CPB Netherlands Bureau for Economic Policy Analysis

CPB Discussion Paper | 233

The effects of technology and offshoring on changes in employment and task-content of occupations

Semih Akcomak
Suzanne Kok
Hugo Rojas-Romagosa

The effects of technology and offshoring on changes in employment and task-content of occupations

Semih Akcomak[*], Suzanne Kok[†] and Hugo Rojas-Romagosa[‡]

February 2013

Abstract

Combining employment data with the British Skill Survey (BSS) –which has comparable within-occupation task data for three waves: 1997, 2001 and 2006– we analyse employment changes between occupations (extensive margin) *and* within occupations (intensive margin). First, we find that the task-content of occupations (i.e. the intensive margin) has experienced significant changes in the United Kingdom between 1997 and 2006. Second, our econometric results suggest that these *intensive* margin changes can be explained by technological improvements (SBTC) and unionisation levels, while offshoring has not been a factor explaining how tasks are organized within occupations. Analysing changes at the *extensive* margin we confirm previous findings in the literature: there has been job polarization for both the UK and the Netherlands, and this job polarization can be explained by both SBTC and offshoring, though SBTC seems to be a more influential factor.

Keywords: employment changes, occupational tasks, technology, offshoring
JEL Classification: J21, J23, J24, O33, F16, F23

1 Introduction

Improvements in information and communication technologies (ICT) since the 1980s and the broadening of economic globalization have deeply influenced the way we work and how firms operate. ICT improvements –specially the computerization of work– have greatly affected labour demand through skill-biased technological change (SBTC)[1], but it has also been a leading force in enhancing the globalization process. In particular, the offshoring of

[*]TEKPOL, Middle East Technical University (akcomak@metu.edu.tr).
[†]CPB Netherlands Bureau for Economic Policy Analysis and University of Groningen (s.j.kok@cpb.nl).
[‡]CPB Netherlands Bureau for Economic Policy Analysis (h.rojas-romagosa@cpb.nl).

[§]We received very helpful comments from Steven Brakman, Casper van Ewijk, Harry Garretsen, Arjan Lejour, Roman Stollinger, Bas ter Weel, Henry van der Wiel, and participants at the 5th FIW Research Conference and the FIW-Seminar in International Economics in Vienna; the T.A.S.K. II workshop in Bonn, Turkish Economic Association Conference in Cesme, Izmir and seminar at TOBB-ETU. Akcomak thanks financial support from NSI of Maastricht University

[1]C.f. Berman *et al.* (1998); Autor *et al.* (2003); Borghans and ter Weel (2006); Acemoglu and Autor (2010); OECD (2010a); Van Reenen (2011).

jobs from rich developed countries to emerging economies has been an influential economic force in the last 20 years.[2]

Most of the recent literature has analysed the labour market effects of ICT improvements –and offshoring to a lesser extent– using the task-based framework pioneered by Autor *et al.* (2003). This framework analyses the labour market using information on tasks performed by individual workers at the occupational levels. In particular, Autor *et al.* (2003) classify tasks in two broad groups: routine and nonroutine tasks. Applying the observation that computers substitute routine tasks and complement certain nonroutine tasks, they explain how computerization depresses the demand for medium-skilled workers (performing routine tasks), while increasing the demand for high-skill and low-skill workers performing nonroutine tasks. This "routinisation" hypothesis has been used to explain the wage and job polarization of the labour market, which has been extensively documented.[3]

Another feature of the paper by Autor *et al.* (2003), is that they analysed a particular database that allowed them to examine both the changes in the task-content within occupations (what they label as the intensive margin) and changes between occupations that have different task-contents (i.e. the extensive margin). In subsequent papers using the task-based approach, most of the analyses have used the ONET dataset, which provides detailed information –at different dimensions– of the task-content of occupations in the United States. Even though this database is regularly updated, it does not allow comparisons over time. Thus, studies using these data are limited to analyse exclusively changes in the extensive margin, and assume (at least implicitly) that the task-content is fixed within occupations.[4] This limitation in the empirical task-based analysis has been pointed by Van Reenen (2011), and the recent theoretical model by Acemoglu and Autor (2010) also emphasizes the importance of both intensive and extensive margin changes as the linkage between exogenous shocks –i.e. SBTC and offshoring– and labour market dynamics.

In this paper we use the British Skill Survey (BSS), which provides information on the relative importance of tasks performed by individual workers in particular jobs. The BSS data, therefore, provides information on the changes in employment at the *intensive* margin. These task data are then merged and complemented with the UK Labour Force Survey (LFS) data from 1997 to 2006 to obtain changes in employment at the *extensive* margin. A particular feature of the BSS data is that it provides comparable data for three different years: 1997, 2001 and 2006. This time-varying characteristic of the BSS allows us to analyse changes in the task structure of occupations over time (i.e. the intensive margin).[5] Combining the information on the BSS and LFS data, we can answer our first

[2]See Feenstra and Hanson (1996); Blinder (2006); Head *et al.* (2009); Jensen and Kletzer (2010); Goos *et al.* (2011); Firpo *et al.* (2011).

[3]For instance, Autor *et al.* (2006, 2008); Goos and Manning (2007); Michaels *et al.* (2010); Goos *et al.* (2011); Firpo *et al.* (2011); Autor and Dorn (2011), while Bloom *et al.* (2010) distinguish the differentiated impacts of communication *and* information technology on mid- and low-level occupations. In addition, there is also evidence of trade induced technical change (Bloom *et al.*, 2011).

[4]These papers include Autor *et al.* (2006, 2008); Firpo *et al.* (2011); Goos *et al.* (2011).

[5]Only three countries have task data available: the United States (see Autor *et al.*, 2003), Germany (see Spitz-Oener, 2006), and Britain (see Felstead *et al.*, 2007). As explained in Akcomak *et al.* (2011) only the British data is suitable to our framework because it provides comparable information for different time periods.

research question: has the task-content of occupations changed in the UK between 1997 and 2006; and has this been a result of changes at the intensive margin, the extensive margin or both?

At the extensive margin, we find that both the UK and the Netherlands have experienced a job polarization process, where the relative number of medium-skill jobs has been decreasing relative to low- and high-skill jobs. This follows the findings by Goos and Manning (2007) for the UK and Goos *et al.* (2009, 2011) for Europe.

To analyse changes at the intensive margin we start our analysis using the routine/non-routine task classification proposed in Autor *et al.* (2003). We then complement this approach by analysing changes in the task-content of occupations using alternative classifications, which employ the full range of tasks performed by each occupation and their relative importance.[6] In total we use three different analytical tools: (*i*) the routinisation analysis; (*ii*) factor analysis to obtain eight groups of tasks and analyse their changes over time, and; (iii) summary indicators of changes in all 36 tasks that are available in the BSS dataset (i.e. changes on the task-occupation connectivity, on the rank-correlation of task, and changes on task-concentration indexes).

Using this empirical approach, we find that the task-content of occupations (i.e. changes at the intensive margin) in the UK has changed between 1997 and 2006 and that these changes are pervasive and of a magnitude similar to changes at the extensive margin (i.e. changes in occupational employment levels). Using the routinisation hypothesis we find that the routine task intensity (RTI) index is changing at both the extensive and intensive margins, and the magnitude of the changes is similar for both margins. When we group tasks using factor analysis, we also find that both the extensive and intensive margins are changing. In this case, the magnitude of the intensive margin is usually larger than that of the extensive margin. Finally, when we use summary indicators we find that the relative importance of tasks (i.e. task-rank correlation), the connectivity between tasks (task-occupation connectivity), as well as the number of relatively important tasks (i.e. task-concentration indicators) has changed when task are ranked by skill levels.

Our second research question is: how has technology and offshoring affected the changes in occupational employment at both the extensive and intensive margin?

To test this question empirically, we first construct a series of indicators for offshoring and SBTC for both the UK and the Netherlands. We then test how these indicators have affected employment changes in both countries at the extensive margin. In particular, we regress changes in employment (extensive margin) against these variables and additional control variables such as initial size of occupations and the degree of unionisation. Our econometric results show for both the UK and the Netherlands that SBTC and offshoring are important factors explaining changes in employment by occupations, and that the effect of SBTC is somewhat larger than offshoring. These results are in line with recent findings in the literature (Firpo *et al.*, 2011; Goos *et al.*, 2011). In addition, the robustness of our results is checked using different offshoring and SBTC indicators.

With respect to changes at the intensive margin, we can only test for the changes in our task-content indicators for the UK. We find that the SBTC is statistically significant for changes in the task-rank correlation indicator and the task-occupation connectivity indicator. On the other hand, the effect of the offshoring indicators are not significant.

[6]The use of alternative tasks classifications was first explored in Akcomak *et al.* (2011).

Moreover, the econometric results show that occupations which high degrees of unionisation experience less changes at the intensive margin (task-content). These results suggest that computerization has changed the way in which tasks are bundled within occupations *and* the demand for certain occupations, while offshoring has only changed employment levels but not how tasks are organized within occupations.

The contribution of this paper is twofold. First, we analyse if the task-content of occupations has changed at the intensive margin. Since we find compelling evidence that the intensive margin for the UK has changed in the period 1997-2006, our results indicate that it might be problematic to construct variables based on the assumption of a constant task-content of occupations over time. In particular, task-routinisation indicators that are assumed to be time-invariant based on the ONET database are not capturing potentially important changes at the intensive margin. In addition, at the extensive-margin we confirm previous findings of the literature: there has been job polarization for both the UK and the Netherlands which can be explained by both SBTC and offshoring, even when SBTC seems to be a more influential factor. The second contribution of our paper is that we analyse the factors that explain changes at the intensive margin. We find that SBTC and unionisation are influential factors affecting the way tasks are organized within occupations, while offshoring has not been a critical factor in this respect.

The paper is organized in the following way. Section 2 presents the theoretical background, while Section 3 describes the employment data, the BSS task data and the construction of the SBTC and offshoring indicators. In addition, in subsection 3.2 we present the results of our task-content analysis and how employment has been changing at the intensive margin in the UK. In Section 4 we present the econometric results testing how offshoring and SBTC affect employment changes at both the extensive and intensive margin. Sensitivity analyses are presented in section 5. We summarize our results in Section 6.

2 Theoretical background

In their seminal paper Autor *et al.* (2003), henceforth ALM, introduced a task-based framework to analyse changes in the labour market induced by computerization. They classify all tasks into two broad groups: routine and non-routine tasks; and then into five subgroups: routine manual tasks, routine cognitive tasks, non-routine manual tasks, non-routine analytical and non-routine interactive tasks.[7]

ALM argue that the significant fall in computer prices increased the demand for non-routine tasks while reducing it for routine tasks. This hypothesis is based on three stylized facts[8]: (*i*) Computers are strong substitutes to routine tasks groups; (*ii*) Computers are complements to analytical and interactive (abstract) non-routine tasks, and; (*iii*) Computers have limited effects on manual non-routine tasks.

[7] In Autor *et al.* (2006, 2008) this five subgroups were divided into three groups: manual (non-routine), routine, and abstract (non-routine) tasks, which can be directly assigned to three different skill classification of workers: Low, medium and high-skill workers.

[8] In Autor *et al.* (2008) a fourth observation is added: workers ability to perform certain tasks is conditional on their skill levels. Thus, low-skill workers perform manual non-routine tasks, medium-skill workers do routine tasks and high-skill workers perform abstract non-routine tasks. The mapping between skills and tasks is formalized in the model by Acemoglu and Autor (2010), as we explain below.

To test this hypothesis, ALM constructed a panel database with the task-content both at the industry and occupational levels. They paired task-requirements from the Dictionary of Occupational Titles (DOT) with employment data from the Census and Current Population Survey in the US from 1960 to 1998. This particular dataset allowed them to exploit two sources of variation. First, ALM define the "extensive" margin as changes over time in the occupational distribution of employment, holding task content constant within occupations. They can measure this extensive margin consistently over the period 1960 to 1998. Second, ALM define the "intensive" margin as the changes in task content measures within occupations. They can measure this intensive margin using two years: 1977 and 1991, which corresponded to the Fourth Edition and Revised Fourth Edition of the DOT.[9]

ALM found that starting in the 1970s, the task-content of jobs (occupations) became gradually more non-routine and less routine intensive. In other words, routine to non-routine ratio declined. Moreover, they found that this shift was pervasive, as they found changes by industry, gender, education and occupations. They found that this was a combination of changes in both the intensive and extensive margins.

After the ALM paper, most of the task-based empirical papers in the literature use the ONET database, which is the successor of the DOT database. The ONET database, however, does not have time variation. Thus, the task-based empirical papers written after Autor *et al.* (2003) have only analysed changes in the extensive margin, i.e. changes in the employment levels of occupations. As explained above, the BSS data allows us to conduct an inter-temporal analysis that can track changes in both the extensive *and* intensive margins.

The distinction and importance of the changes in both the intensive and extensive margin is well captured in the theoretical model by Acemoglu and Autor (2010), henceforth the AA model. This model also formalises the task-based approach first introduced in ALM, which was later used to explain how SBTC in general –and computerization in particular– can account for the polarization of the labour market in the US (Autor *et al.*, 2006, 2008). This approach has also been labelled as the nuanced-view of the SBTC hypothesis (or the "routinisation" hypothesis). Therefore, the AA model provides a suitable theoretical background for our own analysis, since it captures changes at both the intensive and extensive margin, and discusses how SBTC and offshoring may affect the labour demand.[10]

The AA model is a Ricardian trade model with one final good that is produced using a continuum of tasks, such that:

$$Y = \exp[\int_0^1 \ln y(i)\,\mathrm{d}i] \tag{1}$$

where Y denotes the output of a unique final good and $y(i)$ the production level of task i. There are four production factors. Labour is represented by three different skill levels: low

[9]However, in their paper ALM only present the results separated by intensive and extensive margin changes at the industry level, but not at the occupational level. This makes it difficult to compare their results with ours.

[10]There are other models that use task-based approach to analyse the impact of SBTC and international trade on the labour market. These include: Grossman and Rossi-Hansberg (2006, 2008), Costinot and Vogel (2010), Autor and Dorn (2011) and Firpo *et al.* (2011). However, the AA model is the only one that emphasizes the importance of both margins in explaining the adjustments in the labour market.

(L), medium (M) and high (H); and capital K which is defined as machines/computers in the model. Using these factors, each task has the following production function:

$$y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_H(i)h(i) + A_K\alpha_K(i)k(i) \tag{2}$$

where A_S represents factor-augmenting technology for each skill $S = L, M, H$, and $\alpha_S(i)$ are the task productivity schedules for task i, while $s(i)$ is the number of workers with skill $s = l, m, h$ allocated to task i.

In general, all workers can eventually perform all tasks, but the model assumes a structure of comparative advantages that assures that workers specialize in certain tasks depending on their skill level. A key feature of the model is that the continuum of tasks $i \in [0, 1]$ is ordered in such a way that low-indexed tasks are less complex than high-indexed tasks. This task complexity order is directly associated with skill levels in the assumption that: $\frac{\alpha_L(i)}{\alpha_M(i)}$ and $\frac{\alpha_M(i)}{\alpha_H(i)}$ are continuously differentiable and strictly decreasing. Thus, low-skill workers perform only low-indexed (less complex) tasks and high-skill workers perform the high-index (more complex) tasks, while medium-skilled workers perform those tasks in the middle of the task ordering. Their core model further assumes that there is a fixed inelastic supply of labour.[11]

It is important to mention that in the AA model occupations are defined as bundles of tasks. Given the equilibrium conditions of the model, where particular sets of tasks (classified by their task "complexity") are performed by one of the three skill groups, one can directly associate skills with occupations (or groups of occupations).[12]

The equilibrium conditions of the model are given by two key variables: the equilibrium threshold tasks I_L and I_H. These variables define the endogenous assignment of tasks to skills. Hence, low-skill workers perform tasks $i < I_L$, medium-skill workers perform tasks $I_L < i < I_H$ and high-skill workers perform tasks $i > I_H$.

