Job Polarization and Labour Supply Changes in the UK

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Abstract

During the past two decades, the UK has experienced dramatic changes in the composition of its labour force, mainly due to a rapid educational upgrading and immigration surges. Over the same period, unlike the US, the UK has shown a persistent pattern of occupational polarization. This paper provides first empirical evidence on the causal effect of technological exposure on local labour markets in the UK. The analysis combines 1993-2013 QLFS data with a longitudinal Census sample spanning 1971-2011. The identification strategy exploits geographical variation across local labour markets stemming from their historical specialization in routine-intensive activities. Results confirm the leading role of technology in hollowing out middle paid jobs and pushing the reallocation of less skilled workers to the bottom of the employment distribution. However, no significant effect of technological exposure is found on skilled non-routine cognitive employment. Local labour markets show a generalized catch-up with education during the 1990s. Because of this, higher start-of-the-period local relative graduate labour supply is significantly negatively associated with top employment growth during this decade. The analysis of individual occupational transitions uncovers an occupational downgrading pattern that emerged since the 1990s, in coincidence with the substantial increase in the pool of graduates.

Key Words: Job Polarization, Labour Supply Changes, Local Labour Markets, Occupational Mobility

JEL Codes: J21, J23, J24, O33

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1 Introduction

The demographic composition of the labour force in the UK in the last two decades has changed dramatically, mainly reflecting a rapid educational upgrading and surging immigrant inflows. Figure 1 shows the shares of graduates and of immigrants among employee between 1979 and 2012. The plot shows that both shares have started to accelerate significantly during the 1990s, more than doubling between 1993 and 2012.

Over the same period a growing number of studies have documented the polarization of employment across a number of developed countries (see for example Autor and Dorn, 2013 for the US; Goos and Manning, 2007, Salvatori, 2015 for the UK; Goos et al., 2014, Michaels et al., 2014 for Europe).

In the seminal paper of Autor, Levi and Murnane (2003, ALM henceforth) job polarization is explained through the so called routinization or routine-biased technical change (RBTC) hypothesis, stating that continuously cheaper computerization progressively replaces human labour in routine tasks, thereby leading to an increase in the relative demand for workers performing non-routine tasks.

The prevailing economic literature has so far provided empirical support to this hypothesis (Autor and Dorn, 2013; Goos and Manning, 2007; Goos et al., 2014; Michaels et al., 2014).

Nevertheless, while this thesis seems to fit well the US employment distribution during the 1990s, it falls short in explaining a number of recent empirical puzzles that emerged since the year 2000.

Major pitfalls are the unexplained downturn in the growth of high-skilled occupations and the disappearance of wage polarization (Beaudry, Green and Sand, 2014 forthcoming; Autor, 2015). In particular, as regards the deceleration of employment growth in top occupations, Autor (2015) suggests that high-skill jobs may not be growing enough to absorb the increasing supply of educated workers.

A recent contribution from Salvatori (2015) raises doubts on the leading role of technology while highlights the contribution of changes in the structure of the labour supply in explaining the job polarization phenomenon in the UK. This study shows how the UK distinguishes itself from the US counterpart in two main features: the persistent polarized shape of the employment distribution since at least the 1980s, with growth in high skilled occupations always by far exceeding that in bottom ones, and the absence of wage polarization in any decade.

In light of the emerging literature debate, the UK offers an interesting context for testing the causal effect of exposure to technological change.

On the policy side, understanding the determinants of job polarization can advice policy makers in designing policies to best promote a sustainable economic growth. This is especially salient given the widespreading feeling of technological anxiety (Mokyr et al., 2015). The changing structure of the labour market raises important policy challenges in terms of job quality and occupational mobility. On the one hand, middling workers facing loss of their jobs are most likely to look towards lower-paying jobs. On the other hand, the decline in middle-pay jobs can undermine the chances of the low-paid workers of moving up the occupational ladder.

This paper provides new evidence on employment polarization in the UK. The aim is to disentangle the causal effect of technological exposure while providing suggestive evidence on the role of labour supply changes in shaping the polarized structure of employment during the last two decades (1993-2013).

The empirical strategy builds on the spatial analysis approach of Autor and Dorn (2013) and exploits geographical variation across local labour markets in their historical specialization in routine-intensive industries to identify the causal effect of technological exposure on employment changes. Employment data is derived from the Quarterly Labour Force Survey (QLFS) and local labour markets are proxied by Travel to Work Areas (TTWAs), statistical units developed by the Office for National Statistics (ONS) for the specific purpose to bound commuting zones. The construction of time-consistent local labour markets is based on the novel use of geographical weights mapping wards to TTWAs. The use of TTWAs as measures of local labour markets is validated by the unresponsive mobility of the working-age population to technological exposure observed across these areas.

The instrumental strategy relies on variation obtained from the industrial and employment mix across TTWA observed in the Census for England and Wales in the year 1971, about a decade before the boom in workplace computerization (Autor et al. 1998, Bresnahan, 1999; Nordhaus, 2007). The study is complemented by the use of longitudinal Census data spanning 1971-2011 in order to provide a finer insight into employment changes.

The econometric analysis confirms the fundamental role of technology in shaping the hollowed out structure of employment. Local labour markets that were initially specialised in routine intensive occupations exhibit larger declines in non-graduate routine employment, with its reallocation to non-routine manual occupations. However, no effect of technological exposure is found on skilled top occupational employment changes. This evidence may indicate that the growing pool of graduates may have out-weighted the demand for skills.

Because of the rapid educational catch-up, higher start-of-the-period local human capital is in fact negatively associated with employment growth in graduate non-routine cognitive occupations during the 1990s. High-skilled immigrant concentrations are instead positively associated with graduate top employment growth in both decades. At the bottom, initial local labour supply factors do not show any relevant significance. However, graduate supply changes appear negatively related with growth in non-routine manual occupations in both decades and the magnitude of this association grows over time. This set of resutls provide supportive evidence of a mere supply-side effect of the educational upgrading of the population.

Finally, the analysis of individuals' occupational transitions uncovers that the UK seems to have entered an occupational downgrading process since the 1990s, but affecting non-graduates twice as much as graduates. The suggestive evidence is that there are two major forces at play: the decline in routinization explains the hollowing out of the employment distribution, while the raising supply of graduates is increasing job competition along the employment distribution.

The remainder of the paper is as follows. Section 2 reviews the relevant economic literature, section 3 describes the data sources, the definition of local labour markets and the routine intensity measure. Section 4 presents descriptive evidence on employment polarization by occupational, educational, demographic groups and by labour market area. Section 5 specifies the estimation strategy and section 6 discusses the empirical results. Section 7 analyses individual occupational transitions. Section 8 concludes.

2 Literature Review

The ALM thesis predicts that technological change is biased toward replacing human labour in routine tasks, while leading to an increase in the relative demand for workers performing non-routine tasks. Routine tasks are defined as limited and well-defined activities which can be accomplished by following a set of rules and therefore are more easily codifiable to be executed by machines. These are typical of many middle-paid cognitive and manual jobs, such as bookkeeping, clerical work, repetitive production and monitoring. At the opposite ends of the occupational-skill distribution lie non-routine abstract and manual tasks. The former are typically performed by high-skilled workers such as managers, professionals as they require activities such as intuition, creativity, problem-solving. The latter refer to activities requiring physical dexterity or interpersonal communication, that are instead typical of low-skilled occupations, such as transportation, cleaning, meal preparation, personal care.
Technology substitutes for labour in routine tasks while complements it in non-routine abstract tasks. Non-routine manual tasks are instead not directly affected by technology. However, these are subject to general equilibrium effects. Autor and Dorn (2013) explain the growth of low-skilled service occupations through the interaction of two forces: on the one hand technological progress replacing low-skilled labour in routine occupations, while on the other hand, consumer preferences favouring variety over specialization such that goods cannot substitute services. The authors use repeated cross-sectional data from the US Census and Current Population Survey (CPS) and identify the effect of technological exposure on local labour markets exploiting variation in the degree of local historical specialization in routine-intensive occupations. Results show a RBTC-consistent greater decrease in routine employment and greater increase in service employment in historically routine-intensive areas. Beyond routine-intensity, Autor and Dorn (2013) have considered alternative hypotheses of job polarization, i.e. the increasing relative supply share of graduates and of low skilled immigrants, the aging of the population and the growing offshorability of job tasks. Many of these explanatory factors receive empirical support but none of them appears to play a leading role.
Cortes (2016) uses individual-level panel data from the Panel Study of Income Dynamics (PSID) for the period 1976-2007 and focuses on testing the RBTC effect by looking at the occupational transition patterns and wage changes of routine workers. The study shows that since the 1990s routine workers become more likely to switch to either non-routine cognitive or manual jobs. In particular, there is strong evidence of selection on ability, with low-ability routine workers more likely to reallocate to non-routine manual jobs and high-ability routine workers more likely to move upward into non-routine cognitive jobs. This U-shape pattern is not found in non-routine

occupational categories. Also, the wage premium for stayers in routine occupations has significantly fallen with respect to non-routine manual occupations. This evidence is interpreted as supporting the RBTC hypothesis.

In the UK, the first evidence on job polarization has been provided by Goos and Manning (2007). The study uses repeated cross-sectional data from the Labour Force Survey (LFS) and looks at the period 1979-1999. A conterfactual exercise tests the routinization hypothesis against changes in the composition of the labor force, i.e. the increasing employment of women, of graduates, and the changing age structure in the labour market. The authors conclude that the routinization hypothesis provides the most plausible explanation for the polarized shape of the employment distribution.

Goos et al. (2014) and Akcomak et al. (2013) investigate the role of routinization and offshoring for Europe and the UK respectively. Both factors contribute in explaining employment changes, although routinization has a much more substantial effect.

More recently, Salvatori (2015) complements and extends the analysis of Goos and Manning (2007) up to 2012. The contribution of compositional changes in shaping the employment structure is assessed using a shift-share analysis where the labour force is divided into education-age-immigration-gender cells. Results indicate that the most distinctive feature of the UK labour market is the increase in the share of graduates that has accounted for the reallocation from middling to top occupations in each decade. In parallel, median wages of high-skilled workers has progressively deteriorated reaching the lowest growth across the employment distribution. Furthermore, the loss in middling occupations during this 30-year span is entirely experienced by non-graduates, who mostly appeared to reallocate to the lower tail of the distribution. Finally, also graduates have been sustaining employment growth in bottom occupations, but only during the 2000s their contribution exceeded that of non-graduates for the first time. Immigrants also started to play a more important role in the last decade and appear employed in all three categories, with larger contribution at the extremes. This study suggests that changes in the structure of the labour supply in the UK could play a much more important role than what previously considered by the literature.

The demographic composition of the labour force in the UK in the last two decades has in fact changed dramatically, mainly reflecting a rapid educational upgrading and surging immigrant inflows. As Salvatori (2015) points out, while these labour force changes might be partly endogenously driven by changes in demand, they are likely to have been largely affected by important institutional changes.

