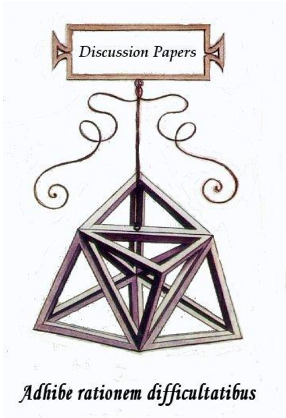
Discussion Papers

Collana di

E-papers del Dipartimento di Economia e Management – Università di Pisa



Martina Bisello

Job polarization in Britain from a task-based perspective. Evidence from the UK Skills Surveys

Discussion Paper n. 160

2013

Discussion Paper n. 160, presented: March 2013

Revised version*: May 2013

* Section VI has undergone substantial revision and the rest of the paper has been updated accordingly.

Corresponding author:
Dipartimento di Economia e Management, via Ridolfi 10
56100 PISA – Italy
Email: martina.bisello@for.unipi.it

Acknowledgments

I am deeply grateful to Lorenzo Corsini, Paul Gregg, Nicola Meccheri and Arrigo Opocher for helpful comments on preliminary drafts and to Francis Green for sharing some program codes. I also thank the Centre for Market and Public Organization (CMPO) for hosting me and the UK Data Archive for making the data available. The usual disclaimer applies.

Please quote as:

Martina Bisello (2013), "Job polarization in Britain from a task-based perspective. Evidence from the UK Skills Surveys", Department of Economics and Management, University of Pisa Discussion Papers n. 160, revised version May. (http://www.dse.ec.unipi.it/index.php?id=52)

Discussion Paper

n. 160

Martina Bisello

Job polarization in Britain from a task-based perspective. Evidence from the UK Skills Surveys

Abstract

This paper analyses occupational changes in Britain between 1997 and 2006 from a task-based perspective using data from the UK Skills Surveys. In line with the existing literature, we show that employment has been polarizing. We analyse in detail the task content of the occupations which display the most significant employment changes during the period under consideration in light of ALM (2003) "routinization hypothesis". We show that changes in employment shares are negatively related to the initial level of routine intensity. Unlike previous studies using the same data, we explore the impact of computerization on routine task inputs excluding low-paying occupations that are not supposed to be directly affected. We show that our routine measure, which is negatively related to computerization, is likely to capture both the manual and the cognitive routine dimension. Finally, by using retrospective questions on past jobs, we provide evidence that middle-paid workers did not predominantly reallocate their labour supply to low-paying occupations.

Classificazione JEL: J21, J23, J24, J62

Keywords: Job polarization, technological change, occupations, tasks

Contents

I. Introduction

From the 1990s onwards, radical changes in the employment structure at the occupational level occurred in several industrialized countries, notably the United States and the United Kingdom. Together with the employment growth in high-paying managerial and professional occupations and the fall in the share of middle-income jobs, low-paying service occupations started to grow. These changes led to a shift from a monotonic to a U-shaped relationship between growth in employment share and occupation's percentile in the wage distribution. This phenomenon has been defined as "job polarization".

The economic literature highlights the role of demand shocks - particularly the technology-based ones - as the driving force behind these changes. Autor, Levy and Murnane (2003) (hereafter ALM) explain job polarization in light of the impact of technological change on the categories of workplace tasks. Substitution or complementarity opportunities between computer use and the activities performed by workers led to a polarized labour market. Middle-income workers performing routine activities, replaced by machines, were induced to reallocate their labour supply in non-routine intense occupations and to perform tasks with a higher marginal productivity.

We contribute to the literature on employment polarization in the United Kingdom at the occupational level using data from the UK Skills Surveys, which allow a detailed analysis of activities performed in British workplaces and the use of computers. Differently from Goos and Manning (2003 and 2007), we do not rely on task measures for the United States[1] to quantify the task intensities associated to each occupation. No assumption on the same task composition of occupations and the same impact of technology in the two countries is therefore needed.

[1] The US Department of Labor's Dictionary of Occupational Titles (DOT) and the subsequent online database Occupational Information Network (O*NET) are used to impute to workers the task measures associated with their occupations. ALM provide details on how the DOT/O*NET task measures are constructed.

We first provide preliminary evidence of job polarization in our sample, confirming that between 1997 and 2006 employment shares increased at the two extremes of the occupation wage distribution, while they decreased in the middle. There is no evidence instead that wages followed the same pattern. We classify occupations in manual/non-manual and routine/non-routine accoring to the ALM theoretical framework. We analyse in detail the task content of those occupations which display the most significant employment changes during the period under consideration.

Next, we explore the relationship between computer use and routine task inputs, which we define on the basis of the frequency of repetitive activities that workers are asked to perform on the job. Unlike previous studies using the same data at the occupational level (e.g. Green, 2009 and 2012)[2], we exclude from the analysis low-paying occupations that are not supposed to be directly affected by technological change and for which there are no clear predictions from a theoretical standpoint. We deem that this exclusion is also appropriate in light of the findings on the routine dimension in these occupations, which could be a source of bias. The negative impact of computerization that we find is therefore clearly associated with routine middling-paying jobs.

Claiming that the *a priori* identification of routine tasks is problematic, Green (2012) considers as such only repetitive manual activities. We show that our repetitive task index is equally correlated both with the O*Net manual and cognitive routine measures, once low-paying occupations are excluded. Although we cannot disentangle the negative effect of computarization on routine tasks into a cognitive and a manual component (typical of clerical and production work, respectively), we deem that both aspects are embedded in our index.

Finally, we exploit retrospective questions on past jobs, relating the phenomenon of employment polarization to the displacement of middle-paid workers. We find evidence of an increasing tendency

[2] Lindley (2012) explores the gender dimension of technological change but at the industry level and not considering the routineness of tasks.

over time of middle-paid workers to change occupation. The fact that these workers did not predominantly shift towards low-paying occupations is consistent with the argument that also low-skilled immigrants played a major role in the expansion of low-paid jobs.

The paper is organized as follows. Section 2 provides a review of the literature. In Section 3 we describe the data used. Section 4 provides preliminary evidence on labour market polarization. Section 5 examines the association between employment changes and the task content of occupations. Section 6 focuses on the impact of computer adoption on routine tasks, considering only high and middling-paying occupations for which there are clear predictions of substitution or complementarity effects. Section 7 analyses the occupational mobility of middle-paid workers. Section 8 concludes.

II. Literature Review on Job Polarization

Evidence of employment polarization, that is a relative employment increase of low and high-paid (skilled)[3] jobs with respect to the middle-paid (skilled) ones, have been found for the United States (Wright and Dwyer, 2003; Autor and Dorn, 2009; Acemoglu and Autor, 2011), the United Kingdom (Goos and Manning, 2003 and 2007), Germany (Spitz-Oener, 2006; Dustmann et al. 2009; Kampelmann and Rycx, 2011) and Japan (Ikenaga and Kambayashi, 2010). With regards to Europe, results are more mixed. Goos et al. (2010) conclude that on average the employment structure in Western European countries has been polarizing between 1993 and 2006. Conversely, Fernández-Macías (2012) and Nellas and Olivieri (2012), show very heterogenous results among European countries and do not provide evidence of a pervasive polarization[4].

[3] The term *skilled* is here used as a synonym for *educated*. Formal education is a traditional skill measure widely used in the skill-biased technological change (SBTC) literature. Being education positively related to wages at the occupational level, we consider high, middle and low-skilled workers to be on average also high, middle and low-paid.

