Employee Involvement, Technology and Job Tasks

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Abstract

Using new job requirements data for Britain I show that there has been a rise in various forms of communication tasks: influencing and literacy tasks have grown especially fast, as have self-planning tasks. External communication tasks, and numerical tasks have also become more important, but physical tasks have largely remained unchanged. Although the classification of tasks as programmable or otherwise is found to be problematic, computer use accounts for much of the changed use of generic skills. Going beyond the technology, I investigate whether organisational changes requiring greater employee involvement explain some of the new skill requirements. Using either industry or occupation panel analyses, I find that employee involvement raises the sorts of generic skills that human resource management models predict, in particular three categories of communication skills and self-planning skills. These effects are found to be independent of the effect of computers on generic skills.

Keywords: communication skill, literacy, numeracy, computers, autonomy.

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1. Introduction: theory and recent evidence on the use of generic skills.

While there may be no consensus as to the best explanation for increasing wage inequality, it is widely accepted that technological change in the modern era is broadly skill-biased, and there are many studies in support (e.g. Berman et al., 1994; Machin and Van Reenen, 1998; Gera et al., 2001). Yet this theory is now being refined as a result of closer inspection of the fundamental role of computerised technologies (Brynjolfsson and Hitt, 2000; Bresnahan et al., 2002). An intriguing series of papers have proposed a nuanced theory of skill-biased technical change, in which new technology generates reductions or increases in demand for particular types of generic skills in modern workplaces, according to whether the skills are used for carrying routine tasks or non-routine interactive tasks.[1] Since routine tasks have historically been concentrated around the middle of the occupation and wage spectra, the consequences are an overall relative upskilling of jobs, modified by persistence of jobs that use certain low-rewarded but hard-to-replace skills – a "polarisation" of the labour market (Autor et al, 2003; Autor et al., 2006; Autor and Dorn, 2008; Goos and Manning, 2007; Spitz-Oener, 2006; Manning, 2004; Dustmann et al., 2009; Manning et al., 2009).

The significance of studying skills use, including the use of different types of skills, stems both from the backward connection with the education and training system – is the system generating the needed generic skills for modern industry? (e.g. Stasz et al, 1998; Levy and Murnane, 2004) – and from the forward link with labour market rewards – which skills are being rewarded? (e.g. Murnane et al., 1995; Dickerson and Green, 2004; Bleakley and Chin, 2004; Egger and Grossman, 2005). This paper offers some further evidence for the role of computers in complementing interactive tasks, using new data that describes changes in the use of several detailed generic job tasks in Britain. There has, in particular, been a rise in various forms of communication tasks. The classification of all tasks as routine or non-routine is found, however, to be problematic. Going beyond the technology, and following many pieces of qualitative research, I investigate whether organisational changes requiring greater employee involvement explain some of the new skill requirements.

To further motivate this extension to the empirical application of new technology theory, I consider first both the achievements and some of the empirical problems that the distinction between routine and non-routine tasks encounters. The new data is introduced in Section 2, and detailed findings about the roles of both technology and employee involvement are reported in Section 3.

a) The ALM model.

Autor, Levy and Murnane (2003) (hereinafter ALM) distinguish between routine and non-routine job tasks, and propose that computers substitute for workers carrying out routine manual or routine cognitive tasks, yet are complements for workers involved in non-routine analytic and interactive tasks. This paper is important because it provides a fundamental theoretical framework for what computers do to jobs, and thereby an explanation for why new computer technologies are indeed skill-biased. In the ALM model firms react to an exogenous and radical fall in the price of computers by changing the task mix towards those demanding more non-routine activities,

[1] By generic skills is meant the ability to perform a task that is widely required across a variety of occupations and jobs; generic skills are also largely "general" in the sense of Becker.

comprising both 'expert thinking' (managing and solving analytical problems) and complex communication skills (Levy and Murnane, 2004). This switch in comparative advantage increases the demand for college-educated workers, because they have the knowledge and ability to carry out non-routine analytical and interactive tasks. Autor et al. (2003) provide some strong supportive evidence using data on job tasks derived from the Dictionary of Occupational Titles: in US workplaces there are rises in the prevalence of non-routine analytic and interactive tasks, and relative falls for routine cognitive and manual tasks. Both the timing and the distribution among industries and occupations of these changes are accounted for by computer capital investments.[2] Autor and Dorn (2008) find that spatial variation within the US in the rise of service employment is associated with the initial spatial distribution of routine-task-intensive occupations. Spitz-Oener (2006) provides some striking additional evidence from Germany, using micro-data to focus on within-occupation changes over two decades in the types of tasks carried out; her findings are also consistent with the ALM model, showing that computer capital substitutes for certain routine tasks while complementing nonroutine analytic and nonroutine interactive tasks.

In a related key paper that looks inside the black box of skill-biased technological change (SBTC), Bresnahan et al. (2002) theorise that the declining price of computers makes profitable a cluster of new information technologies, work re-organisation and product innovation. The work reorganisation comes about because of 'information overload': managers in firms with old-style organisations cannot cope with the increased data available for raising efficiency and so must distribute information-processing tasks down firm hierarchies in order to capture the gains. The consequence is an increased demand for analytical skills, and for the non-cognitive skills of communicating with and influencing colleagues and customers. Using firm-level data they show that the use of computer capital is greater in more decentralised workplaces, and that the productivity effect of IT stocks is greater in decentralised than more centralised organisations. They also find a robust association between computer capital, an index of decentralisation in the organisation, and various human capital measures (education level, occupation and managers' assessments of production workers). Their evidence is also consistent with other studies which find complementarities between organisational changes and changes in skills demand (e.g. Greenan, 2003; Caroli and Van Reenen, 2001; Piva et al., 2005; Brynjolfsson and Hitt, 2000).

The ALM model is especially significant as a possible explanation for a partial polarisation of labour markets. It is found in the UK that, while high-wage jobs expanded most rapidly between 1979 and 1999, consistent with SBTC, growing second-fastest were the lowest-paying jobs in services, leading to a declining middle: the so-called 'hour-glass economy' of burgeoning low-quality jobs (Goos and Manning, 2007). This polarisation is attributed by Goos and Manning, after consideration of some alternative explanations, to the ALM conjecture that computers do not substitute for non-routine manual labour tasks. "Hotel porter" and "Window dresser" are examples of fast-growing jobs which are known to require intense non-routine activities; yet, since they require comparatively low levels of education and very large numbers of people are capable of doing them, they are low-paid. Thus some non-routine jobs can be low-skilled and paid low wages, and if consumer

[2] This evidence contrasts with that of an earlier study (Howell and Wolff, 1991) which found, also using DOT data, that new technologies shifted occupational structures so as to demand higher cognitive skills, but had mixed effects on the demand for interactive skills.

demand grows in the industries where such jobs are concentrated there can still be growing low-skills demand. A similar picture, with reductions in middle-level jobs has been found in the cases of the US (Wright and Dwyer, 2003; Autor et al., 2006; Autor and Dorn, 2008) and Germany (Dustmann et al., 2009). The ALM model, together with technical limitations to trade, thus offers respite for low-skilled workers' job prospects, especially those located close to (and providing services for) rich high-skilled workers (Manning, 2004).[3] This explanation of polarisation does not negate the essential claims of SBTC theory but it is a significant modification, a more nuanced account of change in the employment structure. Moreover, polarisation of jobs can contribute a partial explanation of the rise of wage inequality.

Within the general framework of SBTC and the ALM model, case study work uncovers similar changes in routine tasks as new technology is introduced, but reveals also that there have been rises in demand for certain generic skills (Bartel *et al.*, 2003; Autor *et al.*, 2003; Ballantine and Ferguson, 2003). Among rank-and-file jobs, communication skills are found to be complementary with the introduction of new technologies as are problem-solving skills and a facility for learning new tasks. Reports are common of increased demands for reading and math skills, needed to work with newly automated equipment. Changes in skills demand are, however, quite heterogeneous even within narrowly-defined industries, reflecting varying managerial strategies and product complexity (Bartel et al., 2003; Mason, 2004).

The ALM model is thus a powerful framework for understanding the evolution of skills demand in the modern era, and offers a way to organise thinking and further empirical work on generic skills changes across the industrialised world. The model is deterministic, in that it takes the driving force to be exogenous reductions in the price of computers. Computer price reductions may lead certain organisational changes to become profitable, such as the delayering of management hierarchies, because they are complementary with the new technologies. Thus new management practices and organisational forms play an important role, but are endogenous.

b) An extension: the role of employee involvement.