Moreover, there is a "law of one price" equilibrium condition that implies that:

$$w_L = p(i)A_L\alpha_L(i) \text{ for any } i < I_L \tag{3}$$

$$w_M = p(i)A_M\alpha_M(i) \text{ for any } I_L < i < I_H \tag{4}$$

$$w_H = p(i)A_H\alpha_H(i) \text{ for any } i > I_H \tag{5}$$

These equilibrium conditions determine that every worker is paid the same skill type wage, while the wage paid to perform specific tasks is however different but proportional to the productivity of each worker performing that particular task. Finally, relative wages are defined as functions of I_L and I_H, which highlight the central role of the allocation of tasks to skills in the AA model.

The workings of the model are illustrated using three different comparative statistic exercises:

- The first, is to model SBTC as an increase in A_H, corresponding to high skill biased technical change. This shock creates a decrease in both I_L and I_H, which increases the scope of tasks performed by high-skill workers, and also increases their relative wages. Both $\frac{w_H}{w_L}$ and $\frac{w_H}{w_M}$ increase as a result. Perhaps more interestingly, $\frac{w_M}{w_L}$

[11] These assumptions are relaxed later on, to provide different applications to the model, such as SBTC, offshoring, directed technical change and endogenous choice of skill supply.

[12] This direct association is later used to relate their theoretical model to the data.

is decreasing, even though SBTC is reducing the set of tasks performed by both medium and low-skill workers.[13] Thus, SBTC produces a clear wage polarization pattern in the AA model.

- The second exercise is to analyse the effects of computerization –i.e. the introduction of computers that displace workers. In the AA setting this is modelled by including capital (embodied by machines and computers) which perform a particular set of tasks. They assume that computers substitute for routine tasks located in the middle of the task-ordering, which results in medium-skill workers being displaced and performing tasks previously done by low or high-skill workers. The shock yields an increase in $\frac{w_H}{w_M}$ and a decrease in $\frac{w_M}{w_L}$. Thus, we also obtain a wage polarization pattern from computerization.

- Finally, the AA model can also accommodate for the offshoring of tasks. This is done by assuming that offshoring is also displacing tasks from medium-skilled workers. Modelling offshoring in this way has the equivalent effect of computerization, and thus, also yield wage polarization.[14]

Thus, the AA model provides a theoretical setting that summarizes the extensive and intensive margin changes using two variables: I_L and I_H. These variables, by giving the cutoff points in the distribution of tasks between the three skill levels, provide direct information on the changes in the intensive margin. For instance, an increase in I_L is associated with low-skill workers performing tasks previously done by middle-skill workers, and thus, the task-content of both skill groups is changing. Moreover, changes in I_L and I_H –by increasing the scope of tasks performed by certain skill groups– also increases the demand for different skill-type workers (and accordingly, reduces the demand for those skill groups that perform less tasks). These changes in the number of different skill-type workers (i.e. $s(i)$, for $s = l, m, h$) is directly associated with changes in the extensive margin of occupations.

Finally, the model predicts that SBTC and offshoring levels will affect both I_L and I_H, and thus, both the extensive margin (changes in the number of workers by occupation) and the intensive margin (changes in the task-content of occupations) will also change. As explained in the following section, we estimate regressions on changes at *both* the intensive and extensive margin of occupational employment against technology (computerization) and offshoring levels. Note that the impact of changes in technology and offshoring will likely crystal out in the period after the change. Thus, with our dataset we can empirically test the implications of the AA model mentioned above.[15]

[13] This result indicates that the skill-intensity of the tasks performed by medium-skill workers decreases relatively more than the skill-intensity of the tasks performed by low-skill workers.

[14] However, modelling offshoring in this way is problematic, since it assumes that offshoring is affecting only medium-skill tasks. Following Blinder (2006, 2009) it is expected that the offshorability of a task is related to perform that task in physical proximity, but is unrelated to the complexity of the task. In terms of the AA model this means that the ordering of tasks by complexity can be uninformative of the offshorability of certain tasks within that particular indexation and thus, increased offshoring may have untraceable effects on the variables I_L and I_H, which ultimately determine the equilibrium of the model.

[15] The functional relations between these exogenous variables (SBTC and offshoring) with I_L and I_H are determined by the productivity schedules $\alpha_S(i)$ (for which the AA model only requires their comparative advantage assumption, but no exact functional form) and on how the exogenous variables affect the demand

3 Data and descriptive statistics

Following the insights from Autor *et al.* (2003) the task-content of occupations can be analysed at both the intensive and the extensive margin. The common approach in the literature is to use employment data to assess changes at the extensive margin, i.e. changes in the task-content *between* occupations assuming that the task-content *within* occupations is fixed. Employment data by occupations are readily available for most countries on a yearly basis, and thus, it is relatively simple to assess changes in employment between occupations.

Data on the intensive margin (i.e. the changes in the task-content *within* occupations) is constrained to only three countries: the United States (see Autor *et al.*, 2003), Germany (see Spitz-Oener, 2006), and Britain (see Felstead *et al.*, 2007). However, the widely used ONET task database from the US has information for only one point in time and thus, is not suitable to analyse changes over time. German task data has time variation but there are only about 20 broad categories (compared to more than 100 in ONET and 36 questions in BSS) and besides the scaling varies between the years and not all questions are asked in all years. In this paper we use the British Survey Skills (BSS), which has three comparable waves(1997, 2001 and 2006) that allows us to analyse changes in the task-content of occupations at the intensive margin.

3.1 Employment data and job polarization

For the UK, employment data is taken from the British Labour Force Survey (LFS), for 1997, 2001 and 2006 –to be consistent with the three BSS waves. It is straightforward to measure changes in employment levels by occupation. Thus, the LFS data provides direct information on occupational changes at the extensive margin. In addition, we obtain wage data from the Annual Survey of Hours and Earnings (ASHE).[16] We create an education-level variable (*educ*97) for 1997 which is a weighted average of the six education levels in the LFS. With education and wage data we can proxy a skill classification of occupations, which we use below to analyse the changes in employment and the task-content of occupations ranked by skills.

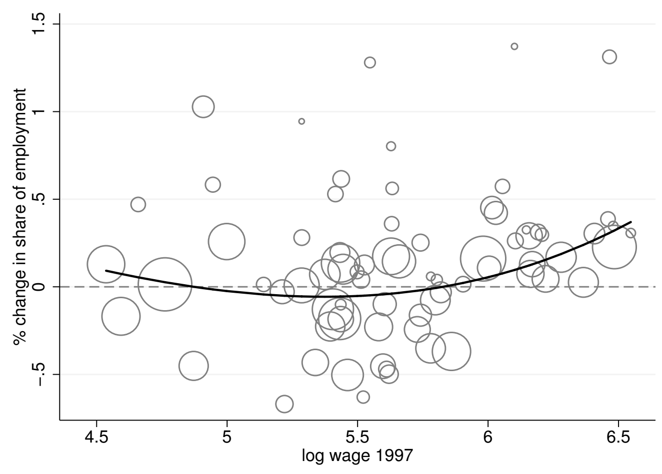
As reported in other studies (Goos *et al.* (Cf. 2009, 2011)), we find job polarization in the UK. Figure 1 shows how medium-skill occupations (with wages in the middle of the wage distribution) are losing employment with respect to high-skill occupations and also with respect to low-skill occupations.

We find that in the UK the share of service jobs has grown at the expense of technical jobs. If we consider medium and low level occupations (major group 5 and below) the technical job loss accounts to about 750,000 jobs between 1997 and 2006 (sub major groups 52, 53, 54, 81 and 91, see Table C.1 in the Appendix). During the same period about 900,000 jobs were created in the service sector (sub major group, 61, 62, 71, 82

of the continuum of tasks i (for which the AA model assumes broad demand changes). Therefore, it is not possible to obtain a reduced form of the AA model that can be tested empirically –unless one can obtain detailed information on the task-specific productivity schedules and how SBTC and offshoring may affect these schedules and/or task-specific demand changes.

[16]We use the gross weekly earnings from ASHE excluding overtime payments, multiplied by four to arrive at the monthly wages.

Figure 1: United Kingdom, changes in employment between 1997 and 2006 by occupations classified by wages per hour, 3-digit SOC-2000 occupational codes



Source: Own estimations using BSS and ASHE data.

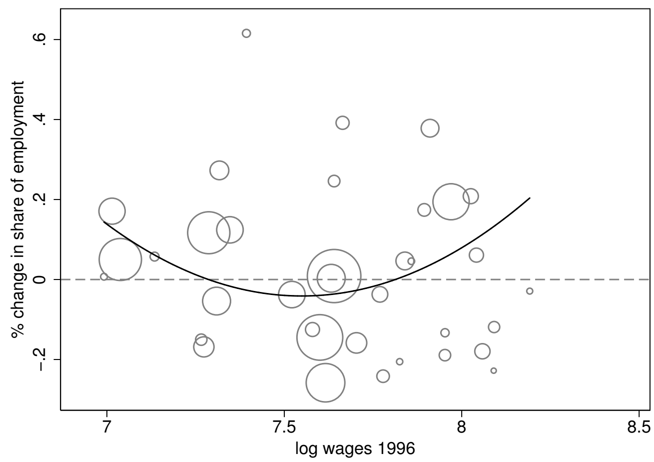
and 92). These broad 2-digit category changes, however, also hide some interesting sub-category variations. For example, process plant and machine operatives jobs (SOC-2000, 81) shrunk by 25% in the designated period. But if we look at the 3-digit level we find that the employment in construction operatives (SOC-2000, 814) has grown by more than 40% whereas all other sub-categories have shrunk. For such detailed results we present the employment changes at the 3-digit SOC-2000 level in Table C.2.

For the Netherlands we use the Dutch Labour Force Survey (Enquête Beroeps Bevolking: EBB) from 1996 to 2005 to obtain information on employment by occupation. We use the 2-digit codes from the Dutch Occupation Classification from 1992 (SBC92). To obtain information on wages at the occupational level, we merge the EBB data to administrative wage data from the Sociaal Statistisch Bestand (SSB) and the Dutch Socio-Economic Panel (SEP). Using these data we also find job polarization in the Netherlands (see Figure 2). Similar to the case of UK technical occupations have lost about 100,000 jobs and about 450,000 new administrative, commercial and health related jobs were created in the designated period. In Table C.3 we show the employment shares, relative and absolute employment changes by 2-digit occupational codes.

3.2 Task data and changes in the task-content of occupations

We use the task data provided by the British Skills Survey (BSS), which is available for three years: 1997, 2001 and 2006 (cf. Felstead *et al.*, 2007; Green, 2012). The BSS dataset gives detailed information on the tasks performed by individual workers, which can then be classified according to occupations or industries. It consists of 36 tasks, ranging from basic tasks such as the use of physical strength and physical stamina, to complex tasks

Figure 2: Netherlands, changes in employment between 1996 and 2005 by occupations classified by wages, 2 digit SBC92 codes



Source: Own estimations using EBB, SSB and SEP data.

such as thinking of solutions to problems and analysing complex problems in depth.[17] It is more correct to view these tasks as general attributes or skills that all workers perform –up to certain degrees– at their given occupations. However, we follow the rest of the literature and refer to these attributes/skills as tasks for the rest of the paper.

The dataset provides the importance of each task in performing the job of each individual workers. In particular, each task is rated on a scale of 1 to 5: with 1 denoting "not important at all" and 5 denoting "essential". It is important to note that these scale ratings are provided directly by each individual worker in the survey. Therefore, we standardize the scales to reflect relative importance at an aggregated level.[18] The use of person (worker) level data using self-reported job tasks is not unique to the BSS task database. For instance, Handel (2008) and Autor and Handel (2009) find that these type of self-reported job tasks at the person-level –in their case the Princeton Data Improvement Initiative (PDII) survey– provide substantial within and between occupations variations, which are significantly related to workers' characteristics, and are robustly predictive of wage differentials both between occupations and among workers in the same occupation. Moreover, the OECD is recently undertaking a multi-country database collection process: the Programme for the International Assessment of Adult Competencies (PIAAC) which

[17]A full list of all 36 tasks is provided in Table A.1. Note that tasks are defined as a broad set of assignments and/or operations performed by workers *across* different occupations and industries. Thus, tasks are not equivalent to jobs or occupations, as sometimes assumed in the literature. Moreover, the BSS task definitions are not directly related to goods or intermediate inputs, as in the trade in tasks model of Grossman and Rossi-Hansberg (2008).

[18]On the other hand, the BSS does not provide information on the input-use or the frequency of tasks being performed. Even though the ONET database has this input-use information, most of the task-based studies only employ the relative importance information present in the data.

also uses a self-reported individual worker's survey.[19] We find that the use of the subjective evaluation of each individual worker on the importance of tasks for his job does produce, in aggregate, sensible task-content orderings.

The interaction of the 36 different tasks together with its relative importance provides a very rich information source: the task-content of individual workers' jobs. Since each worker is linked to an occupation (using SOC-2000 codes) we can aggregate the individual workers' task-content information to the occupational level.[20] The data can be aggregated at the 2-digit level for 25 occupations and at the 3-digit level for 75 occupations (see Tables A.2 and A.3). We obtain information on the task-content of occupations by standardising the relative importance of all tasks within each occupation. Since this information is comparable for the three waves of the BSS, we can then observe how the task-content is changing over time.

Finally, this rich information set contained in the BSS also allows us to use the common division of tasks between routine and non-routine tasks. But in addition, we can also employ alternative classifications that use other features of the task-content information provided by the BSS. For instance, similar to Green (2012) we use factor analysis to classify all 36 BSS tasks into eight factor-groups and we also create summary indicators that use all 36 tasks at once. As mentioned before, the use of other task-classification approaches allows us to exploit different dimensions in the task data, which are not captured by the commonly used routinisation classification.[21]

Analysing changes in the task-content of several occupations is a complex undertaking. Given the number of tasks that are analysed and their broad/generic definitions, there are different dimensions in the analysis. For instance, changes in task-content can occur with particular sets of tasks and not only for individual tasks. The task-content information is very broad and therefore, it is not possible to measure such a big array of changes with a single indicator. This is the main reason why we complement the routinisation-analysis with two alternative ways to classify the task data. By doing this we provide insight in several facets of the task-content of occupations. All the indicators cover a different facet and are complementary. Furthermore, this is a useful robustness check as the BSS tasks do not fit neatly into the routinisation categories. Hence, in this section we analyse changes in the task-content of occupations employing three different task-classification approaches: (*i*) The routinisation classification (section 3.2.1), (*ii*) factor-analysis to create task-groups (section 3.2.2), (*iii*) summary indicators using all tasks at once (section 3.2.3).

3.2.1 Routine and non-routine classification

Our starting point is the routinisation classification first introduced by Autor *et al.* (2003), which is widely used in the literature. The routine task intensity (RTI) is usually defined as the ratio of the routine tasks with respect to the non-routine tasks (cf. Goos *et al.*, 2011; Acemoglu and Autor, 2010). However, both papers construct the RTI using the ONET database, and since there is no time variation in the ONET data it is assumed that the

[19] See www.oecd.org/piaac for detailed information and the scope of the project. The survey questionnaire is in OECD (2010b).