[4] It should be noted, however, that the methodology used in these analyses is not exactly the same. Differently from Goos et al. (2010), Nellas and Olivieri (2012) rank occupations according to the average educational attainments and not the average wage. Fernández-Macías (2012) classify occupations in three equally-sized groups in terms of employement shares instead

Whereas in the United States there was a clear correspondence between employment (quantity) and wage (price) movements, the polarization of wages does not seem to be common to other countries. Dustmann et al. (2009) show that Germany and the United States experienced similar changes at the top of the wage distribution from the 1980s and 1990s, but the pattern of lower-tail movements was distinct. Similarly, Antonczyk et al. (2010) find little evidence of wage polarization in Germany. Concerning more specifically the United Kingdom, the well-documented increase in overall wage inequality since the early 1980s (e.g. Machin, 1996 and 2008) began to slow in the mid-1990s. Trends in inequality then split into two, with the ratio of middle to bottom earnings flattening out and the ratio of top to middle continuing to grow (Stewart, 2012). However, there is no evidence that low wages grew faster than the middle ones leading to a polarized trend (Holmes and Mayhew, 2010)[5]. More generally, Massari et al. (2013) conclude that there are no wage polarization trends in Europe, neither at the industry nor at the individual level.

The positive and monotonic relationship between wage and employment growth characterizing the 1980s is well explained by the skill-biased technological change (SBTC) hypothesis[6] (Bound and Johnson, 1992; Katz and Murphy, 1992; Berman et al., 1998; Machin and Van Reenen, 1998). The SBTC hypothesis relates the job expansion at the top quintiles of the wage distribution and the increase in college wage to technological progress favoring high-skilled work-

---

of using the uneven grouping followed by Goos et al. (2010).

[5] Oesch and Rodríguez Menés (2011) provide evidence of a positive correlation coefficient between changes in wages and employment across quintiles in Britain from 1993 to 2008. However, the authors claim that their findings should be treated with caution given that the analysis is not based on high quality data for wages (ie. the Labor Force Survey).

[6] Other explanations are considered, but the technology-based one is the most prominent. Several studies focus on the role of expanding international trade and offshoring, which involves the relocation to lower wage countries of only certain parts of the production process and therefore specific occupations (Feenstra and Hanson, 2005, Blinder, 2007; Grossman and Rossi-Hansberg, 2008; Acemoglu and Autor, 2011). Other studies investigate the role of labour market institutions, wage-setting in particular, which can affect employment opportunities of different kind of workers (DiNardo, Fortin and Lemieux, 1996; Acemoglu et al., 2001; Card, 2001; Lemieux, 2007).

ers at the expense of the others. However, it is not able to explain an increase of employment shares in low-skilled jobs and it therefore does not provide a wholly satisfactory framework for interpreting recent key trends in labour markets[7].

In light of the above remarks, a more nuanced and refined version of SBTC was put forward to explain the phenomenon of job polarization, focusing on the impact of computerization on the different categories of workplace tasks. ALM provided the so called "routinization" hypothesis which is consistent with a "task-biased" version of technological change. In the ALM model, technological progress takes the form of an exogenous drop in the price of computers which leads to a reduction of both non-manual and manual routine tasks.

Non-manual routine tasks are characteristic of clerical and administrative occupations while manual routine tasks are typical of production and operative occupations. Given a strong substitution with technology, these tasks can be easily replicated by machines and automated. On the contrary, non-manual non-routine tasks carried out mainly within managerial, professional and creative occupations and usually performed by high-skilled workers, are productive complements to computers. Finally, concerning manual non-routine tasks, the ALM framework does not explicitly predict neither strong substitution nor strong complementarity with computers because this category is not supposed to be directly affected by technological change. Indeed, manual non-routine tasks which are typical of service occupations are difficult to automate as they require direct physical proximity or flexible interpersonal communication, and they rely on dexterity. At the same time, they do not need problem solving or managerial skills to be carried out, hence there are limited opportunities for complementarity.

Despite manual non-routine tasks that comprise many of the unskilled jobs are not directly influenced by technological progress, its impact in other parts of the economy is likely to lead to a rise in

[7] See Acemoglu and Autor (2011) for an extensive analysis of the limits of the SBTC hypothesis (the "canonical model") in this context.

employment in these kind of works. Goos et al. (2007) apply Baumol's (1967) predictions - a shift of employment from technologically progressive industries (eg. manufacturing) to non-progressive industries (eg. services) in order to keep the balance of output in different products - to explain the increase in low-paid service jobs and employment falls in routine middling jobs. Productivity growth favours the increase in output of goods which, under imperfect substitution between goods and services, ultimately leads to an increase in the demand for service outputs and employment (Autor and Dorn, 2009). In a closed economy, this can lead to the displacement of middle-skilled workers towards service occupations as a side effect. Because routine and non-routine tasks are q-complements in production, the net increase of routine tasks input, due to an inflow of computer capital, raises the marginal productivity of non-routine tasks. According to the ALM theoretical framework, marginal middle-skilled workers who mainly perform routine tasks are induced to supply non-routine tasks with a higher marginal productivity. Under the assumption that the relative comparative advantage of middle-skilled workers is greater in low than high-skilled tasks, Autor et al. (2011) interpret employment growth in low-paid services as an implication of the susbtitution of skills across tasks (i.e. shifts of middle-paid workers towards low-paying occupations).

III. Data

The data that we use come from three UK Skills Surveys of 1997, 2001 and 2006. The main aim of these surveys is to provide an analysis of the level and distribution of skills being used in British workplaces. At each wave, information on job characteristics and working conditions are collected: these include details on the intensity of the tasks being performed, the degree of repetition of the activities carried out and the use of computers or computerized equipment in the workplace. Additional information on wages, educational qualification levels and past jobs are available, as well as other demographic variables.

The three repeated cross-sections cover altogether 14,717 workers (men and women), respectively 2,467 in 1997, 4,470 in 2001 and 7,780 in 2006. Sampling weights adjusted for response rate are used throughout the analysis[8]. We restrict our analysis to individuals aged 20 to 60 and we drop from the third wave Northern Ireland and Highlands and Islands respondents due to their exclusion in 1997 and 2001, reducing the observations in 2006 to 6,704. We classify occupations according to the ISCO-88 nomenclature at the three-digit level. We retain only those occupations which appear in all the three years with at least 5 observations, reducing the total number from 104 to 67. At this point the average number of individual observations in each occupation was around 34 in 1997, 63 in 2001 and 88 in 2006.

Differently from the US O*NET database, whose original purpose was an administrative evaluation by Employment Services offices of the fit between workers and occupations, the UK Skills Surveys were conducted exclusively for research[9]. In the O*NET, analysts at the Department of Labor assign scores to each task according to standardized guidelines to describe their importance within each occupation. Spitz-Oener (2006) claims that this process encourages experts to underestimate true changes on job content. Although the UK Skills Surveys present a higher level of subjectivity, this feature has the advantage of giving a more precise idea of the tasks performed within each occupation. Autor and Handel (2009), who use a similar type of survey to derive individual task measures (the Princeton Data Improvement Initiative survey, PDII), prove that their data have a greater explanatory power for wages than those derived from the O*NET.

We derive three tasks masures using 35 questions on job content. At each wave, every respondent is asked how much a particular activity is important for his/her job on a 5-point scale ranging

[8] See Felstead et al. (2007) for further details.

[9] The study was directed by the following researchers: Francis Green, Alan Felstead, Duncan Gallie and Ying Zhou.

from 1 ("not at all/does not apply) to 5 ("essential"). All these variables in Likert scale are coverted into increasing cardinal scale from 0 ("not at all/does not apply) to 4 ("essential"). We manually assign the different activities performed by workers to three broad categories: the first two, analytical and interpersonal, represent non-manual tasks (including respectively 25 and 6 activities); the third comprises manual tasks (4 activities) (see Appendix A.1 for a complete list). The Cronbach's scale reliability coefficient for the internal consistency of the three groups is respectively 0.93, 0.72 and 0.79. Examples of analytical tasks are: problem solving, analysing complex problems in depth and doing calculations using advanced mathematical or statistical procedures. Among interpersonal tasks we include persuading or influencing others, selling a product or service and counseling, advising or caring for customers or clients. Finally, we consider as manual those tasks such as working for long periods on physical activities or carrying, pushing and pulling heavy objects. For each one of the three categories above mentioned (analytical, interpersonal and manual) a principal component analysis is performed[10]. Further details on how the pricipal component analysis was conducted can be found in Appendix AA, together with the derivation of all the other variables used in the empirical analysis.