Until the mid-1980s, the UK was particularly lagging behind other OECD countries in terms of educational achievement. Since then, successive governments have pursued the objective to improve educational stardards (Machin and Vignoles, 2005).

In part, this was achieved with the introduction of the General Ceritificate of Secondary Education (GCSE) in 1988, which switched the grading method from "norm-referencing" to "criteria referencing", thereby increasing the proportion of pupils achieving higher grades and potentially enrolling in higher education (Bolton, 2012). Another relevant reform was the abolition of the so called binary divide between polytechnic institutions and universities in 1992, granting university status to 48 polytechnics and therefore widening the available university places. As a result, the participation rate in higher education increased sharply from 19.3% in 1990 to 33% in 2000 (Salvatori, 2015; Bolton, 2012).

In addition, the UK has started to experience large flows of immigration since 1997. In 1997 the incoming labour government shifted from a strict immigration policy limited to asylum and family reunion to considering immigrants as a resource and thereby favouring economic immigration. Further on 1st May 2004, the UK was one among very few countries in Europe (i.e. Ireland and Sweden) that opened the doors to new EU member states' citizens (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia). Immigration to the UK unexpectedly skyrocketed. the Worker Registration Scheme (workers from A8 countries were required to register on this scheme within a month of joining a new employer) concluded in 2011 with nearly 1,1 million applications (Home Office, 2009, 2011) of which about 700,000 were made by Polish nationals.

Salvatori's (2015) evidence highlights the contribution of labour supply changes while challenging the leading role of technological exposure. Indeed, the main challenge in disentangling the effect of labour supply changes from technology is the embedded relationship between the two. This paper focuses on isolating the causal effect of technological exposure on employment, while tries to provides some suggestive evidence on the role of labour supply changes. To the best of my knowledge, this is the first study which investigates the causal effect of technological exposure on the UK local labour markets. Another important contribution is the use of longitudinal information on individuals' occupational transitions which allows to provide more disaggregated evidence on the evolution of the UK skill-employment distribution.

3 Data sources and measurement

The main data source comes from the UK Quaterly Labour Force Survey (QLFS) and covers the two-decade period 1993-2013. The QLFS represents the primary source of labour market statistics for the UK including a wide range of employment-related and demographic information. The QLFS is a household survey conducted by the Office for National Statistics (ONS). It comprises a single-stage sample of households, implicitly stratified by geographical ordering. Since 1992 it has a quarterly frequency and a rotating panel structure such that each individual is staying in the sample for five consecutive quarters. Each quarter covers approximately 100,000 individuals, making up about 0.2 % of the UK population.

In order to avoid duplicates due to the rotating sample design of the QLFS, only individuals at their first interview are retained. In addition, I boost the sample size by pooling together 1993-1994, 2003-2004 and 2013-2014 waves. I make use of the available personal weights to make the sample representative of the UK population and to correct for non-response.

The analysis is complemented by a random longitudinal data sample from the ONS Longitudinal Study (LS). The LS includes a complete set of individual records linked between successive censuses during 1971-2011. The sample is composed of people born on one of four selected dates of birth, covering about 1% of the total population of England and Wales.

I restrict the sample of analysis to employees in paid work aged between 16 and 64 in England and Wales. Occupations in the QLFS and LS were originally coded according to either the UK Classification of Occupations or Standard Occupational Classification (CO70, CO80, SOC-90, SOC-2000 and SOC-2010). I reclassify occupations according to the International Standard Classification of Occupations (ISCO-88) and use probabilistic matching to create concordance across occupational codes over time. Occupations are defined at the two-digit level. Armed forces and agriculture-related occupations are excluded from the sample (ISCO 10, 61 and 92). An extra number of occupations (ISCO 11, 23, 44, 99) are dropped in order to match the data to the Routine Intensity index measure from Goos et al. (2014). Employment is measured as total usual weekly hours multiplied by 52 calendar weeks. Hourly wages are measured as average gross earnings over average total paid hours during the reference week.

The spatial units of analysis are local labour markets which are proxied by TTWAs. These are generated such that at least 75 percent of an areas' resident workforce live and work in the same area. The QLFS did not include TTWA information until 2002. Furthermore, these areas are redefined over time. I refer to the 2007 definition, according to which in England and Wales there is a total 186 TTWAs. I construct time-consistent local labour market areas through the novel use of geographical weights mapping wards to TTWAs[1].

Technological change exposure is measured by specialization in routine-intensive occupations with the Routine Task Intensity (RTI) index. This index was first proposed by ALM, who use the 1977 US Department of Labor's Dictionary of Occupational Titles (DOT) to define the routine, abstract and manual task content of occupations. This information is merged to occupational data to provide a summary index increasing in the routine task importance and decreasing in the non-routine manual and abstract task importance. The index formula, applied to the sample base year 1993 is as follows:

$$RTI_k = ln(T^R_{k,1993}) - ln(T^M_{k,1993}) - ln(T^A_{k,1993}) \quad (1)$$

where $T^R_{k,t_0}, T^M_{k,t_0}, T^A_{k,t_0}$ are the routine, manual and abstract task components for occupation k in 1993.

As previously mentioned, I adopt the RTI classification from Goos et al. (2014), who use the same RTI index constructed by Autor and Dorn (2013) based on the ALM DOT task measures. The authors map the RTI index from the US census nomenclature to ISCO-88 and then standardize it across 2-digit occupational codes. Following Autor and Dorn (2013), I then measure routine-intensity within TTWAs by classifying as routine those occupations in the highest employment-weighted third share of the RTI measure in 1993. Accordingly, table 1 shows the 1993 employment distribution ranked from high to low RTI values and shows the

[1]There is a highly unique matching rate (above 96%) between wards and TTWAs. Geographical weights are created for wards overlapping with more than one TTWA. These are proportional to the area share of the ward falling in each TTWA it overlaps with.

occupational mix representing the set routine-intensive occupations in the sample. Finally, the local labour market share of routine employment is computed as:

$$RSH_{jt} = (\sum_{k=1}^{k} L_{jkt} * 1[RTI_k > RTI^{66}])(\sum_{k=1}^{k} L_{jkt})^{-1} \qquad (2)$$

Where L_{jkt} is employment in occupation k in TTWA j at time t, 1[.] is the indicator function taking value of one if routine intensive. The grand mean of RSH is 0.25 in 1993, and the interquartile range (Iqr, henceforth) is 7 percentage points.

4 Descriptive evidence

4.1 Employment polarization by occupational groups

Previous studies document a clear job polarization pattern for the UK, Goos and Manning (2007) for the period 1979 to 1999 and Salvatori (2015) for the period 1979 to 2009.

Figure 2 shows the changes in employment shares during the period 1993-2013. Occupations are grouped into employment-weighted deciles of the 1993 wage distribution. The figure shows the typical U-shaped pattern of employment polarization with greatest growth at the top of the distribution, confirming the literature's findings.

Table 2 shows the levels and changes in employment shares by major occupational groups (2-digit level) in England and Wales between 1993 and 2013. Occupational groups are ranked by average log hourly wages[2]. We can observe the polarization pattern with middle-paying occupations exhibiting relative declining shares with respect to the top and the bottom. The last column shows the RTI index measure from Goos et al. (2014). The categories experiencing higher growth among top occupations are corporate managers (+2.65pp) and physical, mathematical and engineering science professionals (+1.66pp). Bottom occupational categories represent a mixture of service and sales-related jobs. We can observe that bottom employment growth (+5.05pp) is driven by personal and protective service workers (+3.82pp). The middle occupations registering the highest employment losses are machine operators and assemblers (-3.07pp); office clerks (-2.64pp); metal, machinery and related trade workers (-2.43pp).

Importantly, the polarization trend is not unique to the manufacturing industry. Table 12 in the Appendix shows that occupational categories losing the most are machine operators, assemblers and craft related ones in the manufacturing sector while office clerks in the non-manufacturing one.

This is in line with evidence from Autor et al. (2015) for the US, and suggests the pervasive computerization across the economic sectors.

The last column of table 2 reports the RTI values, which appear generally consistent with the polarization pattern. The highest positive values are associated to middle-ranked occupations.

[2]Log hourly average wages are computed across all the years in the period 1993-2013. The wage distribution for the period 1993-1996 is taken from respondents in interview 5 because of data limitation.

Occupations at the top are more intense in the abstract task dimension and show negative RTI values, while at the bottom the values are either negative or near zero.
The occupational categories in bold are defined a routine-intensive following the criteria from Autor and Dorn (2013) as explained in section 3. Finally, I define the occupations in the top category as non-routine cognitive, while the remaining occupations in the bottom category as non-routine manual.

4.2 Employment polarization by demographic groups

Figure 3 shows changes in employment shares in each decade between 1993 and 2013 for graduates and non-graduate workers by major occupational groups, ranked by average log hourly wages.
Graduates represent workers with a degree or higher educational qualification; non-graduates are divided into GCE A level, GCSE educational qualifications, other qualifications and no qualifications.
The plots show that the categories experiencing employment losses in the middle-paying jobs are non-graduates. This negative change is partly counterbalanced by an increase of non-graduate employment in low-paying occupational groups. Graduate workers have instead gained employment shares along the whole occupational distribution, but in larger magnitude at the top and bottom. It is important to point out that the UK QLFS until 2010 included foreign educational qualifications in "other qualifications" category. For this reason the comparison of qualification levels between immigrants and natives is problematic. Figure 4 breaks down employment share changes by immigration status.
Figure 4 shows that only the employment distribution of native workers appears polarized, accounting for the entire decline in middle-paying occupations. Immigrants positively contribute in all major occupational groups, with higher presence at the two extremes of the distribution. During the 2000s the contribution of immigrants to employment growth at the extremes overcomes that of natives. For completion in figure 5 I replicate the same analysis distinguishing by gender. We can observe that the polarization phenomenon does not seem to be gender-specific. Both men and women lose employment share in middle occupations while gain at the extreme. However, the redistribution of employment between the two groups is unequal, with women disproportionately gaining shares in technical and associate professional activities at the top and in sales and services occupations at the bottom.