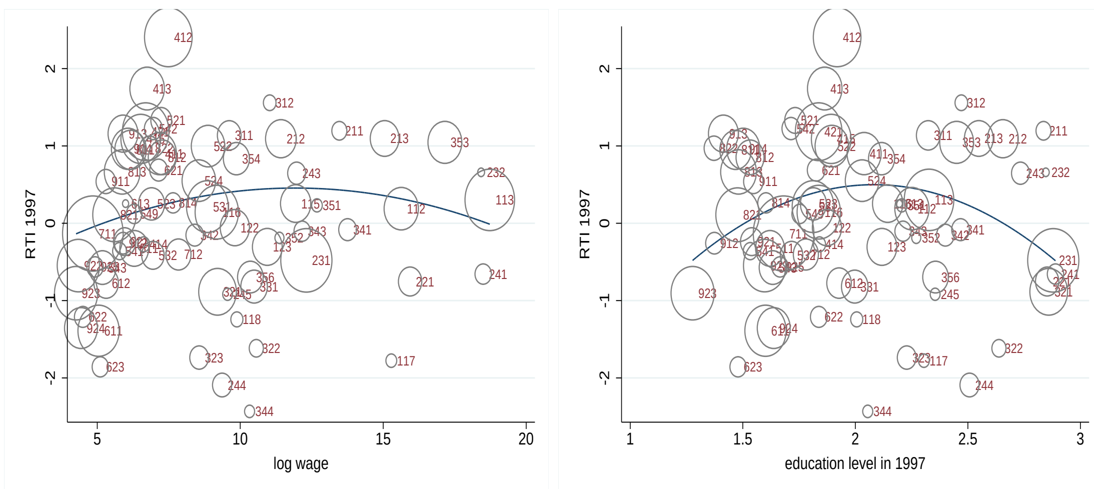
[20] It is also possible to aggregate at the industry level (using ISIC codes), but the general agreement is that labour market dynamics are better explained using occupational classifications (cf. Firpo *et al.*, 2011).

[21] For a discussion on the caveats of classifying tasks as routine and non-routine see Green (2012).

RTI index is not changing over time, and that the information provided by the initial (or final) RTI index is preserved over time and provides a valid measure of the routinisation levels by occupation.

Following this approach we classify all the BSS tasks into three categories: routine, services and abstract. We define the RTI index as the ratio of routine tasks over the services and abstract tasks. The first group includes both manual and cognitive routine tasks, while the last two groups collect non-routine tasks. The 36 tasks of the BSS are not readily translated into these three routine groups. However, we do find that a number of tasks can be classified and this yields comparable results with other routinisation indexes used in the literature.[22] As shown in Figure 3 we find the common inverted U-shaped relationship between the RTI index and skill levels. Especially occupations with wages and skill levels in the middle of the distribution obtain high scores on our RTI index. Low-skilled and high-skilled (and low and high paid) occupations obtain lower scores on our RTI index.

Figure 3: United Kingdom: RTI index 1997 by occupations classified by wages per hour (left) and education levels (right), 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings average for 1997 and 2001. Circle sizes reflect occupation's employment levels in 1997 and circle numbers are the 3-digit SOC-2000 codes. The solid line is a quadratic fit using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

As mentioned before, changes in the task structure of the labour market rely on the changes within occupations (i.e. the intensive margin) and between occupations (i.e. the extensive margin). The BSS data allows us to decompose the changes of the importance of the three routine and non-routine task groups into changes in the intensive and the extensive margin. For this analysis we use the ranking of the importance of the three

[22] The precise matching between BSS tasks and the three routinisation groups is explained in Appendix B. In addition, we also compared our RTI index (using the BSS data) with other RTI indexes in the literature. Although the correlation is not large (between 0.4 and 0.5) the differences are relatively easy to spot. For instance, we do not classify manual tasks mainly as routine tasks, and clerical jobs (using repetitive cognitive tasks) are clearly classified as routine tasks in our classification.

task groups in each occupation. The first three rows of table 1 present the importance of the three task groups in 1997, 2006 and the change between 1997 and 2006. Routine tasks become less important in the UK economy while the importance of the non-routine service and abstract tasks rises. Similar results have been documented by Goos and Manning (2007) and Goos *et al.* (2009, 2011). In addition, the last two rows in Table 1 present the decomposition of these changes in to changes in the intensive and the extensive margin.[23] The decreasing importance of routine tasks in the UK occurs at the extensive and intensive margins. Both employment shifts between occupations and task importance shifts within occupations lower the importance of routine tasks. non-routine service and abstract tasks win in employment due to employment shifts and increasing task importance within jobs. The impact of the intensive margin is larger for the service tasks while the rising importance of abstract tasks seems to rely mainly on the extensive margin.

Table 1: Tasks shifts, intensive and extensive margin

	Routine	Non-routine	
		Service	Abstract
Importance 1997	34.21	40.30	25.49
Importance 2006	33.14	40.90	25.95
Change	-1.07	0.61	0.46
Extensive margin	-0.65	0.24	0.41
Intensive margin	-0.42	0.37	0.06

It is important to note that the intensive margin effects –i.e. the changes in the RTI due to changes in the task-content of occupations during this period– are of a similar magnitude to those in the extensive margin. Thus, using the routinisation classification we find that changes in task-content of occupations have been significant in the UK.

3.2.2 Task classification using factor analysis

We use factor analysis to construct an alternative grouping of tasks. We rotated the factors (varimax) and retained seven factors that have eigen values above one. The seven factors explain about 91% of the total variation in the data. To show the impact of computers in task composition of jobs we classify the task PCuse as a separate category. The mapping

[23]We decompose the change in importance of task k between 1997 and 2006 (ΔT_k) into shifts in the extensive and intensive margin of occupation j. Thus, $\Delta T_k = \Delta T_k^E + \Delta T_k^I$ in which $\Delta T_k = T_{k,2006} - T_{k,1997}$. The extensive margin reflects the part of the change which is due to employment shifts between occupations: $\Delta T_k^E = \sum_j \Delta E_j \gamma_{jk}$, where E_j is the employment share in national employment of occupation j and γ_{jk} represents the importance of task k in occupation j. Hence, in the extensive margin the task importance is held constant (and represents the average task importance across the two years) and time variation relies on changes in employment across occupations. The intensive margins reflects the part of the change which is caused by changes of task importance within occupations: $\Delta T_k^I = \sum_j \Delta\gamma_{jk} E_j$. Thus, in the intensive margin occupational employment is held constant while the importance of tasks within occupations is allowed to vary over time.

of 35 tasks into seven factor groups are presented in the appendix Table A.4. Hence, 36 tasks in the BSS are classified in to eight factor groups.[24]

We then compute the intensive and extensive margins for the eight task groups described above. The results are displayed in Table 2. The first panel displays the result for all occupations. Table 2 shows that computer use has significantly affected the rankings of tasks within occupations. Therefore, all other task-groups –except literacy and planning related tasks– have lost relative importance. In addition, we see that all task-groups experience changes in the intensive margin and that these changes are of the same magnitude or even bigger (as in the case for problem solving, number and PC use task-groups) than the extensive margin changes.

Table 2: Shifts in task-content using eight factor-groups and changes at the extensive and intensive margins

All occupations	literacy	problem solving	checking	planning	number	physical	interactive	PC use
task1997	3.80	5.68	7.67	5.28	2.15	3.60	4.50	3.33
task2006	3.80	5.07	7.56	5.35	1.92	3.11	4.32	4.87
change	0.00	-0.60	-0.11	0.08	-0.23	-0.49	-0.18	1.54
extensive margin	0.10	-0.06	-0.03	0.09	-0.02	-0.22	0.07	0.08
intensive margin	-0.10	-0.54	-0.08	-0.02	-0.21	-0.27	-0.25	1.47
High-skill occupations								
task1997	4.20	5.68	7.45	6.66	2.77	1.15	4.27	3.83
task2006	3.75	4.96	7.33	6.01	2.05	1.15	4.02	6.72
change	-0.45	-0.72	-0.12	-0.65	-0.73	0.01	-0.24	2.89
extensive margin	0.09	0.09	-0.03	-0.13	-0.03	-0.05	-0.05	0.11
intensive margin	-0.54	-0.80	-0.08	-0.52	-0.70	0.06	-0.19	2.78
Middle-skill occupations								
task1997	4.13	5.77	7.63	4.82	2.20	3.52	3.71	4.22
task2006	4.18	5.21	7.36	5.10	2.33	2.99	3.52	5.33
change	0.04	-0.57	-0.28	0.28	0.13	-0.53	-0.20	1.11
extensive margin	0.04	-0.07	-0.02	0.12	-0.08	-0.14	0.14	0.01
intensive margin	0.00	-0.49	-0.25	0.16	0.21	-0.39	-0.34	1.10
Low-skill occupations								
task1997	3.16	5.57	7.86	4.82	1.66	5.40	5.54	1.99
task2006	3.42	5.02	7.97	5.10	1.36	4.83	5.45	2.85
change	0.26	-0.55	0.11	0.29	-0.30	-0.58	-0.09	0.86
extensive margin	0.14	-0.15	-0.02	0.13	0.00	-0.18	0.10	-0.02
intensive margin	0.12	-0.40	0.12	0.16	-0.29	-0.39	-0.19	0.88

In Table 2, we replicated the analysis for high, middle and low-skill occupations to account for interesting patterns that could emerge because task changes might differ by skill levels. When skill levels of the occupations are taken into consideration the change in the importance of computer use is increasing in skill. This supports the findings of the

[24]The analysis using the individual level BSS data separately in 1997, 2001 and 2006 returns very similar tasks to factor mappings. For this reason we merged BSS data for all years and perform a single factor analysis using the merged data (about 12,000 observations).

skill-biased technical change literature (i.e., computers mostly complement tasks that are performed by high skilled workers). We observe that physical, number and checking tasks are loosing importance in the task composition of UK jobs. In the case of checking and number tasks these changes are mainly as a result of the within occupation changes.[25]

The fact that the importance of computer use increased significantly almost in all occupations may affect the results of the analysis. For this reason we exclude computer use and replicate the analysis for 35 tasks and 7 task groups. The results are presented in Table C.4. Interpreting the Tables 2 and C.4 together we can say that the changes in the task-content of occupations between 1997 and 2006 have been significant in the UK.

It is interesting to observe that problem solving skills and interactive tasks are loosing importance in task ranks within jobs (Table 2). This holds for low, middle and high level occupations. The literature shows that both interactive and analytical skills are gaining importance which contradicts our findings. One reason for this could be that the factor analysis posed some problems. For instance finding faults and finding errors are two similar tasks but the factor analysis grouped the former as a problem solving task and the latter as a checking task. Another issue is the difficulty of assessing the meaning of some tasks. For instance, paying attention to detail could be important in any occupation and skill level. To get a better understanding we replicated the analysis for all 36 tasks. The results are displayed in Table C.5.

Several observations can be made by analysing the detailed results in Table C.5. First, tasks related to calculation and statistics is still important relative to simple computing tasks. This finding holds when the analysis is replicated for high, middle and low skilled jobs. Second, except reading and writing short documents, literacy tasks are gaining relative importance. In low skill jobs writing and reading long documents have lost importance which probably is a result of specialisation. Third, all physical tasks have become less important both at the intensive and extensive margin. Fourth the importance of analysing display a different pattern compared to other tasks associated to problem solving. Analysing tasks have become more important both at the intensive and extensive margin (and for all skill levels). Whereas other tasks associated with problem solving lost importance.

In Table C.6 we present the detailed results for low, middle and high level occupations. One interesting observation is that the changes in the importance of computer use and tasks such as checking for errors, checking for mistakes, finding cause and spotting problems and errors are negatively correlated. This observation holds for all skill levels and strongest in high level jobs. It seems that such tasks are mostly replaced by computers in one way or another. Another interesting observation is that the importance of computer use have increased dramatically in high skill occupations. The change in importance of computer use is increasing in skill conforming our earlier findings on complementarity of skills and computerisation.

3.2.3 Task-composition analysis using summary indicators

In this section we use our third approach and create summary indicators that employ all 36 BSS tasks at once. The main idea is that the importance of some tasks may increase

[25] When we look at the actual importance levels (not shown here) we can talk about skill upgrading (i.e., tasks are gaining importance in low skilled jobs, though rankings may have changed)

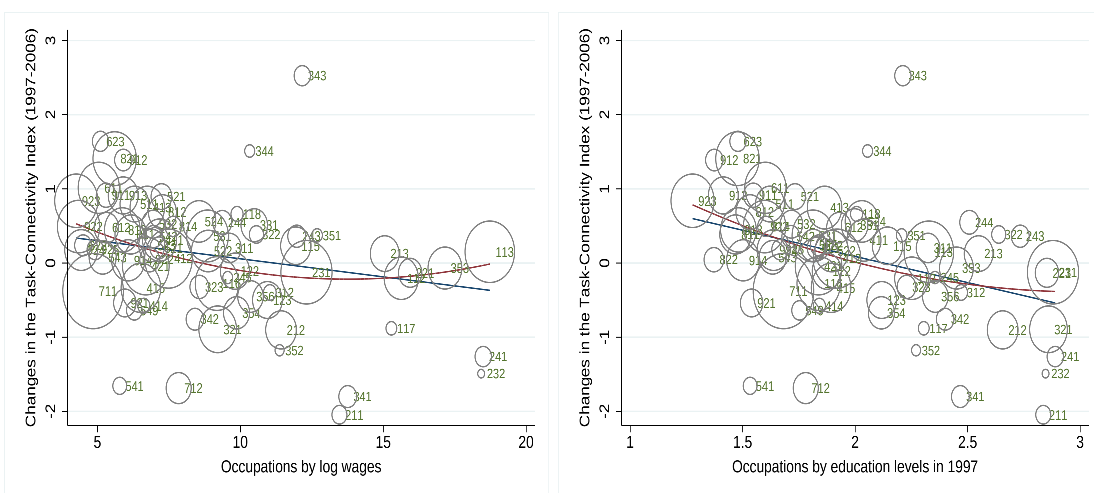
at the expense of others over time. We have two indicators that measure the changes in the relative importance of tasks within occupations: task-occupation connectivity and task-rank correlation. We have one indicator that measures the changes in the number of relatively important tasks: task-concentration indicator. The summary indicators provide information on the behaviour of all tasks within an occupation and are therefore occupation-specific and not task-specific. As these indicators are not task-specific only changes at the intensive margin are analysed.

Task-occupation connectivity The first task-content summary indicator is taken from Akcomak *et al.* (2011) and measures how different tasks within an occupation are correlated to most important core-tasks for that occupation. In particular, the task-occupation connectivity (TOC) is constructed as follows:

$$TOC_{ij} = \sum_{j'} c_{j'j} m_{ij'} \tag{6}$$

where i indexes occupations and j indexes the 36 tasks. The variable $c_{j'j}$ is an element of the task correlation matrix, which shows how tasks are correlated at the individual worker level. The result is a correlation coefficient for all tasks that shows how connected task 1 is to the other 35 tasks and so on. These correlation coefficients are weighted by $m_{ij'}$, which measures the importance of tasks within an occupation –i.e. the core-tasks. Thus, TOC_{ij} measures how much task j is connected to all other tasks weighted by the task-importance of each task in occupation i.