Yet, one can reasonably question this ultimately exclusive focus on computing technology as the driving force. Two divergent criticisms could be made. First, stepping back to a broader sweep, the assumption that technological change in organisations is exogenous has been questioned from a range of perspectives, variously inferring its dependence on the availability of high-skilled labour, openness to trade, employment relations and hysteresis in the evolution of managerial employment policies and practices (e.g. Acemoglu, 1998; Rubery and Grimshaw, 2001). The perspective I develop here comes, however, from the opposite direction, and proposes that organisational change be regarded as an explicit proximate source of changing demand for generic skills. Rather than assuming that organisational changes are rational profit-maximising responses to technology, it may be preferable to take organisational change as reflecting, in part, independent thinking, the outcome of new management knowledge and associated tools and technologies. While there is

[3] Their prospects are raised still further if it is found that the same low-skilled jobs are better insulated against off-shoring to developing economies, since non-rountine tasks typically require local delivery. Jensen and Kletzer (2007) find that low-skilled jobs are less "offshorable" than high-skilled jobs. Maarten Goos also presented preliminary European evidence for this at the conference "Transforming Work", held in Oxford, 4-5 Sept. 2008.

evidence of complementarity between new technology and organisational change, including the introduction of some employee involvement practices, the connection is not closely determined and there remains scope for a separate role for organisational change (Bresnahan et al., 2002; Crespi et al., 2007). The impact of innovative management practices on productivity is in some cases enhanced when interacted with new technology, but in other cases occurs independently. New management science needs to be learned, is unlikely to accepted immediately, is of heterogeneous value even in narrowly-defined industries, and encounters both real and ideological barriers that raise switching costs; hence it is introduced at a varying pace across firms and industries (Pils and McDuffie, 1996; Ichniowski and Shaw, 2003). In case studies it is found that new technology can help to facilitate, and interacts with, organisational change; however, the same studies find that the new technology is usually neither a necessary nor a deciding factor (Sung and Ashton, 2005). Organisational practices also vary because there may be more than one locally optimal way of organising work. Where the effects of new working practices are mutually reinforcing, marginal innovations, by piecemeal introduction of individual practices, may fail to reveal gains, so evolutionary learning is blocked. In the same vein of argument, writers sometimes distinguish the "high-trust" road from the "low-trust" road, each route being a locally stable equilibrium: even though the high-trust road may give better performance, the low-trust road may persist.[4]

One common organisational change is the tendency for increasing employee involvement in companies – meaning workers becoming better informed about their employer, participating in discussion about immediate production issues or wider organisational matters, teamworking, possible use of profit-sharing reward schemes or similar performance-based incentives, jobs designed for greater autonomy, and associated delayering of management functions. Different studies list varying ranges of practices, but typically, organisational practices such as these are referred to as "high-involvement working practices", "high-performance work systems", "high-commitment practices" or just "workplace practices" (see, e.g. Bryson et al., 2005; Wall and Wood, 2005; Black and Lynch, 2001; Appelbaum et al., 2000; Ichniowski and Shaw, 2003). These practices have implications for generic skills utilisation that run in parallel with the demands of computer technologies. First, compared with organisations that operate more on Taylorist command-and-control principles, the high-involvement environment is one where there is less direct control of employees' work. There is thus more need for workers to plan their time and think forward. Second, there is likely to be an increased need for interaction skills in order to function well in high-involvement corporate environments. Where workers are required to work together more, to cooperate with colleagues, to exchange information and express opinions, and to learn and adopt at least some of the organisation's common values and attitudes, communication activities acquire a greater range and importance in their jobs. Since a good deal of communication is also through the medium of the written word (on paper or on screen), employee involvement also makes literacy more important. In an environment of relatively

[4] By introducing a distinct role for organisational change in affecting generic skills demand, one finds the indeterminacy and scope for managerial discretion insisted upon in sociological accounts of the impact of new technology. Autor et al. (2003b) addressed the issue of indeterminacy rather differently by allowing discretion, at least in the short term, for employers to package tasks in alternative ways in jobs. By separating tasks (which they see as technologically determined) from jobs (which are subject to discretionary design), they propose to reconcile the views of economists and sociologists as to the effects of technology.

increased autonomy, there is also more call for the higher forms of communication that are entailed in inducing others to follow desired courses of action. These higher forms of communication are part of what I below refer to as “Influence Skills”. As a shorthand I refer to these arguments as the HRM model of generic skills determination, which I cast as additional to, rather than subsumed within, the ALM model.

Further to the evidence noted above, that organisational change has typically been biased towards higher-level skill groups (usually defined by a simple broad skill indicator), and beyond the evidence that links high-involvement working practices explicitly with training (e.g. Cappelli and Rogovsky, 1994; Osterman, 1995; Whitfield, 2000), there is also case-study evidence of an association between high-involvement working practices and changing demands for several generic skills. Examples are Thompson et al. (1995), Kelly (1989), Ashton and Sung (2002), and the emphasis in such studies is typically on communication, teamworking and problem-solving skills. Sometimes this association is revealed through the difficulties of introducting new work practices where these skills are scarce (Bishop *et al*., 2008; Cheng *et al.*, 2004; De Vilbiss and Leonard, 2000). As for formal quantitative evidence, Gale et al. (2002) find a link between indicators of certain “new” organisational practices in manufacturing industries and management-perceived changes over three years in certain generic job-skill requirements (basic maths, basic reading, interpersonal, problem-solving, computing); and Felstead and Gallie (2004) find that high-involvement work practices tend to be associated at one point in time with high uses of several generic skills. The evidence I present below comes closest in spirit to these studies, but uses comprehensive indicators of the changing use of a wide range of generic skills, covers a much longer period, and is applied to the whole labour force.

To summarise this part of the discussion, because schemes to induce greater employee involvement may be introduced independently, following normal variations in strategies in the context of the evolution of management philosophies and changing power relations, it would be to omit a significant variable if the role of employee involvement were to be seen only as a subsidiary by-product of (or channel for the effect of) new technologies, and not as a potential independent source of skill change. In the empirical investigation of the determinants of generic skills that is to follow, therefore, an index of employee involvement is explicitly introduced alongside indices for the use of computers.

c) Empirical issues concerning the ALM model

Concern about the unifocal theoretical approach in the ALM model is enhanced by the fact that the evidence in its favour, while strongly suggestive, is far from complete. A lynchpin in the evidence is the subjective identification of programmable tasks from descriptions and classifications that are not obviously comprehensive across industries. Yet the validity of the categorisation is not always clear-cut. Sensitive to this concern, Autor et al. (2003) use an alternative specification drawing on a wider range of DOT variables, using principal components analysis, and find that their main findings hold though with some alteration: unsurprisingly, they find that “variable choice does matter.” To illustrate the potential for misclassification, observe that ‘routine cognitive’ tasks comprise, in the classification of Spitz-Oener (2006), ‘calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature'. Probably many of these tasks are truly routine (hence programmable) as classified, but the attribution is by no means certain. For example, the task of calculating is quite general and may easily be incorporated in non-routine processes: in Autor et al.'s analysis, "adds and subtracts 2-digit numbers" is a task included in the GED Math score which is classified as non-routine analytic. Conversely, the activity of 'selling' is not classified in Spitz-Oener's study as routine, yet can be, and frequently is, partly automated – one has only to think of the spread of internet sales. There will also be many more cognitive functions that have been automated than are contained in the above list.

In fact, the classification of job tasks into distinct generic domains is by no means an exact science (Handel, 2008; Ashton et al., 1999). It involves grouping multiple job tasks that are linked in theory and go together in practice (as derived from exploratory factor analysis or some other data reduction technique). Often, a plausible classification is made into cognitive, physical and interactive task domains, with corresponding knowledge and skill domains. More disaggregated domains follow, reflecting the concerns thrown up by specific debates, for example over literacy or over problem-solving activities within the cognitive domain, or over communication skills, "emotional labour" or "caring labour" in the interactive domain. Yet we lack a comprehensive and consensual theory of job functions, especially in the realm of interpersonal tasks. Moreover, some tasks can easily fall into more than one domain, making their allocation problematic. For example, giving a lecture is both a cognitive process and an act of communication. According to Darr (2004) selling and technical functions are increasingly becoming "fused together" in some sectors. There is, therefore, often a judgement to be made as to how tasks are to be classified into domains. Judgement over the categorisation of tasks as programmable or not is especially problematic in many cases. In particular, the range of functions considered to be programmable is narrower than the list that can safely be categorised as non-programmable (at present). As a result the generic activities included in the analyses of the changing distribution of routine/non-routine work are only subsets of the totality of generic tasks measured in job requirements data. Added to this, occupation-specific tasks, crucial in most occupations, are not delineated in economy-wide job-requirements surveys. Their levels are typically proxied by education, training and work experience requirements, and the extent to which they involve routine tasks are not captured by such indicators.[5]

Potential misclassifications of tasks, and the selectiveness of the tasks included because whether they are routine can only be captured in some cases, are of concern because they generate an element of imprecision in the extent to which industries' and occupations' programmable-task-intensity is accurately captured. This might matter less if the measurement error which such misclassification gives rise to were random (for then the direction of biases could be predicted), but the assumption of randomness would be a strong one.

