Technology, offshoring and the task-content of occupations: Evidence from the United Kingdom

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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 organised within occupations. Analysing changes at the *extensive* margin we confirm previous findings in the literature: there has been job polarisation in the UK, and this job polarisation 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 globalisation have deeply influenced the way we work and how firms operate. ICT improvements –specially the computerisation 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 globalisation process. In particular, the offshoring of jobs from rich developed countries to emerging economies has been an influential economic

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[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).

force in the last 20 years.[2] For instance, Foxconn (the manufacturer of Apple) plans to employ about 1 million robots by 2014 to replace workers that do simple tasks such as spraying, welding and assembling. On the other hand, Boeing has organised the production of its new 787 Dreamliner Jumbo Jet in 135 different geographic locations. Thus investigating the impact of technological change and globalisation on the labour market is economically and socially relevant.

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 in their jobs. In particular, Autor *et al.* (2003) classify tasks in two broad groups: routine and non-routine tasks. Applying the observation that computers substitute routine tasks and complement certain non-routine tasks, they explain how computerisation depresses the demand for medium-skilled workers (performing routine tasks), while increasing the demand for high-skill and low-skill workers performing non-routine tasks. This "routinisation" hypothesis has been used to explain the wage and job polarisation of the labour market, which has been extensively documented.[3]

A distinguishing feature of Autor *et al.* (2003) is the analyses of the changes in the task-content within occupations (what they label as the intensive margin) as well as the changes between occupations that have different task-contents (i.e. the extensive margin). However, within occupation changes have been largely ignored in subsequent papers due mainly to data limitations. Most papers using the task-based approach employ the ONET dataset, which provides detailed information 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 implicitly that the task-content is fixed within occupations.[4] This limitation in the empirical task-based analysis has recently been pointed by Van Reenen (2011). Nevertheless, the recent theoretical model by Acemoglu and Autor (2010) emphasises 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) and UK Labour Force Survey (LFS) data from 1997 and 2006 to analyse both the changes at the *intensive* and *extensive* margin. BSS data 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 in the BSS and LFS data, we can answer our first 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?

[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 the United Kingdom (see Felstead *et al.*, 2007).

To analyse changes at the intensive margin we start by 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. First we look at the full set of 36 tasks and changes in their relative importances over time in a detailed manner. Then we propose two summary indicators that reflect changes in the task-composition of occupations: changes in the task-occupation connectivity and the rank-stability of tasks within occupations.[6]

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 has changed at both the extensive and the intensive margins. The magnitude of the changes is similar for both margins. Our findings are similar when we look at the full set of 36 tasks: both the extensive and intensive margins are changing. Finally, when we use summary indicators we find that the task-rank correlations between 1997 and 2006 are quite different in some occupations (i.e. rank-stability of tasks) and the connectivity between tasks (task-occupation connectivity) has changed over the years.

Our second research question is: how has technology and offshoring affected the changes in occupational employment at both the extensive and intensive margins? To test this question empirically, we first construct a series of indicators for offshoring and SBTC for the UK. We then test how these indicators have affected employment changes at the extensive margin. In particular, we regress changes in employment against these variables and additional control variables such as initial size of occupations and the degree of unionisation. At the extensive margin, we find that UK has experienced a job polarisation 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. 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 (e.g., Goos *et al.*, 2011; Firpo *et al.*, 2011). Moreover we check the robustness of our results using different offshoring and SBTC indicators. With respect to changes at the intensive margin we find that the SBTC returns a statistically significant coefficient in regressions where the dependent variables are the changes in the rank-stability of tasks and the task-occupation connectivity indicators. On the other hand, the effect of offshoring is not significant. Moreover, the econometric results show that occupations with high degrees of unionisation experience less changes at the intensive margin (task-content). These results suggest that computerisation 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 the task-composition of jobs.