Figure 4: United Kingdom, changes in task-occupation connectivity (TOC) indicator between 1997 and 2006 by occupations classified by wages per hour (left) and education levels (right), 3-digit SOC-2000 occupational codes

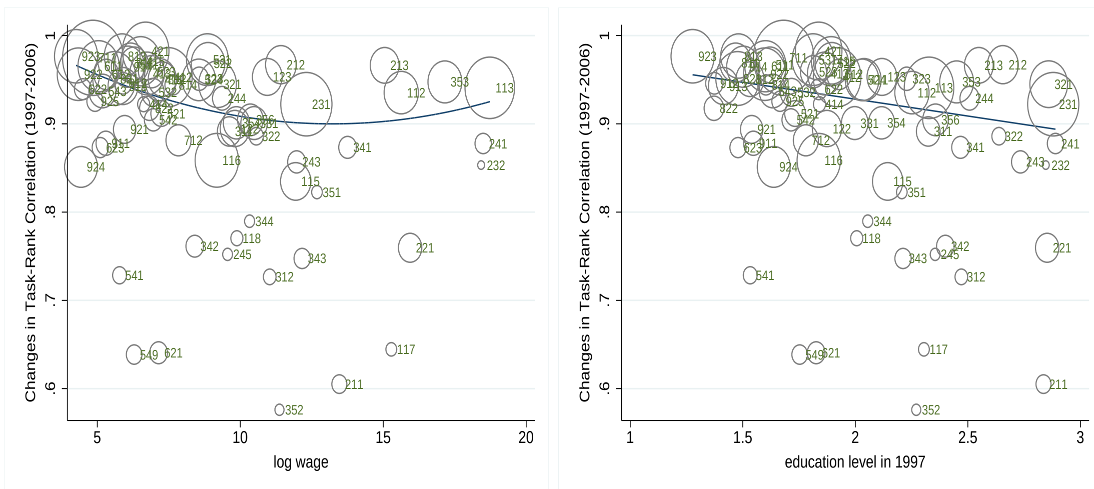


Notes: log wage is the occupation's gross hourly earnings average for 1997 and 2001. Circle sizes reflect the occupation's employment levels in 1997 and circle numbers are the 3-digit SOC-2000 codes. The solid lines are linear and quadratic fits using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

Task-rank correlation The task-rank correlation measures the changes in the relative importance of tasks. For each occupation the importance of the 36 tasks is ranked in 1997 and 2006. Task-rank correlation measures the correlation between the task importance ranks in 1997 and 2006. The lower values of the indicator reflect a change in task-content of the occupation.

Figure 5 shows the relation between the task-rank correlation and skill levels (proxied by log wages *and* education levels). We find that task-rank correlation has a slight U-pattern with respect to skill levels when we use log wages to proxy for skills. Medium-skill occupations have experienced more changes in their task-content than the other two skill groups. When we proxy skills using education levels we find that task-rank correlations are decreasing by education levels.

Figure 5: United Kingdom: Changes in task-rank correlations between 1997 and 2006 by occupations classified by wages per hour (left) and education levels (right), 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings average for 1997 and 2001. Circle sizes reflect the occupation's employment levels in 1997 and circle numbers are the 3-digit SOC-2000 codes. The solid line is a linear or quadratic fit using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

A common pattern to both graphs is that low-skill occupations have experienced less shift in their task-rank correlation. This suggests that those tasks that were relatively more important in 1997 were still the most important tasks in 2006. For high-skill –and especially medium-skill– occupations the changes in the relative importance of tasks has been more pronounced. Another interesting pattern is the relation between the size of the occupations (initial employment levels) and the task-rank correlations. It seems that the task-compositions have not changed that much in occupations that are relatively larger in size. Even though many of the occupations maintain a task-rank correlation between 0.9 and one, we do observe sizeable changes for some occupations and in general, a pattern of task-content change between 1997 and 2006.

Task-concentration indicator As an indicator of task specialisation within jobs we look at changes in task concentration. If the more important task for a particular occupation is changing (at the expense of the less important) then task specialisation within that occupation increases. Alternatively the occupation may become more generalised when the number of essential tasks increase or when tasks that were previously not important gain importance while other tasks keep their relative weight in an occupation.[26] To evaluate changes in task-concentration we use the Gini coefficient. A Gini coefficient of zero indicates that tasks are equally important within the occupation, while a Gini coefficient of one indicates that only one task is important. Our indicator for task-concentration measures the change in the Gini-coefficient between 1997 and 2006 by occupations. A positive value indicates that the task-content has become more concentrated. In other words, a higher task-concentration value shows that *less* number of tasks are crucial for a given occupation. We can also associate a higher task-concentration value with less number of tasks being performed in that particular occupation.[27]

In Figure 6 we show the relation between task-concentration and occupations ranked by wages.[28] First, we observe that in 1997 task-concentration was higher for low-skilled than for medium- and high-skill occupations. This reflects that low-skill jobs were more specialized in the performance of a certain group of tasks. On the other hand, high-skill jobs were more generalized, in the sense that workers in those occupations tended to perform a broader range of tasks. Another way to phrase these results is that high-skill workers have relatively higher levels of multi-tasking than medium- and low-skill workers.

The second observation, is that this specialization/generalization pattern declined between 1997 and 2006. Task-concentration have decreased for low-skill jobs, while there was a slight increase for high-skill occupations. This means that low-skill jobs are becoming more general and less specific in their task content. However, the task-concentration indicator still has a negative relation with skills in 2007 (Figures not shown).[29]

3.3 Offshoring and offshorability indicators

We use two main indicators to assess the effect of offshoring on changes in employment and the task-content within occupations. Both concepts are widely used in the literature, even if what they measure is conceptually different.

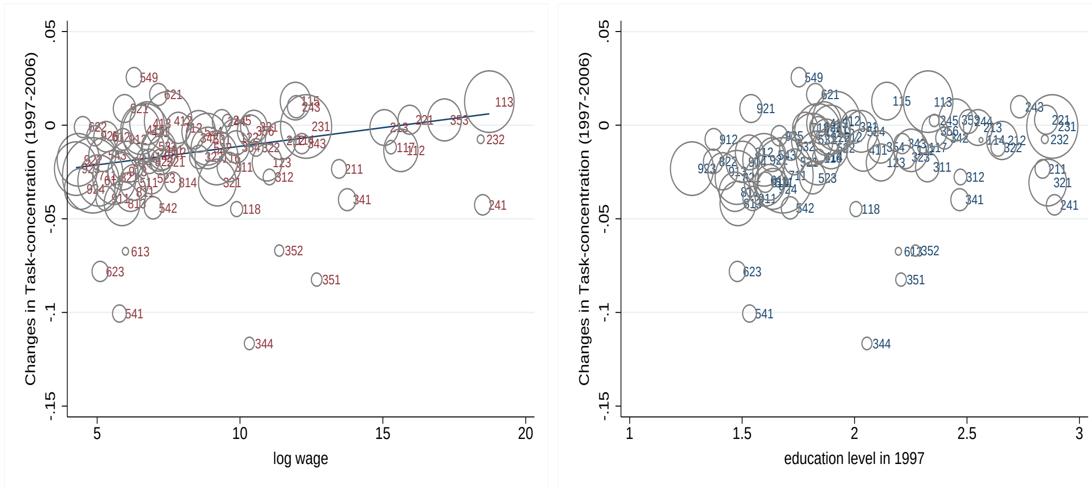
[26]For instance, Bloom *et al.* (2010) associate increases in communication technology (as differentiated from information technology) to decrease the number of tasks performed by certain mid- and low-level occupations.

[27]Given the very broad way in which tasks are defined in the BSS it is hard to imagine that any particular task is *never* performed in an occupation. However, when the relative importance of this task is very low with respect to other tasks, we assume that particular task is *effectively* not performed in that occupation.

[28]The results do not change if we use education levels as a proxy for skill.

[29]For an alternative concentration measure we counted the number of most important tasks per occupation in the BSS. The idea is that workers in elementary occupations concentrate on few tasks and as the job gets more complicated the variety increases. This is shown in Figure C.1. As the skill-content of occupations increase task variety increases. The relation among two alternative concentration indicators is depicted in Figure C.2. The correlation among two indicators is above -0.70 (significant at the 1 percent level) for 1997 and 2006. The conclusions above do not change when this alternative measure is used.

Figure 6: United Kingdom, changes in task-concentration between 1997 and 2006 by occupations classified by wages per hour (left) and education (right), 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings average for 1997 and 2001. Circle sizes reflect the occupation's employment levels in 1997 and circle numbers are the 3-digit SOC-2000 codes. The solid line is a linear fit using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

3.3.1 Actual offshoring index

We use the approach developed by Feenstra and Hanson (1996) to define our first offshoring indicator: actual-offshoring index (AOI). They measure offshoring based on a proxy of the share of non-energy imported intermediate goods in total non-energy intermediate inputs. This concept is based on the assumption that output of offshored activities has to be imported back into the UK to be combined with other inputs to produce final products (Crinò, 2010). In this context, AOI is measuring all past offshored activity, but using changes on AOI we can also obtain an indicator of current changes in offshoring levels.

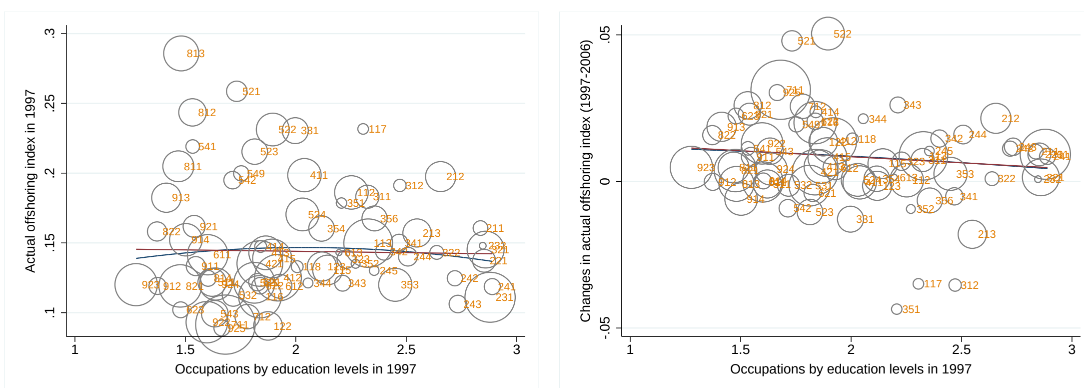
The AOI index is constructed using detailed input-output tables that are organized at the industry level.[30] Since our labour data is organized by occupations we need to map the input-output industry data to occupational data. This is done by using the employment share by industry for each occupation.[31]

[30]For the UK we use the WIOD input-output tables for 1997 and 2006 and we define the energy sectors as: Coke, Refined Petroleum and Nuclear Fuel; and Electricity, Gas and Water Supply. These energy sectors are eliminated and then we divide the imported input value (industry i imports from all industries) by the total input value of industry i. Using this methodology we obtain the AOI at the industry level. We use a similar methodology for the Netherlands, but using the input-output tables from Statistics Netherlands (CBS).

[31]From the LFS dataset we have employment data at the industry level. For 1997, the LFS uses the UK-SIC-1992 industry classification, so we first have to map the NACE codes (provided in the WIOD input-output tables) to the UK-SIC-1992 codes. For 2000 the LFS uses the NACE codes and the mapping is straightforward.

In Appendix C we present Figure C.3 with the values of AOI for 1997 and 2006. We observe that the average value of AOI is around 15%, with occupations like SOC-2000_52 (skill metal, electrical and electronic trade), SOC-2000_81 (process, plant and machine operatives), and SOC-2000_54 (textiles, printing and other skilled trades) all having above average AOI values, as expected. On the other hand, it is surprising that SOC-2000_33 (protective service occupations) and SOC-2000_31 (science, engineering and technology associate professionals), also have above average values. In Figure C.3 we show that AOI by occupations at the 2-digit level has not changed that much. At the 3-digit level, we do find larger changes for specific occupations, and overall offshoring has been increasing for most occupations (see right-hand graph in Figure 7). Moreover, in Figure 7 we see that neither the offshoring levels (measured by the AOI in 1997) nor the changes in offshoring (measured by changes in AOI between 1997 and 2006) are related to skill levels (proxied by education levels). In both graphs of Figure 7 we plot quadratic and linear fits which are both flat. It is important to note that this relation between offshoring levels (and changes) and skill levels is against the assumption that offshoring is relatively more important for middle-skill levels (cf. Acemoglu and Autor, 2010).

Figure 7: United Kingdom, actual-offshoring index (AOI) for 1997 (left graph) and changes in AOI between 1997 and 2006 (right graph), by occupations classified by education levels in 1997, 3-digit SOC-2000 occupational codes, with linear and quadratic fit (weighted by 1997 employment levels)



Source: Own estimations using WIOD, BSS and ASHE data.

3.3.2 Offshorability index

The second concept we use is offshorability, i.e. the potential of a specific task or occupation to be offshored. This concept was first introduced by Blinder (2006, 2009). The fact that a task could be offshored (due for instance to high wage differentials between countries) does not imply that it can by physically (spatially) separated and actually offshored. Some tasks cannot be performed at a distance, e.g., the cleaning of a firm, even if it is economically feasible to offshore. In other words, if a task/job cannot be spatially separated, then it cannot be offshored. Thus, spatial-separability indicator (SSI) provides information on the offshorability of a specific occupation. It captures the likelihood that a job can be performed at a distance, even if it currently –given wage differentials and coordination costs– is not economically feasible to offshore.

Using the ONET data we replicate the Blinder offshoring index on spatial separability (cf. Blinder, 2009).[32] The index consist of five ONET tasks: Establishing and Maintaining Interpersonal Relationships, Assisting and Caring for Others, Performing for or Working Directly with the Public, Selling or Influencing Others and Social Perceptiveness.[33] For each occupation, ONET provides information on the importance (scale 1-5) and the required level (scale 1-7) of the tasks. Blinder (2007) assigns a weight of one third to the importance and a weight of two third to the level of the task. The Blinder index represents the standardized sum of the score on these five tasks. To equal signs with the AOI, we define the Blinder index in such a way that higher values represent higher spatial separability. The higher the index, the easier it is to perform the occupation at distance and thus the higher the offshorability. The ONET database, however, is a cross-section without any time variance, so we cannot measure the changes in spatial separability over time.

In Figure 8 we find that the Blinder offshoring index is decreasing in skill/education levels. This means that low-skill occupations are easier to spatially-separate from the workplace, and thus, are potentially more offshorable than higher skilled occupations.

3.4 Indicators for SBTC

Finally, the last set of indicators we use are those that reflect changes in skill-biased technological change (SBTC). From Section 3.2.1 we already have the RTI-BSS indicator, which provides information on the routine/non-routine share of tasks using the BSS dataset. Accordingly, we can estimate an RTI index using the ONET database. To calculate the RTI-ONET index we match the ONET occupations to the BSS occupations and use the ONET task classifications and values as in Acemoglu and Autor (2010).[34] Even though the RTI-ONET index does not have variation over time, it provides us with a variable that is easily comparable to the rest of the literature.

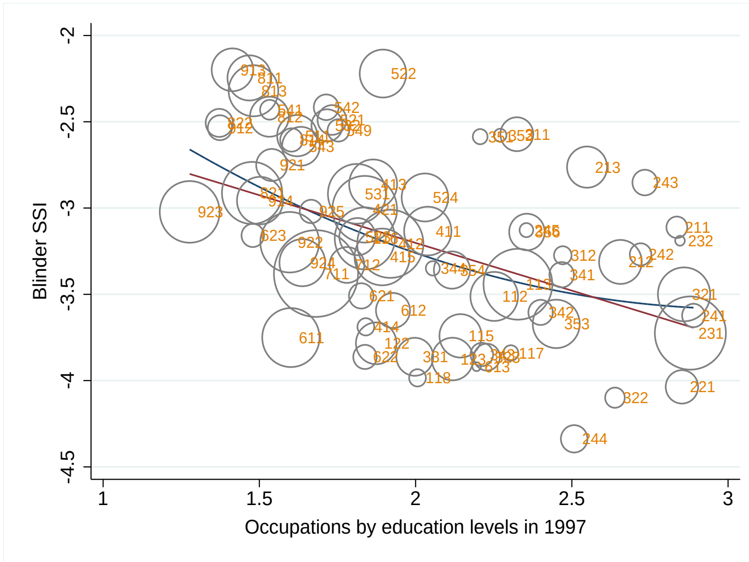
In addition, we also construct a computer-use index (CUI) based on the information provided by the BSS task "usepc" and additional indicators from the BSS database that measures the extent of computer use in occupations. RTI index is an indirect measure of computerisation in the labour market (e.g., Goos *et al.*, 2011). It is based on the assumption that computers and computerised equipments have significantly changed how workers perform the tasks that they are assigned. As such computerisation have changed the ratio of routine to non-routine tasks, thus affecting RTI (e.g., Autor *et al.*, 2003;

[32]The BSS task data does not provide information concerning the possibility of tasks to be physically or spatially separated from a job. For this reason we cannot construct a spatial-separability index using the BSS data. However, we can match the ONET data to the BSS database to obtain the SSI for the UK. Since the ONET uses the US Standard Occupational Classification 2000, we first need to match these US occupation codes to the UK SOC 2000 codes and aggregate the data at the 3-digit level to obtain spatial-separability index for each 3-digit UK occupation.