We take into account an additional dimension related to the possibility of tasks being easily replicated by machines and readily subject to automation. Individuals in the UK Skills Surveys were asked the following question about the frequency of routine activities they performed within their job: "How often does your job involve carrying out short, repetitive tasks?". To this item they could respond on a 5-point scale ranging from "never" to "always" (intermediate answers were "rarely", "sometime" and "often"). Arguing that the *a priori* identification of routine activities is difficult, Green (2012) considers as such only repetitive manual activities. The author obtains a repetitive physical skill index by combining the physical skill

[10] Previous studies use 32 items to generate eight skill indeces, identified by an exploratory factor analysis, as average scores from the responses.

measure (derived exactly from the same items of our manual dimension) with the question on task repetition.

IV. Job Polarization: Preliminary Evidence

In this section we investigate the phenomenon of employment polarization as a preliminary step for the subsequent analysis. We compute, on the basis of the number of workers, employment shares for each occupation and their changes over time. We then rank occupations according to their initial median hourly wage. Finally we plot the percentage point change in employment share against the (log) median wage. Figure 1 shows that, between 1997 and 2006, employment in low and high-paying occupations increased while it decreased in the middle of the distribution. We can clearly detect a U-shaped curve in the evolution of employment shares when occupations are ranked according to their average wage.

To test in a more rigorous way employment polarization we follow Goos and Manning (2007) estimating models of the quadratic form:

$$\Delta E_k = \alpha_0 + \alpha_1 \log(w_{k,0}) + \alpha_2 \log(w_{k,0})^2 + \varepsilon_k \quad (1)$$

where ΔE_k is the change in employment shares of occupation k between the initial and the final year considered and $\log(w_{k,0})$ is the initial log median wage of occupation k. A U-shaped relationship between employment growth and the initial level of wages corresponds to a negative linear term and a positive quadratic term. Table 1 shows the results of OLS regressions using initial number of observations in each occupation as weights to ensure that results are not biased by compositional changes in small occupations. Coefficients have the expected signs and are all statistically significant at the 1% level. Coefficients are also increasing in absolute value the longer the period considered, as well as the adjusted R-square. Because employment growth at the lower tail of the distribution could be linked to part-time rather than full time jobs, we further test the same model using weekly hours worked[11] as a measure for employment shares rather than expressing them in terms of bodies. Results are robust to this alternative specification. The phenomenon of employment polarization is also robust to the use of the mean instead of the median.

We also analyse polarization by defining occupation wage quintiles. Quintiles are created ranking occupations by their initial median wage and then aggregating them into five equally-sized groups. Each group contains almost the same percentage of employment in the initial year[12]. We plot in Figure 2 the change in the employment share from 1997 to 2006 by occupation wage quintiles. The period from 1997 to 2006 is characterized by a marked polarization in employment growth: there is a rapid employment growth at the first quintile, a decline in the employment shares of middle-skilled jobs and increasing employment shares at the top of the wage distribution (fifth quintile).

Next, we examine whether changes in the labour market's quantity side find their natural counterpart in changes in the price side, as the United States. We test with OLS regression the correspondence between changes in occupational employment shares and changes in occupational wages between 1997-2006. We find that the link between changes in employment shares and changes in (log) median wages is not statistically significant: we estimate β=0.012 (t-value: 1.50)[13]. These findings suggest that in Britain, between 1997 and 2006, wages did not experience the same polarized pattern of employment shares. As a robustness check for our findings on the absence of wage polarization, we follow Kampelmann and Rycx (2011) estimating the following model:

[11] We decided to drop those individuals reporting negative values, zero or more than 80 hours per week.

[12] This methodology has been first applied by Wrigth and Dwyer (2003). It is not possible to create groups which contain exactly the same percentage of employment since occupations are defined as unseparable units.

[13] Our regression includes a constant and is weighted by the number of individuals within an occupational group in 1997.

$$\Delta log(w_k) = \alpha_0 + \alpha_1 \log(w_{k,0}) + \alpha_2 \log(w_{k,0})^2 + \varepsilon_k \qquad (2)$$

Because of possible wage measurement error in our main source which would cause attenuation bias in the estimates, we prefer to use data from the Annual Survey of Hours and Earnings[14]. The ASHE provides information about earnings and hours worked for employees by sex and full-time/part-time workers in all industries and occupations. Given that the ASHE is based on a one per cent sample of employees taken from payroll records collected by the HM Revenue & Customs, we consider it to be a more reliable and accurate source to analyse the evolution of gross hourly pay at the occupation level. Table 2 reports estimates only for the same 67 occupations that are considered in the UK Skill Surveys. Results obtained from this additional dataset confirm that there is no evidence of wage polarization at the occupational level for the period 1997-2006.

V. Employment Changes and Task Intensities

To interpret previous findings on the pheonomenon of job polarization in Britain, we follow a task-based approach exploiting information on the activities carried out on workplaces. All workers perform a wide range of tasks but they do it with different intensities. This means that occupations are not uniquely associated with one single type of task; still, they can be classified as predominantly non-manual or manual according to the intensity of analytical, interpersonal and manual activities. Likewise, occupations can be categorized as routine or non-routine depending on how much the required activities are repetitive.

Table 3 presents the correlation among the task and routine measures and the education variable at the occupation level. The manual dimension is negatively correlated with the analytical and inter-

[14] Available at: http://data.gov.uk/dataset/annual_survey_of_hours_and_earnings.. We manually map the SOC nomenclature into the ISCO-88 three-digit classification to allow comparability between results.

personal measures and the education variable. Education is instead positively correlated with the two non-manual dimensions. The routine measure is negatively correlated with the analytical and interpersonal dimension and with the level of educational attainment and positively with the manual measure[15].

We proceed with our analysis aggregating the 67 occupations so far considered at the ISCO-88 two-digit level. This aggregation offers a clear interpretation of the tasks content of the occupations that mainly contributed to the polarization of the employment structure. Table 4 presents the 24 two-digit occupations ranked in ascending order by their median wage in 1997[16], which is reported in column 1, and the percentage point change in their employment share during the period 1997-2006. The Table also shows the mean of the educational attainment in 1997, computed from a three-level education variable ranging from 1 (low-skilled) to 3 (high-skilled).

We draw on the work of Goos et al. (2009) to classify these occupations into three major groups which we label as low, middling and high-paying[17]. This grouping reflects the theoretical classification of the ALM model with service and elementary occupations being the low-paying, productive and administrative occupations the middling-paying, professional and managerial the high-paying.

Column 1 to 4 of Table 5 report the average values of the task measures for each occupation. Matching these figures with the statistics on changes in employment shares, we have a clear picture of the task content of the occupations which determined employment polarization between 1997 and 2006.

[15] Results are similar to those reported in Green (2012) who explores at the individual level the correlation of nine job skill indices with the education variable, but using the required education level of the job and not worker's actual highest qualification. We additionally provide an estimate of the correlation between the routine and the manual measures.

[16] The high value of the Spearman rank correlation coefficient (0.93) suggests that the wage ranking was fairly stable over time.