4.3 Employment polarization by labour market area

Table 3 shows the grandmean, standard deviation and interquartile range for TTWA's routine employment shares and the relative graduate and immigrant population shares. The relative

supply shares are taken as ratios with respect to the non-graduate population.[3].
As expected, on average the employment share in routine-intensive occupations decreases over time, losing 7 percentage points in two decades. On the contrary, the relative shares of graduates and immigrants increase over time. In particular, $GradSH$ increase substantially in both decades, more than doubling between 1993 and 2013 (+0.32 pp). $ImmSH$ registers an acceleration during the 2000s, due to higher inflows of both high and low skilled immigrants. Over the two decades, the relative shares of high and low skilled immigrants increase by 4 and 5 percentage points respectively.
Figure 6 gives a visual idea of the geographical variation in relevant variables across TTWAs in the year 1993. Local labour markets that are more intense in routine employment seem to be most concentrated in regions with higher manufacturing specialization, i.e. in the Midlands, Northern England and in Wales. Graduate and immigrant working shares are instead quite spread geographically, with high presence also in the Southern-East regions which are typically more specialized towards professional, scientific and technical activities.
The UK, like the US and other European countries documents a two-fold trend in employment. On the one hand the economy exhibits a long-run trend of increasing education, with younger cohorts better educated than older ones. On the other hand it shows a long-run trend of declining routine-intensive employment. In the remaining part of this section I provide geographical evidence of such trends across UK local labour markets.
In the top panel of figure 7 I plot for each decade the start-of-the-period routine employment share on the x-axis against the next period routine employment share on the y-axis for each TTWA in the sample and I superimpose the 45 degree line. The plots document that local routine employment shares have not fallen everywhere but it is clear that the bulk of areas with initial routine intensity above the grandmean (0.25) lie below the 45 degree line.
Secondly, I plot the start-of-the-period levels of local routine employment share on the x-axis versus the relative decadal changes on the y-axis. The figures highlight a strong negative relationship in both decades, indicating that TTWAs with higher starting routine employment shares exhibit the larger declines.
The same exercise is repeated for the graduate population share. The plots in the top panel of figure 8 show that the average share of graduate labour supply has increased almost in all TTWAs. When looking at employment changes in the bottom panel, the bottom left plot shows a generalized educational catch-up during the 1990s: TTWAs starting with lower levels of human capital stock in 1993 exhibit the greater increases in the local labour supply of graduates. This pattern halts in the 2000s, where no significant relationship is found.
Finally, figure 9 plots the contemporaneous change in the graduate population share against the change in the routine employment change for each decade. Both decades show a negative relationship between the two variable. The pattern is consistent with the skill-complementarity of routine biased technological change, i.e. TTWAs experiencing the highest declines in routine employment register positive changes in the population share of graduates. However, the

[3]I follow the literature (Manacorda et al.,2012; Bisello,2014) in defining as low-skilled immigrants who left education before 21 years of age or that never had education, and viceversa for high-skilled immigrants.

relationship is clearly two-way so that no causal statement can so far be claimed.

5 Estimation strategy

In order to disentangle the causal effect of technology exposure on the polarization of employment I build on Autor and Dorn (2013) and adopt a spatial analysis approach exploiting variation across UK local labour markets depending on their intrinsic historical specialization in routine intensive occupations.

The RBTC hypothesis predicts the progressive substitution of technology for labour in routine tasks. On the one hand, this force will raise the relative demand for high-skill labour, who hold comparative advantage in performing non-routine cognitive tasks. On the other hand, the marginal routine worker will reallocate to non-routine manual occupations under the assumption that their relative comparative advantage is higher in low-skilled than high-skilled tasks. As a consequence, local labour markets with initially higher specialization in routine-intensive occupations should experience greater relative employment decline in routine employment (1) while experience greater relative employment growth in non-routine manual (2) and cognitive occupations (3). I test the routinization hypothesis with the following regression model:

$$\Delta Y_{jt} = \alpha + \beta_1 RSH_{jt-1} + X'_{jt-1}\beta_4 + \gamma_s + \delta_t + \epsilon_{jt} \tag{3}$$

Where ΔY_{jt} may represent the decadal change (1993-2003, 2003-2013) in local employment share in either (1) routine, (2) non-routine manual or (3) non-routine cognitive occupations measured as described in sections 3 and 4.1. The main regressor of interest, RSH_{jt-1}, is the local employment share in routine occupations. The vector X includes a set of covariates controlling for potential shifts in the local supply and demand. The set includes the local relative shares of graduates and immigrants, measured as ratios to the non-graduate working-age population, and the local initial share of manufacturing employment. The latter may proxy for other labour demand shifts than technological change occurring in the manufacturing sector such as the recent acceleration in the exposure to international import competition since China's accession to the WTO.

All specifications include dummies for 11 Nomenclature of Territorial Units for Statistics (NUTS1) to control for time-invariant geographical unobserved heterogeneity[4]. The stacked regression also includes dummies for each decade to account for aggregate changes over time. Regressors in the main specifications are taken at their start-of-the-period levels rather than as contemporaneous changes in order to avoid simultaneity bias.

However, estimates may be biased due to the presence of time-varying local specific unobservables, which might affect both routine or non-routine employment and our regressors of interest. To address this endogeneity issue I exploit 1971 Census data and follow Autor and Dorn (2013) in using the historical local industry and employment mix in order to instrument current rou-

[4]NUTS1 regions are: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales and Scotland.

tine employment share levels. This generates an exogenous source of variation across TTWAs which will isolate the long-run quasi-fixed component of routine employment pre-determined by the initial differences in industry specialization from contemporaneous technological shocks. The instrument is constructed as follows:

$$RSH_j^{IV} = \sum_i E_{i,j,1971} * R_{i,-j,1971} \quad (4)$$

Where $E_{i,j,1971}$ is the employment share in industry i in TTWA j in 1971, while $R_{i,-j,1971}$ is the routine occupation employment share in industry i in all regions except the one including TTWA j.

The use of the 1971 industrial structure to predict RSH, two decades before the sample of analysis and around a decade before computer technology boomed across the UK, should lessen any endogeneity concerns arising from current economic shocks affecting routine employment.

6 Results

6.1 Hollowing-out of routine employment

The first outcome of interest is changes in routine employment. Table 4 compares OLS and 2SLS results for the stacked and single period regressions. RSH coefficients appears smaller in the 2SLS analysis where endogeneity has been controlled for by the instrument. While OLS results suggest a significant negative effect of technology exposure on both graduate and non-graduate wokers, 2SLS estimates confirm previous descriptive evidence depicting job polarization as a non-graduate phenomenon. Recall that the Iqr for RSH in 1993 is 0.07. 2SLS estimates in column 1 indicates that a TTWA with a routine employment share at the 75th percentile in 1993 decreased the non-graduate routine employment share on average by decade by around 3.3 percentage points more than a TTWA at the 25th percentile. Single decade estimates (columns 2-3) reveal that the magnitude of this effect decreases over time but appears significant only during the 1990s. The RSH coefficient for the second decade is in fact quite imprecisely estimated and thus not significantly different from zero.

The 2SLS estimates in columns 1-3 suggest a significant effect of technological exposure on total routine employment changest. However, the RSH coefficients in columns 4-6 lose their overall negative sign and do not appear statistically significant. The RSH coefficients in columns 7-9 suggest instead a sizeable technology-induced contraction in local non-graduate routine employment. In particular, the 2SLS RSH point estimate in column 4 indicates that the decadal average Iqr differential effect is of around 3 percentage points. Single decade estimates (columns 5-6) reveal that the magnitude of this effect seems to decrease only marginally for non-graduate employment over time but again results significant only during the 1990s.

These estimates appear somewhat larger than what found by Autor and Dorn (2013) for the US. Their OLS findings show a 1980-2005 decadal average negative association of 1.8 percentage points higher for commuting zones starting at the 80th percentile of the routine employment distribution than those at 20th percentile.

The instrumental variable strategy I exploit is appropriate as long as the historical local differences in industrial specialization have significantly persisted over time. The table reports the Kleibergen-Paap F-statistics from each of the first-stage regression. The 1971 industrial structure is a significant predictor of recent routine employment but naturally decreasing over time. The statistics' values for 1990s and 2000s are 47 and 18, both above the Staiger and Stock's (1997) rule of thumb threshold of 10.

In table 5 I further investigate the role of labour supply and demand shifters in hollowing out of non-graduate employment in middling occupations. In columns 1-3 the specifications include the start-of-the-period relative local shares of graduates and immigrants. $GRADSH$ appears only significant in the stacked regression specification. Given an Iqr of 0.09, the point estimate for $GRADSH$ indicates that the average differential negative effect for TTWAs with initially higher stock of human capital is of around 0.5 percentage points. Higher local initial immigrant concentrations appear instead positively associated with employment changes in non-graduate routine employment during the 1990s.

In columns 4-6 I condition on the initial share of manufacturing employment, which is highly correlated with the main variable of interest (ρ_{1993}=0.58 and ρ_{2003}=0.38). This makes the RSH coefficient increase in magnitude in the first decade regression even though statistically non-significant, while in the 2000s, where the effect of RSH is entirely captured by the manufacturing variable.

Overall, these estimates provide a quite robust piece of evidence of technology-induced polarization, mainly happening during the 1990s.

6.2 Reallocation to non-routine manual employment

In the ALM model, workers' supply is driven by comparative advantage. Autor and Dorn (2013) provide a framework in which the continuosly falling price of technology induces low-skilled workers to reallocate from routine to non-routine manual tasks, at the bottom of the employment distribution. Table 3 suggests the progressive displacement of non-graduate employment in routine intensive occupations. In table 6 I investigate the employment changes at the bottom tail of the distribution, testing the reallocation of non-graduate workers in non-routine non-manual jobs. Table 6 displays the estimates of the regression model for the employment changes in non-graduate non-routine manual employment. The first panel shows the OLS results. Columns 1-3 enter the start-of-the-period local routine employment share alone, while columns 4-6 control for the initial relative labour supply shares of graduates and low-skilled immigrants. The inclusion of the control variables decreases the magnitude of the RSH coefficient. 2SLS estimates do not substantially differ from OLS ones. Looking at the most restrictive 2SLS specifications, the Iqr differential effect for RSH on local non-routine manual employment across the two decades is about 1.5 percentage point. This estimate is again slightly higher than in Autor and Dorn's (2013) analysis. Their 2SLS estimates suggest an average decadal effect of 0.8 percentage points for the 80-20th percentile differential of the routine employment specialisation during 1980-2005. found in Autor and Dorn (2013) for the employment growth in service occupations alone in the US between 1980 and 2005.

When separating the analysis by decade, the reallocation effect appears to get stronger over time, from 1.5 percentage points in the 1990s to almost 2 percentage points in the 2000s. Although, again the RSH coefficient is poorly estimated and turns not significant in the second decade regression. The initial relative shares of graduates and of low-skilled immigrants do not appear to play any role.

In the last columns (7-9) the specification includes the initial local share of manufacturing. Estimates appear in line with previous findings in table 5. Manufacturing concentration is in fact significantly positively correlated with employment changes in non-graduate non-routine manual employment in the last decade. Following the literature, in the next table (7) I explore alternative hypotheses for the reallocation of workers to non-routine manual employment, i.e the role of offshoring and of demographic changes in the labour force.

I measure offshorability using an index developed Blinder and Krueger(2013) and mapped by Goos et al. (2014) into ISCO88 2-digit occupational codes [5]. I compute the local offshorable employment share following the same procedure as for local the routine-employment share, i.e. the TTWA-level top employment third of the Offshorability Index. The variable grandmean is 0.27 and the Iqr is 0.06.