The contribution of this paper is twofold. First, we analyse if the task-content of occupations has changed. 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 that the task-content of occupations

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

is fixed. 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. 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 organised within occupations, while offshoring has not been a critical factor in this respect. In addition, at the extensive-margin we confirm previous findings of the literature: there has been job polarisation in the UK which can be explained by both SBTC and offshoring, even when SBTC seems to be a more influential factor.

The paper is organised as follows. 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 margins. Sensitivity analyses are presented in section 5. We summarise 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 computerisation. 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 stylised 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.

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

[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 formalised in the model by Acemoglu and Autor (2010), as we explain below.

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 computerisation in particular– can account for the polarisation 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 by assembling a continuum of tasks i. There are four production factors that produce each task. Labour is represented by three different skill levels: low (L), medium (M) and high (H); and capital K which is defined as machines/computers in the model.

In general, all workers can eventually perform all tasks, but the model assumes a structure of comparative advantages that assures that workers specialise 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. 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

[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 emphasises the importance of both margins in explaining the adjustments in the labour market.

[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.

(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 determines that every worker is paid the same skill type wage w, 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 high-skill labour productivity, which corresponds with 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, $\frac{w_M}{w_L}$ 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 polarisation pattern in the AA model.

- The second exercise is to analyse the effects of computerisation –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 polarisation pattern from computerisation.

- 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 computerisation, and thus, also yield wage polarisation.[14]

Thus, the AA model provides a theoretical setting that summarises the extensive and intensive margin changes using two variables: I_L and I_H. These variables, by giving the cut-off points in the distribution of tasks between the three skill levels, provide direct

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

[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.

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 (computerisation) and offshoring levels. Thus, with our dataset we can empirically test the implications of the AA model mentioned above.[15]

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 polarisation

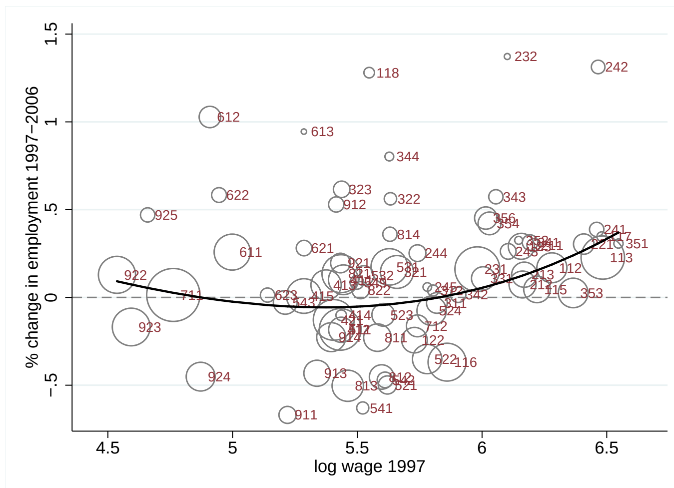
Employment data is taken from the British Labour Force Survey (LFS), for 1997, 2001 and 2006 –to be consistent with the three BSS waves. It is straightforward to measure changes

[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 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.

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] Following the literature we use log wages as a proxy to quality of jobs (see for example, Van Reenen, 2011).

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

Figure 1: Changes in employment between 1997 and 2006 by occupations ranked by wages per hour, 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings in 1997. 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 quadratic fit using 1997 employment levels as weights. Source: Own estimations using BSS and ASHE data.

From Table 1 we see that 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). During the same period about 900,000 jobs were created in the service sector (sub major group, 61, 62, 71, 82 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 (not shown in Table 1).

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

We obtain task data from the British Skills Survey (BSS) 1997, 2001 and 2006 rounds (cf. Felstead *et al.*, 2007; Green, 2012). The BSS dataset gives detailed information on

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

Table 1: 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.

the tasks performed by individual workers, which can then be aggregated 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 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 in the rest of the paper.