A second empirical question surrounds the implications of the ALM model for job polarisation. The European evidence of structural employment changes in recent years (which have been a period of major ICT innovation), for which the ALM model could expect to be a good explanation, is mixed and conflicting. In the UK, according to Fitzner (2006) the earlier sharp polarisation of the workforce appears to have ceased

[5] The ONET content model, the successor to the US DOT system, incorporates occupation-specific skill requirements. They are not classified according to whether they correspond to routine tasks.

in the latest decade. Across continental Europe, according to Fernandez-Macias and Hurley (2008), jobs defined by occupation-industry cells in a diverse quartet of countries – the Netherlands, France, Slovakia and Hungary -- show distinct polarisation tendencies between 1995 and 2006; but another 21 countries exhibit either a mixed picture of employment growth, or unambiguous skill upgrading, or a tendency for middle-level jobs to rise the fastest. Such divergence is suggestive that skill changes may not be understandable solely in terms of ubiquitous technological changes. In contrast, using a slightly different period (1993-2006), Manning et al. (2009) report a consistent picture of job polarisation within 14 out of 16 European countries, using 2-digit occupation cells. Reconciliation work is ongoing between these two methodologies that have produced different results for largely the same period.

d) Main findings

In light of the above, the empirical analysis that follows examines changes in the use of generic skills in Britain, using a reasonably general categorisation of generic skills as proposed in occupational psychology involving a range of cognitive or intellectual tasks, interpersonal tasks and physical tasks. The classification is made using task data on individual jobs. The precise scales to be constructed reflect the covariance of items in the data itself as well as theory. The motivation is quite straightforward: a better understanding of the trends in generic skills use in industry, and of the driving forces behind them, should be of value to education and training policy-researchers; in addition it throws further light inside the black box of skill-biased technological change that is often used to explain the evolution of labour markets.

First, I examine the growth of generic skills in the last decade. It turns out that the various forms of communication have expanded rapidly over the recent period of 1997 to 2006. One form that has expanded particularly fast is "influencing" tasks, involving the sorts of skills that are traditionally associated with managers and professionals but need not be so confined. A close second is the growth in "Self-planning" skills. Numerical skills have expanded less rapidly than Literacy, and the use of Physical Skills have hardly changed much over the period.

Second, in spite of the difficulty of classifying skills exactly as required in the ALM model, I find that this pattern of growth is nevertheless broadly consistent with that model, which predicts a rapid growth of non-routine interactive skills in an era of rapid computerisation. Moreover, using an industry panel analysis I find that these communication skills are robustly related to the use of computing technology.

I also find, however, that employee involvement raises the sorts of generic skills that the HRM model predicts, in particular three categories of communication skills and self-planning skills. Moreover, these effects are found to be independent of the impact of technology on generic skills.

2. Data and measurement.

To address the issues at stake, I needed data on generic skills being used in jobs, which is scarce, but which is now available in Britain over a reasonable time span. With collaborators I had since 1997 collected job-skills data using the "job requirements approach", essentially an adaptation of occupational psychologists' methods to the context of a socio-economic survey.[6] The idea is to collect information on the generic tasks that are being done in jobs, where the same tasks might be done to greater or lesser degrees, or at differing levels, across the whole spectrum of jobs. Tasks are then grouped into task/skill domains. Some occupation-specific skills cannot be captured in this way, but in principle all generic skills can be. The method underlies the computation of skill needs attached to occupations used in the US Dictionary of Occupational Titles (DOT), and the subsequent ONET system, which provides careers advice to students and to human resource professionals, and the similarly-motivated Quality and Careers Surveys in Germany. While these data have been used by researchers as a by-product of the original objectives of data collection, the data I use here were gathered solely for research.[7] They come from the three UK Skills Surveys of 1997, 2001 and 2006, supplemented for background purposes by the 1992 Employment in Britain Survey. All these surveys used random probability sampling methods, and with the adjustment of sampling and response weights yield nationally representative samples of the employed population in Britain aged 20 to 60. Details can be found in Felstead et al. (2007) and in Felstead and Green, (2008). The three Skills Surveys achieved samples of, respectively, 2467, 4470 and 7780 workers, with gross response rates of 67%, 66% and 62%. Sample sizes for the analysis below are reduced through the exclusion of Northern Ireland and Highlands and Islands respondents (both regions only covered in 2006), through the focus on employees, and because of a very small number of respondents with missing occupation data.[8]

Measures of the usage of generic skills were derived from 35 items which began with the stem[9]: "We are interested in finding out what activities your job involves and how important these are …". To illustrate, one item refers to "making speeches and presentations", and respondents rate the importance of this activity on a 5-point scale ranging from "essential" (scored 4) to "not at all important/not applicable" (scored 0). All items used the same scale. The covariance of the responses to these items was examined using exploratory factor analysis, and an oblique rotation of axes. This yielded 8 factors that were easily interpreted as indices for the following generic skills domains: Literacy, Numeracy, External Communication, Influencing, Self-planning, Problem-solving, Physical tasks, and Checking tasks. One generic skill is specifically excluded from this list, namely computing skill, since its relationship to our technology measure would be tautologous. Table 2, below, details under each sub-heading the items upon which each factor loaded strongly. To obtain indices for further analysis, I generated average scores from the responses to the component items.[10]

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[6] Collaborators were Alan Felstead, Duncan Gallie, David Ashton, Bryn Davies and Ying Zhou.

[7] Similar motives underpin the recent Survey of Technology and Managerial Practices (STAMP) in the US (Handel, 2008). There are now growing moves to integrate job requirements methods into skills research in a number of other nations, including Northern Ireland, Spain, Italy and across all OECD countries through the forthcoming Programme for International Assessment of Adult Competences.

[8] All these survey data have been deposited in the UK Data Archive, and can be used for further analyses and for replication studies.

[9] As with other studies using task data, throughout this paper I refer to generic task requirements as equivalent to generic skills requirements.

[10] Where I use title case this refers to the constructed index. An alternative is to compute factor scores, and use these in subsequent analyses, the method used in a study using the earlier data (Dickerson and Green, 2004); I now prefer the scales developed here because they provide figures that are more transparent and more easily interpretable, but the findings are not particularly sensitive to the method used. Also, there remains a small degree of flexibility in the allocation of some activities to domains, and one could envisage minor differences in the groupings.

With the exception of the 2001 survey, there are no matched data from the respondents' employers. In a survey of individuals the indicators for the HRM model of employee involvement that can most reliably be collected are those in which the individual directly participates. Not all employee involvement indicators that are commonly referred to in the "high involvement work practices" literature were included in every year.[11] However, reliable and consistent data for all three years were collected for whether the company holds meetings in which people are informed about what is happening in the organisation, and similarly whether there are meetings where the individual can express views to management; data were also collected on whether the individual participated in each of three schemes or policies: a suggestion scheme, an appraisal system, and an improvement group or "quality circle". Finally, respondents indicated whether working with a team of people was important, and I computed a teamworking dummy variable for those who reported that this was "essential".[12] These variables are well correlated in the data, and are typically seen as indicators of an individual's participation in the wider organisation. The responses are combined in a single index, hereinafter termed "Employee Involvement", ranging from 0 to 1, which scales with a Cronbach's alpha coefficient of internal consistency reliability of 0.70.[13]

Also relevant to the HRM model as an indicator of involvement is the extent to which a worker is afforded control over his or her immediate job tasks: workers who have little influence, as in command and control systems of work organisation, have little direct involvement in decision-making about their own jobs. Conversely, designing jobs to have high levels of autonomy is typically seen as part of a high-involvement work system. Respondents were asked how much influence they personally had over four aspects of their work tasks: how hard to work, what tasks to do, how to do them, and the quality standards to which they worked. To each item they could respond on a 4-point scale ranging from "none at all" to "a great deal" (of influence). The average scores across the four items form a "Task Discretion Index", ranging from 0 to 3, with an internal consistency coefficient of 0.77. In the analysis, the impact of the Employee Involvement Index is considered alongside the Task Discretion Index, the former capturing organisational participation, the latter direct employee involvement with work tasks.