[17] Our groups include respectively 6, 10 and 8 occupations. Fernández-Macías (2012) criticizes the methodological strategy developed by Goos et al. (2009), claiming that a division in even groups would not lead to conclude that there was a pervasive polarization in Europe. Our findings for Britain are instead robust to an alternative classification in three even groups, with the middle group still declining in terms of employment shares and the two extreme groups increasing.

V.A. Non-manual and Manual Dimensions

Among the group of high-paying occupations, "Corporate Managers" (ISCO 12), "Life science and health associate professionals" (ISCO 32) and "Other Professionals" (ISCO 24) are those that experienced the most significant employment growth. All these three major occupations score higher on the non-manual dimension, an average of analytical and interpersonal measures, than on the manual one.

Within middling-paying occupations, those losing more employment share between 1997 and 2006 were "Office clerks" (ISCO 41), scoring on average higher on the non-manual dimension; "Metal, machinery and trade workers" (ISCO 72) and "Machine operators and assemblers" (ISCO 82), scoring respectively 0.78 and 0.66 in the manual measure.

Concerning the group of the lowest paying occupations, four out of six have growing employment shares. Those occupations with a positive percentage point change over 1997-2006 are low-paying services, such as "Personal and protective service workers" (ISCO 51) and "Salespersons, models and demonstrators" (ISCO 52) and low-paying elementary occupations, such as "Sales and services elementary occupations" (ISCO 91) and "Labourers in mining, construction, manufacturing and transport" (ISCO 93). Within the elementary occupations (ISCO 91 and 93) the categories growing more were "Messengers, porters, doorkeepers" (ISCO 915, +2.19 percentage points change) which can be classified as private consumer services, and "Transport labourers and freight handlers" (ISCO 933, +1.27 percentage points change) which are instead considered business services. Our findings confirm that the increase of employment at the lower tail of the wage distribution is mainly driven by a job expansion in the service sector. The task content of these jobs is mixed, with elementary occupations being predominanlty manual and service occupations scoring higher in the interpersonal dimension. This is in line with the fact that low-paid service jobs rely both on physical proximity and interpersonal communication, therefore are not directly affected by technological progess.

V.B. Routine Intensity

After having classified the occupations in manual and non-manual, we take into account an additional dimension related to the extent to which the involved activities are repetitive. The ALM theoretical framework split the routine dimension into two components: routine cognitive tasks (for example documenting or processing informaton) and routine manual (for instance the importance of repetitive motions and physical activities). However, the single question on repetitiveness in the UK Skills Survey does not allow this decomposition. Using O*Net data on task measures at the occupational level[18], we find that that the correlation between the UK Skills Survey routine measure and the O*Net routine manual and cognitive scales is respectively 0.62 and 0.33 (see Table 6). One can see that, despite our routine measure is more strongly related to the manual rather than the cognitive O*Net routine dimension, we still observe a positive correlation also for this second case. Using data from the Princeton Data Improvement Initiative survey (PDII), Autor and Handel (2009, p. 20) find instead that their measure of routine activity correlates positively with the O*Net routine manual scale (0.36) and negatively with the O*Net routine cognitive scale (-0.22), concluding that it placed far greater weight on the manual rather than cognitive dimension of repetitiveness. The question on repetitiveness in the UK Skill Survey is almost identical to that included in the Princeton Data Improvement Initiative survey (PDII).

In light of the above findings, we analyse the routine measure among the occupations previously considered. As expected, high-paying managerial and professional occupations (ISCO 12, 24, 32) are predominantly characterized by non-routine activities; on the contrary, declining middling-paying occupations such as ISCO 41

[18] U.S. Census 2000 codes in the O*net data are matched to the International Standard Classification of Occupations (ISCO-88). We thank David Autor for making the data publicly available at: http://economics.mit.edu/faculty/dautor/data.

or 82 mainly involve routine tasks. These results are compatible with the ALM routinization hypothesis which clearly predicts that the impact of computerization caused a substantial substitution with routine tasks typical of middling-paying occupations and strong complementarities with non-routine tasks performed high-paying occupations.

Surprisingly, low-paying occupations are mostly routine. However, one caveat must be espressed. The repetitiveness dimension could have been interpreted by respondents as mundane and tedious rather than mechanistic and readily subject to automation. This is the reason why also Autor and Handel (2009), who evalutate this dimension using a similar question on repetitiveness, find that service occupations score really high in the routine measure. Similarly, Kampelmann and Rycz (2011) suggest that in Germany gains in employment shares at the low-wage occupations are linked to low-skilled services both routine and non-routine. Their definition of routine tasks is also based on whether a job is characterized by monotony of procedures. These findings should therefore be interpreted carefully in light of the above reasoning and not considered in contrast to the ALM theoretical framework.

Table 7 present results of OLS regressions of changes in employment shares between 1997-2006 and the initial level of routine intensity for each occupation. Panel (a) show estimates using all the 67 three-digit occupations, while panel (b) considers only middling and high-paying occupations. As expected, in both cases there is a negative relationship between the two variables. However, the coefficient is statistically significant only in the second case, possibly because of a misguided interpretation of the routine question by low-paid workers.

VI. Technological Change and Routine Tasks

Similarly to Green (2012), we analyse the relationship between computarization and routine task inputs at the occupational level creating a pseudo-panel. Unlike previous studies using the same data, we exclude from the analysis workers in low-paid service and elementary occupations for which the ALM theoretical framework predicts limited opportunities for substitution or complementarity. We deem that this exclusion is not only relevant from a theoretical standpoint but also from an empirical one, given our findings on the repetitiveness dimension in these occupations.

Furthermore, we decide to evaluate the routine index by itselft and not combined with the manual one as in Green (2012). In the previous section we showed that the routine measure in the UK Skill Surveys is more strongly related to the manual rather than the cognitive measures available in the O*Net data. However, after dropping low-paying occupations, the correlation coefficient between our routine measure and the routine cognitive O*Net variable increases substantially from 0.33 to 0.57, while the other essentially stays constant (from 0.61 to 0.65). It is therefore reasonable to assume that, when testing the ALM model on those occupations for which there are clear theoretical predictions, the basic routine measure available in our data well captures both the manual and the cognitive dimension of repetitive tasks, despite we are treating two factors as one.

We collapse the variables of interest at the 3-digit ISCO-88 occupation level, specifying the following model:

$$\bar{T}_{jt} = \beta \bar{C}_{jt} + \sum_{t=1}^{T-1} \theta_t + \delta_j + \bar{\varepsilon}_{jt} \tag{3}$$

where $\bar{T}_{jt}$ is the routine task measure at the occupation level at time t, $\bar{C}_{jt}$ is the variable capturing computer intensity (see Appendix AB for further details on how it is derived) in occupation j at time t, θ_t is a set of year effects and δ_j is a set of occupation effects. Time fixed effects control for omitted variables which are constant across occupations but evolve over time; occupation fixed effects are included to control for omitted variables that vary across occupations but not over time.

Table 8 reports the estimates using fixed effects with occupation cell size as weights. We find that technology is significantly negatively related with routine task inputs. Since low-paying occupations were excluded from the analysis, the negative impact of computerization is only associated with routine middle-paid jobs. As Column 2 shows, interacting the repetitive and the manual indices improves the estimate significantly. However, this would imply to classify as routine only repetitive physical activities as in Green (2012) and we are not imposing this restriction. Although one important limitation is that we cannot disentangle the effect of computarization on the routine cognitive and manual components (typical of clerical and production work, respectively), it is reasonable to think that both aspects are embedded in the basic measure.

For the sake of completeness, we estimate equation (3) also for analytical and interpersonal tasks. This is done to investigate whether non-manual tasks, which mainly refer to those individuals working in professional, managerial and creative non-routine occupations, are complements with computer use. Our findings are in line with the positive effect of computer technologies on the use of greater generic skills (such as literacy, numeracy, influencing and self-planning) found in Green (2009 and 2012). This is not surprising since the exclusion of low-paying occupations is not suppose to affect results for the high-paying ones.