The dataset provides information on the importance of each task in performing the job of each individual worker. 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.[18] The use of worker level data using self-reported job tasks is not unique to the BSS task database. The OECD is recently undertaking a multi-country data collection process which also

[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]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.

uses a self-reported individual worker's survey.[19] The work of Handel (2008) and Autor and Handel (2009) discusses the use of self-reported job tasks. We find that the use of the subjective evaluation of each worker on the importance of tasks in his/her job does produce, in aggregate, sensible task-content orderings.

The interaction of the 36 different tasks together with its relative importance provides a 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. 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. This rich information 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 employ alternative classifications that use other features of the task-content information.[21]

Analysing changes in the task-content 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 alternative ways to classify the task data. By doing this we provide insight in several (but complementary) facets of the task-content of occupations. Furthermore, this is a useful robustness check as the BSS tasks do not fit neatly into the routine/non-routine classification. Hence, in this section we analyse changes in the task-content of occupations employing two different task-classification approaches: (*i*) The routine/non-routine classification (section 3.2.1) and (*ii*) summary indicators using all task information (section 3.2.2).

3.2.1 Routine and non-routine classification

Our starting point is the routine/non-routine 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 RTI index is not changing over time.

We challenge this statement and allow time variance in the RTI index using the BSS tasks. Following the common 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 non-routine services and abstract tasks. The first group includes both manual and

[19]The programme is called the Programme for the International Assessment of Adult Competencies (PIAAC). 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)

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 groups. However, we do find that a number of tasks can be classified and this yields comparable results, e.g. the U-shaped relationship between the RTI index and skill levels, with other routinisation indexes used in the literature.[22]

Table 2 presents the time variation in the RTI index when we rank the tasks in each occupation according to importance of the three task groups. The first three rows of the table 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 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 2 present the decomposition of these changes in to changes in the intensive and the extensive margin.[23] The RTI Index is indeed changing over time. 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 routine/non-routine classification we find that the task-content of occupations have changed significantly in the UK over the period 1997-2006.

Table 2: 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

The distinction between routine, services and abstract tasks is an arbitrary choice. Taking all tasks into account without any beforehand grouping is preferable (for a detailed discussion see Green, 2012). We deal with this problem in two ways. First we performed a factor analysis in the individual task data and obtained 7 factor groups and replicated

[22]The precise matching between BSS tasks and the three task 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.

[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 of occupation j in total employment 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 margin 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.

the analysis above.[24] We find that the intensive margin changes are about the same magnitude of changes in the extensive margin. These qualitative results do not change when we replicate the analysis for high, middle and low-skilled occupations separately. Secondly we computed the intensive and extensive margins for the whole 36 task set. Table C.1 in the appendix displays the result.

Several observations can be made from Table C.1. First, the use of computers was the single most important change in the within occupation composition of tasks.[25] Second, tasks related to calculation and statistics is still important relative to simple computing tasks. Third, except reading and writing short documents, literacy tasks are gaining relative importance. Fourth, all physical tasks have become less important both at the intensive and extensive margin. Fifth, 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. Whereas other tasks associated with problem solving lost importance.[26]

3.2.2 Task-composition analysis using summary indicators

In this section we use our second approach and create summary indicators that include information on all 36 tasks. The main idea is that the importance of some tasks may increase at the expense of others over time. We have two indicators that measure the changes in the relative importance of tasks within occupations: task-rank stability and task-occupation connectivity. 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-rank stability The first indicator 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 stability 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 2 shows the relation between the task-rank stability and wages. We find that task-rank stability decreases slightly with respect to quality of jobs. Jobs in the high-end of the distribution have experienced more changes in their task-content than the other jobs. Low-jobs have experienced less shifts in their task-rank stability. This suggests that for low-skill jobs those tasks that were relatively more important in 1997 were still the most