Results are shown for the 2SLS estimates. Columns 1-3 control the start-of-the-period share of local offshorable employment. The $Offsh$ coefficients suggest quantitatively very small effects and do not appear significant. The RSH point estimates barely change while turning not significant possible because of the very high correlation between the two measures (ρ_{1993}=0.86 and ρ_{2003}=0.84). In line with Autor and Dorn (2013) I further consider the role of local demographic changes and analyse two different channels: the increasing graduate working share could boost non-routine manual employment through either a substitution effect or an income effect. Such hypotheses suggest that the employment of unskilled workers is increasingly dependent on the physical proximity to skilled ones as the latter have a high opportunity cost of time and are expected to be net buyers of time-intensive services performed by the former. Other related demand-based hypotheses are the increasing feminization of the labour market or the ageing of the population, as working women or pensioners could in turn raise the demand for in-house services (Manning, 2004; Ragusa and Mazzolari, 2013; Autor and Dorn, 2013). Consumption spillovers of high-skilled workers subsituting market for home services is proxied by changes in average annual usual hours worked by graduates. Income effects are proxied by changes in the 90^{th} percentile of weekly wages[6]. Table 6 shows the 2SLS estimates. The direction of the

[5] Goos et al. (2014) adopt Blinder and Krueger's (2013) preferred offshorability measure. This measure is based on professional coders' offoshorability assessment of workers' description of their job tasks in the Princeton Data Improvement Initiative (PDII) survey. The questions in the survey to evaluate self-reported offshorability regard the requirement of face-to-face or physical presence at the job and whether the task could be performed at a remote location without substantial quality deterioration.

[6] Results do not change if the 75th percentile is used instead

estimated associations appear in line with Autor and Dorn (2013). The negative point estimate for changes, $GradHRS$, shows evidence against consumption spillovers while pointing towards a mere supply-side substitution effect. $GradHRS$ is significantly associated with non-routine manual employment changes in both decades and increases in magnitude over time. Furthermore, there is no evidence for income effects. Finally, neither the change in the population share of senior citizens (aged 65+) nor the change in the share of working women show relevant contributions. Results appear in line with Autor and Dorn's (2013) findings and confirm the driving role of technological exposure in fuelling employment growth at the bottom of the occupational skill distribution.

6.3 Changes in non-routine cognitive employment

The analysis has so far provided empirical evidence for non-graduate routine-task work displacement and its subsequent reallocation at the bottom of the employment distribution. A further emerging relevant factor is that changes in graduate employment are significantly negatively related to employment growth in non-graduate bottom occupations and the association is growing over time.

I complete the picture by switching the focus to the upper tail of the occupational distribution and investigate employment changes in non-routine cognitive employment.

The RBTC hypothesis predicts increases in the relative demand for non-routine cognitive tasks, through a direct complementarity between high-skilled workers and computer technologies. In this section I test whether historically routine intensive areas have registered any employment growth in high-skill (high-wage) occupations such as professional and managerial ones.

Table 8 focuses therefore on graduate employment outcomes.[7]. While the OLS point estimates for RSH suggest significant employment gains, this association is wiped away when using the instrumental variables estimation. Furthermore, the 2SLS RSH point estimates decrease substantially when labour supply controls are plugged-in.

The absence of a technology-induced effect may indicate that the increase in the supply of high-skilled workers might have out-weighted the demand for skills. This hypothesis is reinforced by the negative point estimate for the start-of-the-period local relative graduate labour share.

$GradSH$ is significantly negatively associated with top employment changes only during the 1990s. This association reflects the descriptive evidence from section 4.3, which depicts a general educational catch-up across areas during the 1990s, where TTWAs with initially higher human capital stock registering the smallest increases in the share of graduates. The coefficient for $GradSH$ indicates that the Iqr differential for initially more human capital-intensive areas is of about -2 percentage points.

Initial local high-skilled immigrants' relative labour supply is instead strongly positively related to graduate employment changes at the top of the distribution during each decade. The average decade Iqr differential association for $HighImmSH$ is of about 4 percentage points. Single

[7]The estimated results for non-graduate employment are non-significant, confirming the essential reallocation of the marginal non-graduate routine worker to lower-skilled occupations.

decade regressions show that this effect is higher during the 1990s. This is consistent with the outlined policy context of the UK. Between the late 1990s and the enlargement of the European Union, the government specifically supported high-skilled economic immigration. Finally, in the last three columns (7-9) I plug in the initial share of manufacturing employment. This does not alter the main results. However, the initial share of manufacturing employment appears significantly negatively correlated with changes in graduate non-routine cognitive employment during the 2000s. The variable may capture the impact of exposure to international trade. The negative association of $ManufSH$ appears broadly in line with Bilici's (2015) findings of a detrimental effect of China's import exposure on graduate employment during the period 1998-2013.

6.4 Effects on the working-age population and robustness checks

The empirical evidence from the spatial analysis described above is valid as long as the mobility responses to technological shocks of the local population are weak. If technological change induces local workers to move in or out of localities, the employment effect of technology would disperse through the national economy. This would undermine the ability to identify the direct effect of technology within local labour markets. The dependent variable in table 9 denotes the change in the log of the overall, graduate and non-graduate local working-age population. 2SLS estimates show that local initial routine intensity does not lead to any significant substantial change in the working age population. This confirms the adequacy of the empirical strategy.

In table 10 I check the sensitivity of the technological exposure effect when controlling for contemporaneous labour supply changes. The table reports the OLS and 2SLS RSH coefficients for the routine, non-routine manual and non-routine cognitive main specifications. The plug-in of contemporaneous labour supply changes does not significantly alter the interpretation of the main results.

Finally, as a robustness check with respect to the definition of routine intensity, table 11 reports the estimated RSH coefficients where the set of routine-intensive occupations is extended to the top employment-weighted 40% of the RTI index. The results do not relevantly differ from the main analysis, although show a more substantial relevance of labour supply changes in the polarization of the employment distribution. Furthermore, the negative RSH coefficient in panel C confirms that technological change does not appear to have contributed to growth in non-routine cognitive employment.

7 Occupational transitions

In this last section I complement the analysis with the use of a 1% random longitudinal Census sample covering the period 1971-2011.

This sample links individuals' census records over their lifespan. The tracking of individuals' job transitions allows to perform a finer-level analysis on the employment changes. Furthermore, transitions are analysed decade by decade in a longer time span and separately for graduates

and non-graduates. This is specifically done with the purpose to assess the contribution of the recent labour supply changes in shaping the current employment structure.
The mobility process can be depicted using a transition matrix, such that:

$$Occ_t = P * Occ_{t-1} \tag{5}$$

Where Occ_{t-1} and Occ_t represent the vectors of the marginal occupational distributions in periods $t-1$ and t respectively. P is the m x m probability matrix characterising the transition process by determining the probability that an individual in occupation i at time $t-1$ remains in the same job or transits to another occupation $j \neq i$ in next period.
Occupational concordance has been created following the same probabilistic matching procedure used for the main sample of analysis as discussed in section 2. Such method assigns each individual A with a conditional probability $w_{i,j}$ at each point in time for each occupational pair (i,j). With the simplifying assumption of independence between occupational distributions over time, I compute the transition probability entries of matrix P as following:

$$p_{i,j} = P_{i,j}/p_{i,0} = \sum_{A=i}^{n}(w^A_{i,j,t-1} * w^A_{i,j,t}) / \sum_{A=i}^{n} w^A_{i,t-1} \tag{6}$$

where, for each individual A, the first component gives an estimate of the joint probability to belong to the occupational transition pair (i, j) during the period $t-1$ to t and the second component gives an estimate of the marginal probability of being employed in occupation i at time $t-1$.
I compare the exit probabilities for each skill category of workers, middle, bottom and top across each decade. The whole matrices are available in the Appendix.
The first two decades are characterized by a similar occupational trend, with relatively high occupational mobility. The picture changes since the 1990s, in coincidence with the great expansion in the pool of graduates. There is a sharp increase in the probability of switching from middle to bottom occupations, twice more pronounced for non-graduate individuals. The percentage of non-graduate middle workers reallocating towards the bottom of the distribution appears stable at around 3% between 1971 and 1991, while jumping thereafter to 8% in the 1990s and again to 15% during the 2000s.
However, this pattern is not unique to middle workers. Non-graduate employees in top jobs become more likely to move down the occupational ladder to middle jobs. The occupational transition probability again changes from a stable 6% between 1971-1991 to 12.5% during the 1990s and further to 31% during the 2000s. At the same time, non-graduate bottom workers register a progressive marked decline in the probability to move to top occupations within the decade.
Results contrasts with literature findings for the US. Cortes (2016) observes that, since 1990s, the probability of switching to both types of non-routine occupations increases. This is interpreted as confirming the RBTC hypothesis. Furthermore, the probability to switch to non-routine cognitive jobs increases more than the probability to switch to non-routine manual jobs.

This is clearly not the case for the UK, where there the increase in the outflows is concentrated towards the bottom of the distribution. This uncovers the role of the educational upgrading as an accelerating force of polarization.

8 Conclusions

This paper advances the literature on employment polarization in the UK. The main contribution is the identification of the effect of technological exposure on the occupational structure. The empirical strategy builds on the spatial analysis approach of Autor and Dorn (2013) and exploits geographical variation across local labour markets stemming from their historical specialization in routine-intensive activities to identify the causal effect of technological exposure during the period 1993-2013. The study is complemented with longitudinal census data spanning 1971-2011 in order to provide a further test for the routinization phenomenon and look at the evolution of the employment-skill distribution.

The econometric analysis shows that technological change has merely substituted routine labour and caused a downward shift of the marginal less-skilled middle workers. However, no effect is found at the top of the employment distribution.

Additionally, there is some suggestive evidence on the long-run effect of demographic factors on employment changes. TTWAs show a general educational catch-up during the 1990s, with initially higher human capital-intensive areas showing the smaller increases. These same areas are significantly associated with lower growth in graduate non-routine cognitive employment during this decade.

Initial local high-skilled immigrants' concentrations are instead strongly positively associated with graduate employment changes at the top of the distribution during each decade.

At the bottom, initial local human capital stock conditions do not show any relevant association. Contemporaneous changes in the relative graduate labour supply shares are instead significantly negative related to non-routine manual occupations and the magnitude of this association is growing over time.

While the polarization phenomenon has been detected in the literature since at least the 1980s, the transitional analysis uncovers that the reallocation of non-graduates to the bottom of the distribution significantly accelerates during the 1990s, in coincidence with the dramatic changes in graduate labour supply. However, the 1990s also mark the progressive downgrading from top to middle to bottom occupation. The UK seems in fact to have entered an occupational downgrading process, but affecting non-graduates twice as much as graduates.