VII. The Displacement of Middle-paid Workers

In this section we explore the occupational mobility of middle-paid (skilled) workers[19]. Increasing demand for low-paid services can be considered as a side-effect of the impact of technological change on other parts of the economy. In a closed economy context, this demand is compensated by labour supply shifts of middle-skilled workers performing routine activities, easily substituted by machines, which ultimately lead to employment growth in low-paid jobs. ALM model predicts that marginal routine workers are induced to reallocate their labour supply to non-routine intense occupations.

[19] The terms *paid* and *skilled* are interchangeable in our context.

We use information on past jobs for 2,503 national workers[20]. In 1997 and 2001 respondents were asked whether their historical job (5 years before) was the same as the current job (same employer). Workers also declared whether the job was in the same occupation or not. We compute the percentages of high, middle and low-skilled workers who changed occupation, given the total number of high, middle and low-skilled individuals in the sample indicating an historical occupational code. Looking at Table 9, we observe that middle-skilled workers became increasingly more mobile over time (+12.49 percentage points, against -2.8 of high-skilled and +6.64 of low-skilled).

Next, we want to establish where the displaced middle-paid workers moved by looking at the direction of their shifts, either towards low or high-paying occupations. Given that each survey covers exclusively workers, we can analyse only downward and upward mobility and not flows into unemployment or inactivity. Our enquiry builds on the analysis of transition probability matrices[21]. According to the economic theory, we should see over time an increasing probability of middle-income workers to move towards low-paid services. In 2006 the employment history question was related to the past industry and not occupation, hence it is not comparable to the other waves. We decide to integrate our main source with an additional dataset to extend the period of analysis. Using the BHPS (British Household Panel Survey), we investigate occupational mobility from 2001 to 2006 after having applied to the data all the necessary restrictions to obtain a comparable sample. From Table 10 one can see that the probability that workers in middling-paying occupations did not change group decreased (from 0.69 to 0.58), while it increased for those in low and high-paying occupations (re-

[20] The Uk Skills Surveys contain information on ethnicity which we use as a proxy to distinguish natives from foreign-born, given the absence of a variable on nationality. This restriction is minimal as a low number of observations is dropped.

[21] In a transition probability matrix each cell corresponds to the transition probability from one state to another given by: $p_{ij} = \Pr(X_t = j|X_t = i)$. This is computed as: $p_{ij} = N_{ij}/\sum_{j=1}^{n} N_{ij}$, where N_{ij} is the number of workers changing from state i to j (the cell count) and $\sum_{j=1}^{n} N_{ij}$ the total number of workers in a certain occupation group (the row count).

spectively from 0.58 to 0.69, and from 0.73 to 0.81).

We further check whether these shifts were due to a self-selection process rather than a forced displacement. According to the Roy (1951) model of wage determination and self-selection, workers chose occupations endogenously moving into those with the highest average reward to their bundle of tasks. If this were the case we would expect that middle-paid displaced workers earn more that the average wage of the selected low or high-paying occupation. Among those workers who moved out middling-paying occupations (i.e. 1,030, of which 654 from BHPS), we find that 74.57% of those moving upwards and 57.81% of those moving downwards earn an hourly wage lower than the average. While the former figure could simply reflect differences in returns from educational attainments, the latter seems to indicate that displaced middle-paid workers are not well rewarded despite a reasonable comparative advantage.

Our findings suggest that there was a forced reallocation of middle-paid workers' labor supply. However, these workers did not predominantly move towards low-paid services. The probability of moving towards high-paying occupations increased too. Our interpretation is that explanations of the significant job expansion at the lower tail of the distribution entirely based on the displacement of national middle-skilled workers are not fully satisfactory.

One has to consider that since the mid-1990s immigration flows increased sharply in the United Kingdom[22]. Apart from the concentration in very high-skilled jobs, notably health professionals, there has been an increasing tendency over time for immigrants to be predominant also in jobs at the bottom end of the occupational classification. Nickell and Saleheen (2009) show that the ratio between recent immigrants and natives has increased by proportionately more in low skilled elementary and operative occupations over the last two decades. Oesch and Rodríguez Menés (2011), by resorting to an exercise in counterfactuals, find that between 1991 and 2008 the expansion in the low-paid occupations of the lowest

[22] Statistics on international migration flows for the UK are available at:http://www.statistics.gov.uk/hub/population/migration/international-migration.

quintile in Britain was mainly determined by job growth among foreign-born and not national workers.

VIII. Summary and Conclusions

In this paper we contribute to the debate on labor market polarization in Britain using UK task data to measure the job content of occupations. We confirm that employment in Britain experienced a polarizing trend at the occupational level between 1997 and 2006 but there is no evidence of a similar course in wages. Our sample suggests that jobs in high and low-paying occupations increased, while employment shares decreased in the middle of the distribution.

We interpret the evolution of occupational employment from a task-based perspective exploring ALM model's predictions. We find that high-paying occupations which increased the most can be safely classified as non-manual non-routine, while middling-paying occupations which have lost significant employment shares are predominantly routine (both manual and non-manual). The task content of low-paying occupations is more mixed, with elementary occupations being predominantly manual and service occupations scoring higher in the interpersonal dimension, and the routine dimension appers more difficult to evaluate. Still, we find that changes in employment shares are negatively related to the initial level of routine intensity.

Similarly to Green (2012), we formally test the association between routine task inputs and technology in workplaces, but we decide to exclude from the analysis low-paying occupations for which the ALM model predicts limited opportunities for substitution or complementarity. Moreover, we do not constrain our routine measure to represent only repetitive physical activities. From a comparison with O*Net data, we show that the routine measure in the UK Skills Surveys well captures both the manual and the cognitive routine dimension once low-paying occupations are dropped. The negative impact of computerization that we find is therefore likely to be associated both with manual and cognitive routine middling-paying jobs, although we are not able to disentangle the effect.

Finally, we exploit retrospective questions on past jobs to evaluate the extent to which the displacement of middle-paid workers, caused by an adverse impact of technological advances, contributed to the employment growth at the lower tail of the distribution. We find that workers in middling-paying occupations became more mobile over time. However, they did not predominantly move towards low-paying occupations. This is consistent with the argument that the surge of low-skilled immigrants in Britain from 1997 onwards played a major role in the expansion of low-paid jobs.

References

Acemoglu, D., Aghion, P. and Violante G. (2001), "Deunionization, Technical Change and Inequality", Carnegie-Rochester Conference Series on Public Policy.

Acemoglu, D. and Autor, D. H. (2011), *"Skills, Tasks and Technologies: Implications for Employment and Earnings"*, in Handbook of Labor Economics, Volume 4, Part B, pp. 1043-1171 Orley Ashenfelter and David E. Card, ed. (Amsterdam, NE: Elsevier, 2011).

Antonczyk, D., DeLeire, T. and Fitzenberger, B. (2010), "Polarization and Rising Wage Inequality: Comparing the U.S. and Germany", IZA Discussion Papers No. 4842.

Autor, D. H., Katz, L. and Kearney M. (2006), "The Polarization of the U.S. Labor Market", *American Economic Review*, 96(2), pp. 189–194.

Autor, D. H., Katz, L. and Kearney, M. (2008), "Trends in US wage inequality: re-assessing the revisionists", *Review of Economics and Statistics*, 90 (2), pp. 300–323.

Autor, D. H. and Dorn, D. (2009), "Inequality and Specialization: The Growth of Low-Skill Service Jobs in the United States", IZA Discussion Paper Series, No. 4290, July.

Autor, D.H. and Handel, M.J. (2009), "Putting tasks to the test: human capital, job tasks and wages", NBER Working Paper n. 15116.