To capture the use of technology in individuals' jobs, many studies have included dummy variables for whether or not individuals use a computer, while some differentiate between purposes. Here, I distinguish between types of computer use explicitly ranked in levels of complexity. Computer users were asked directly about the level of their computer use, with several anchored examples for the levels in a 4-point scale. I aggregate the two lower points to capture "low-level" computer use (involving, for example, email use, word processing and equivalents), and the two upper points to give "high level" computing (examples are using statistical packages, programming and equivalents). A third category is those not using computers at all.[14]

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[11] Data on financial participation are available in 2001 and 2006.

[12] Of course, this does not capture the nature of the team, for example the extent to which it is self-managed, data for which is not available for all three years.

[13] Combining in a single additive scale, proxying the latent construct "employee involvement", is further warranted in situations, as here, where it is theorised that practices have their greatest impact on performance when taken together (Ichniowski and Shaw, 2003).

[14] Cognitive interviews at the pilot stage verified that these cateogries and examples were well understood by respondents.

Altogether these data have two advantages, compared with DOT and ONET based analyses, for examining and understanding changes in generic tasks. First, they give consistent worker-level data on tasks at three separate times, so that changes do not have to be inferred from changes in occupations. Second, they provide information about key changes in work organisation and in computer technology as experienced by those workers.

3. Sources of Change in Generic Skills Use.

a)The Growth of Generic Skills.

As a preliminary to looking at the evolution of generic skills over the 1997 to 2006 period (the main focus interval of my analysis), Figure 1 presents a picture of the growth of a subset of the generic skills over the previous 5-year period. The growth was computed from a series of questions in the 1997 Skills Survey which asked respondents to consider the tasks they had been doing in the job they had held five years previously. The response points and scales were constructed in identical ways to the method used for the current job, so the change could be computed as the difference between the skills used at the two time points. This retrospective method of measuring skills growth has its drawbacks – it depends on respondents' recall, excludes the experiences of those not employed five years previously, and conflates trend effects with lifecycle changes. So it should be regarded as an approximate rather than definitive measure of skill change in this period. As such, it is nevertheless informative. As the figure shows, the two domains of communication skill each rose substantially in the 1992 to 1997 period. Problem-solving also rose, while the use of Physical Skills was declining. These changes took place both for those who stayed in the same job over the period and for those who had switched jobs.

Figure 2 and Table 2 show how each of the generic skills requirements changed over 1997 to 2006, using the more satisfactory method of comparing cross-sections. As can be seen Influence, Literacy and Self-Planning skills were the fastest rising generic skills requirements. Looking at some of the detailed items underlying these changes, the largest increases (as measured by the proportions answering at the top of the scale) are found for the items "organising your own time", "writing short documents, e.g. letters or memos", "listening carefully to colleagues". Taking the two figures together, what is striking is that Influence Skills have been the fastest growing domain of generic skills for a sustained period of 14 years.

There were also more modest, but statistically significant, rises in the use of Numeracy, External Communication and Checking Skills over 1997-2006; while there were no significant changes in the deployment of Problem-solving Skills or Physical Skills.

It will be of some interest to education policy makers to note that the rises in the use of Literacy and Numeracy were partly in respect of basic skills. For example, the proportion of employees who did not have to write anything as part of their job fell from 12.8% to 8.3%, while the proportion that did not use even basic arithmetic fell from 18.1% to 14.0%. However, the rises were also due to increases in higher-level activities: the proportion for whom writing long documents was very important or essential rose from 28.6% to 35.3%, while the proportion for whom advanced maths or statistics was very important or essential rose from 17.3% to 22.0%. There would appear therefore to be ongoing employment needs for improvements in school outputs at both high and low levels.

To what extent are the generic skills changes just the consequence of changes in demand which generate changes in industrial structure, rather than changes in the skills being deployed within each industry? It might, for example, be advanced that Literacy Skills were becoming more important because of the expanding service sector. Table 3 presents the outcome of a conventional decomposition of the changes, giving the percentage of each generic skill change that is associated with skill changes within industries, if there had been no changes in 2-digit industry employment shares from their 1997 levels. As can be seen, the within-industry changes form more than four fifths of the total skill change in every case; indeed, in some cases within-industry change accounts for more than 100% of the change.[15]

To what extent are the generic skills changes reflected in a different mix of occupations being present in 2006 compared with 1997, rather than in the skills being used in each occupation? The final column presents an alternative decomposition, by 2-digit occupation. As can be seen, in all but one of the cases where the total skill change is significantly different from zero, most of the change can be accounted for within occupations. Nevertheless, the changing occupational structure accounts for a substantial amount of the total change in all cases. To examine the overall change it will therefore be necessary to look beyond the changes within occupations.

b) Changes in Employee Involvement, Task Discretion and Computer Use.

Consider next the changes in the potential determinants of generic skills use, technology and work organisation. The changes in the Employee Involvement Index, the Task Discretion Index and for the computer skills measures are presented in Table 1. As can be seen, there has been a modest increase in the Employee Involvement Index between 1997 and 2006. A closer examination of its constituents reveals that all increased, though some only very modestly, with the largest rise being in the use of quality improvement circles by 11 percentage points in the period. For context, the table also includes 1992 figures where available (as derived from the earlier Employment in Britain survey (Gallie et al., 1998). One can see that in every case the 1997-2006 rise is a continuation of a longer trend. This pattern of moderately upward-trending participation indicators is also found in other data sources, notably the WIRS/WERS series (Kersley et al., 2006). By contrast, there was a decline in the Task Discretion Index over 1997 to 2001, the continuation of a downward movement since at least 1992. The decline levelled off over 2001 to 2006. This fall in the extent to which employees report personal influence over their job has been documented elsewhere (Gallie et al. 2004), though not fully accounted for. Set against the rising Employee Involvement Index, this presents a somewhat more complex picture of changing work organisation in British workplaces than is found purely on the basis of establishment-level data.

Meanwhile the level of computer use expanded quite considerably over the period. Between 1997 and 2001, computer use expanded by nearly 8 percentage points with

[15] The decomposition equation is:
$\Delta S = \Sigma_j 0.5(S_{j06} + S_{j97})(E_{j06} - E_{j97}) + \Sigma_j 0.5(E_{j06} + E_{j97})(S_{j06} - S_{j97})$, where S is the average skill in cell j, E is the share of cell j in aggregate employment. The first term gives the change in skill that would occur solely through "between" changes in employment shares; the second gives the skill change attributable to skill changes "within" cells if employment shares remained constant.

most of the expansion was at the lower end; in the subsequent five years, there was no further overall expansion in computer use, but there was a 4-point increase in the proportions using computers at the higher level of sophistication. This upward trend is entirely consistent with ongoing large investments in computer capital across all industries over the period (reaching 2% of GDP in 2002 according to Abramovsky and Griffith (2007)).

This overall pattern of change in work organisation, computing and skills appears to be *prima facie* broadly consistent with both the ALM model and the HRM model. The increase in computer use would lead us, in the ALM model, to expect the increase in Influence Skills and Self-planning Skills which are largely non-routine. Also, the Literacy and External Communication domains are partly non-routine, though it is impossible to say how much. None of the domains could with confidence be classified as purely routine and therefore programmable. However, two of the five individual items classified by Spitz-Oener (2006) as routine are separately picked out in the data, namely “calculating”, which corresponds to MATHS1 and/or MATHS2, and “operating or controlling machines” which corresponds to TOOLS (see Table 2). The former pair were virtually static over the decade, and therefore declined relative to the other generic skills, while the latter experienced a statistically significant absolute decline. Meanwhile, the rises in the Employee Involvement Index would, according to the HRM model, also imply rising communication skills (of which Literacy Skills are a part), rising Problem-solving Skills, and rising Self-planning Skills, though the latter prediction is counterbalanced by the decline in the Task Discretion Index.

c) Modelling the Determinants of Skill Use

To investigate formally how skill use is associated with employee involvement and computer use, I estimate models of skill use as follows:

$$S_{ijt} = \alpha E_{ijt} + \varphi D_{ijt} + \beta C_{ijt} + \chi t + \sum_j \delta_j CELL_{ijt} + u_{ijt} + \varepsilon_{ijt} \qquad (1)$$

where S is skill use, E is the Employee Involvement Index, D is Task Discretion, C is computer use, t is time, u captures unobserved components possibly correlated with variables of interest, ε is random error, and subscripts refer to individual i in cell j at time t. $CELL_j$ are dummy variables for the type of job, which can be characterised by the industry, occupation or a combination of the two. The underlying model is that the technology and work organisation determine the generic tasks to be done (hence skills to be deployed). Due to the presence of the u_{ijt}, OLS estimates of the coefficients may give biased estimates of the causal effects. To help counteract this problem, in the absence of panel data or suitable instruments I construct a pseudo-panel where the unit is an industry or occupation 2-digit cell, consistently defined over the three cross-sections in 1997, 2001 and 2006. Aggregating over individuals within cells:

$$\overline{S_{jt}} = \alpha \overline{E_{jt}} + \phi \overline{D_{jt}} + \beta \overline{C_{jt}} + \chi t + \delta_j + \overline{u_{jt}} + \overline{\varepsilon_{jt}} \qquad (2)$$

Pseudo-panel fixed-effect (PPFE) estimation assumes that the $\overline{u_{jt}}$ are time-invariant, i.e. that the unobserved components that may be correlated with our variables of interest average out within cells at the same level over successive waves.[16] The validity of that assumption depends on the presumed distribution of the unobserved components.