[33]These variables (and other related ones like face-to-face and proximity) have also been used by Firpo *et al.* (2011), Blinder (2009) and Blinder and Krueger (2009) to construct offshorability indicators.

[34]The matching of the occupations is done by matching the ONET SOC codes to the ISCO88 codes. Then we match the ISCO88 codes to the UK SOC codes. Mismatches, illogical matches and missing occupations are corrected by hand.

Figure 8: United Kingdom, Blinder spatial-separability index (SSI), when occupations are classified by education levels in 1997, 3-digit SOC-2000 occupational codes



Source: Own estimations using ONET and UK LFS data.

Spitz-Oener, 2006). Whereas CUI is a more direct indicator that measures the extent of computer adoption in different occupation groups (e.g., Borghans and ter Weel, 2006).

In particular, the computer-use index (CUI) is estimated by using principal component analyses (PCA):

$$Y_i = \beta_i PCUSE + \epsilon_i, \tag{7}$$

where i corresponds to different indicators that measures the extent of computer use in occupations, Y is the latent construct composed of six indicators: (i) the importance of using a computer or computerised equipment, rated on a scale 1 (not at all important) to 5 (essential), (ii) the complexity of use of computer, rated on a scale 1 (simple) to 4 (advanced), (iii) the percentage of workers using computers to communicate with colleagues and with others outside the organisation, (iv) the percentage of workers using computers to seek information about the organisation and products and services of suppliers, (v) whether new computerised equipment was introduced in the workplace, and (vi) whether new communication technology was introduced in the workplace.

As can be seen from Table C.8, correlations among indicators are high and significant at the 1 percent level. Estimates yield several principal component factors and a number of principal component loadings, β_i, which could be viewed as weights. Table C.9 lists the principal component loadings and the explained variance. All indicators have positive loadings and similar weights. Therefore we only use the first principal component to capture the extent of technical change in an occupation (i.e., SBTC). The first principal component explains about 0.81 percent of the total variation in six computer use indicators.

4 Econometric results

4.1 Analysing changes in employment

We start the analyses by estimating the effects of technological change, offshoring and offshorability on the employment changes at 3-digit occupational level in UK between 1997 and 2006.[35] Our control variables are employment level in 1997, and unionisation that measures the change in percentage of workers who are member of a trade union between 1997-2006.[36] We expect the changes in union membership to affect employment immediately while technological change and changes in offshoring crystal out after the period of change. As we do not obtain information about changes in technology and offshoring before 1997, we include their 1997 levels. Table C.7 presents the correlation matrix of all included variables. As can be seen from Figure 1, the employment changes in the UK display a polarization pattern. This section provides suggestive evidence regarding to what extent this pattern is caused by offshoring and technology. By construction all indicators have different metric, but for comparability reasons we standardise each indicator such that mean equals 0 and variance equals 1. Thus, the coefficients in all the following regressions are comparable in size.

Table 3 presents the OLS results for 3 digit occupations, which show that the impact of offshoring is negative, significant and robust to different specifications. Thus, we find that occupations that are characterised by high offshoring levels at the start of the sample period (1997) faced employment losses (column 1). As a robustness test we also show the impact of our offshorability measure: the Blinder spatial-separability index (SSI) that measures the likeliness of offshoring a job. The coefficient for the SSI is negative suggesting that offshorable jobs also lost employment between 1997-2006 (column 4). These results provide evidence that offshoring has been a significant factor in the changes in employment in the UK.[37] In this sense our estimates are akin to the findings of Firpo *et al.* (2011) for U.S. and Goos *et al.* (2011) for a set of European countries. Both found evidence that offshoring is important in explaining changes in employment, and in particular, the job polarization pattern.

Labour demand is also affected by skill-biased technological change (SBTC). Following the definition by Acemoglu and Autor (2010), we use the routine task index constructed using ONET data (RTI-ONET). A similar RTI definition was used in Goos *et al.* (2011), however, they combined RTI with a time-trend. We argue that this variable combination is troublesome, since it is based on the assumption that the task-composition of occupations is not changing over time. Our analyses in Section 3.2 shows that this assumption does not hold in the period 1997-2006 for the UK. The estimation results in Table 3, columns (2)

[35]We also replicated the empirical estimations in Section 4 at the 2-digit occupational level. The results are qualitatively similar. Since there are only 24 observations at the 2-digit occupational level we have some reservations on the results and thus present only results of the estimations at the 3-digit level.

[36]We include union membership as an additional control variable because strong unions not only affect the employment levels but also the way how tasks are bundled within a job. Unions bargain regarding the whole package of the job, including the task-package. The source for this indicator is the BSS.

[37]We also mapped the offshoring index by Goos *et al.* (2011) to UK occupations using cross-walk between ISCO88 and SOC2000. The estimated coefficient is about the half of the size of the offshoring (AOI) indicator in 1 and is significant. We did not present this result because offshoring values that are available for ISCO88 codes at the 2-digit level (21 occupations) are mapped to more than 70 SOC2000 codes and thus this indicator may have measurement issues.

Table 3: OLS estimates for the changes in employment between 1997 and 2006, United Kingdom, 3-digit occupational level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment	-0.400***	-0.367***	-0.376***	-0.374***	-0.367***	-0.386***	-0.395***	-0.375***
	[0.104]	[0.098]	[0.096]	[0.102]	[0.098]	[0.104]	[0.098]	[0.099]
Offshoring (AOI)	-0.178***		-0.109**				-0.195***	
	[0.045]		[0.042]				[0.044]	
Blinder index (SSI)				-0.225***	-0.114			-0.213***
				[0.050]	[0.094]			[0.058]
RTI-ONET		-0.234***	-0.189***		-0.149			
		[0.055]	[0.054]		[0.099]			
Computer Use (CUI)						0.113	0.122*	0.043
						[0.077]	[0.072]	[0.084]
Union	0.648	0.644	0.617	0.667	0.656	0.670	0.623	0.658
	[0.435]	[0.426]	[0.419]	[0.403]	[0.406]	[0.468]	[0.436]	[0.407]
Constant	0.321***	0.330***	0.329***	0.332***	0.331***	0.328***	0.329***	0.336***
	[0.083]	[0.081]	[0.080]	[0.081]	[0.080]	[0.089]	[0.084]	[0.082]
Observations	74	73	73	73	73	73	73	72
R-squared	0.368	0.423	0.446	0.414	0.436	0.328	0.413	0.422

Notes: Dependent variable is the change in employment (1997-2006). All independent variables are for 1997 except Union, which measures the change in percentage of workers who are associated to a trade union between 1997-2006. All regressions are at the 3-digit SOC-2000 occupational level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

and (3), show that occupations that on average are composed of relatively more routine tasks (i.e. a higher RTI-ONET value) have lost employment (e.g., Autor *et al.*, 2003). When combined with the Blinder index the coefficient is not significant possibly because of the collinearity between the Blinder Index and RTI-ONET (column 5).

Furthermore, the initial occupation size (log of employment in 1997) is significant with a negative sign, reflecting that occupations that were relatively large in 1997 have been losing workers to smaller occupations. In non of the different specifications in Table 3 the association between unionisation and employment growth is statistically significant. Research on unionisation and employment growth for the UK shows that there is no clear pattern. For instance, Blanchflower and Millward (1988) show that there is no particular relation between strong unions and changes in employment in the 1980s, especially when other factors are taken into consideration. Machin and Wadhwani (1991) argue that there is no systematic link between unions and changes in employment. On the contrary, Bryson (2004) shows that the association is positive in the 1990s.

In summary, for the UK our results show that both SBTC and offshoring are important factors explaining changes in employment in British jobs, and that the effect of SBTC is somewhat larger than offshoring. More precise, if offshoring increases with one standard deviation this results in a decrease in employment change of about 15 to 20%. However, if the RTI increases with one standard deviation employment change decreases with about 20 to 25%.

We replicate these analyses for the Netherlands at the 2 digit occupational level. In the case of the Netherlands, we also find that both offshoring (AOI) and offshorability

(SSI) play a significant role explaining changes in employment between 1997 and 2005. Table 4 also shows that the routinisation index (RTI-ONET) has a significant and negative effect on employment changes, which are usually larger in magnitude than those from the offshoring variables. Finally, the initial employment size (log employment 1997) does not explain employment changes, as it did for the UK. To sum up, for the Netherlands we also find that offshoring and SBTC have a significant role explaining employment changes.[38]

Table 4: OLS estimates for the changes in employment between 1997 and 2005, The Netherlands, 2-digit occupational level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment	0.024	0.043	0.044	0.024	0.035	0.016	0.029	0.017
	[0.027]	[0.029]	[0.028]	[0.026]	[0.029]	[0.043]	[0.041]	[0.038]
Offshoring (AOI)	-0.084**		-0.062*				-0.085**	
	[0.032]		[0.031]				[0.032]	
Blinder Index (SSI)				-0.103***	-0.073*			-0.106***
				[0.028]	[0.038]			[0.030]
RTI-ONET		-0.097***	-0.079***		-0.046			
		[0.025]	[0.023]		[0.032]			
Computer Use (CUI)						0.000	0.012	-0.020
						[0.048]	[0.048]	[0.048]
Constant	0.126***	0.126***	0.126***	0.126***	0.126***	0.126***	0.126***	0.126***
	[0.035]	[0.034]	[0.033]	[0.034]	[0.034]	[0.038]	[0.036]	[0.034]
Observations	36	36	36	36	36	36	36	36
R-squared	0.146	0.182	0.253	0.218	0.240	0.005	0.148	0.224

Notes: Dependent variable is change in employment (1997-2005). All independent variables are for 1997. All regressions are at the 2-digit SBC occupational level. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2 Analysing changes in the task-content of occupations

In Section 3.2 we showed that the task-content of jobs (i.e. the intensive margin) is changing over time in the UK. This is a novel finding because previous studies assumed that the task-content of jobs is stable over time (e.g., Goos *et al.*, 2011). In this section we provide further evidence on this issue. In particular, we analyse if the task-content of jobs has been affected by technology and/or offshoring. Here, we employ the task-rank indicator to measure the changes in the task content of 3 digit occupations.[39] Higher

[38]Similar to the UK case we used the offshoring index by Goos *et al.* (2011) as a robustness check. The estimated coefficient is significant but much smaller in size compared to offshoring (AOI) indicator. The same measurement problem also applies to this case.

[39]To avoid an overwhelming amount of analyses we only present results for one indicator on the task-content of occupations. The summary indicators show different ways in which the task-content of occupations may change. We do not favour one indicator above the other and here we choose to present the indicator of which the changes are easiest to interpret. Analyses of another indicator, the TOC, are presented in the next section as a robustness check. The analyses with the other indicators for the task-contents are available upon request.

values of task-rank indicates that task-content of jobs have been fairly stable over the time. Similar to the previous section all indicators are standardised and thus comparable in size. Table 5 presents the results.[40]

Table 5: OLS estimates for the changes in the task-rank correlation indicator between 1997 and 2006, United Kingdom, 3-digit occupational level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment	0.068***	0.066***	0.066***	0.066***	0.066***	0.067***	0.068***	0.066***
	[0.013]	[0.013]	[0.013]	[0.012]	[0.013]	[0.013]	[0.014]	[0.012]
Offshoring (AOI)	0.003		-0.004				0.005	
	[0.008]		[0.008]				[0.008]	
Blinder Index (SSI)				0.018*	0.015			0.017
				[0.010]	[0.018]			[0.011]
RTI-ONET		0.016**	0.017**		0.005			
		[0.007]	[0.008]		[0.014]			
Computer Use (CUI)						-0.011	-0.011	-0.005
						[0.011]	[0.011]	[0.012]
Union	0.198**	0.201**	0.200**	0.199**	0.200**	0.200**	0.201**	0.201**
	[0.084]	[0.084]	[0.086]	[0.080]	[0.080]	[0.084]	[0.085]	[0.080]
Constant	0.893***	0.892***	0.892***	0.892***	0.892***	0.892***	0.892***	0.891***
	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]	[0.010]
Observations	74	73	73	73	73	73	73	72
R-squared	0.542	0.560	0.561	0.566	0.566	0.553	0.554	0.571

Notes: Dependent variable is task-rank correlation 1997-2006. All independent variables are for 1997 except Union, which measures the change in percentage of workers who are associated to a trade union between 1997-2006. All regressions are at the 3-digit SOC-2000 occupational level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Looking at the results in Table 5 we see that the effect of both offshoring (AOI) and offshorability (SSI) on changes in task-content is not stable. Albeit statistically significant results in some specifications, the sign of the indicator alternate, and in addition, is not robust to the inclusion of other variables (see also section 5 below).

The impact of technology on the changes in task-content of jobs, on the other hand, is statistically significant. The results indicate that occupations which are one standard deviation more routine experienced 20 to 25% of a standard deviation less changes in the task-ranking between 1997 and 2006.

Moreover, the results in Table 5 show that changes at the intensive margin (task-content) are strongly associated with higher degrees of unionisation. The union indicator has positive, significant and robust coefficients. Strong unions put stress on wages and task-packages of occupations. A high degree of unionisation lowers therefore the possibilities to separate tasks from jobs which explains the high task-rank correlation.[41] It seems that both the size and the degree of unionisation of occupations act as a barrier to changes

[40] Note that since we do not have Dutch task data we do not run the regressions on changes in task-content indicators for the Netherlands.

[41] A high task-rank correlation indicates that the relative importance of tasks within an occupation hardly changed.

in task-content.[42] On the other hand, the initial size of the occupation (log employment in 1997) is never significant for the task-rank correlation. In the previous section we showed that occupations with larger shares have lost employment. Together with the findings in this sections this indicates that in occupations with larger shares changes in employment mainly mediates through the extensive margin. Thus in occupations with higher shares of employment jobs are lost but the task-content of the remaining jobs have been fairly stable during the period 1997-2006.

In summary, our analyses suggest that technological change affected the organisation of tasks within occupations. The size of the effect equals the effect of technological change on employment changes. A one standard deviation change in SBTC results in 20 to 25% of a standard deviation more (or less) changes between 1997 and 2006.

5 Sensitivity analyses

We conduct two main sensitivity analyses. First we replicate the estimations in Table 5 by using another dependent variable that also measures the changes in task content of jobs. We use the changes in task–occupation connectivity (TOC) index for the period 1997-2006 instead of task-rank correlations. The results of this exercise is presented in Table 6.