Autor, D.H., Levy, F. and Murnane, R.J. (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration", *The Quartely Journal of Economics*, 118, pp. 1279-1333.

Baumol, W.J. (1967) "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis", *American Economic Review*, 57(3), pp. 415–426.

Berman, E., Bound, J. and Machin, S. (1998), "Implications of Skill-Biased Technological Change: International Evidence", *The Quarterly Journal of Economics*, 113(4), pp. 1245-79.

Blinder, A. S. (2007), "How Many U.S. Jobs Might Be Offshorable?", CEPS Working Paper No. 142, March.

Bound, J. and Johnson, G. (1992), "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations", *The American Economic Review*, 82(3), pp. 371-392.

Card, D. (2001), "The effect of unions on wage inequality in the U.S. labour market", *Industrial and Labor Relations Review*, 54, pp. 296-315.

Dickens, R. and Manning, A. (2004a), "Has the national minimum wage reduced UK wage inequality?", *Journal of the Royal Statistical Society A*, 167, pp. 613-626.

Dickens, R. and Manning, A. (2004b), "Spikes and spillovers: The impact of the national minimum wage on the wage distribution in a low wage sector", *Economic Journal*, 114, pp. 95-101.

DiNardo, J., Fortin, N. and Lemieux, T. (1996), "Labor market institutions and the distribution of wages, 1973-1992: A semi-parametric approach", *Econometrica*, 64, pp. 1001-1044.

Dustmann, C., Frattini, T. and Preston, I. (2008), "The Effect of Immigration along the Distribution of Wages ", CReAM Discussion Paper Series 0803, Department of Economics, University College London.

Dustmann, C., Ludsteck, J. and Schönberg, U. (2009), "Revisiting the German Wage Structure", *The Quarterly Journal of Economics*, 124(2), pp. 843-881.

Feenstra, R. and Hanson, G. (2005), "The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United

States, 1979-1990", *The Quarterly Journal of Economics*, 114(3), pp. 907-940.

Felstead, A. and Gallie, D. and Green, F. and Zhou, Y. (2007), "Skills at Work, 1986 to 2006 ", University of Oxford, SKOPE.

Fernández-Macías, E. (2012), "Job Polarization in Europe? Changes in the employment structure and Job Quality, 1995-2007, *Work and Occupations*, 39(2), pp. 157–182.

Goos, M. and Manning, A. (2003), "Lousy and lovely jobs: the rising polarization of work in Britain", CEPR Working Paper No. 0604, December.

Goos, M. and Manning, A. (2007), "Lousy and lovely jobs: the rising polarization of work in Britain", *The Review of Economics and Statistics*, 89(1), pp.118-133.

Goos M., Manning, A. and Salomons, A. (2009), "Job Polarization in Europe.", *American Economic Review*, 99(2), pp. 58-63.

Goos M., Manning, A. and Salomons, A. (2010), "Explaining Job Polarization in Europe: The Roles of Technology, Globalization and Institutions", CEP Discussion Paper No 1026, November.

Green, F. (2009), "Employee involvemen,. Technology and Job Tasks. ", National Institute for Economic and Social Research, Discussion Paper Number 326.

Green, F. (2012), "Employee Involvement, Technology and Evolution in Job Skills: A Task-Based Analysis", *Industrial & Labor Relations Review* , 65 (1), pp. 35-66.

Grossman, G. and Rossi-Hansberg, E. (2008), "Trading Tasks: A Simple Theory of Offshoring", *American Economic review*, 98(5), pp. 1978-1997.

Holmes, C. and Mayhew, K. (2010), "Are UK labour markets polarizing?", SKOPE Research Paper No. 97, September.

Ikenaga, T. and Kambayashi, R. (2010), "Long-term trends in the polarization of the Japanese labor market: the increase of non-routine task input and its valuation in the labor market", Hitotsubashi University Institute of Economic Research Working Paper, January.

International Labour Organization (1990), "International standard classification of occupations (ISCO-88)". Geneva: International Labour Office.

, Jolliffe I.T. (2002), "Principal Component Analysis", Springer Series in Statistics, 2nd ed., NY.

Kampelmann, S. and Rycx, F. (2011), "Task-biased Changes of Employment and Remuneration: The Case of Occupations", IZA Discussion Paper, No. 5470, January.

Katz, L. and Murphy, K. M. (1992), "Changes in the Relative Wages, 1963-1987", *The Quarterly Journal of Economics*, 107, pp. 357-358.

Lemieux, T. (2007), "The Changing Nature of Wage Inequality", NBER Working Paper 13523, October.

Lindley, J. (2012) "The gender dimension of technical change and the role of task inputs ", *Labour Economics*, 19(4) pp. 516-526.

Machin, S. (1996), "Wage inequality in the UK", *Oxford Review of Economic Policy*, 7, pp. 49-62.

Machin, S. (2008), "An Appraisal of Economic Research on Changes in Wage Inequality", *Labor*, 22, pp. 7-26.

Machin, S. and Van Reenen, J. (1998), "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries", *The Quarterly Journal of Economics*, 113 (4), pp. 1215-1244.

Manning, A. (2004), "We Can Work It Out: The Impact of Technological Change on the Demand for Low-skill workers", *Scottish Journal of Political Economy* vol. 51(5), pp. 581-608, November.

Massari R., Naticchioni P. and Ragusa G. (2012), "Unconditional and Conditional Wage Polarization in Europe", NEUJOBS Working Paper, No. D3.6, March.

Mazzolari, F. and Ragusa, G. (2007), "Spillovers from High-Skill Consumption to Low-Skill Labor Markets", IZA Discussion Paper No. 3048, September.

Nellas, V. and Olivieri, E. (2012), "The Change of Job Opportunities: the Role of Computarization and Institutions", Working Paper No. 804, Department of Economics, University of Bologna.

Nickell, S. and Saleheen, J. (2009) "The Impact of Immigration on Occupational Wages: Evidence from Britain ", SERC Discussion Papers 0034, Spatial Economics Research Centre, LSE.

Oesch, D. and Rodríguez Menés, J. (2011), "Upgrading or Polarization? Occupational Change in Britain, Germany, Spain and Switzerland, 1990-2008", *Socio-Economic Review,* 9(3), pp. 503-531.

Roy, Andrew D. (1951), "Some Thoughts on the Distribution of Earnings",*Oxford Economic Papers,* 3(2), pp. 135-461.

Schneider, S. L. (2008), "The application of the ISCED 97 to the UK's educational qualifications", in The International Standard Classification of Education (ISCED 97). An Evaluation of Content and Criterion Validity for 15 European Countries, Silke Schneider, ed. (Mannheim, GE: MZES, 2008).

Spitz-Oener, A. (2006), "Technical Change, Job Tasks and Rising Educational Demands: Looking outside the Wage Structure", *Journal of Labor Economics*, 24, pp.235-270.

Stewart M. B. (2012), "Wage inequality, Minimum Wage Effects and Spillovers", *Oxford Economic Papers*, 64(4), pp.616–634.

Wadsworth, J. (2012) "Immigration and the UK Labour Market: The latest evidence from economic research", CEP Policy Analysis Papers 014, Centre for Economic Performance, LSE.

Wright, E. O. and Dwyer, R. E. (2003), "The patterns of job expansions in the USA: a comparison of the 1960s and 1990s", *Socio-economic review*, 1 (3), pp. 289-325.