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Tables

Table 1: **RTI classification using the 1993 employment distribution**

Occupations	**Code**	**RTI**	**Level**	**Cumulative**	**Top 33%**
Office clerks	41	2.24	15.08	15.08	x
Precision, handicraft, printing and related trades workers	73	1.59	1.25	16.33	x
Customer service clerks	42	1.41	3.37	19.70	x
Other craft and related trades workers	74	1.24	1.87	21.57	x
Machine operators and assemblers	82	0.49	5.49	27.06	x
Metal, machinery and related trades workers	72	0.46	7.489	34.55	
Labourers in mining, construction, manufacturing and transport	93	0.45	2.84	37.39	
Stationary plant and related operators	81	0.32	1.02	38.41	
Models, salespersons and demonstrators	52	0.05	3.74	42.15	
Sales and services elementary occupations	91	0.03	4.08	46.23	
Extraction and building trade workers	71	-0.19	2.82	49.05	
Life science and health associate professionals	32	-0.33	1.36	50.41	
Physical, mathematical and engineering science associate professionals	31	-0.4	2.48	52.89	
Other associate professionals	34	-0.44	5.07	57.96	
Personal and protective service workers	51	-0.6	8.19	66.15	
Other professionals	24	-0.73	3.84	69.99	
Corporate managers	12	-0.75	8.97	78.96	
Physical, mathematical and engineering science professionals	21	-0.82	4.71	83.67	
Life science and health professionals	22	-1	3.34	87.01	
Drivers and mobile plant operators	83	-1.5	4.77	91.78	
General Managers	13	-1.52	8.23	100.01	

Table 2: Levels and changes in employment shares (2-digit), 1993-2013

Occupations	**Code**	**Log wage**	**1993**	**2003**	**2013**	**1993-2013**	**RTI**
Top							
Corporate managers	12	2.31	8.97	9.73	11.62	2.65	-0.75
PMES professionals	21	2.28	4.71	5.44	6.37	1.66	-0.82
Other professionals	24	2.18	3.84	4.26	4.91	1.07	-0.73
Life, science and health professionals	22	2.12	3.34	3.84	4.7	1.36	-1
PMES associate professionals	31	2.04	2.48	2.04	2.23	-0.25	-0.4
Other associate professionals	34	2.03	5.07	5.6	6.17	1.1	-0.44
General managers	13	1.98	8.23	8.16	8.6	0.37	-1.52
Middle							
Stationary plant and related operators	81	1.9	1.02	0.55	0.36	-0.66	0.32
Metal, machinery and related trades workers	72	1.85	7.48	6.17	5.05	-2.43	0.46
Life science and health professionals	32	1.8	1.36	1.5	2.24	0.87	-0.33
Precision, handicraft, printing and related trades workers	73	1.76	1.25	0.81	0.55	-0.69	1.59
Office clerks	41	1.72	15.08	14.74	12.44	-2.64	2.24
Extraction and building trade workers	71	1.71	2.82	3.49	2.73	-0.09	-0.19
Machine operators and assemblers	82	1.66	5.49	3.43	2.42	-3.07	0.49
Drivers and mobile plant operators	83	1.65	4.77	5.08	4.07	-0.7	-1.5
Customer service clerks	42	1.57	3.37	2.8	2.45	-0.92	1.41
Labourers in mining, construction, manufacturing and transport	93	1.51	2.84	2.5	2.16	-0.68	0.45
Bottom							
Personal and protective service workers	51	1.47	8.2	10.05	12.02	3.82	-0.6
Other craft and related trades workers	74	1.46	1.87	1	0.67	-1.2	1.24
Sales and services elementary occupations	91	1.35	4.08	4	3.75	-0.34	0.03
Models, salespersons and demonstrators	52	1.32	3.74	4.8	4.51	0.77	0.05

Note: Occupational categories is bold are those defined as roiutine-intensive following Autor and Dorn's (2013) criteria. Sample includes workers aged 16-64. Hourly wages are defined as average hourly earnings for the reference week. All calculations use labour supply weights.
Source: LFS, author's calculations.

Table 3: **Summary statistics of relevant variables, 1993**

	1993			2003			2013		
	Mean	**Std. Dev.**	**Iqr**	**Mean**	**Std. Dev.**	**Iqr**	**Mean**	**Std. Dev.**	**Iqr**
RSH	0.246	0.573	0.071	0.207	0.053	0.057	0.174	0.056	0.06
$GradSH$	0.237	0.075	0.093	0.35	0.115	0.143	0.563	0.339	0.267
$ImmSH$	0.042	0.031	0.037	0.055	0.04	0.042	0.096	0.06	0.069
$HighImmSH$	0.013	0.014	0.014	0.026	0.026	0.025	0.058	0.057	0.051
$LowImmSH$	0.039	0.029	0.036	0.045	0.035	0.042	0.081	0.057	0.069
$ManufEmpSH$	0.275	0.0915	0.12	0.213	0.083	0.103	0.163	0.078	0.091

Note: Sample includes workers aged 16-64. Hourly wages are defined as average hourly earnings for the reference week. All calculations use labour supply weights.
Source: LFS, author's calculations.

Table 4: **Changes in routine employment**

	All			Graduate			Non-graduate		
	1993-2013	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OLS									
$RSH_{j,t-1}$	-0.820***	-0.749***	-0.923***	-0.086**	-0.063**	-0.111***	-0.731***	-0.681***	-0.816***
	(0.051)	(0.052)	(0.083)	(0.020)	(0.020)	(0.040)	(0.044)	(0.051)	(0.070)
R^2	0.474	0.559	0.417	0.139	0.097	0.309	0.446	0.526	0.406
2SLS									
$RSH_{j,t-1}$	-0.465***	-0.519***	-0.347	0.021	-0.018	0.098	-0.488**	-0.499**	-0.454
	(0.406)	(0.108)	(0.296)	(0.041)	(0.042)	(0.118)	(0.108)	(0.106)	(0.278)
1Stage									
K-P F-stat	48.906	46.989	17.751	48.906	46.989	17.751	48.906	46.989	17.751
N	372	186	186	372	186	186	372	186	186
Period dummies	x			x			x		
Region dummies	x	x	x	x	x	x	x	x	

Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.

Table 5: **Changes in routine employment**

	Non-graduate					
	1993-2013	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**
OLS						
$RSH_{j,t-1}$	-0.785**	-0.720**	-0.926***	-0.825***	-0.778***	-0.961***
	(0.046)	(0.051)	(0.067)	(0.054)	(0.061)	(0.072)
$GradSH_{j,t-1}$	-0.103***	-0.073*	-0.151***	-0.095***	-0.069*	-0.145***
	(0.024)	(0.039)	(0.029)	(0.024)	(0.039)	(0.028)
$ImmSH_{j,t-1}$	0.037	0.180**	0.089	0.030	0.179**	0.096*
	(0.054)	(0.072)	(0.060)	(0.058)	(0.071)	(0.058)
$ManufSH_{j,t-1}$				0.057***	0.066*	0.057
				(0.028)	(0.035)	(0.038)
R^2	0.482	0.541	0.501	0.488	0.548	0.506
2SLS						
$RSH_{j,t-1}$	-0.443**	-0.569**	-0.242	-0.381**	-0.575**	-0.004
	(0.105)	(0.108)	(0.388)	(0.153)	(0.186)	(0.680)
$GradSH_{j,t-1}$	-0.060**	-0.037	-0.075	-0.062**	-0.038	-0.067
	(0.024)	(0.044)	(0.049)	(0.023)	(0.045)	(0.061)
$ImmSH_{j,t-1}$	-0.012	0.132*	-0.067	-0.011	0.132*	-0.120
	(0.042)	(0.072)	(0.112)	(0.039)	(0.076)	(0.170)
$ManufSH_{j,t-1}$				-0.046	0.004	-0.104
				(0.045)	(0.066)	(0.125)
1Stage						
P-K test	54.135	60.437	10.859	26.335	25.872	4.783

Notes: N=372, all specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regression. Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.
Source: QLFS, author's calculations.
*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 6: **Changes in non-routine manual employment**

	Non-graduate								
	1993-2013	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**
OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RSH_{j,t-1}$	0.210***	0.224***	0.258***	0.205***	0.235***	0.248**	0.156***	0.263***	0.152
	(0.046)	(0.063)	(0.097)	(0.049)	(0.066)	(0.101)	(0.052)	(0.077)	(0.093)
$GradSH_{j,t-1}$				0.003	0.029	-0.003	0.011	0.028	0.017
				(0.021)	(0.043)	(0.029)	(0.021)	(0.044)	(0.031)
$ImmSH_{j,t-1}$				0.071	0.035	0.044	0.066	0.036	0.062
				(0.056)	(0.102)	(0.091)	(0.055)	(0.103)	(0.095)
$ManufSH_{j,t-1}$							0.070**	-0.032	0.165***
							(0.028)	(0.042)	(0.057)
R^2	0.209	0.185	0.123	0.212	0.189	0.124	0.220	0.191	0.167
2SLS									
$RSH_{j,t-1}$	0.270***	0.242**	0.332	0.210**	0.211**	0.282	0.081	0.254	-0.194
	(0.081)	(0.118)	(0.287)	(0.087)	(0.106)	(0.397)	(0.134)	(0.178)	(0.586)
$GradSH_{j,t-1}$				0.003	0.025	-0.000	0.005	0.027	-0.003
				(0.023)	(0.043)	(0.046)	(0.023)	(0.043)	(0.047)
$ImmSH_{j,t-1}$				0.070	0.043	0.034	0.081	0.038	0.161
				(0.059)	(0.096)	(0.145)	(0.060)	(0.099)	(0.194)
$ManufSH_{j,t-1}$							0.087*	-0.029	0.222**
							(0.045)	(0.068)	(0.111)
1Stage									
P-K F-test	48.91	46.99	17.75	62.92	67.46	16.34	24.942	26.506	5.280

Notes: N=372, all specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regression. Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.
Source: QLFS, author's calculations.
*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 7: **Changes in non-routine manual employment, 2SLS**

	Non-graduate											
	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013	1993-2013	1993-2003	2003-2013
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$RSH_{j,t-1}$	0.279	0.331	0.299	0.289***	0.254**	0.384	0.254***	0.171	0.328	0.276***	0.252**	0.365
	(0.564)	(0.584)	(4.384)	(0.079)	(0.114)	(0.296)	(0.098)	(0.144)	(0.287)	(0.081)	(0.117)	(0.302)
$Offsh_{j,t}$	-0.008	-0.088	0.026									
	(0.457)	(0.482)	(3.230)									
Δ $GradHRS_{j,t}$				-0.138***	-0.127**	-0.221***						
				(0.048)	(0.056)	(0.055)						
Δ $Wage(p90)_{j,t}$							-0.033**	-0.027*	-0.045**			
							(0.013)	(0.015)	(0.021)			
Δ $OldSH_{j,t}$										-0.010	-0.211	-0.012
										(0.086)	(0.188)	(0.086)
Δ $FemaleHRS_{j,t}$										0.065	0.053	0.095
										(0.047)	(0.062)	(0.066)
N	372	186	186	372	186	186	340	154	186	372	186	186
P-K F-test	2.931	4.594	0.145	48.77	47.761	17.51	35.066	26.694	17.991	45.916	46.801	15.499

Notes: All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regression. Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.
Source: QLFS, author's calculations.
*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 8: **Changes in non-routine cognitive employment**