Spitz-Oener (2006) argued that occupation was the appropriate unit for analysing the substitution and complementing processes between technology, employee involvement and skills. However, one can see from the decomposition that some of the generic skill changes derive from changes in the shares of occupations. It is possible that the factors affecting switching of job-titles and hence occupations might differ from those affecting job tasks within given occupations. Since my aim is to try to account for all the changes – including the occupation switching that may accompany task changing – it seems important to look at the within-industry shifts, provided that "industry" can be consistently defined over the examination period. This will capture both the within and between occupation sources of skill change within industries, though not the sources of skill changes associated with industry-switching. For robustness, I use 2-digit industries in one specification, and check results using an alternative decomposition using 2-digit occupation. Finally, it is possible that the relevant characteristics of an occupation differ across industries; hence I also use cells defined by both industry and occupation, but in this case each are defined at the 1-digit level, in order to obtain a reasonable sample size of well-populated cells.

Panel estimates with but three waves to work with cannot convincingly aspire to tackle potential dynamics, though there seems no reason to expect substantive lags in the impact of organisations and technologies on skills use. A potentially more serious issue surrounds other conceivable sources of bias. Reverse causation might be postulated, with, for example, generic skills determining employee involvement or computer use. I return to this issue below.

c) Findings

The estimates, for industry-based and occupation-results respectively, are shown in Table 4 and Table 5. For each skill/task domain column (1) gives the raw time trend using the pooled data, with no other variables added; thus the estimate corresponds to the 9-year changes depicted for each index in Table 3.

Column (2), Table 4, includes a set of 2-digit industry dummy variables, and hence the estimated coefficient on Year gives the estimated annual change conditional on industry. These results parallel the within-industry change reported in Table 3. The findings thus reflect again the earlier conclusion that changes in industrial composition cannot account for the changes in the uses of generic skills in British workplaces. Equivalently, column (2) of Table 5 shows that the increases in skills are smaller after controlling for occupation dummies, but remain statistically significant in all the skills for which the overall increase is significant.

Columns (3) present the OLS estimates for the associations of the organisation and computing variables with the generic skills, again including a year dummy. As can be seen, coefficients on the RHS variables register as significantly different from zero in every case. In most cases the coefficient is positive, implying that in cases where there

[16] This procedure is similar to that followed by Spitz-Oener (2006), who used a first-difference estimator, giving identical point estimates when there are just two waves, and estimates that are typically very close when there are more than two waves. I prefer, here, the fixed-effects estimator as providing more efficient estimates, which is especially useful when I have relatively few observations.

is higher Employee Involvement or Task Discretion or Computer Skills use, there is a higher use of the generic skill; the exception is for Physical Skills, for which all the coefficient estimates are negative. These estimates also control for industry in Table 4 or occupation in Table 5. However, as is evident from specification (1), they cannot be taken as estimates of the causal impact on skills use, since it is very possible that, in many instances, workplaces which are high on employee involvement or computer use are also high on other unobserved factors, such as a long-termist managerial culture or top-end product specification, either of which could also affect the skills needed from workers.

Columns (4) to (6) are the pseudo-panel fixed effects estimates which control for unobserved heterogeneity at the industry cell level. In some cases, for example Literacy skills, the estimated effects are quite close to the OLS specification, indicating that unobserved heterogeneity may not be a major problem in such cases. In some other domains, by contrast, the PPFE estimates are distinctly different from the OLS estimates. A case in point is the impact of Employee Involvement on Numeracy, where the OLS estimate is positive and significant but the PPFE point estimate is negative and insignificant in both Table 4 and Table 5. I conclude that it does matter that one controls for unobserved heterogeneity, and reserve the bulk of my discussion of substantive findings for the preferred PPFE estimates.

In Column (4) I enter just the Employee Involvement Index and the Task Discretion Index. Then Column (5) includes just the Computing variables. Finally, Column (6) includes all the theorised determinants of generic skill use. In every instance the coefficients on both the employee involvement measures and the computing indicators are not significantly different from those found in Columns (4) and (5). This means that the effects of the two sources of generic skill use are largely orthogonal, giving support to the proposition in this paper that organisational factors should be considered in addition to technological factors.

To pursue this issue further, I sought evidence for a strong association between the use of computing at any level and the level of employee involvement, treating the latter as a potential dependent variable to be explained by the former as regressor. In a cross-section across industry cells, employee involvement and computer use are strongly positively correlated. However, the 1997-2006 changes in employee involvement are only weakly positively correlated with the change in computing skills, when using industry cells,[17] and the same correlation is insignificant when using occupation cells. In a further test, in order to investigate the possibility that technology use and employee involvement were complementary practices in their effects on skill use, I included an interaction variable combining the employee involvement index with the computer use indicators. There was, again, no evidence for any complementary interaction.[18]

Consider now the substantive findings as shown in column (6) of Tables 4 and 5. The Employee Involvement index explains with a significant estimate the three types of generic communication skills that are predicted in the HRM model, namely Literacy, External Communication and Influencing. The effects are quite striking and fairly

[17] A fixed-effects regression of Employee Involvement on Computing gave:

$$\underset{}{E} = \underset{(0.0015)}{0.0053}.Year + \underset{(0.11)}{0.097}.LowComputing + \underset{(0.15)}{0.27}.HighComputing$$

[18] Results available on request to author.

substantial, and constitute a good reason to take organisational change seriously as a source of skill change. For example, an increase in the Employee Involvement Index of one standard deviation (0.13) would increase the use of Literacy Skills within occupations by 0.12, which is one fifth of the standard deviation of Literacy Skills across occupations (0.61). In the within-industry analysis of Table 4, the Employee Involvement Index also significantly affects the use of Checking Skills.

In the within-occupations analysis the role of work organisation is enhanced in two cases when considering the Task Discretion Index, which significantly raises both Influencing Skills and Self-Planning skills. However, Task Discretion has no significant effect on other generic skills; moreover in the within-industry analysis the positive impacts of the task discretion on Influencing and Self-planning Skills are found to be insignificant.

Neither the Employee Involvement Index nor the Task Discretion Index has a significant positive impact on Problem-solving tasks, as would have been predicted from HRM case studies. This finding suggests, either that the case studies in the literature are exceptional, or that the kinds of problem-solving being picked up in the survey do not correspond closely enough with what case-study researchers are referring to. The latter seems quite possible.[19]

The Task Discretion Index and, in the case of Table 5, also the Employee Involvement Index, are significantly negatively associated with Physical Tasks. Since neither the ALM model nor the HRM model carry any prediction for the link between employee involvement and Physical tasks, I will not speculate here as to the possible sources of this apparent process of substitution. The implication is that employee involvement, as a source of improving efficiency, appears from this finding to be especially effective at improving efficiency for those doing skilled manual tasks.

As can be seen, compared to jobs that use no computing, computing tasks are an important source of increased use of Literacy skills, Numeracy Skills, Influencing tasks, Self-Planning tasks, Problem-solving, Physical Tasks and Checking Tasks. The magnitudes are also very striking: for example, compared with an industry where the employees are not using computers at all, in industries where employees work with computers just at a low level would be using 0.85 higher Numeracy Skills, which is equivalent to 2.36 times the cross-industry standard deviation in Literacy Skills (0.36). However, the relationship is only sometimes monotonic: for example, in the occupations-based analysis of Influencing skills in Table 5, higher-level computing tasks do not appear to matter more than lower-level computing tasks.

These findings for the effect of the computing indices are only partially consistent with the ALM model. In support, the use of computers appears to be strongly complementary with the higher-level interactive skills involved in Influencing Tasks, as also with External Communication tasks and the other type of communication through literacy. However, there is no sign of computers substituting for Physical Tasks which are, at least in part, classified as routine in the earlier studies. To pursue this question further, I also experimented with including separately the individual items that are the closest equivalents to the routine tasks identified in Spitz-Oener's study, i.e. MATHS1, MATHS2, and CHANDS: none of these had negative associations with computing.