As mentioned before, TOC measures the degree of connectivity of tasks within a job (see Akcomak *et al.*, 2011). Higher positive values indicate that tasks have become even more connected to a job, thus less prospects for changes in task composition. Looking at the estimation results in Tables 5 and 6 we see that except the computer use index the result are more or less comparable. Both measures of SBTC significantly affect task-occupation connectivity. Computerisation loosens task-connectivity which means that some tasks could be separated from the task bundle and could be outsourced or offshored. Thus the task composition of jobs changes. The effect of offshoring is not robust in both tables (see also Table 7). The results indicate that SBTC rather than offshoring has impact on task-content of occupations.

Second, we estimate a set of 30 regressions for each dependent variable by including other covariates that could be related to changes in employment and task-content. This not only addresses the robustness of the main independent variables to inclusion of other covariates but also assesses the importance of other covariates in explaining changes in employment and task-content of occupations. We include (*i*) two indicators for technical change, RTI-ONET and computer use index (CUI). Note that the sign of CUI and RTI-ONET is different in Tables 3 to 6. This is because more computer use in an occupation is associated with a reduction in the routine tasks being performed in that occupation; (*ii*) two indicators of offshorability instead of the Blinder index. We first use face-to-face interactions that measure how often the worker has face-to-face discussions with individuals or teams at work. Second we use physical proximity that indicates to what extent the occupation requires the worker to perform the job tasks in close physical proximity to other people. For both indicators a higher value indicates that it is easier to perform the occupation at a distance, (*iii*) two indicators that measure the changes (rather than

[42] There is almost no research on the effect of unions on changes in task-composition of jobs. Machin and Wadhwani (1991) report a positive association between unions and organisational change (i.e., work practices) in the late 1980s in the UK, and through this channel unions may increase productivity as Freeman and Medoff (1984) suggest.

Table 6: OLS estimates for the changes in the task-occupation connectivity (TOC) index between 1997 and 2006, United Kingdom, 3-digit occupational level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment	0.124	0.096	0.084	0.113	0.096	0.118	0.119	0.115
	[0.117]	[0.106]	[0.106]	[0.111]	[0.107]	[0.105]	[0.107]	[0.103]
Offshoring (AOI)	-0.027		-0.145*				0.018	
	[0.083]		[0.086]				[0.073]	
Blinder Index (SSI)				0.135	-0.136			0.081
				[0.093]	[0.167]			[0.096]
RTI-ONET		0.264***	0.323***		0.365**			
		[0.066]	[0.078]		[0.138]			
Computer Use (CUI)						-0.250***	-0.251***	-0.204**
						[0.091]	[0.093]	[0.094]
Union	2.142***	2.229***	2.193***	2.216***	2.243***	2.201***	2.205***	2.255***
	[0.710]	[0.715]	[0.720]	[0.674]	[0.755]	[0.710]	[0.717]	[0.696]
Constant	0.162	0.149	0.148	0.148	0.150	0.139	0.139	0.127
	[0.103]	[0.097]	[0.096]	[0.103]	[0.097]	[0.097]	[0.097]	[0.097]
Observations	74	73	73	73	73	73	73	72
R-squared	0.291	0.378	0.395	0.328	0.386	0.382	0.382	0.397

Notes: Dependent variable is changes in TOC (1997-2006). All independent variables are for 1997 except Union, which measures the change in percentage of workers who are associated to a trade union between 1997-2006. All regressions are at the 3-digit SOC-2000 occupational level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Summary results of the robustness analysis for the United Kingdom

	change in employment		change in task-rank		change in TOC	
	sign (1)	significance (2)	sign (3)	significance (4)	sign (5)	significance (6)
log employment	always (-)	always	always (+)	always	always (+)	never
offshoring (AOI)	always (-)	always	sign alternates		mostly (-)	seldom
Blinder index (SSI)	always (-)	mostly	always (+)	seldom	sign alternates	
RTI-ONET	always (-)	mostly	always (+)	mostly	always (+)	always
Computer use (CUI)	always (+)	seldom	always (-)	never	always (-)	always
Union	always (+)	never	always (+)	always	always (+)	always
Robustness checks						
face-to-face	always (-)	always	always (+)	always	mostly (+)	seldom
proximity	always (-)	seldom	always (+)	never	sign alternates	
change in CUI	sign alternates		always (-)	never	always (-)	never
change in AOI	sign alternates		always (+)	never	sign alternates	

the levels) in offshoring and computer use between 1997-2006. Table 7 summarizes the results of the robustness exercise. Odd columns summarizes the behaviour of the sign of the coefficients (i.e., whether all estimated coefficients have the same sign) and even columns the significance of the estimated coefficients (i.e., whether estimated coefficients are significant).

In columns (1) and (2) in Table 7 we see that the main independent variables are robust to the inclusion of other covariates. The effect of offshoring and Blinder index on employment changes are more robust compared to SBTC indicators. In Table 3 columns

(6) to (8) we find that the coefficient of CUI is positive but is not robust to different specifications. The results in Table 7 confirms the findings in Table 3. Among the set of 4 covariates the indicators that measure the changes in offshoring (AOI) and computer use (CUI) never return robust estimates. There is not even an agreement in sign of the coefficients of these indicators. One interesting finding is that the extent of face-to-face interactions in a job also returns robust estimates similar to the estimates with the Blinder index. The importance of physical proximity is not robust. This finding is persistent in all estimations for all dependent variables.

Columns (3) to (6) presents the robustness results for the changes in task-content of occupations. We observe that union and RTI-ONET is robust no matter which dependent variable is used to measure task-content changes. The effect of computer use index is statistically significant only in the task-connectivity estimations. The results reveal that in occupations where computerisation was high the task-content of jobs has been changing significantly. As we have discussed above in these occupations it is easier to separate specific tasks from the core-tasks in an occupation. The initial size of the occupation (log employment in 1997) is only positive, significant and robust when TOC indicator is used, but it is never significant when task-rank correlations is used as a dependent variable. None of the included covariates return robust estimates except face-to-face interactions.

6 Summary

Task-composition of occupations in the United Kingdom has changed significantly between 1997 and 2006. Using the occupational task data from the British Skill Survey (BSS) we show that changes in both within and between jobs are important to explain these overall changes. The BSS provides information for three different waves: 1997, 2001 and 2006, which allows us to analyse the changes in the task structure of occupations over time. Until now, most task-data analyses are based on task information provided for a single year. Thus, these studies assume that the task-content of occupations remains constant over time. Our analyses show that this is a restrictive assumption. We find that the changes in the task-content of occupations (i.e. changes at the intensive margin) are pervasive and of a magnitude similar to changes in at the extensive margin (i.e. changes in occupational employment levels).

We use indicators on technological change (SBTC) and offshoring to assess if they can explain these changes in employment at the intensive margin. Our econometric results suggest that both SBTC and unionisation levels explain how the task-content of occupations has changed in the UK in the period 1997-2006. However, we also find that offshoring has not been a factor affecting the organization of tasks within-occupations.

When we analyse changes in employment at the extensive margin, we find that for both the UK and the Netherlands there was a job polarization pattern, where middle-skill occupations lost employment with respect to low- and high-skill jobs. Moreover, our econometric results confirm that these employment changes can be explained by computerization (SBTC) and offshoring, while SBTC has had a larger effect on job polarization.

All in all we find evidence that SBTC has a dual role at changing the task-content of occupations. It has changed the way in which tasks are organized within occupations (i.e. the use of computers has affected the way tasks are assigned to occupations), but also it has affected the employment levels of certain occupations (i.e. it has made some occupations redundant). On the other hand, offshoring only affects the employment levels (i.e. certain occupations have been offshored), while it has no significant effect on the way how tasks are organized within jobs. Unions, however, have affected changes at the intensive margin, but not changes at the extensive margin.

References

Acemoglu, D. and Autor, D. H. (2010). "Skills, Tasks and Technologies: Implications for Employment and Earnings", *in* O. Ashenfelter and D. E. Card (eds.), *Handbook of Labor Economics Volume 4*, Elsevier, Amsterdam.

Akcomak, I. S., Borghans, L. and ter Weel, B. (2011). "Measuring and Interpreting Trends in the Division of Labour in The Netherlands", *De Economist* 159(4): 435–482.

Autor, D. H. and Dorn, D. (2011). "The Growth of Low-Skill Service Jobs and the Polarization of the U.S.LaborMarket", Working paper, MIT.

Autor, D. H. and Handel, M. J. (2009). "Putting Tasks to the Test: Human Capital, Job Tasks and Wages", NBER Working Paper 15116.

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

Autor, D. H., Katz, L. F. and Kearney, M. S. (2008). "Trends in U.S. Wage Inequality: Revising the Revisionists", *Review of Economics and Statistics* 90(2): 300–323.

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

Berman, E., Bound, J. and Machin, S. (1998). "Implications of Skill-Biased Technological Change: International Evidence", *Quarterly Journal of Economics* 113(4): 1245–1279.

Blanchflower, D. G. and Millward, N. (1988). "Trade Unions and Employment Change", *European Economic Review* 32(2-3): 717–726.

Blinder, A. S. (2006). "Offshoring: The Next Industrial Revolution?", *Foreign Affairs* 85(2): 113–128.

Blinder, A. S. (2009). "How Many U.S. Jobs Might Be Offshorable?", *World Economics* 10(2): 41–78.

Blinder, A. S. and Krueger, A. B. (2009). "Alternative Measures of Offshorability: A Survey Approach", NBER Working Paper 15287.

Bloom, N., Draca, M. and Van Reenen, J. (2011). "Trade Induced Technical Change? The Impact of Chinese Imports on ITandInnovation", NBER Discussion Paper 16717.

Bloom, N., Garicano, L., Sadun, R. and Van Reenen, J. (2010). “The Distinct Effects of Information Technologies and Communication Technologieson Firm Organization”, Working Paper 11-023, Harvard Business School.

Borghans, L. and ter Weel, B. (2006). “The Division of Labour, Worker Organization and Technological Change”, *Economic Journal* 116: F45–F72.

Bryson, A. (2004). “Unions and Employment Growth in British Workplaces During the 1990s: APanel Analysis”, *Scottish Journal of Political Economy* 51(4): 477–506.

Costinot, A. and Vogel, J. (2010). “Matching and Inequality in the World Economy”, *Journal of Political Economy* 118(4): 747–786.

Crinò, R. (2010). “Service Offshoring and White-Collar Employment”, *Review of Economic Studies* 77(2): 595–632.

Feenstra, R. C. and Hanson, G. H. (1996). “Globalization, Outsourcing, and Wage Inequality”, *American Economic Review* 86(2): 240–245.

Felstead, A., Gallie, D., Green, F. and Zhou, Y. (2007). *Skills at Work, 1986 to 2006*, ESRC Centre on Skills, Knowledge and Organisational Performance, Universities of Oxford and Cardiff.

Firpo, S., Fortin, N. M. and Lemieux, T. (2011). “Occupational Tasks and Changes in the Wage Structure”, IZA Discussion Paper 5542, University of British Columbia.

Freeman, R. and Medoff, J. (1984). *What Do Unions Do?*, Basic Books, New York.

Goos, M. and Manning, A. (2007). “Lousy and Lovely Jobs: The Rising Polarization of Work in Britain”, *Review of Economics and Statistics* 89(1): 118–133.

Goos, M., Manning, A. and Salomons, A. (2009). “Job Polarization in Europe”, *American Economic Review* 99(2): 58–63.

Goos, M., Manning, A. and Salomons, A. (2011). “Explaining Job Polarization in Europe: The Roles of Technology, Offshoringand Institutions”, Discussion Paper, Katholieke Universiteit Leuven.

Green, F. (2012). “Employee Involvement, Technology and Evolution in Job Skills: A Tasks-basedApproach”, *Industrial and Labor Relations* 65(1): 36–67.

Grossman, G. M. and Rossi-Hansberg, E. (2006). “The Rise of Offshoring: It’s Not Wine for Cloth Anymore”, *Proceedings: Federal Reserve Bank of Kansas City* pp. 59–102.

Grossman, G. M. and Rossi-Hansberg, E. (2008). “Trading Tasks: A Simple Theory of Offshoring”, *American Economic Review* 98(5): 1978–1997.

Handel, M. J. (2008). “Measuring Job Content: Skills, Technology, and Management Practices”, Discussion Paper 1357-08, Northeastern Universty, Institute for Research on Poverty.

Head, K., Mayer, T. and Ries, J. (2009). “How Remote is the Offshoring Trend?”, *European Economic Review* 53(4): 429–444.

Jensen, J. B. and Kletzer, L. G. (2010). “Measuring Tradable Services and the Task Content of Offshorable ServicesJobs”, *in* K. G. Abraham, J. R. Spletzer and M. Harper (eds.), *Labor in the New Economy*, University of Chicago Press, pp. 309–335.

Machin, S. and Wadhwani, S. (1991). “The Effects of Unions on Organisational Change and Employment”, *The Economic Journal* 101(407): 835–854.

Michaels, G., Natraj, A. and Van Reenen, J. (2010). “Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25years”, NBER Working Paper 16138.

OECD (2010a). “Income Distribution and Growth: Outline and Literature Review”, Discussion Paper ECO/CPE/WP1(2010)16, OECD, Economics Department, Economic Policy Committee.

OECD (2010b). “PIAAC Background Questionnaire”, MS version 2.1 d.d. 15-12-2010, www.oecd.org/dataoecd/1/41/48442549.pdf.

Spitz-Oener, A. (2006). “Technical Change, Job Tasks, and Rising Educational Demands: Looking Outsidethe Wage Structure”, *Journal of Labor Economics* 24(2): 235–270.

Van Reenen, J. (2011). “Wage Inequality, Technology and Trade: 21st Century Evidence”, *Labour Economics* 18(6): 730–741.

Appendix

A Tasks definitions, classifications and mappings

Table A.1: British Skill Survey: Task codes and descriptions

code	task name	task description
1	detail	paying close attention to detail
2	people	dealing with people
3	teach	teaching people (individuals or groups)
4	speech	making speeches/ presentations
5	persuad	persuading or influencing others
6	selling	selling a product or service
7	caring	counselling, advising or caring for customers or clients
8	teamwk	Working with a team of people
9	listen	Listening carefully to colleagues
10	strength	physical strength (e.g., to carry, push or pull heavy objects)
11	stamina	physical stamina (e.g., to work for long periods on physical activities)
12	hands	skill or accuracy in using hands/fingers (e.g., to mend or repair, assemble etc.)
13	tools	knowledge of use or operation of tools/equipment machinery)
14	product	knowledge of particular products or services
15	special	specialist knowledge or understanding
16	orgwork	knowledge of how organisation works
17	usepc	Using a computer, 'PC', or other types of computerised equipment
18	faults	spotting problems or faults (in your own work or somebody else's work)
19	cause	working out cause of problems/ faults (in your own work or somebody else's work)
20	solutn	thinking of solutions to problems (in your own work or somebody else's work)
21	analyse	analysing complex problems in depth
22	noerror	checking things to ensure no errors (in your own work or somebody else's work)
23	mistake	noticing when there is a mistake (in your own work or somebody else's work)
24	planme	planning own activities
25	planoth	planning the activities of others
26	mytime	organising own time
27	ahead	thinking ahead
28	read	reading written information (e.g., forms, notices and signs)
29	readsh	reading short documents such as reports, letters or memos
30	readlg	reading long documents such as long reports, manuals, articles or books
31	write	writing materials such as forms, notices and signs
32	writesh	writing short documents (e.g., reports, letters or memos)
33	writelg	writing long documents with correct spelling and grammar
34	calca	adding, subtracting, multiplying and dividing numbers
35	percent	calculations using decimals, percentages or fractions
36	stats	Calculations using more advanced mathematical or statistical procedures

Source: British Skills Survey (BSS).