	Graduate								
	1993-2013	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OLS									
$RSH_{j,t-1}$	0.175**	0.239***	0.124	0.175**	0.185***	0.110	0.225**	0.151*	0.249
	(0.072)	(0.071)	(0.151)	(0.072)	(0.070)	(0.158)	(0.088)	(0.091)	(0.166)
$GradSH_{j,t-1}$				-0.042	-0.193***	0.019	-0.052	-0.190***	0.004
				(0.036)	(0.065)	(0.061)	(0.036)	(0.065)	(0.060)
$IMMSH_{j,t-1}$				0.725***	1.389***	0.591*	0.747***	1.384***	0.474
				(0.105)	(0.415)	(0.313)	(0.110)	(0.412)	(0.304)
$ManufSH_{j,t-1}$							-0.070	0.039	-0.225***
							(0.045)	(0.058)	(0.066)
R^2	0.288	0.127	0.262	0.352	0.191	0.306	0.356	0.193	0.341
2SLS									
$RSH_{j,t-1}$	0.194	0.089	0.416	0.056	0.030	0.091	0.115	-0.160	0.625
	(0.152)	(0.172)	(0.392)	(0.141)	(0.156)	(0.424)	(0.204)	(0.250)	(0.616)
$GradSH_{j,t-1}$				-0.054	-0.226***	0.017	-0.058*	-0.233***	0.044
				(0.035)	(0.078)	(0.068)	(0.034)	(0.079)	(0.076)
$ImmSH_{j,t-1}$				0.742***	1.475***	0.602*	0.752***	1.497***	0.250
				(0.100)	(0.429)	(0.353)	(0.103)	(0.422)	(0.440)
$ManufSH_{j,t-1}$							-0.044	0.136	-0.291**
							(0.062)	(0.089)	(0.129)
1Stage									
K-P F-test	48.906	49.989	17.751	62.915	67.458	16.341	32.516	28.450	8.825
N	372	186	186	372	186	186	372	186	186
Period dummies	x			x			x		
Region dummies	x	x	x	x	x	x	x	x	x

Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.

Table 9: **Effects on the working-age population, 2SLS**

	All			**Graduate**			**Non-graduate**		
	1993-2013	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**
Panel A	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$RSH_{j,t-1}$	0.183**	-0.019	0.597**	0.030	-0.408	0.891	0.080	-0.076	0.411
	(0.081)	(0.068)	(0.291)	(0.531)	(0.741)	(1.096)	(0.227)	(0.202)	(0.591)
Panel B	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$RSH_{j,t-1}$	0.102	-0.016	-0.016	-0.707	-0.491	0.387	0.789**	0.052	0.922
	(0.072)	(0.069)	(0.069)	(0.633)	(0.642)	(1.382)	(0.358)	(0.222)	(0.859)
$GradSH_{j,t-1}$	0.019	-0.004	-0.004	-1.017***	-1.650***	-0.458**	0.155	0.106	-0.020
	(0.023)	(0.025)	(0.025)	(0.159)	(0.289)	(0.180)	(0.105)	(0.091)	(0.123)
$ImmSH_{j,t-1}$	0.065**	-0.004	-0.004	1.178***	1.009**	0.462	-0.726**	-0.260	-0.237
	(0.027)	(0.049)	(0.049)	(0.299)	(0.463)	(0.369)	(0.29)	(0.165)	(0.258)
N	372	186	186	371	186	185	372	186	186

Notes: All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regression. Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.

Source: QLFS, author's calculations.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 10: **Conditioning on local labour supply changes, 2SLS**

	1993-2013	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**
Panel B. Non-graduate non-routine manual employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	-0.488***	-0.499***	-0.454	-0.478***	-0.510***	-0.350
	(0.108)	(0.106)	(0.278)	(0.094)	(0.102)	(0.262)
$\Delta\ GradSH_{j,t-1}$				-0.064***	-0.121***	-0.060**
				(0.021)	(0.026)	(0.027)
$\Delta\ ImmSH_{j,t-1}$				-0.006	0.065	-0.075
				(0.042)	(0.069)	(0.049)
1Stage						
P-K F-test	48.906	46.989	17.751	48.568	46.315	16.018

Panel B. Non-graduate non-routine manual employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	0.270***	0.242**	0.332	0.252***	0.261**	0.317
	(0.081)	(0.118)	(0.287)	(0.082)	(0.123)	(0.290)
$\Delta\ GradSH_{j,t-1}$				-0.031**	-0.044	-0.051***
				(0.015)	(0.033)	(0.016)
$\Delta\ ImmSH_{j,t-1}$				0.070	-0.066	0.031
				(0.069)	(0.131)	(0.079)
1Stage						
P-K F-test	48.906	46.989	17.751	48.686	45.455	16.963

Panel C. Graduate non-routine cognitive employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	0.194	0.089	0.416	0.182*	0.094	0.272
	(0.152)	(0.172)	(0.392)	(0.108)	(0.127)	(0.288)
$\Delta\ GradSH_{j,t-1}$				0.220***	0.437***	0.191***
				(0.058)	(0.038)	(0.069)
$\Delta\ ImmSH_{j,t-1}$				-0.015	-0.343**	0.177
				(0.153)	(0.172)	(0.148)
1Stage						
P-K F-test	48.906	46.989	17.751	48.672	46.648	17.079

Notes: All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regression. Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.

Source: QLFS, author's calculations.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

Table 11: **Robustness Check II:Routine-Intensity measure (Top employment-weighted 40%), 2SLS**

	1993-2013	**1993-2003**	**2003-2013**	**1993-2013**	**1993-2003**	**2003-2013**
Panel A. Non-graduate routine employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	-0.229**	-0.185	-0.281	-0.131	-0.121	-0.178
	(0.107)	(0.159)	(0.212)	(0.106)	(0.166)	(0.232)
$GradSH_{j,t-1}$				0.003	0.081	-0.051
				(0.043)	(0.093)	(0.065)
$ImmSH_{j,t-1}$				-0.165***	-0.160	-0.150
				(0.051)	(0.112)	(0.095)
1Stage						
P-K F-test	40.99	24.354	30.424	58.246	34.968	28.300
Panel B. Non-graduate non-routine manual employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	0.333***	0.190	0.511***	0.307***	0.152	0.537***
	(0.070)	(0.118)	(0.159)	(0.076)	(0.114)	(0.182)
$GradSH_{j,t-1}$				0.065**	0.040	0.104*
				(0.033)	(0.063)	(0.057)
$ImmSH_{j,t-1}$				0.063	0.086	0.008
				(0.057)	(0.095)	(0.107)
1Stage						
P-K F-test	40.990	24.354	30.424	57.457	35.739	30.158
Panel C. Graduate non-routine cognitive employment changes						
	(1)	(2)	(3)	(4)	(5)	(6)
$RSH_{j,t-1}$	-0.145	-0.027	-0.295	-0.216	-0.046	-0.446
	(0.135)	(0.192)	(0.271)	(0.140)	(0.168)	(0.313)
$GradSH_{j,t-1}$				-0.124**	-0.253**	-0.122
				(0.049)	(0.104)	(0.097)
$ImmSH_{j,t-1}$				0.806***	1.522***	0.878***
				(0.110)	(0.451)	(0.332)
1Stage						
P-K F-test	40.990	24.354	30.424	61.975	39.755	28.885

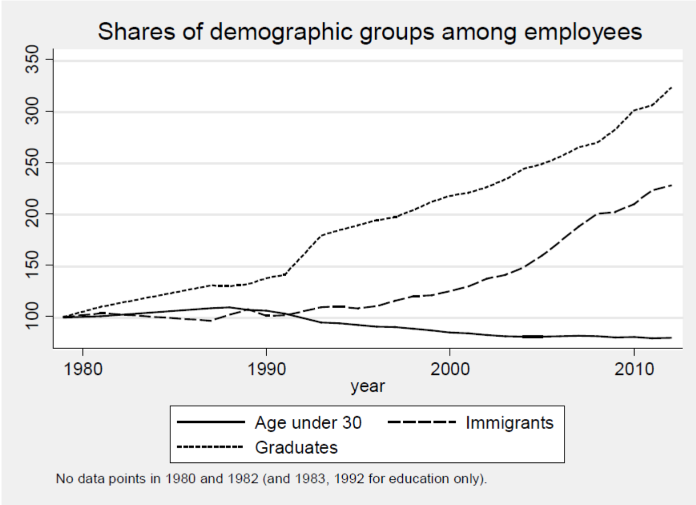
Notes: All specifications include intercept, region (Nuts-1) dummies. Period dummies are included in the stacked regression. Standard errors in parentheses are clustered by TTWA in the stacked regression, robust standard errors are used for single period regressions. Observations are weighted by the start-of-the-period TTWA share of national population.

Source: QLFS, author's calculations.

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level

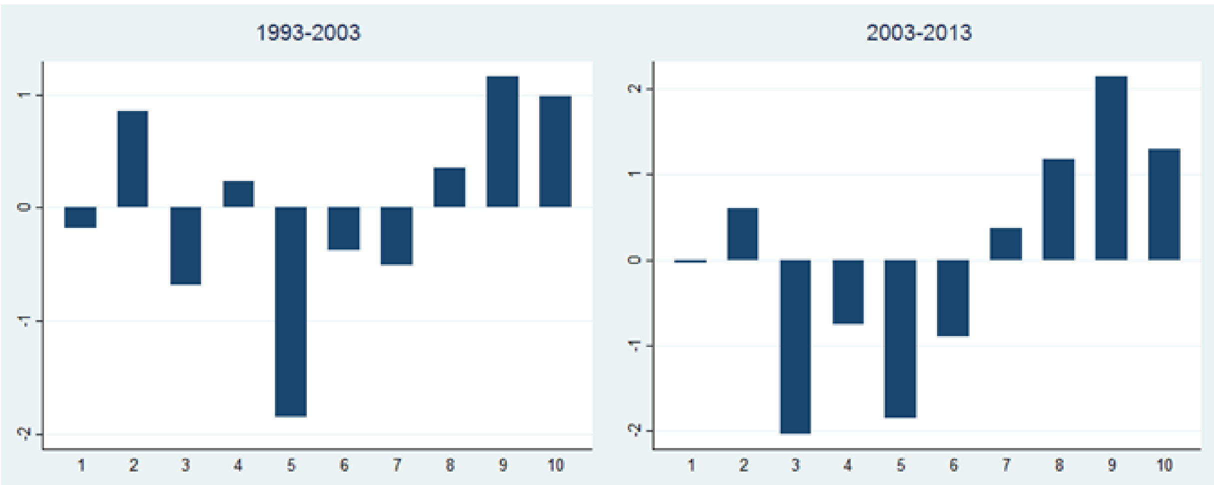
Figures

Figure 1: **Demographic groups'shares for employees, 1979-2012**



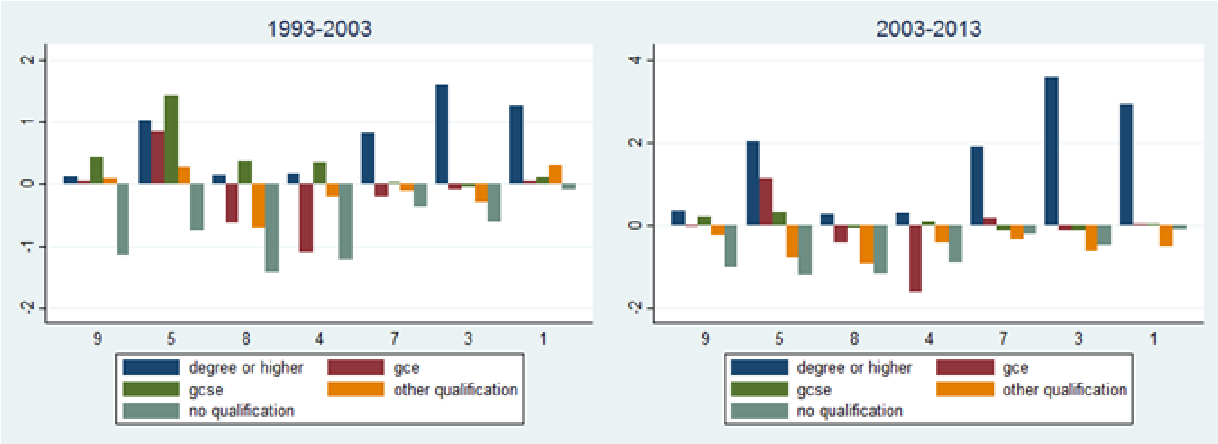
Source: Salvatori, 2015 (Figure 1)