[19] Handel (2008) utilises what may be a better-specified item identifying problem-solving in the STAMP survey in the US.

For those skills that increased in use over time, an inspection of the Year coefficients in Columns (4), (5) and (6) is also of interest, in comparison with the Year coefficients shown in Column (2). Can within-industry and within-occupation changes in skills be accounted for by changes in computing and/or employee involvement? In the case of Literacy skills, neither Employee Involvement nor Computing tasks on their own adequately account for the growth in skills, in that a significant growth is found even after controlling for each on their own: but with both variables inputted in Column (6) the remaining change in Literacy skills is small and insignificant. For Numeracy and for Self-Planning the computer variables alone are sufficient, while the organisation variables are not, to account for change. In the latter case, the decline in task discretion is the reason (Table 1): this would have led, ceteris paribus, to lower skill levels.[20] For a similar reason, the rise of Influence Skills is only partly accounted for by both computing and organisational change. Finally, the rise in the use of External Communication Skills or Checking Skills can be accounted for by either source of change.

None of these findings are immune from a possible alternative interpretation, involving reverse causation. Changes in task requirements, driven by some external factor such as market competition, could be seen as calling forth changes in technology or in work organisation within industry cells. There are no suitable instruments for the independent variables; nor are there enough waves to explore dynamics in ways which might allow reverse causation to be ruled out or in. The interpretation I give in this paper is that computerisation of jobs, and the attachment of greater employee involvement to the ways in which they are carried out, do quite plausibly determine the generic tasks that have to be done. It is reasonable, for example, to theorise that employee involvement through meetings and suggestion schemes requires the use of literacy and other communication skills. Nevertheless, one of the considerations an employer might have to take on board when deciding to try to involve employees more might be the literacy level in the workforce, which itself would reflect the literacy needed in the job.

d) Robustness Checks.

In addition to alternative analyses already reported, as a check on the above findings the following sensitivity analyses were performed. First, even though I have weighted the above findings according to the number of observations in each cell, it is possible that remaining biases might arise from smaller occupation cells where there might by chance be a disproportionate number of respondents with above or below average values for unobserved variables. In the analyses shown the minimum size of occupation cell is set to be at least 25 in every year. This restriction removed a certain number of the less sparsely populated industries or occupations from the analysis. Even though the average cell sizes are reasonably large in every case (see Tables 4 and 5), there is a trade-off between keeping the minimum cell size high, and reducing the number of observations for analysis. I tested the sensitivity of the findings to raising the minimum cell size to 35, which reduced the number of industry cells from 83 to 69. While unsurprisingly the coefficient estimates changed, the differences were not significant and the pattern of findings was similar.

[20] Omitting the Task Discretion index from the estimation in column (4) leaves the Year coefficient small and insignificant.

Second, I constructed cells alternatively according to both industry and occupation, defined at the 1-digit level. With the same size restriction this gave 133 cells for the panel analysis. The findings, which are presented in the appendix but not discussed here in detail, give a similar pattern to those reported above.

Third, as an alternative to characterising technology with two indicators for the level of complexity of computer use, I utilised another pair of indicators which captured the respondents' views of the importance of computer use in their jobs. The higher level indicator was the proportion of employees for whom computer use was "very important" or "essential", while the lower level was for those where computer use was "fairly important" or "not very important", the reference category being "not at all important/does not apply". Utilising these indicators, instead of the two level dummies used in Tables 4 and 5, gave the same pattern of results, though with somewhat lower precision for the computing variable.[21]

4. Conclusion.

In this paper new measures have been obtained from bespoke surveys designed using "job requirements analysis" embodying principles adapted from those of occupational psychology. I have thus been able to provide a more comprehensive classification of the generic skills used in jobs, to track the changes that have occurred in Britain, and to study the effects of both organisational change and technology.

It turns out that the model of automation's effects on the labour market proposed by Autor et al. (2003) has some considerable traction in Britain. Communication skills and other kinds of interactive activities, summarised in my index of Influence Skills, are among those that increased especially fast over the 1997 to 2006 period. Though it is hard or impossible to determine *a priori* which skill domains are routine (and therefore programmable), the communication and influencing activities covered in these scales can reasonably safely be regarded as largely utilising non-routine skills. Computing activities are complementary with these skill domains, and the rise in the use of computer technology explains a good part of the increased skill utilisation. Compared with previous accounts, the additional factor to note, especially relevant in the context of education policy, is the prominence of the growth of Literacy skills, which is also accounted for in part by computer usage.

On the other hand, there were no significant increases in Physical Skills, and a small decline in the practice of certain tasks which could be regarded as more routine. Lower-level numerical activities rose, but only quite modestly. However, there is no evidence in this study that computing is substituting for any skill domain that might be thought to involve more routine activities, including those most closely similar to the activities identified in the study by Spitz-Oener (2006). That does not necessarily prove that no substitution is taking place, because the technology used in one occupation (or industry) might substitute for activities earlier performed by members of another, or because manifestations of computer technology other than those reported by individual workers might be relevant.

As well as technology, work organisation indicators provide strong explicators of the rises in generic skills use. This formal evidence for the importance of employee involvement and task discretion in determining generic skills use across the whole

[21] These results are available on request to the author.

range of a country's workforce broadly supports the findings of a number of recent case studies in a small number of companies. The rising Employee Involvement index, in particular, helps to explain the increases in use of Literacy, Horizontal Communication, External Communication and Influencing skills. The Task Discretion index is also a significant determinant of Self-Planning skills and Influence Skills, but this fact makes the actual rises in these skills more noteworthy because they occurred despite the decline in task discretion. All these effects turn out to be largely independent of the effects of technology.

As of now, there is mixed evidence about the extent of employment polarisation in different countries. One perspective, however, points to differential changes in employment structure in different European countries. While there could be several explanations for any cross-national diversity, one candidate suggested by the findings in this paper could be that organisational change has been happening at a different pace across Europe, and affecting jobs at all parts of the spectrum, not focused on the middle. Other institutional and demographic changes might also be sufficient to dominate the effects of technological change in the medium term.

The growth of Literacy Skills usage is especially relevant in the context of educational policy, and suggests that, assuming the trend persists, there will be a continuing strong rationale for the improvements in literacy standards in schools. In addition, however, the increasing importance of other forms of communication may have implications for education and training policy makers: are the new skills to be provided solely by firms as and when they are needed, or should there be more of a focus on communication skills in the classroom? The implications for the labour market depend on the availability of these skills in the pool of the labour force. Recent evidence suggests that Influence Skills may have acquired a scarcity premium in the labour market above that associated with education level (Green et al., 2007). On the other hand, some generic skills can be relatively abundant at each education level and therefore not attract a premium in themselves, while nevertheless increasing demand for them contributes to the rising demand for education.

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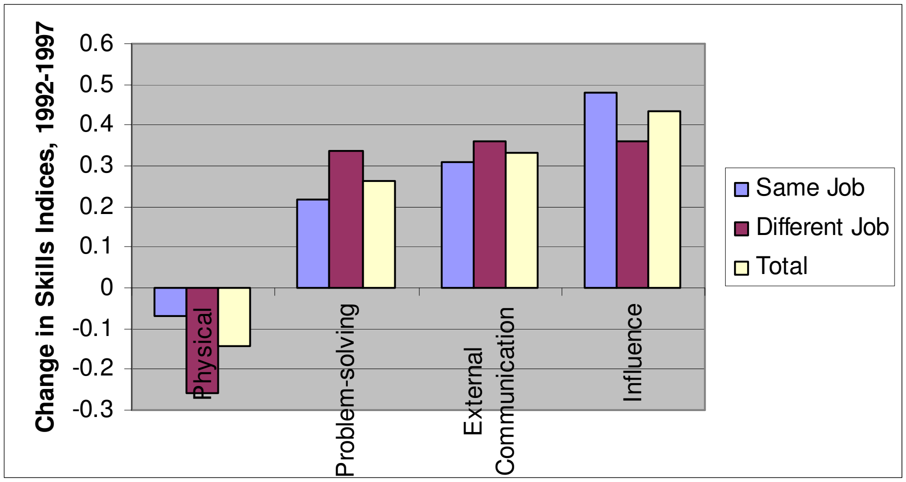
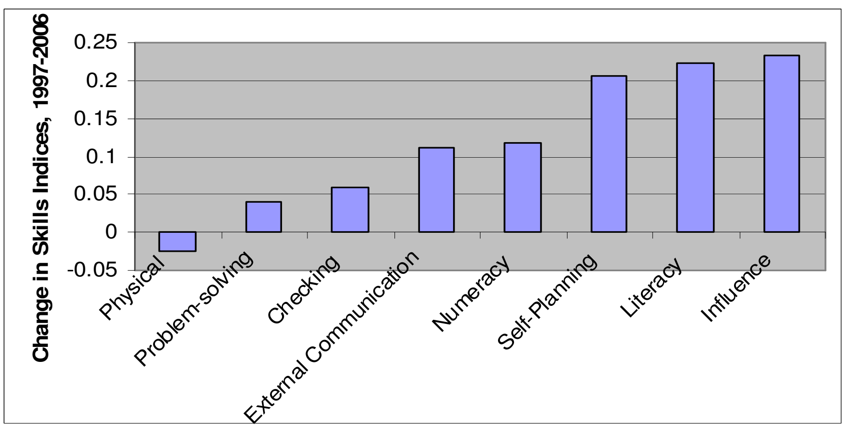
Figure 1 Changes in the Use of Generic Skills, 1992-1997.