A Appendix

AA. List of tasks

Analytical
Paying close attention to detail
Teaching people (individuals or groups)
Making speeches/ presentations
Working with a team of people
Specialist knowledge or understanding
Knowledge of how organisation works
Spotting problems or faults
Working out cause of problems/faults
Thinking of solutions to problems
Analysing complex problems in depth
Checking things to ensure no errors
Noticing when there is a mistake
Planning own activities
Planning the activities of others
Organising own time
Thinking ahead
Reading written information (e.g. forms, notices and signs)
Reading short documents (e.g. reports, letters or memos)
Reading long documents (e.g. manuals, articles or books)
Writing materials (e.g. forms, notices and signs)
Writing short documents (e.g. reports, letters or memos)
Writing long documents with correct spelling and grammar
Adding, subtracting, multiplying and dividing numbers
Calculations using decimals, percentages or fractions
Calculations using advanced statistical procedures

Interpersonal
Dealing with people
Persuading or influencing others

Selling a product or service
Counselling, advising or caring for customers or clients
Listening carefully to colleagues
Knowledge of particular products or services

Manual
Physical strength (e.g. to carry, push or pull heavy objects)
Physical stamina (e.g. to work on physical activities)
Skill or accuracy in using hands/fingers (e.g. to assemble)
Knowledge of use or operation of tools/equipment machinery

AB. Variables construction

Wages. Our wage variable is the gross hourly pay (gpayp). This derived variable is available for all the three waves of the UK Skill Survey. For most cases gpayp was computed as gross usual weekly pay divided by usual hours worked per week (including usual overtime). In 1997 respondents quoted an hourly rate directly: these values, when available, were used to replace gpayp (727 cases). Nominal gross hourly wages are deflated by the Consumer Price Index, with 2005 as the base year. Wages are measured in British Pounds. We trim our data such that hourly wages lower than 1 and higher than 100 are excluded.

Occupations. We classify occupations according to the International Standard Classification of Occupations (ISCO−88) (see ILO, 1990). Occupations were originally classified according to the Standard Occupation Classification (SOC 90 in 1997, SOC 2000 in 2001 and 2006). Codes are manually matched on the basis of the guidelines distributed by the Occupational Information Unit of the Office for National Statistics, correcting both for employment status and the size of the organization/establishment (number of people working) when available. The same procedure is applied to the variables indicating the past occupation. Crosswalks are made available by the CAMSIS project at: http://www.camsis.stir.ac.uk/occunits. This harmonization allows to compare occupations over time and to make our results strictly comparable to other papers. ISCO-88 defines four levels of aggregation, consisting of 10 major groups (one-digit), 28 sub-major groups (two-digits), 116 minor groups (three-digits) and 390 unit groups (4-digits).

Education. Our education variable distinguishes three groups of workers: high, medium and low educated (skilled). For all the three waves we exploit the variable dquals1 which indicates the highest qualification held by the interviewee. Both educational and vocational qualification levels are available in the list provided to respondents. In 2001 and 2006 one more options, “Masters or PhD degree”, was added whereas earlier respondents were not allowed to differentiate the type of degree. We follow Schneider (2008) to convert the UK's educational and vocational qualifications to International Standard Classification of Education (ISCED-97) levels. The usual ISCED division into low, medium and high is then adopted where low is equivalent to ISCED 0-2 (i.e. primary and lower secondary education), medium is given by ISCED 3-4 (i.e. upper secondary and post-secondary non-tertiary education) and high is ISCED 5-7 (i.e. tertiary education). The derived categorical variable for education takes value of 1 for low educated, 2 for medium and 3 for high.

Task measures. We create task content measures which capture the intensity of the different activities carried out by each worker. This is done by performing a principal component analysis (PCA) for each of the three groups into which we categorize the 35 tasks (analytical, interpersonal and manual). The PCA is a statistical technique which aims at reducing correlated variables into a smaller number of principal components. It is a common procedure in the existing literature on job content analysis (see Autor et al., 2003; Autor and Handel, 2009; Goos et al. 2010). A detailed description of the PCA technique can be found in Jolliffe (2002).

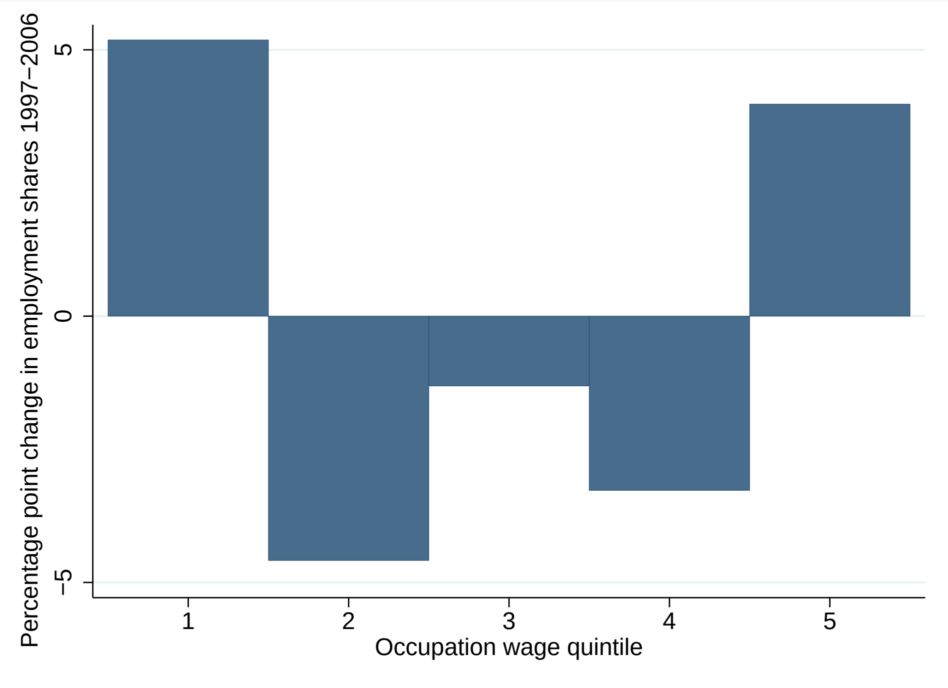
The routine measure is derived from a question related to the frequency of routine activities performed by workers on the job (b13 in 1997, brepeat in 2001 and 2006). All task measures above described are rescaled to range between 0 and 1.

Computer use. We create a measure which captures the intensity of computer adoption, interacting the scores of two questions: one related to the importance of computer use (from "essential" to "not at all/does not apply"); the other to its complexity (from "simple" to "advance"). The variables used are ja17 and m1 for the 1997 survey, cusepc and dusepc for 2001 and 2006. This variable is normalized to [0-1].

Figure 1: Employment shares growth in Britain (1997-2006) by median hourly wage (Ranking: wages 1997)

Notes: Scatter plot and quadratic prediction curve. The dimension of each circle corresponds to the number of observations within each ISCO-88 three-digit occupation in 1997; the grey area shows 95% confidence interval. Employment shares are measured in terms of workers. *Source*: Uk Skill Surveys.

Figure 2: Evolution of employment changes between 1997 and 2006 by occupation wage quintiles (Ranking: wages 1997)



Notes: Occupation wage quintiles are based on three-digit ISCO-88 median wages in 1997. *Source*: Uk Skill Surveys.

Table 1: OLS regressions for employment polarization analysis

	Dependent variable	
	Change in employment share	
	1997-2001	1997-2006
	(1)	(2)
(log) median hourly wage 1997	-6.820***	-9.402***
	(2.363)	(3.389)
sq. (log) median hourly wage 1997	1.773***	2.406***
	(0.597)	(0.854)
constant	6.185***	8.738**
	(2.299)	(3.314)
N	67	67
Adj. R-square	0.161	0.156
F	4.545	3.994

Notes: Each occupation is weighted by the initial number of observations. Robust standard errors in parentheses, significance levels *** $p < 0.01$, ** $p < 0.05$,*$p < 0.10$. *Source*: UK Skills Surveys.