Figure 2: **Changes in employment shares by deciles, 1993-2013**



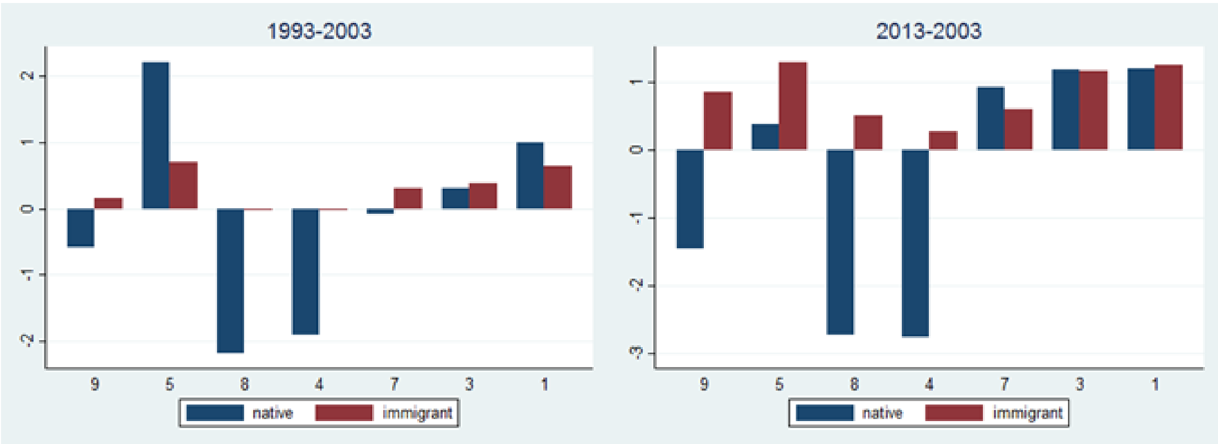
Source: QLFS, author's calculations

Figure 3: **Changes in major occupational groups' employment shares by educational qualification, 1993-2013**



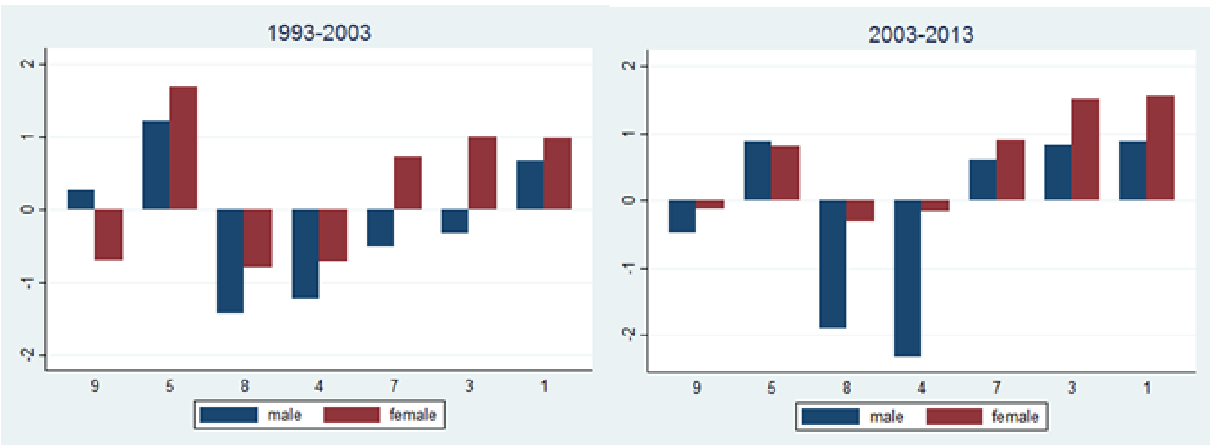
Source: QLFS, author's calculations

Figure 4: **Changes in major occupational groups' employment shares by immigration status, 1993-2013**



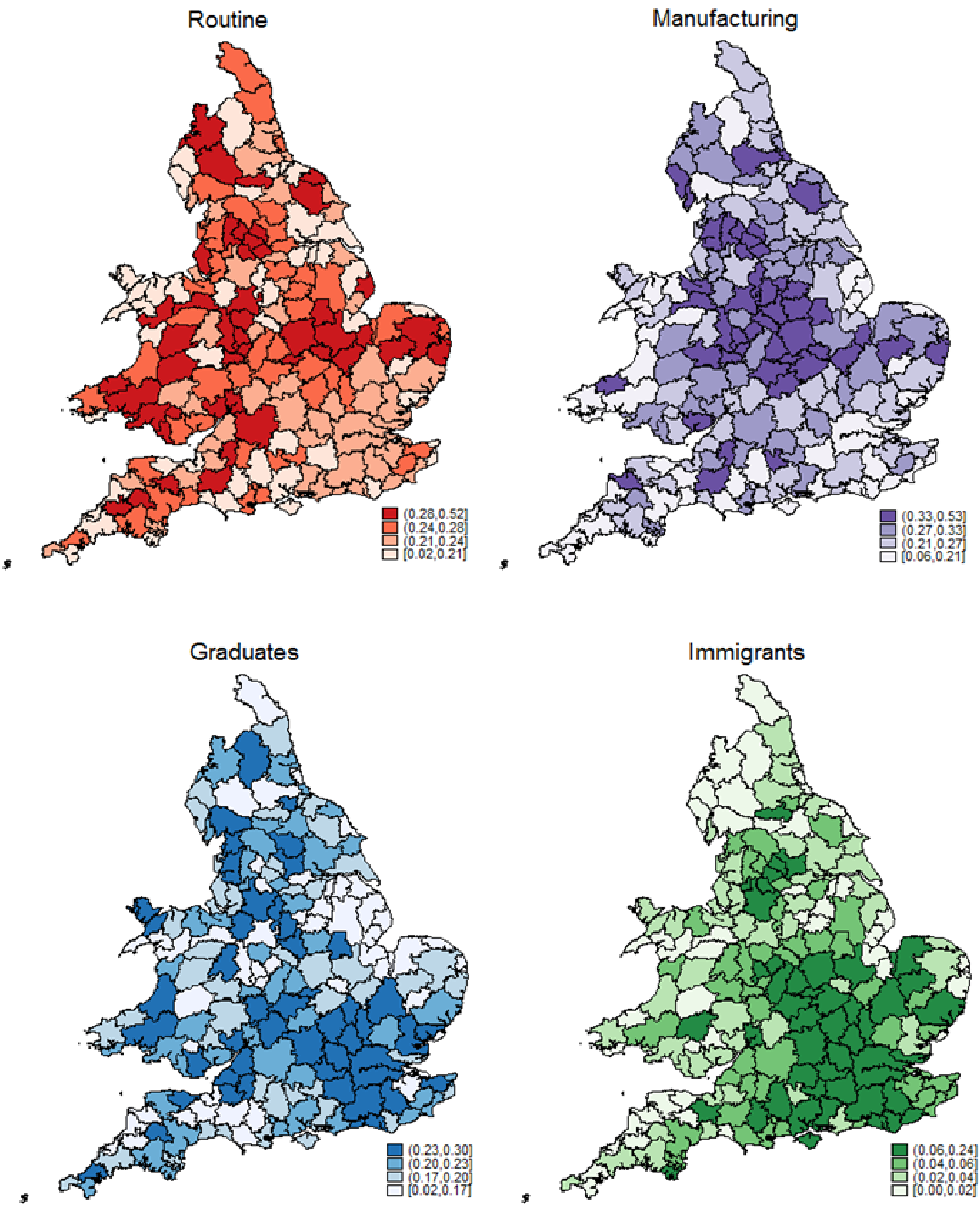
Source: QLFS, author's calculations

Figure 5: **Changes in major occupational groups' employment shares by gender, 1993-2013**



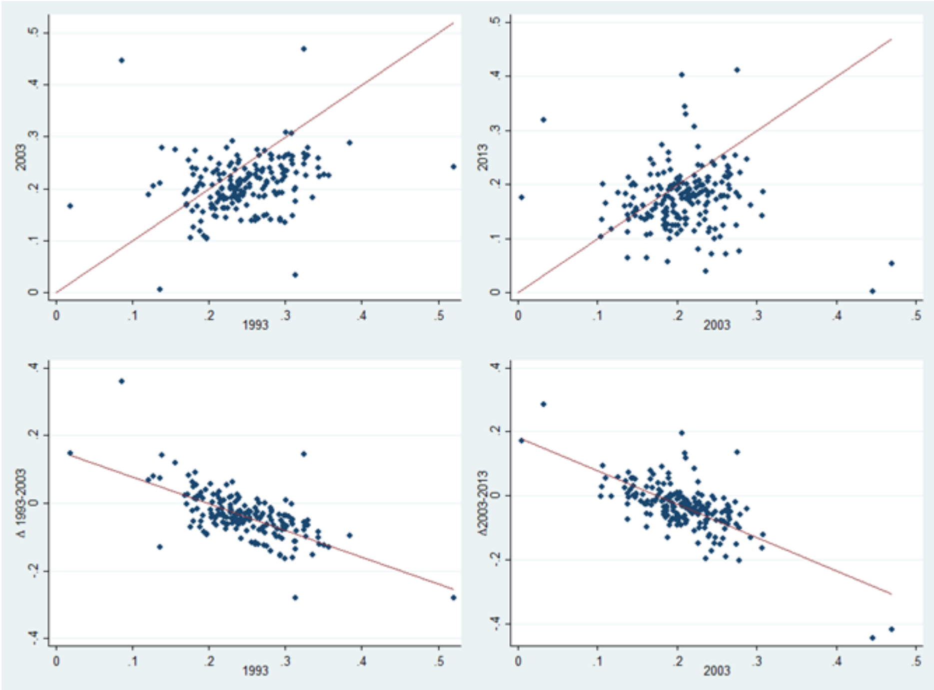
Source: QLFS, author's calculations

Figure 6: **Geographical distribution of routine employment, graduate and immigrant labour supply shares in 1993**