Source: Skill Survey, 1997, calculated from retrospective questions. Base: is all workers who had also been in work in 1992.

Each skills index ranges from 0 to 4.

Figure 2 Changes in the Use of Generic Skills, 1997-2006.



Source: Skill Surveys, 1997 and 2006.

Each skills index ranges from 0 to 4.

Table 1 Employee Involvement, Task Discretion and Computing in 1992, 1997, 2001 and 2006.

	1992	1997	2001	2006
Involvement Scale [1]	--	0.577	0.584	0.644
Constituents				
Participation in Quality Circle (%)	19.9	31.2	37.2	42.2
Participation in Appraisal (%)	--	57.9	62.7	71.1
Makes Production Suggestions (%)	67.4	72.5	69.3	74.7
Expression of Views (%)	62.5	66.5	65.5	70.9
Company gives Information (%)	70.0	73.3	70.6	75.7
Teamworking (%)		45.0	45.8	52.9
Task Discretion Index [2]	2.44	2.25	2.18	2.18
High-level Computing [3] (%)	--	16.3	18.8	22.7
Low-level Computing [4] (%)	--	55.3	60.6	56.8

Notes: Base is employees, aged between 20 and 60, living in Great Britain.
1. Scale averaged from the five constituent elements; Cronbach's alpha = 0.701.
2. Scale averaged from the 4 sources of task discretion delineated in the text, Cronbach's alpha = 0.771
3. Level of computer use is, at least, complex (e.g. use of statistical packages).
4. Computers are used in either a moderate or a simple way, for example for emailing or wordprocessing. The residual category is computers not used.

Table 2 The Evolution of Job Tasks in Britain, 1997 to 2006.

JOB TASKS[a]	% for whom task is "essential" 2006	Change in % for whom task is "essential". 1997-2001	1997-2006
LITERACY			
READFORM: reading written information, eg forms, notices or signs	53.48	0.89	**4.59**
READSHORT: reading short documents eg letters or memos	44.91	2.17	**7.20**
READLONG: reading long documents eg long reports, manuals, etc	28.42	2.41	**6.25**
WRITFORM: writing material such as forms, notices or signs	41.64	3.69	**6.81**
WRITESHORT: writing short documents, eg letters or memos	35.18	4	**8.05**
WRITLONG: writing long documents with correct spelling/grammar	20.82	2.79	**6.10**
NUMERACY			
MATHS1: adding, subtracting, multiplying or dividing numbers	33.69	0.41	**-0.29**
MATHS2: calculations using decimals, percentages or fractions?	25.93	0.66	**1.29**
MATHS3: more advanced mathematical or statistical procedures	11.99	0.72	**1.57**
COMMUNICATION: EXTERNAL			
PRODUCT: knowledge of particular products or services	40.99	2.69	**5.74**
SELLING: selling a product or service.	21.18	-2.06	**-2.81**
CLIENT: counselling, advising or caring for customers or clients	39.24	1.45	**2.96**
PEOPLE: dealing with people	64.97	-0.21	**4.81**
COMMUNICATION: INFLUENCING OTHERS			
INSTRUCT: instructing, training or teaching people	30.45	2.53	**5.00**
PERSUADE: persuading or influencing others	21.46	1.11	**4.95**
SPEECH: making speeches or presentations	11.02	2.2	**3.97**
PLANOTH: planning the activities of others	15.26	1.26	**1.43**
LISTEN: listening carefully to colleagues	47.04	3.48	**8.87**
SELF-PLANNING			
OWNACT: planning your own activities	37.83	3.52	**6.05**
OWNTIME: organising your own time	44.43	4.98	**8.89**
AHEAD: thinking ahead	44.01	3.33	**6.26**
PROBLEM SOLVING			
FAULT: spotting problems or faults	43.45	-0.08	**-3.14**
CAUSE: working out the cause of problems or faults	36.26	0.54	**-1.02**
PROBSOLVE: thinking of solutions to problems	38.1	0.7	**2.20**
ANALYSE: analysing complex problems in depth	26.02	-1.14	**6.49**
PHYSICAL			
STRENGTH: physical strength eg, carry, push or pull heavy objects	14.08	-1.73	**-0.69**
STAMINA: work for long periods on physical activities	16.19	-0.67	**1.05**
HANDS: skill or accuracy in using your hands or fingers	22.53	3.33	**-1.68**
TOOLS: use or operate tools, equipment or machinery	31.42	-0.07	**-3.13**
CHECKING			
MISTAKE: noticing when there is a mistake	50.42	1.74	**3.53**
CHECK: checking things to ensure that there are no errors	48.3	0.21	**2.54**
DETAIL: paying close attention to detail	61.36	-4.27	**-4.26**

a. For each item, respondents were asked "In your job, how important is …[each task]", answering against a scale: "essential", "very important", "fairly important", "not very important", "not at all important/does not apply". In some cases, fuller descriptions are provided to respondents, together with further examples. The table presents the proportion answering at the top point of the scale

Table 3 Job Task Indices, 1997 to 2006.

JOB TASK INDEX	α [a]	2006	1997-2006	% within 2-digit Ind. 97-06	% within 2-digit Occ. 97-06
LITERACY	0.92	2.630	0.223*	81.2	69.1
NUMERACY	0.88	1.892	0.118*	137.2	59.5
COMMUNICATION: EXTERNAL	0.66	2.633	0.111*	88.3	45.7
COMMUNICATION: INFLUENCING OTHERS	0.81	2.292	0.225*	90.3	55.3
SELF-PLANNING	0.85	3.020	0.207*	87.6	60.7
PROBLEM SOLVING	0.85	2.819	0.100*	155.4	5.2
PHYSICAL	0.79	1.889	-0.024	-158.1	-0.2
CHECKING	0.79	3.328	0.06*	130.3	82.4

* indicates change in mean value of index is significantly different from zero (p>=95%, two-tailed test).
a. Cronbach's Internal Consistency Reliability Coefficient.

Table 4 Estimate of the Determinants of Generic Skills Use

Industry-Level Results.

a. Literacy

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0236***	0.0183***	0.00649***	0.0112*	0.00881*	0.00598
	[0.00295]	[0.00282]	[0.00236]	[0.00610]	[0.00459]	[0.00614]
Emp. Involvement			1.012***	1.117**		0.812*
			[0.0317]	[0.469]		[0.458]
Task Discretion			0.293***	0.137		0.158
			[0.0129]	[0.297]		[0.281]
Low Computing			0.762***		0.680**	0.599*
			[0.0225]		[0.316]	[0.309]
High Computing			1.000***		1.453***	1.212**
			[0.0285]		[0.449]	[0.451]
Observations	11549	11549	11549	83	83	83
R-squared	0.006	0.121	0.393	0.953	0.956	0.960

b. Numeracy

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00932***	0.0146***	0.00294	0.0198**	0.00740	0.0151*
	[0.00348]	[0.00340]	[0.00306]	[0.00749]	[0.00556]	[0.00765]
Emp. Involvement			0.404***	-0.448		-0.752
			[0.0411]	[0.577]		[0.570]
Task Discretion			0.242***	0.359		0.391
			[0.0167]	[0.365]		[0.350]
Low Computing			0.912***		0.783**	0.853**
			[0.0291]		[0.382]	[0.385]
High Computing			1.522***		1.047*	1.201**
			[0.0369]		[0.544]	[0.562]
Observations	11549	11549	11549	83	83	83
R-squared	0.001	0.075	0.264	0.920	0.926	0.930