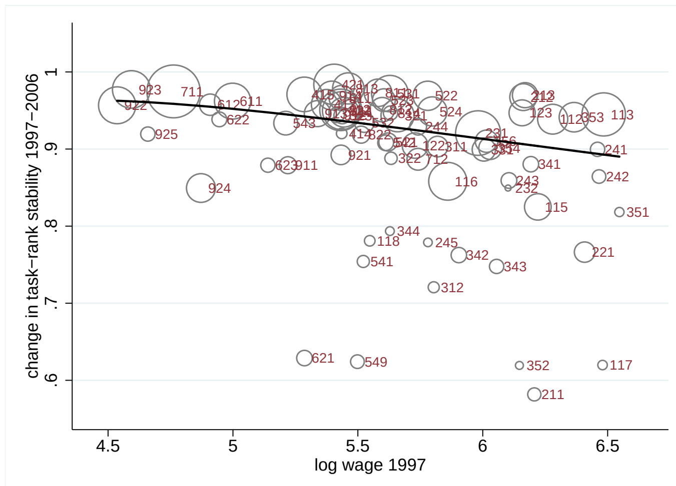
[24] The seven groups are: literacy, problem solving, checking, planning, number, physical, interactive. We also used a separate grouping where we have 7 factor groups + computer use. The factor groupings are very similar to the ones in Green (2012). These analyses are not included in the text but are available on request.

[25] This confirms the findings by Dickerson and Green (2004), who analysed the period between 1997 and 2001.

[26] We also replicated the analysis 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 confirming earlier findings on complementarity of skills and computerisation.

important tasks in 2006. For middle-level and high-level 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 stability. 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 1.0, we do observe sizeable changes for some occupations and in general, a pattern of task-content change between 1997 and 2006.

Figure 2: Changes in task-rank stability between 1997 and 2006 by occupations ranked by wages per hour, 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings in 1997. 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 quadratic fit using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

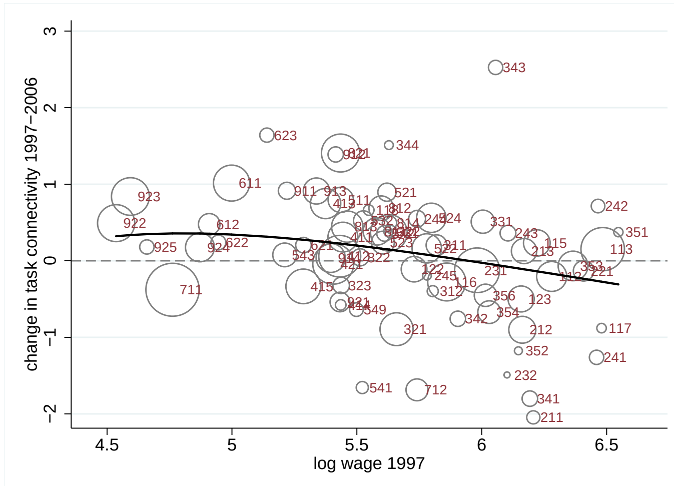
Task-occupation connectivity The second task-content summary indicator is taken from Akcomak *et al.* (2011) and measures how different tasks within an occupation are correlated to most important core-tasks in that occupation. In particular, the task-occupation connectivity (TOC) is constructed as follows:

$$TOC_{ij} = \sum_{j'} c_{j'j} m_{ij'} \tag{1}$$

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. We can also interpret this indicator as a measure of task-bundling. In essence the indicator shows whether task bundling in 1997 is different from the one in 2006 in a given occupation.

In Figure 3 we see a similar pattern as with the task-rank stability measure: TOC is decreasing in wages. Moreover, we find that the task-connectivity is increasing for low- and middle-skill occupations, but decreasing for high-skill ones.

Figure 3: Changes in task-occupation connectivity (TOC) between 1997 and 2006 by occupations ranked by wages per hour, 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings in 1997. 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 quadratic fit using 1997 employment levels as weights.
Source: Own estimations using BSS, LFS and ASHE data.

3.3 Offshoring indicators

We use two main indicators to assess the effect of offshoring on changes in employment and the task-content within occupations. First, we have a measure of past offshoring levels using input-output tables. The second indicator measures future offshorability of certain tasks. Both concepts are widely used in the literature, even if what they measure is conceptually different.