Table 2: OLS regressions for wage polarization analysis, ASHE data

	Change in (log) median wage, 1997-2006
(log) median hourly wage 1997	0.009
	(0.256)
sq. (log) median hourly wage 1997	-0.016
	(0.059)
constant	0.303
	(0.260)
N	67
Adj. R-square	0.021
F	1.190

Notes: Results are based on the same 67 occupations selected for the UK Skills Survey analysis. *Source*: Annual Survey of Hours and Earnings (ASHE), 1997 and 2006.

Table 3: Correlations among task measures and the education variable

	Analytical	Interpersonal	Manual	Routine	Education
Analytical	1				
Interpersonal	0.664	1			
Manual	-0.501	-0.531	1		
Routine	-0.675	-0.578	0.497	1	
Education	0.736	0.528	-0.571	-0.705	1

Notes: Correlations are computed at the 3-digit occupational level. *Source*: UK Skills Surveys.

Table 4: Occupations, median wages and education

Occupations	ISCO-88 code	Median wage in 1997 (1)	Mean level of education in 1997 (2)	Total change in employment share 1997-2006 (3)
Sales and services elementary occupations	91	3.90	1.13	1.61
Salespersons, models and demonstrators	52	4.26	1.17	0.23
Personal and protective services workers	51	4.68	1.34	1.69
Market-oriented skilled agricultural and fishery workers	61	4.85	1.41	-0.48
Agricultural, fishery etc. labourers	92	4.87	1.79	-0.11
Labourers in mining, construction, manufacturing and transport	93	4.96	1.03	1.66
Other craft and trades workers	74	5.02	1.11	-0.77
Customer services clerks	42	5.31	1.41	-0.25
Drivers and mobile-plant operators	83	5.41	1.14	-0.26
Machine operators and assemblers	82	5.68	1.34	-2.72
Extraction and building trades workers	71	6.42	1.33	1.45
Stationary-plant operators	81	6.58	1.07	-0.22
Office clerks	41	6.69	1.50	-5.01
Managers of small enterprises	13	6.69	1.38	-0.29
Metal, machinery and trades workers	72	7.61	1.49	-2.72
Precision, handicraft, printing and trades workers	73	7.78	1.37	-0.52
Physical and engineering science associate professionals	31	8.93	2.15	0.02
Other associate professionals	34	9.00	1.74	0.80
Life science and health associate professionals	32	9.27	1.95	3.26
Corporate managers	12	10.72	1.95	2.06
Other professionals	24	10.72	2.45	0.98
Physical, mathematical and engineering science professionals	21	11.40	2.39	-1.43
Teaching professionals	23	11.47	2.76	0.49
Life science and health professionals	22	15.64	2.72	0.52

Notes: Occupations ranked in ascending order by the median hourly wage in 1997; column 2 reports the mean of the educational attainment in 1997, based on a three-values variable ("low"=1, "medium"=2 and "high"=3); column 3 shows the percentage point change in employment share over the period 1997-2006. *Source*: UK Skills Surveys.

Table 5: Task measures by occupation

Occupations	ISCO-88 code	Analytical (1)	Interpersonal (2)	Manual (3)	Routine (4)
Sales and services elementary occupations	91	0.41	0.45	0.48	0.61
Salespersons, models and demonstrators	52	0.54	0.77	0.45	0.63
Personal and protective services workers	51	0.60	0.68	0.53	0.63
Market-oriented skilled agricultural and fishery workers	61	0.48	0.60	0.75	0.63
Agricultural, fishery etc. labourers	92	0.49	0.37	0.71	0.68
Labourers in mining, construction, manufacturing and transport	93	0.48	0.46	0.71	0.65
Other craft and trades workers	74	0.52	0.44	0.67	0.75
Customer services clerks	42	0.59	0.73	0.37	0.74
Drivers and mobile-plant operators	83	0.46	0.54	0.62	0.60
Machine operators and assemblers	82	0.60	0.51	0.66	0.66
Extraction and building trades workers	71	0.60	0.63	0.83	0.60
Stationary-plant operators	81	0.59	0.44	0.72	0.65
Office clerks	41	0.61	0.61	0.34	0.64
Managers of small enterprises	13	0.69	0.80	0.60	0.56
Metal, machinery and trades workers	72	0.65	0.59	0.78	0.54
Precision, handicraft, printing and trades workers	73	0.62	0.55	0.70	0.64
Physical and engineering science associate professionals	31	0.67	0.68	0.50	0.53
Other associate professionals	34	0.71	0.79	0.28	0.45
Life science and health associate professionals	32	0.65	0.75	0.57	0.49
Corporate managers	12	0.75	0.79	0.34	0.46
Other professionals	24	0.78	0.73	0.30	0.43
Physical, mathematical and engineering science professionals	21	0.76	0.70	0.33	0.39
Teaching professionals	23	0.79	0.76	0.37	0.39
Life science and health professionals	22	0.76	0.74	0.53	0.50

Notes: Occupations are ranked in ascending order by the median hourly wage in 1997. Column 1 to 4 report normalized task measures in 1997, ranging [0,1]. *Source*: UK Skills Surveys.

Table 6: Correlation between UK Skills Surveys routine measure and O*Net routine-cognitive and routine-manual indices

	Skill Surveys routine	O*Net routine-cognitive	O*Net routine-manual
Skill Surveys routine	1		
O*Net routine-cognitive	0.325	1	
O*Net routine-manual	0.617	0.339	1

Notes: Correlations are computed at the 3-digit occupation level.
Source: UK Skills Surveys and O*Net data.

Table 7: OLS regression of changes in employment share and the initial level of routine intensity

	Dependent variable	
	Change in employment share 1997-2006	
	(1)	(2)
Routine intensity 1997	-1.716	-3.076**
	(1.421)	(1.441)
N	67	52
Adj. R-square	0.028	0.128
F	1.459	4.557

Notes: All regressions include a constant. Column 1 shows results for all occupations; column 2 reports estimates excluding the low-paying ones. Robust standard errors between brackets.
Source: UK Skills Surveys.

Table 8: Impact of computer adoption on task measures

	Dependent variable			
	Routine	Repetitive physical	Analytical	Interpersonal
Computer use	-0.151*	-0.170***	0.225***	0.193***
	(0.076)	(0.063)	(0.050)	(0.061)
N	156	156	156	156
R-squared	0.860	0.955	0.932	0.948
F(Year dummies)	2.83	1.51	6.81	0.06

Notes: Fixed-effects estimates at the 3-digit occupation level are weighted by cell size. Robust standard errors in parenthesis. *Source*: UK Skills Surveys.

Table 9: Occupational mobility by educational group

	Occupational change	
	1992-1997	1996-2001
Education	(1)	(2)
Low	64.57	71.21
Medium	58.39	70.88
High	57.01	54.21
N	727	1,776

Notes: The table shows the percentages of workers who changed occupation among those with the same educational attainment.
Source: UK Skills Surveys.

Table 10: Transition probability matrix

		Occupation in 1997			
		Low	Middling	High	Total
Occupation in 1992	Low	0.58	0.26	0.17	1
	Middling	0.14	0.69	0.17	1
	High	0.08	0.19	0.73	1
		Occupation in 2001			
		Low	Middling	High	Total
Occupation in 1996	Low	0.56	0.29	0.14	1
	Middling	0.19	0.60	0.21	1
	High	0.07	0.17	0.75	1
		Occupation in 2006			
		Low	Middling	High	Total
Occupation in 2001	Low	0.69	0.14	0.17	1
	Middling	0.17	0.58	0.25	1
	High	0.06	0.12	0.81	1

Notes: Each cell corresponds to the transition probability form one state to another. Occupations are grouped into low, middling and high-paying. N=739 in 1997, 1,785 in 2001 and 3,645 in 2006.
Source: UK Skills Surveys and BHPS.