Table A.2: BSS 2-digit occupational codes and descriptions

SOC-2000 codes	Occupation description
11	corporate managers and directors
12	other managers and proprietors
21	science, research, engineering and technology professionals
22	health professionals
23	teaching and educational professionals
24	business, media and public service professionals
31	science, engineering and technology associate professionals
32	health and social care associate professionals
33	protective service occupations
34	culture, media and sports occupations
35	business and public service associate professionals
41	administrative occupations
42	secretarial and related occupations
51	skilled agricultural and related trades
52	skilled metal, electrical and electronic trades
53	skilled construction and building trades
54	textiles, printing and other skilled trades
61	caring personal service occupations
62	leisure, travel and related personal service occupations
71	sales occupations
72	customer service occupations
81	process, plant and machine operatives
82	transport and mobile machine drivers and operatives
91	elementary trades and related occupations
92	elementary administration and service occupations

Source: British Skills Survey (BSS).

Table A.3: BSS 3-digit occupational codes and descriptions

SOC-2000 codes	Occupation description
111	Corporate Managers And Senior Officials
112	Production Managers
113	Functional Managers
114	Quality And Customer Care Managers
115	Financial Institution And Office Managers
116	Managers In Distribution, Storage And Retailing
117	Protective Service Officers
118	Health And Social Services Managers
122	Managers And Proprietors In Hospitality And Leisure Services
123	Managers And Proprietors In Other Service Industries
211	Science Professionals
212	Engineering Professionals
213	Information And Communication Technology Professionals
221	Health Professionals
231	Teaching Professionals
232	Research Professionals
241	Legal Professionals
242	Business And Statistical Professionals
243	Architects, Town Planners, Surveyors
244	Public Service Professionals
245	Librarians And Related Professionals
311	Science And Engineering Technicians
312	Draughts persons And Building Inspectors
321	Health Associate Professionals
322	Therapists
323	Social Welfare Associate Professionals
331	Protective Service Occupations
341	Artistic And Literary Occupations
342	Design Associate Professionals
343	Media Associate Professionals
344	Sports And Fitness Occupations
351	Transport Associate Professionals
352	Legal Associate Professionals
353	Business And Finance Associate Professionals
354	Sales And Related Associate Professionals
356	Public Service And Other Associate Professionals
411	Administrative Occupations: Government And Related Organisations
412	Administrative Occupations: Finance
413	Administrative Occupations: Records
414	Administrative Occupations: Communications
415	Administrative Occupations: General
421	Secretarial And Related Occupations

Continued on next page...

Table A.3 – continued from previous page

SOC-2000 codes	Occupation description
511	Agricultural Trades
521	Metal Forming, Welding And Related Trades
522	Metal Machining, Fitting And Instrument Making Trades
523	Vehicle Trades
524	Electrical Trades
531	Construction Trades
532	Building Trades
541	Textiles And Garments Trades
542	Printing Trades
543	Food Preparation Trades
549	Skilled Trades n. e. c.
611	Healthcare And Related Personal Services
612	Childcare And Related Personal Services
613	Animal Care Services
621	Leisure And Travel Service Occupations
622	Hairdressers And Related Occupations
623	Housekeeping Occupations
711	Sales Assistants And Retail Cashiers
712	Sales Related Occupations
811	Process Operatives
812	Plant And Machine Operatives
813	Assemblers And Routine Operatives
814	Construction Operatives
821	Transport Drivers And Operatives
822	Mobile Machine Drivers And Operatives
911	Elementary Agricultural Occupations
912	Elementary Construction Occupations
913	Elementary Process Plant Occupations
914	Elementary Goods Storage Occupations
921	Elementary Administration Occupations
922	Elementary Personal Services Occupations
923	Elementary Cleaning Occupations
924	Elementary Security Occupations
925	Elementary Sales Occupations

Source: British Skills Survey (BSS).

Table A.4: Factor analysis groups and BSS tasks

Factor group	BSS task
Literacy	reading, reading short documents, reading long documents, writing, writing short documents, writing long documents
Problem solving	finding faults, finding cause, finding solutions, analyse
Checking	detail, noerror, finding mistakes
Planning	plan own activities, plan others activities, see ahead, manage own time
Number	arithmetic calculations, calculating percents etc., calculating statistics
Physical	strength, stamina, using hands, using tools
Interactive	teaching, speech, persuading others, team work, listening caring, dealing with people, selling, organisational functioning, product knowledge, specialist knowledge
PC use	Using PC and computerised equipment

B Construction of the RTI index based on the BSS tasks

The conceptual broadness of the BSS tasks does not make for a natural mapping of these 36 tasks into the three main routinisation groups: routine, services and abstract tasks. The main difficulty is that several BSS tasks can easily fit into any of the routinisation groups. The most clear set of these tasks are the codes: detail, orgwork, usepc, planme, mytime, ahead, read, readsh, write, and writelg. The broad definition of each code was presented in Table A.1. Other tasks can readily be classified in two of the three groups. The most obvious set of these tasks include: strength, stamina, hands and tools, which are associated with manual tasks but cannot be divided between routine and non-routine manual groups. In the same way, the tasks: persuad and caring could be classified as both services and abstract tasks. The rest of the tasks are easier to classify along the three routinisation groups and this mapping is presented in Table B.1. Finally, RTI is standardized to have mean zero and unit standard deviation.

Table B.1: Routine and Non-routine tasks mapping using BSS

non-routine Service	Routine	non-routine Abstract
people	faults	solutn
selling	noerror	analyse
listen	mistake	teach
product	calca	speech
special	percent	writelg
	stats	readlg
		planoth
		teamwk

C Additional tables

Table C.1: United Kingdom, changes in employment by 2-digit SOC-2000 occupation codes

SOC-2000	Occupation description	employment share 1997	employment share 2006	relative change	absolute change
11	Corporate managers	0.12	0.12	0.12	379,736
12	Managers in agriculture and services	0.03	0.03	0.13	99,001
21	Science and technology professionals	0.03	0.03	0.13	115,001
22	Health professionals	0.01	0.01	0.36	84,037
23	Teaching and research profs.	0.04	0.05	0.22	259,124
24	Business and public service profs.	0.02	0.03	0.76	429,135
31	Science and technology associate profs.	0.01	0.02	0.58	181,845
32	Health and social welfare associate profs.	0.03	0.04	0.34	291,769
33	Protective service occupations	0.01	0.01	0.11	35,145
34	Culture, media, sports occupations	0.02	0.02	0.45	194,716
35	Business and public service associate profs.	0.04	0.05	0.34	396,632
41	Administrative occupations	0.11	0.09	-0.03	-73,267
42	Secretarial occupations	0.04	0.03	-0.12	-112,961
51	Skilled agricultural trades	0.01	0.01	-0.17	-60,714
52	Skilled metal, electrical trades	0.06	0.04	-0.19	-281,415
53	Skilled construction trades	0.04	0.04	0.18	172,891
54	Textiles, printing trades	0.02	0.02	-0.11	-65,974
61	Caring personal service occupations	0.04	0.06	0.70	710,106
62	Leisure, travel occupations	0.01	0.02	0.40	153,218
71	Sales occupations	0.07	0.06	-0.01	-18,052
81	Process, plant and machine operatives	0.05	0.04	-0.25	-353,221
82	Transport and mobile machine drivers	0.04	0.04	0.13	125,514
91	Elementary trades	0.04	0.03	-0.19	-216,551
92	Elementary administrative and service	0.09	0.08	-0.03	-71,823

Notes: The last two columns are the relative and absolute changes in employment between 1997 and 2006, respectively
Source: Own estimations using the British LFS data.

Table C.2: United Kingdom, changes in employment by 3-digit SOC-2000 occupation codes

SOC-2000	Employment share 1997	Employment share 2006	relative change	absolute change
112	0.020	0.022	0.184	93,514
113	0.041	0.048	0.255	271,230
114	0.000	0.005	18.545	121,986
115	0.015	0.015	0.047	18,589
116	0.031	0.020	-0.308	-251,351
117	0.002	0.003	0.415	21,032
118	0.002	0.008	2.598	164,194
122	0.014	0.010	-0.216	-79,943
123	0.015	0.018	0.338	129,823
211	0.004	0.005	0.346	33,860

Continued on next page...

Table C.2 – continued from previous page

SOC-2000	Employment share 1997	Employment share 2006	relative change	absolute change
212	0.016	0.016	0.077	31,382
213	0.014	0.015	0.138	49,759
221	0.009	0.011	0.355	84,037
231	0.044	0.048	0.175	198,283
232	0.001	0.003	2.944	60,841
241	0.004	0.006	0.473	55,093
242	0.004	0.014	2.716	284,190
243	0.005	0.006	0.300	41,733
244	0.006	0.007	0.287	45,539
245	0.002	0.002	0.061	2,580
311	0.009	0.008	-0.031	-7,504
312	0.003	0.003	0.040	2,782
321	0.024	0.025	0.156	95,926
322	0.003	0.005	0.754	65,231
323	0.006	0.010	0.851	130,612
331	0.012	0.012	0.115	35,145
341	0.005	0.007	0.367	49,817
342	0.005	0.005	0.015	2,051
343	0.004	0.007	0.774	88,944
344	0.002	0.003	1.231	53,904
351	0.002	0.002	0.359	17,539
352	0.001	0.002	0.384	13,804
353	0.019	0.018	0.026	12,866
354	0.011	0.016	0.525	154,197
356	0.011	0.016	0.572	162,290
411	0.019	0.020	0.106	53,217
412	0.038	0.029	-0.167	-163,932
413	0.020	0.020	0.074	38,081
414	0.002	0.002	-0.097	-6,104
415	0.026	0.025	0.008	5,471
421	0.036	0.030	-0.120	-112,961
511	0.014	0.011	-0.168	-60,714
521	0.007	0.004	-0.393	-73,791
522	0.019	0.012	-0.296	-144,209
523	0.011	0.010	-0.094	-27,749
524	0.019	0.016	-0.073	-35,666
531	0.029	0.032	0.190	143,705
532	0.008	0.009	0.133	29,186
541	0.003	0.002	-0.467	-38,713
542	0.005	0.003	-0.375	-52,215
543	0.012	0.011	-0.028	-8,883

Continued on next page...

Table C.2 – continued from previous page

SOC-2000	Employment share 1997	Employment share 2006	relative change	absolute change
549	0.004	0.004	0.089	9,428
611	0.028	0.034	0.295	217,162
612	0.010	0.026	1.795	467,151
613	0.001	0.002	1.572	25,793
621	0.005	0.006	0.324	44,109
622	0.005	0.008	0.792	98,086
623	0.004	0.004	0.014	1,547
711	0.061	0.058	0.014	22,582
712	0.010	0.008	-0.149	-40,634
811	0.017	0.012	-0.205	-88,362
812	0.013	0.008	-0.364	-123,809
813	0.021	0.012	-0.395	-218,928
814	0.004	0.006	0.433	49,888
821	0.032	0.033	0.145	118,484
822	0.006	0.006	0.042	7,030
911	0.006	0.003	-0.488	-80,504
912	0.005	0.008	0.698	92,039
913	0.015	0.009	-0.351	-136,002
914	0.018	0.014	-0.203	-96,848
921	0.008	0.009	0.217	47,262
922	0.030	0.032	0.137	106,774
923	0.031	0.024	-0.155	-124,863
924	0.018	0.011	-0.363	-170,575
925	0.004	0.007	0.600	69,579

Notes: The last two columns are the relative and absolute changes in employment between 1997 and 2006, respectively

Source: Own estimations using the British LFS data.

Table C.3: Netherlands, changes in employment by 2-digit SBC92 occupation codes

SBC92 code	Occupation description	employment share 1997	employment share 2005	relative change	absolute change (thousands)
11	elementaire beroepen	0.08	0.08	0.05	66
24	agrarisch	0.02	0.02	-0.17	-8
26	technisch	0.09	0.07	-0.26	-86
28	transport	0.04	0.04	-0.04	13
29	(para)medisch	0.00	0.01	0.62	18
31	administratief, commercieel	0.09	0.10	0.12	109
33	beveiliging	0.01	0.01	-0.15	-3
37	verzorgend	0.03	0.03	0.17	40
42	docenten	0.00	0.00	0.01	1
44	agrarisch	0.00	0.00	-0.16	-1
46	technisch	0.12	0.10	-0.14	-35
48	transport	0.01	0.01	-0.24	-8
49	(para)medisch	0.04	0.04	0.12	50
51	administratief, commercieel	0.16	0.16	0.01	94
53	juridisch, bestuurlijk, beveiliging	0.02	0.01	-0.04	5
55	taalkundig, cultureel	0.00	0.00	0.06	4
56	gedrag en maatschappij	0.01	0.01	0.39	30
57	verzorgend	0.03	0.03	-0.05	8
62	pedagogisch	0.04	0.04	0.00	25
64	landbouwkundig	0.00	0.00	0.05	2
66	technisch	0.02	0.02	0.05	15
68	transport	0.00	0.00	-0.03	1
69	(para)medische beroepen	0.02	0.02	0.27	36
71	administratief, commercieel	0.06	0.08	0.19	110
73	juridisch, bestuurlijk, beveiliging	0.00	0.00	-0.13	-1
75	taalkundig, cultureel	0.01	0.00	-0.12	-1
76	gedrag en maatschappij	0.02	0.02	0.38	50
78	managers	0.01	0.01	-0.12	-1
85	wiskundig, natuurwetenschappelijk	0.00	0.00	0.00	0
86	technisch	0.01	0.01	-0.19	-4
89	(para)medische beroepen	0.01	0.01	0.06	7
91	economisch, administratief	0.01	0.01	0.21	22
93	juridisch, bestuurlijk	0.01	0.01	0.17	13
96	gedrag en maatschappij	0.01	0.01	0.25	15
98	managers	0.01	0.01	-0.18	-7

Notes: The last two columns are the relative and absolute changes in employment between 1997 and 2005, respectively
Source: Own estimations using the Dutch EBB data.