3.3.1 Offshoring index (OI)

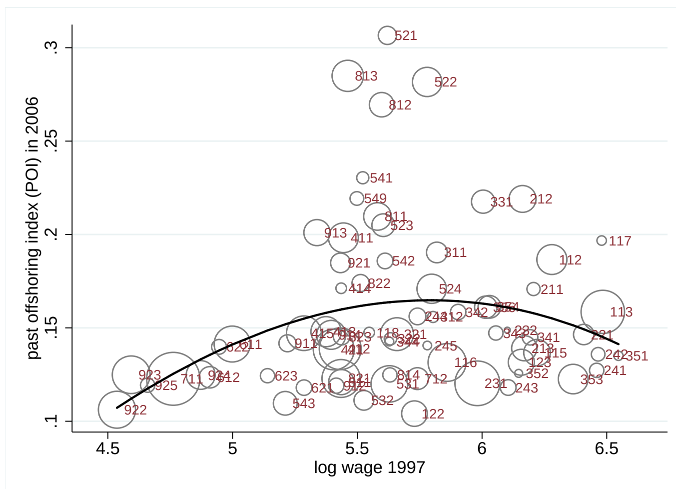
We use the Feenstra and Hanson (1996) offshoring indicator that is calculated as the share of non-energy imported intermediate goods in total non-energy intermediate inputs. This concept is based on the assumption that output of offshored activities has to be imported back into the UK to be combined with other inputs to produce final products (Crinò, 2010). In this context, the offshoring index (OI) is measuring all past offshored activity, but using changes in OI we can also obtain an indicator of current changes in offshoring levels. The OI index is constructed using detailed input-output tables that are organised at the industry level.[27] Since our labour data is organised by occupations we need to

[27]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

map the input-output industry data to occupational data. This is done by using the employment share by industry for each occupation.[28]

In Figure 4 we show the offshoring levels in 2006 ordered by wages. We observe that the average offshoring level is around 15%, with occupations within 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 OI values. Moreover, the offshoring index has an inverted-U pattern, with medium-skill occupations being offshored more than low- and high-skill jobs, as expected.[29] On the other hand, the changes in the offshoring levels between 1997 and 2006 have been evenly spread among different skill groups, with offshoring increasing on average just around two percentage points during this period (figure not shown).

Figure 4: Offshoring index (OI) for 2006 by occupations ranked by wages per hour, 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings in 1997. 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 quadratic fit using 1997 employment levels as weights.
Source: Own estimations using WIOD, BSS and ASHE data.

3.3.2 Blinder offshorability index

The second concept we use is offshorability, i.e. the potential of a specific task or occupation to be offshored in the future. This concept was first introduced by Blinder (2006, 2009). The fact that a task is offshorable (due for instance to high wage differentials between countries) does not imply that it can by spatially separated and offshored tasks.

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 OI at the industry level.

[28]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.

[29](cf. Acemoglu and Autor, 2010)

Some tasks cannot be performed from a long distance (e.g. office cleaning, hair cuts, restaurant services) even if it is economically feasible to offshore them. In other words, if a task/job cannot be spatially separated, then it cannot be offshored. Thus, the spatial-separability of tasks 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 offshorability index (cf. Blinder, 2009).[30] 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.[31] 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 standardised sum of the score on these five tasks. To equal signs with the OI, 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 5 we find that the Blinder offshorability index has an inverted-U pattern with respect to wage levels. Hence, medium skill occupations are more offshorable than low- and high-skill jobs.

3.4 Indicators for SBTC

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).[32] 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.

