse complex problems	cognitive
22	Checking there are no errors	routine
23	Noticing when there is a mistake	routine
24	Planning your own activities	-
25	Planning the activities of others	-
26	Organise your own time	-
27	Thinking ahead	-
28	Reading forms notices signs	-
29	Reading short docs, reports, letters	-
30	Reading long docs	-
31	Writing forms, notices, signs	-
32	Writing short documents	-
33	Writing long documents	-
34	Calculating (basic)	routine
35	Calculating using decimals, percentages, or fractions	routine
36	Using advanced maths or statistics	routine