Table C.4: Shifts in task-content using seven factor-groups (excluding PC use) and changes at the extensive and intensive margins

	literacy	problem solving	checking	planning	number	physical	interactive
All occupations							
task1997	3.15	4.92	6.76	4.55	1.73	3.12	3.78
task2006	3.40	4.60	6.87	4.83	1.76	2.75	3.79
change	0.25	-0.32	0.11	0.28	0.03	-0.37	0.01
between	0.10	-0.05	-0.03	0.09	-0.01	-0.18	0.08
within	0.16	-0.27	0.14	0.18	0.04	-0.18	-0.07
High-skill occupations							
task1997	3.59	4.91	6.52	5.81	2.43	1.09	3.65
task2006	3.73	4.76	6.80	5.62	2.05	1.12	3.92
change	0.14	-0.15	0.28	-0.19	-0.38	0.03	0.27
between	0.11	0.10	-0.04	-0.12	0.01	-0.03	-0.03
within	0.03	-0.25	0.32	-0.07	-0.39	0.06	0.29
Middle-skill occupations							
task1997	3.60	5.23	6.81	4.27	1.88	3.05	3.17
task2006	3.77	4.81	6.82	4.68	2.14	2.68	3.10
change	0.17	-0.42	0.02	0.42	0.26	-0.37	-0.06
between	0.04	-0.07	-0.03	0.12	-0.07	-0.12	0.14
within	0.13	-0.35	0.04	0.30	0.33	-0.25	-0.20
Low-skill occupations							
task1997	2.33	4.57	6.86	3.99	1.08	4.62	4.54
task2006	2.73	4.23	6.97	4.35	1.11	4.17	4.45
change	0.40	-0.34	0.10	0.35	0.03	-0.45	-0.09
between	0.11	-0.15	-0.01	0.12	-0.01	-0.17	0.10
within	0.29	-0.19	0.12	0.23	0.03	-0.29	-0.19

Table C.5: Changes at the extensive and intensive margins for all 36 BSS tasks in all occupations

	task 1997	task 2006	change 97-06	between	within
detail	34.82	34.43	-0.39	-0.14	-0.25
people	29.72	30.31	0.59	0.66	-0.08
teach	13.22	13.07	-0.15	0.33	-0.48
speech	3.43	3.46	0.03	0.44	-0.41
persuad	10.92	10.88	-0.04	0.63	-0.67
selling	7.43	6.91	-0.52	0.44	-0.96
caring	15.30	14.40	-0.90	0.93	-1.83
teamwk	24.37	23.80	-0.57	0.05	-0.62
listen	25.12	25.86	0.74	0.09	0.65
strengt	10.30	7.89	-2.42	-0.42	-1.99
stamina	10.39	9.53	-0.86	-0.20	-0.66
hands	16.38	14.32	-2.07	-1.01	-1.06
tools	19.62	16.40	-3.21	-1.00	-2.21
product	20.42	21.39	0.96	-0.30	1.26
special	24.81	28.38	3.57	0.43	3.15
orgwork	18.81	20.75	1.94	0.01	1.93
usepc	18.25	22.66	4.41	-0.24	4.65
faults	29.38	26.31	-3.06	-0.59	-2.47
cause	25.20	21.64	-3.56	-0.48	-3.08
solutn	24.78	24.40	-0.38	0.07	-0.45
analyse	12.54	13.97	1.43	0.00	1.43
noerror	29.57	29.21	-0.36	-0.57	0.21
mistake	30.65	31.25	0.60	-0.41	1.01
planme	22.27	23.09	0.82	0.63	0.18
planoth	7.63	6.64	-0.99	0.21	-1.21
mytime	24.29	26.71	2.42	0.51	1.90
ahead	26.04	26.39	0.36	0.31	0.04
read	26.14	24.58	-1.55	-0.10	-1.45
short	22.82	23.54	0.72	0.17	0.55
long	13.15	14.00	0.85	0.16	0.69
write	15.10	14.70	-0.40	0.09	-0.49
writesh	14.56	15.89	1.33	0.42	0.91
writelg	7.64	8.41	0.78	0.18	0.60
calca	16.56	15.18	-1.37	-0.59	-0.78
percent	10.76	11.02	0.27	-0.49	0.76
stats	3.62	4.61	0.99	-0.22	1.21

Table C.6: Changes at the extensive and intensive margins for all 36 BSS tasks, when occupations are classified by skill group

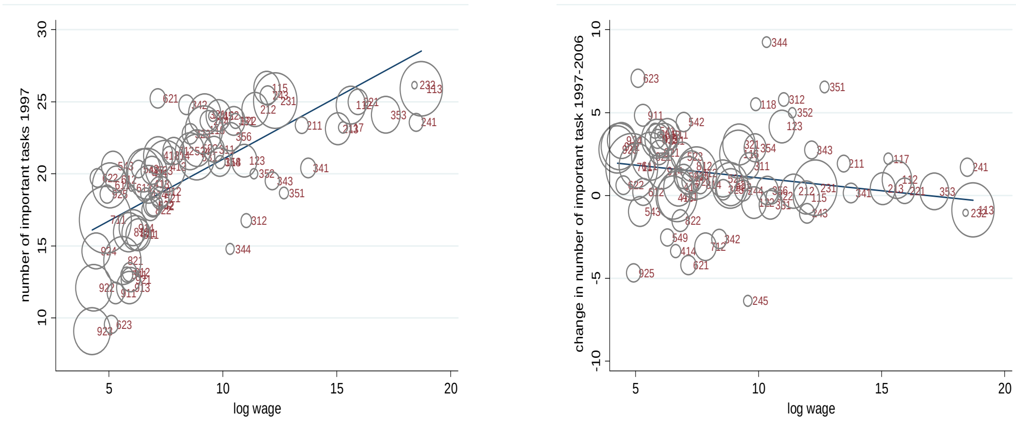
	Low occupations					Middle occupations					High occupations				
	task 1997	task 2006	change 97-06	extensive	intensive	task 1997	task 2006	change 97-06	extensive	intensive	task 1997	task 2006	change 97-06	extensive	intensive
detail	33.38	32.89	-0.48	0.06	-0.54	34.82	34.43	-0.39	-0.14	-0.25	34.00	34.13	0.12	-0.30	0.43
people	33.89	33.70	-0.19	-0.21	0.02	29.72	30.31	0.59	0.66	-0.08	31.43	32.49	1.06	1.08	-0.02
teach	18.02	16.40	-1.62	-0.56	-1.06	13.22	13.07	-0.15	0.33	-0.48	14.24	16.40	2.16	0.59	1.58
speech	6.26	7.93	1.67	0.47	1.20	3.43	3.46	0.03	0.44	-0.41	1.93	1.83	-0.10	0.13	-0.22
persuad	16.80	16.93	0.13	0.37	-0.24	10.92	10.88	-0.04	0.63	-0.67	11.43	12.08	0.65	0.07	0.58
selling	10.64	8.03	-2.61	-0.70	-1.91	7.43	6.91	-0.52	0.44	-0.96	15.11	12.86	-2.25	0.29	-2.54
caring	19.95	18.83	-1.12	-0.53	-0.59	15.30	14.40	-0.90	0.93	-1.83	20.24	21.19	0.95	1.98	-1.03
teamwk	23.93	27.18	3.25	-0.62	3.86	24.37	23.80	-0.57	0.05	-0.62	29.13	29.97	0.84	0.10	0.74
listen	24.27	27.39	3.12	0.17	2.95	25.12	25.86	0.74	0.09	0.65	27.91	29.30	1.39	0.26	1.13
strengt	2.62	1.89	-0.72	-0.46	-0.26	10.30	7.89	-2.42	-0.42	-1.99	21.49	18.54	-2.95	-0.63	-2.32
stamina	5.77	4.41	-1.36	-0.49	-0.87	10.39	9.53	-0.86	-0.20	-0.66	23.42	20.89	-2.53	-0.59	-1.94
hands	3.76	3.64	-0.12	-0.12	0.00	16.38	14.32	-2.07	-1.01	-1.06	17.33	16.56	-0.77	-1.17	0.40
tools	7.02	5.83	-1.19	-0.14	-1.06	19.62	16.40	-3.21	-1.00	-2.21	23.44	19.38	-4.06	-1.43	-2.62
product	20.90	18.62	-2.28	-0.62	-1.66	20.42	21.39	0.96	-0.30	1.26	23.81	23.59	-0.22	-0.68	0.46
special	28.19	31.19	3.00	1.00	2.01	24.81	28.38	3.57	0.43	3.15	22.10	24.95	2.85	0.24	2.61
orgwork	16.94	21.05	4.11	0.19	3.92	18.81	20.75	1.94	0.01	1.93	20.72	22.36	1.65	0.59	1.06
usepc	14.27	28.17	13.90	0.52	13.38	18.25	22.66	4.41	-0.24	4.65	7.00	10.42	3.43	-0.34	3.76
faults	25.61	23.46	-2.14	-0.28	-1.86	29.38	26.31	-3.06	-0.59	-2.47	29.42	27.98	-1.44	-0.68	-0.76
cause	24.36	19.19	-5.17	-0.10	-5.07	25.20	21.64	-3.56	-0.48	-3.08	22.22	20.49	-1.74	-0.85	-0.88
solutn	27.27	25.67	-1.59	0.17	-1.76	24.78	24.40	-0.38	0.07	-0.45	20.21	19.92	-0.29	-0.43	0.13
analyse	14.25	16.43	2.18	1.22	0.95	12.54	13.97	1.43	0.00	1.43	8.01	8.30	0.30	-0.09	0.39
noerror	24.34	23.48	-0.86	-0.20	-0.65	29.57	29.21	-0.36	-0.57	0.21	26.87	27.37	0.50	-0.58	1.09
mistake	27.36	26.86	-0.50	-0.17	-0.33	30.65	31.25	0.60	-0.41	1.01	29.64	30.81	1.17	-0.47	1.64
planme	29.11	25.87	-3.24	-0.03	-3.21	22.27	23.09	0.82	0.63	0.18	20.05	19.58	-0.47	0.29	-0.76
planoth	13.23	9.84	-3.39	-0.53	-2.85	7.63	6.64	-0.99	0.21	-1.21	6.65	7.24	0.59	0.44	0.15
mytime	30.12	29.85	-0.28	-0.30	0.03	24.29	26.71	2.42	0.51	1.90	21.59	22.90	1.30	0.44	0.86
ahead	30.92	29.77	-1.15	-0.10	-1.06	26.04	26.39	0.36	0.31	0.04	25.51	26.50	1.00	0.53	0.47
read	22.84	20.18	-2.66	-0.53	-2.13	26.14	24.58	-1.55	-0.10	-1.45	25.62	26.69	1.07	0.11	0.96
short	20.73	23.70	2.97	0.29	2.68	22.82	23.54	0.72	0.17	0.55	19.13	20.15	1.01	0.40	0.62
long	12.51	14.97	2.47	0.90	1.57	13.15	14.00	0.85	0.16	0.69	11.07	10.79	-0.28	0.12	-0.40
write	12.86	12.07	-0.79	0.06	-0.85	15.10	14.70	-0.40	0.09	-0.49	14.14	13.83	-0.31	0.14	-0.46
writesh	16.11	18.48	2.36	0.95	1.41	14.56	15.89	1.33	0.42	0.91	8.43	10.43	2.00	0.65	1.35
writelg	9.71	10.64	0.94	0.78	0.15	7.64	8.41	0.78	0.18	0.60	6.30	5.32	-0.98	0.22	-1.19
calca	19.75	15.32	-4.42	-0.74	-3.68	16.56	15.18	-1.37	-0.59	-0.78	17.04	12.53	-4.51	-0.11	-4.40
percent	14.10	11.34	-2.75	0.06	-2.81	10.76	11.02	0.27	-0.49	0.76	6.97	5.39	-1.58	-0.19	-1.38
stats	4.21	4.75	0.54	0.22	0.32	3.62	4.61	0.99	-0.22	1.21	2.40	2.82	0.42	-0.09	0.52

Table C.7: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Employment 97-06	1.00								
(2) TOC 97-06	-0.12	1.00							
	(0.29)								
(3) Task-rank 97-06	-0.28	0.57	1.00						
	(0.01)	(0.00)							
(4) Log employment	-0.50	0.31	0.66	1.00					
	(0.00)	(0.01)	(0.00)						
(5) Offshoring	-0.25	-0.06	-0.03	-0.06	1.00				
	(0.03)	(0.59)	(0.81)	(0.64)					
(6) Blinder Index	0.38	-0.17	-0.21	-0.09	-0.35	1.00			
	(0.00)	(0.14)	(0.07)	(0.44)	(0.00)				
(7) RTI-ONET	-0.26	-0.09	0.09	0.25	0.31	-0.49	1.00		
	(0.03)	(0.43)	(0.47)	(0.03)	(0.01)	(0.00)			
(8) Computer Use (CUI)	0.21	-0.27	-0.13	-0.09	0.05	0.26	0.39	1.00	
	(0.07)	(0.02)	(0.25)	(0.46)	(0.67)	(0.03)	(0.00)		
(9) Union	0.00	0.53	0.55	0.39	-0.06	-0.06	0.10	-0.02	1.00
	(0.99)	(0.00)	(0.00)	(0.00)	(0.60)	(0.63)	(0.40)	(0.86)	

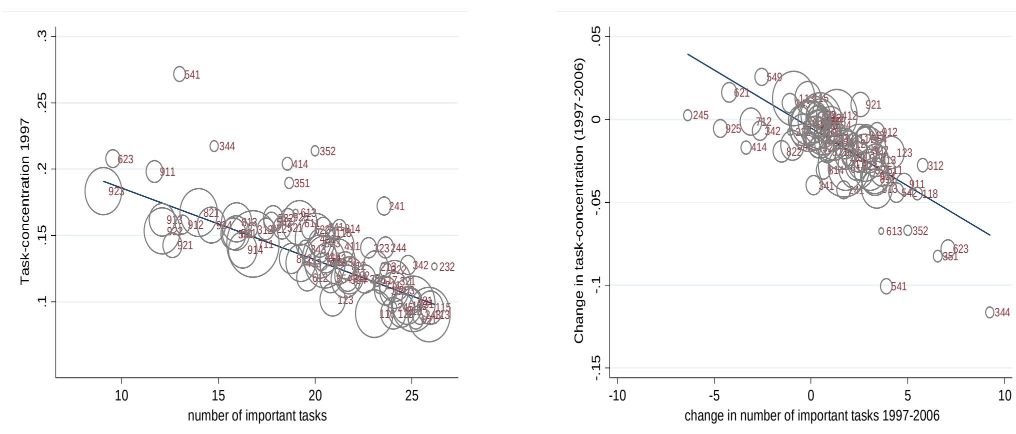
Note: P-values in parentheses

Figure C.1: Alternative task-concentration indicator in 1997 (left) and changes between 1997 and 2006 (right) by occupations classified by wages per hour, 3-digit SOC-2000 occupational codes



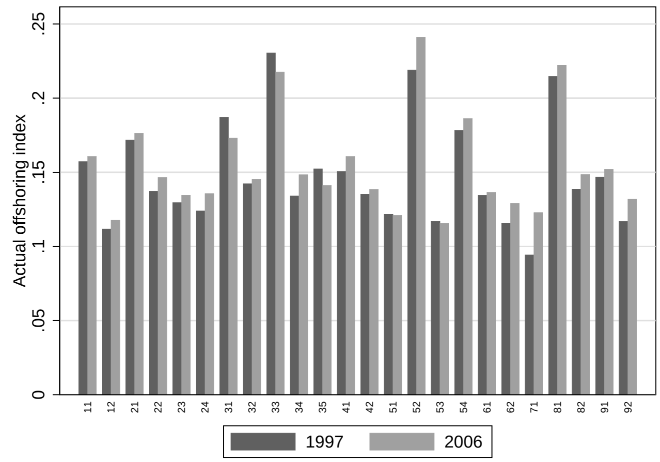
Notes: log wage is the occupation's gross hourly earnings average for 1997 and 2001. Circle sizes are the occupation's employment levels in 1997 and circle numbers are the 3-digit SOC-2000 codes. The solid line is a linear fit using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

Figure C.2: Comparison of alternative task-concentration indicators in 1997 (left) and changes between 1997 and 2006 (right)



Notes: Circle sizes are the occupation's employment levels in 1997 and circle numbers are the 3-digit SOC-2000 codes. The solid line is a linear fit using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

Figure C.3: United Kingdom, actual-offshoring index (AOI) by 2-digit SOC-2000 codes for 1997 and 2006



Source: Own estimations using WIOD, BSS and ASHE data.

Table C.8: Correlations among computer use indicators

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) importance of PC use	1.000					
(2) complexity of PC use	0.770	1.000				
(3) use for communication_01	0.830	0.796	1.000			
(4) use for information	0.877	0.787	0.947	1.000		
(5) PC in workplace	0.760	0.545	0.758	0.743	1.000	
(6) communication in workplace	0.784	0.574	0.751	0.806	0.845	1.000

Table C.9: PCA results for use of computers

	CUI loadings for first principal component
importance of PC use	0.422
complexity of PC use	0.374
use for communication	0.434
use for information	0.427
PC in workplace	0.390
communication in workplace	0.400
explained variance	0.812

Publisher:

CPB Netherlands Bureau for Economic Policy Analysis
P.O. Box 80510 | 2508 GM The Hague
T (070) 3383 380

February 2013 | ISBN 978-90-5833-584-5