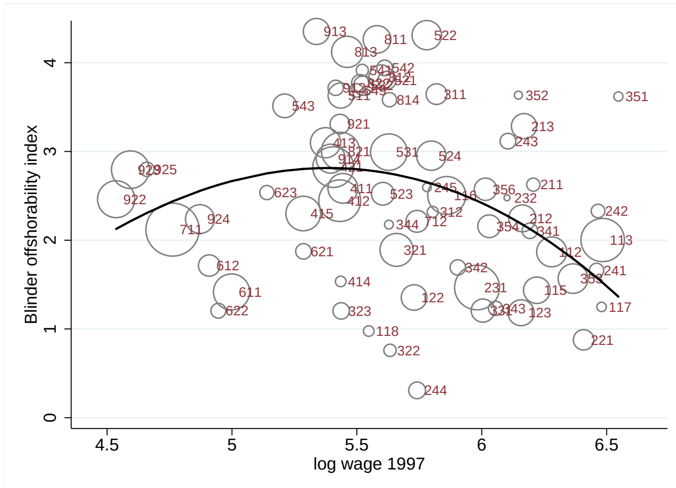
In addition, we also construct a computer-use index (CUI) based on the information provided by the BSS task "usepc" and five additional indicators from the BSS database that measures the extent of computer use in occupations. It is important to note that the RTI indexes are indirect measures of computerisation in the labour market (e.g., Goos *et al.*,

[30] 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 Blinder offshorability index 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.

[31] 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.

[32] 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 5: Blinder offshorability index for occupations ranked by log wages 1997, 3-digit SOC-2000 occupational codes



Notes: log wage is the occupation's gross hourly earnings in 1997. 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 quadratic fit using 1997 employment levels as weights.
Source: Own estimations using ONET and UK LFS data.

2011). 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). As can be seen from Table C.3, correlations among indicators are high and significant at the 1 percent level. All indicators have positive loadings and similar weights in the PCA loadings. 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 81 percent of the total variation in six computer use indicators.

4 Econometric results

4.1 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 stability indicator to measure the changes in the task content 3 digit SOC-2000 occupations.[33] Higher values of task-rank stability indicates that task-content of jobs

[33]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

have been fairly stable over the time. 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.[34] 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.2 in the appendix presents the correlation matrix of all included variables. 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 results.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment	0.530***	0.515***	0.513***	0.517***	0.515***	0.526***	0.527***	0.519***
	[0.104]	[0.102]	[0.102]	[0.096]	[0.098]	[0.105]	[0.106]	[0.097]
Offshoring (OI)	0.022		-0.028				0.035	
	[0.060]		[0.064]				[0.060]	
Blinder Index				0.144*	0.116			0.134
				[0.081]	[0.138]			[0.089]
RTI-ONET		0.124**	0.135**		0.037			
		[0.056]	[0.064]		[0.108]			
Computer Use (CUI)						-0.082	-0.084	-0.038
						[0.083]	[0.084]	[0.090]
Union	0.347**	0.352**	0.351**	0.349**	0.350**	0.349**	0.351**	0.351**
	[0.148]	[0.148]	[0.150]	[0.139]	[0.141]	[0.147]	[0.148]	[0.140]
Constant	-0.000	-0.007	-0.007	-0.007	-0.007	-0.008	-0.008	-0.014
	[0.080]	[0.081]	[0.081]	[0.080]	[0.081]	[0.082]	[0.082]	[0.082]
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 stability 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 3 we see that the effect of both offshoring (OI) and offshorability 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).

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. 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.

[34]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.

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 12 to 14% of a standard deviation less changes in the task ranking between 1997 and 2006.

Moreover, the results in Table 3 show that changes at the intensive margin are strongly associated with higher degrees of unionisation. The union indicator has positive, significant and robust coefficients. One explanation could be that 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 why tasks orderings are stable in jobs where unions are strong. It seems that both the size and the degree of unionisation in occupations act as a barrier to changes in the task-content of jobs.[35]

The initial size of the occupation (log employment in 1997) is always significant in the regressions for the task-rank stability. In the next section we also show that occupations with larger shares have lost employment. Together with the findings in this section this indicates that in occupations that are larger in size changes in employment mediates both through the intensive and extensive margin. Thus in occupations with higher shares of employment jobs are being lost and the task-content of the remaining jobs have also changed 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 12 to 14% of a standard deviation more (or less) changes in task-rank stability between 1997 and 2006.