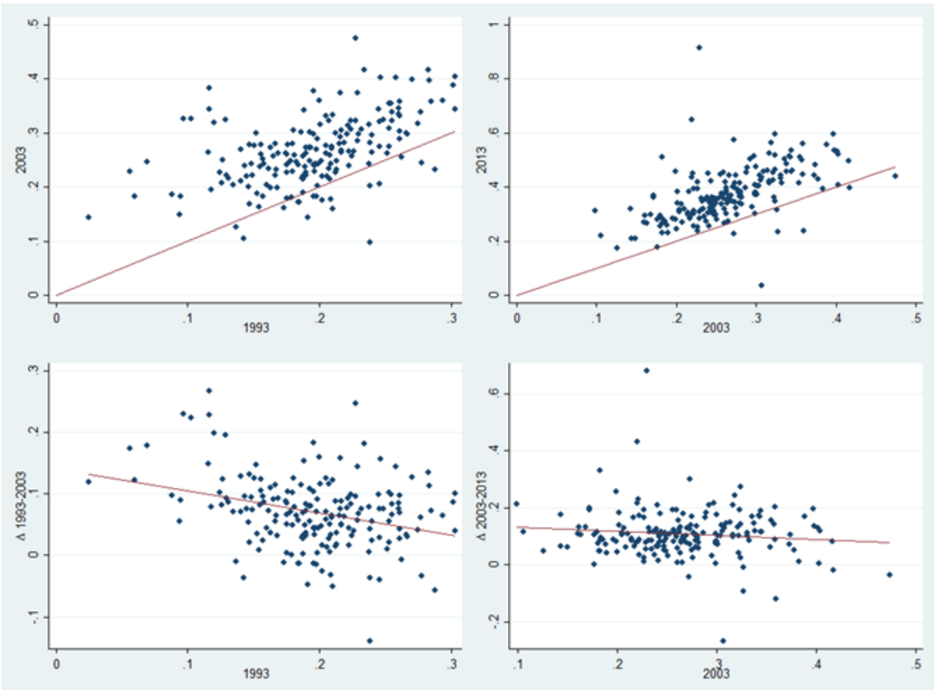
Source: QLFS, author's calculations

Figure 7: **Changes in routine employment share by TTWA, 1993-2013**



Note: N=186xperiod. Source: QLFS, author's calculations

Figure 8: **Changes in graduate population share by TTWA, 1993-2013**

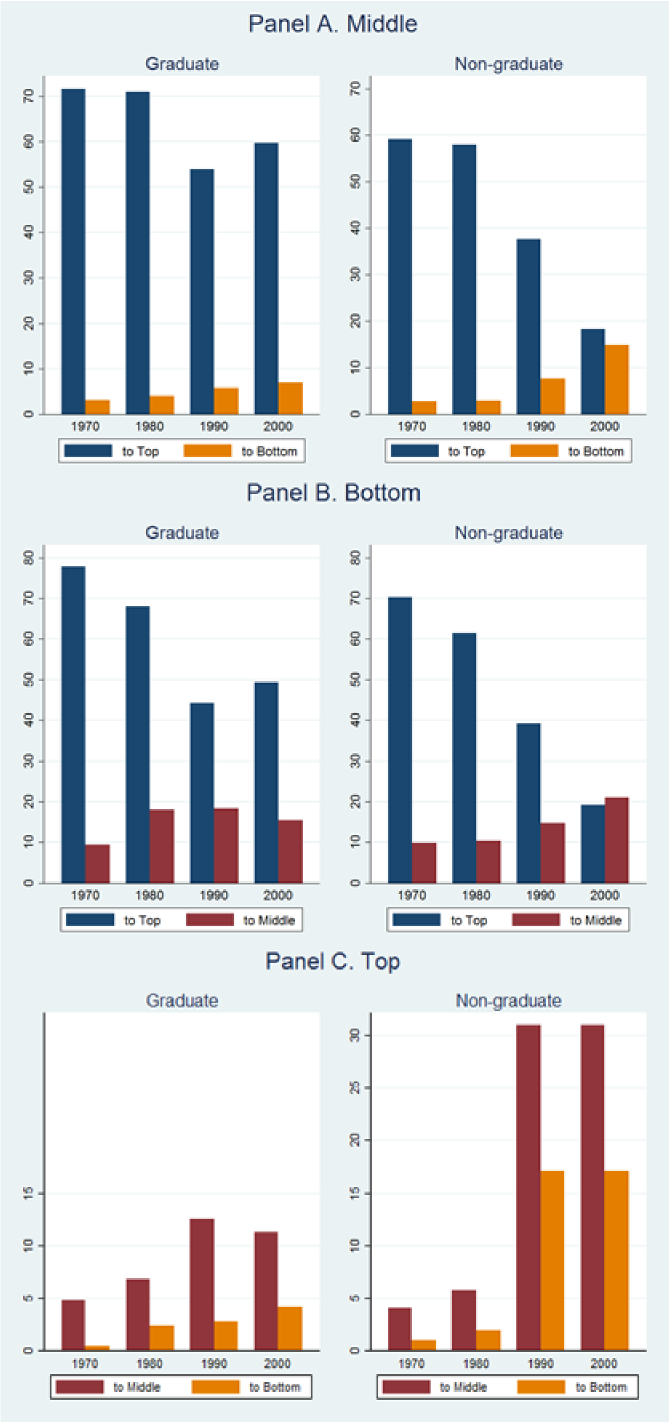


Note: N=186xperiod. Source: QLFS, author's calculations

Figure 9: **Changes in graduate population share and routine employment share by TTWA, 1993-2013**

Note: N=186xperiod. Source: QLFS, author's calculations

Figure 10: **Exit occupational probabilities, 1971-2011**



Source: QLFS, author's calculations

Appendix

Table 12: Levels and changes in employment shares (2-digit) by sector, 1993-2013

		Manufacturing				**Non-manufacturing**			
Occupations	**Code**	**1993**	**2003**	**2013**	**1993-2013**	**1993**	**2003**	**2013**	**1993-2013**
Top									
Corporate managers	12	6.1	6.68	8.99	2.89	4.23	5.15	5.97	1.74
Physical, mathematical and engineering science professionals	21	9.14	10.25	11.57	2.43	8.92	9.61	11.63	2.71
Other professionals	24	1.54	1.96	1.1	-0.44	4.64	4.79	5.49	0.85
Life, science and health professionals	22	0.33	0.6	0.62	0.29	4.39	4.59	5.32	0.93
Physical, mathematical and engineering science associate professionals	31	2.8	2.55	3.25	0.45	2.36	1.92	2.07	-0.29
Other associate professionals	34	3.99	4.43	4.41	0.42	5.45	5.86	6.43	0.98
General managers	13	6.73	8.61	8.95	2.22	8.75	8.05	8.55	-0.2
Middle									
Stationary plant and related operators	81	2.96	2.42	1.88	-1.08	0.33	0.12	0.13	-0.2
Metal, machinery and related trades workers	72	14.25	15.01	15.41	1.16	5.13	4.14	3.47	-1.66
Life science and health professionals	32	0.07	0.11	0.4	0.33	1.81	1.82	2.52	0.71
Precision, handicraft, printing and related trades workers	73	3.9	3.42	2.6	-1.3	0.32	0.22	0.24	-0.08
Office clerks	41	10.79	9.77	9.58	-1.21	16.56	15.89	12.88	-3.68
Extraction and building trade workers	71	2.07	3.04	3.13	1.06	3.08	3.59	2.67	-0.41
Machine operators and assemblers	82	18.69	15.51	13.64	-5.05	0.89	0.65	0.7	-0.19
Drivers and mobile plant operators	83	3.51	3.99	3.62	0.11	5.2	5.32	4.13	-1.07
Customer service clerks	42	0.63	0.56	0.46	-0.17	4.32	3.32	2.76	-1.56
Labourers in mining, construction, manufacturing and transport	93	4.77	5.08	5.33	0.56	2.15	1.9	1.67	-0.48
Bottom									
Personal and protective service workers	51	0.68	0.58	0.7	0.02	10.82	12.23	13.75	2.93
Other craft and related trades workers	74	5.48	3.59	2.48	-3	0.62	0.41	0.39	-0.23
Sales and services elementary occupations	91	1.27	1.24	1.12	-0.15	5.06	4.64	4.15	-0.91
Models, salespersons and demonstrators	52	0.3	0.6	0.76	0.46	4.94	5.76	5.08	0.14

Note: Occupational categories is bold are those defined as roiutine-intensive following Autor and Dorn's (2013) criteria. Sample includes workers aged 16-64. Hourly wages are defined as average hourly earnings for the reference week. All calculations use labour supply weights.
Source: LFS, author's calculations.

Table 13: **Occupational transitions, 1971-2011**

1971-1981

		NR-C	R	NR-M
	NR-C	0.948	0.048	0.004
Graduate	R	0.717	0.252	0.031
	NR-M	0.778	0.095	0.126
			N=18874	
		NR-C	R	NR-M
Non	NR-C	0.908	0.068	0.024
Graduate	R	0.591	0.382	0.027
	NR-M	0.703	0.099	0.198
			N=225040	

1981-1991

		NR-C	R	NR-M
	NR-C	0.95	0.04	0.01
Graduate	R	0.71	0.25	0.04
	NR-M	0.68	0.18	0.13
			N=29742	
		NR-C	R	NR-M
Non	NR-C	0.924	0.057	0.019
Graduate	R	0.58	0.393	0.028
	NR-M	0.614	0.103	0.282
			N=13378	

1991-2001

		NR-C	R	NR-M
	NR-C	0.847	0.125	0.028
Graduate	R	0.543	0.4	0.058
	NR-M	0.442	0.184	0.373
			N=70811	
		NR-C	R	NR-M
Non	NR-C	0.78	0.162	0.059
Graduate	R	0.377	0.547	0.076
	NR-M	0.393	0.147	0.46
			N=232703	

2001-2011

		NR-C	R	NR-M
	NR-C	0.846	0.112	0.042
Graduate	R	0.597	0.333	0.07
	NR-M	0.493	0.154	0.353
			N=114683	
		NR-C	R	NR-M
Non	NR-C	0.519	0.309	0.171
Graduate	R	0.183	0.668	0.149
	NR-M	0.192	0.21	0.598
			N=280746	

Source: ONS Longitudinal Study, author's calculations.