4.2 Analysing changes in employment

The employment changes in the UK display a polarisation pattern as shown in Figure 1. This section provides suggestive evidence regarding to what extent this pattern is caused by offshoring and technology. We estimate the effects of technological change, offshoring and offshorability on the employment changes at 3 digit occupational level in UK between 1997 and 2006. Similar to the previous section all indicators are standardised and thus comparable in size.

Table 4 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 index that measures the likeliness of offshoring a job. The coefficient for the Blinder index 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.[36] In this sense our estimates are akin to the findings of Goos *et al.* (2011) for a set

[35]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.

[36]We also mapped the offshoring index by Goos *et al.* (2011) to UK occupations using cross-walk between ISCO1988 and SOC2000. The estimated coefficient is about the half of the size of the offshoring (AOI)

of European countries. They found evidence that offshoring is important in explaining changes in employment, and in particular, the job polarisation pattern.

Table 4: OLS estimates for the changes in employment between 1997 and 2006, 3-digit occupational level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment	-0.600***	-0.552***	-0.565***	-0.562***	-0.552***	-0.580***	-0.592***	-0.563***
	[0.156]	[0.147]	[0.144]	[0.153]	[0.147]	[0.157]	[0.148]	[0.148]
Offshoring (OI)	-0.266***		-0.163**				-0.291***	
	[0.067]		[0.062]				[0.065]	
Blinder Index				-0.337***	-0.172			-0.320***
				[0.076]	[0.141]			[0.087]
RTI-ONET		-0.351***	-0.284***		-0.223			
		[0.082]	[0.081]		[0.149]			
Computer Use (CUI)						0.169	0.182*	0.065
						[0.115]	[0.107]	[0.126]
Union	0.218	0.217	0.208	0.225	0.221	0.225	0.210	0.222
	[0.146]	[0.143]	[0.141]	[0.136]	[0.137]	[0.157]	[0.147]	[0.137]
Constant	0.001	0.015	0.017	0.015	0.015	0.009	0.016	0.023
	[0.095]	[0.090]	[0.089]	[0.091]	[0.090]	[0.099]	[0.094]	[0.092]
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

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 the 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 show that this assumption is strong and does not hold in the period 1997-2006 for the UK. The estimation results in Table 4, columns (2) 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 4 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

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.

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, 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 30%. However, if the RTI increases with one standard deviation employment change decreases by about 25 to 35%.

5 Sensitivity analyses

We conduct two main sensitivity analyses. First we replicate the estimations in Table 3 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 stability. The results of this exercise is presented in Table 5.[37]

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 3 and 5 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 6). The results indicate that SBTC rather than offshoring has impact on task-content of occupations.

Second, we estimate a set of 73 regressions for each dependent variable by including other covariates that could be related to changes in employment and task-content of jobs. 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 4 to 5. 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 (i.e., whether the occupation is tied to geography). For both indicators a

[37] We also ran regressions using industry-specific employment shares, to analyse if changes at the industry level can be also affecting occupational employment and task-composition. However, given the number of observations at the occupational level, we were limited to employ only very aggregate industry variables (at the 1-digit industry level) and some of these aggregate industry variables are highly correlated with our offshoring index (which itself is build based on industry data) and/or with our SBTC indicators.

Table 5: OLS estimates for the changes in the task-occupation connectivity (TOC) index between 1997 and 2006, 3-digit occupational level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log employment	0.123	0.095	0.083	0.112	0.095	0.117	0.118	0.114
	[0.117]	[0.106]	[0.105]	[0.110]	[0.106]	[0.105]	[0.107]	[0.102]
Offshoring (OI)	-0.026		-0.143*				0.017	
	[0.082]		[0.085]				[0.072]	
Blinder Index				0.134	-0.135			0.081
				[0.092]	[0.166]			[0.096]
RTI-ONET		0.263***	0.321***		0.363**			
		[0.066]	[0.077]		[0.137]			
Computer Use (CUI)						-0.248***	-0.249***	-0.202**
						[0.091]	[0.092]	[0.093]
Union	0.477***	0.496***	0.488***	0.493***	0.499***	0.490***	0.491***	0.502***
	[0.158]	[0.159]	[0.160]	[0.150]	[0.168]	[0.158]	[0.160]	[0.155]
Constant	0.000	-0.019	-0.018	-0.019	-0.019	-0.027	-0.027	-0.043
	[0.100]	[0.095]	[0.095]	[0.099]	[0.095]	[0.094]	[0.095]	[0.095]
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

higher value indicates that it is easier to perform the occupation at a distance, (*iii*) two indicators that measure the changes (rather than the levels) in offshoring and computer use between 1997-2006, (*iv*) a dummy variable that takes the value 1 if the occupation is medium-skilled. Table 6 summarises the results of the robustness exercise. Odd columns summarises 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 6 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 4 columns (6) to (8) we find that the coefficient of CUI is positive but is not robust to different specifications. The results in Table 6 confirms the findings in Table 4. Among the set of 5 covariates the indicators that measure the changes in offshoring (OI) 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. The effect of medium-skilled dummy returns coefficients consistent in sign but non are statistically significant.

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

Table 6: 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 (OI)	always (-)	always	sign alternates		sign alternates	
Blinder index (SSI)	always (-)	9/11	always (+)	5/11	sign alternates	
RTI-ONET	always (-)	11/13	always (+)	6/13	always (+)	always
Computer use (CUI)	always (+)	4/13	always (-)	never	always (-)	always
Union	always (+)	never	always (+)	always	always (+)	always
Robustness checks						
Face-to-face	always (-)	23/27	always (+)	24/27	always (+)	12/27
Proximity	always (-)	10/27	always (+)	never	sign alternates	
Change in CUI	sign alternates		always (-)	1/31	always (-)	never
Change in OI	sign alternates		always (+)	never	sign alternates	
Medium skill	always (-)	never	always (-)	never	sign alternates	

Notes: For each dependent variable 73 regressions were estimated. All regressions are at the 3-digit SOC-2000 occupational level. The even columns present information about the significance of the estimated coefficients. When all coefficients are significant this is labelled as "always" and when all are insignificant as "never". Other cells include numbers such that the first is the number of significant coefficients and the second the number of times the indicator included in the regressions.

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 on task-composition of jobs in 1997 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 further investigate the impact of technological change (SBTC) and offshoring on the 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 organisation of tasks within-occupations.

When we analyse changes in employment at the extensive margin, we find that the UK went through a job polarisation 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 SBTC and offshoring, while the effect of SBTC was larger than the effect of offshoring in explaining the job polarisation.

All in all we find evidence that SBTC has a dual role in changing the task-content of occupations. It has changed the way in which tasks are organised 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 organised within jobs.

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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).

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 the 36 tasks into the three main groups of 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 task-groups and this mapping is presented in Table B.1.

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: Changes at the extensive and intensive margins for all 36 BSS tasks

	task 1997	task 2006	change 97-06	extensive margin	intensive margin
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

Source: British Skills Survey (BSS) and LFS.

Table C.2: 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 (OI)	-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

Table C.3: 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

Note: (1) the importance of using a computer or computerised equipment, rated on a scale 1 (not at all important) to 5 (essential), (2) the complexity of use of computer, rated on a scale 1 (simple) to 4 (advanced), (3) the percentage of workers using computers to communicate with colleagues and with others outside the organisation, (4) the percentage of workers using computers to seek information about the organisation and products and services of suppliers, (5) whether new computerised equipment was introduced in the workplace, and (6) whether new communication technology was introduced in the workplace.