c. External Communication

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0132h***	0.0102***	0.00390*	-0.00131	0.00146	-0.00452
	[0.00257]	[0.00250]	[0.00226]	[0.00547]	[0.00446]	[0.00569]
Emp. Involvement			0.815***	1.410***		1.210***
			[0.0304]	[0.421]		[0.424]
Task Discretion			0.285***	0.0315		0.0497
			[0.0123]	[0.267]		[0.261]
Low Computing			0.423***		0.616*	0.497*
			[0.0215]		[0.307]	[0.287]
High Computing			0.405***		1.126**	0.790*
			[0.0273]		[0.437]	[0.418]
Observations	11549	11549	11549	83	83	83
R-squared	0.002	0.090	0.267	0.930	0.922	0.937

d. Influencing

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0263***	0.0238***	0.0135***	0.0178***	0.0177***	0.0153***
	[0.00249]	[0.00242]	[0.00193]	[0.00422]	[0.00365]	[0.00414]
Emp. Involvement			1.250***	1.268***		1.089***
			[0.0259]	[0.324]		[0.309]
Task Discretion			0.357***	0.333		0.358*
			[0.0105]	[0.205]		[0.190]
Low Computing			0.397***		0.754***	0.644***
			[0.0183]		[0.251]	[0.209]
High Computing			0.574***		1.046***	0.703**
			[0.0233]		[0.357]	[0.304]
Observations	11549	11549	11549	83	83	83
R-squared	0.010	0.092	0.435	0.960	0.950	0.968

e. Self-planning

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0207***	0.0176***	0.0137***	0.0118**	0.00638	0.00569
	[0.00258]	[0.00254]	[0.00216]	[0.00572]	[0.00382]	[0.00527]
Emp. Involvement			0.667***	0.766*		0.389
			[0.0289]	[0.441]		[0.393]
Task Discretion			0.549***	0.111		0.145
			[0.0118]	[0.279]		[0.241]
Low Computing			0.345***		0.975***	0.936***
			[0.0205]		[0.263]	[0.266]
High Computing			0.494***		1.619***	1.494***
			[0.0260]		[0.374]	[0.387]
Observations	11549	11549	11549	83	83	83
R-squared	0.006	0.067	0.338	0.905	0.929	0.932

f. Problem-solving

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00163	0.00262	-0.00447*	0.000334	-0.00379	-0.00237
	[0.00259]	[0.00258]	[0.00236]	[0.00597]	[0.00436]	[0.00602]
Emp. Involvement			0.713***	0.435		0.228
			[0.0317]	[0.459]		[0.449]
Task Discretion			0.286***	0.245		0.277
			[0.0129]	[0.291]		[0.276]
Low Computing			0.379***		0.832***	0.807**
			[0.0224]		[0.300]	[0.303]
High Computing			0.598***		0.906**	0.808*
			[0.0285]		[0.427]	[0.442]
Observations	11549	11549	11549	83	83	83
R-squared	0.000	0.040	0.211	0.825	0.843	0.850

g. Physical Tasks

	(1)	(2)	(3)	(4)	(5)	(6)
Year	-0.00418	-8.32e-05	0.00397	-0.0122	-0.00236	-0.0126
	[0.00307]	[0.00290]	[0.00285]	[0.00737]	[0.00581]	[0.00776]
Emp. Involvement			0.129***	0.592		0.504
			[0.0383]	[0.567]		[0.579]
Task Discretion			-0.0306**	-0.825**		-0.798**
			[0.0156]	[0.359]		[0.356]
Low Computing			-0.513***		0.705*	0.663*
			[0.0271]		[0.400]	[0.391]
High Computing			-0.765***		0.368	0.334
			[0.0344]		[0.568]	[0.570]
Observations	11549	11549	11549	83	83	83
R-squared	0.000	0.140	0.181	0.944	0.942	0.948

h. Checking Tasks

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00672***	0.00743***	0.00237	0.000365	0.00392	-0.00129
	[0.00198]	[0.00197]	[0.00186]	[0.00350]	[0.00287]	[0.00353]
Emp. Involvement			0.418***	1.056***		0.931***
			[0.0249]	[0.269]		[0.263]
Task Discretion			0.149***	-0.0445		-0.0260
			[0.0101]	[0.170]		[0.161]
Low Computing			0.352***		0.566***	0.475**
			[0.0177]		[0.198]	[0.178]
High Computing			0.470***		0.738**	0.488*
			[0.0224]		[0.281]	[0.259]
Observations	11549	11549	11549	83	83	83
R-squared	0.001	0.040	0.165	0.896	0.883	0.911

Notes:

1. In every case, columns (2) and (3) include dummy variables for 2-digit industries. Columns (1) to (3) are estimated using OLS.
2. Columns (4) to (6) are fixed-effects estimates using the 2-digit industry pseudo-panel. The average industry cell size per cohort is: 85 in 1997, 122 in 2001 and 165 in 2006; minimum cell size is set to 25; the estimates are weighted by cell size.
3. Significance at 1%, 5% and 10% is indicated by ***, ** and * respectively.

Table 5
Occupation-Level Results.

a. Literacy

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0236***	0.0181***	0.00949***	0.0133***	0.00798*	0.00398
	[0.00295]	[0.00252]	[0.00229]	[0.00492]	[0.00405]	[0.00539]
Emp. Involvement			0.926***	0.913**		0.933**
			[0.0307]	[0.402]		[0.366]
Task Discretion			0.235***	0.249		0.162
			[0.0128]	[0.206]		[0.191]
Low Computing			0.528***		1.072***	1.018***
			[0.0241]		[0.389]	[0.358]
High Computing			0.714***		1.459***	1.369***
			[0.0305]		[0.454]	[0.422]
Observations	11549	11549	11549	68	68	68
R-squared	0.006	0.289	0.422	0.988	0.989	0.991

b. Numeracy

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00932***	0.00675**	-0.000853	0.00838	-0.00500	-0.00332
	[0.00348]	[0.00316]	[0.00301]	[0.00703]	[0.00535]	[0.00792]
Emp. Involvement			0.146***	-0.0354		-0.0134
			[0.0403]	[0.575]		[0.538]
Task Discretion			0.197***	0.232		0.126
			[0.0169]	[0.294]		[0.281]
Low Computing			0.711***		1.334**	1.319**
			[0.0317]		[0.514]	[0.527]
High Computing			1.281***		1.772***	1.727***
			[0.0401]		[0.599]	[0.620]
Observations	11549	11549	11549	68	68	68
R-squared	0.001	0.193	0.279	0.974	0.979	0.979

c. External Communication

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0132***	0.00825***	0.00437**	-0.00140	0.0113**	0.00371
	[0.00257]	[0.00232]	[0.00220]	[0.00627]	[0.00541]	[0.00753]
Emp. Involvement			0.695***	1.193**		1.143**
			[0.0295]	[0.513]		[0.511]
Task Discretion			0.246***	-0.0925		-0.0115
			[0.0123]	[0.263]		[0.267]
Low Computing			0.296***		-0.00678	-0.0474
			[0.0232]		[0.521]	[0.500]
High Computing			0.254***		-0.560	-0.594
			[0.0294]		[0.607]	[0.590]
Observations	11549	11549	11549	68	68	68
R-squared	0.002	0.202	0.295	0.965	0.963	0.967

d. Influencing

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0263***	0.0175***	0.0104***	0.0128***	0.0128***	0.0100*
	[0.00249]	[0.00208]	[0.00178]	[0.00456]	[0.00438]	[0.00535]
Emp. Involvement			1.060***	1.139***		1.113***
			[0.0238]	[0.373]		[0.363]
Task Discretion			0.297***	0.355*		0.356*
			[0.00997]	[0.191]		[0.190]
Low Computing			0.294***		0.800*	0.717*
			[0.0188]		[0.421]	[0.356]
High Computing			0.427***		0.701	0.534
			[0.0237]		[0.490]	[0.419]
Observations	11549	11549	11549	68	68	68
R-squared	0.010	0.325	0.512	0.988	0.983	0.989

e. Self-planning

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0207***	0.0141***	0.0133***	0.0183***	0.00467	0.0113*
	[0.00258]	[0.00231]	[0.00208]	[0.00561]	[0.00453]	[0.00615]
Emp. Involvement			0.549***	0.0948		0.0657
			[0.0279]	[0.459]		[0.418]
Task Discretion			0.496***	0.587**		0.560**
			[0.0117]	[0.235]		[0.218]
Low Computing			0.200***		1.400***	1.332***
			[0.0219]		[0.436]	[0.409]
High Computing			0.296***		1.397***	1.190**
			[0.0277]		[0.508]	[0.482]
Observations	11549	11549	11549	68	68	68
R-squared	0.006	0.219	0.375	0.974	0.976	0.980

f. Problem-solving

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00163	-0.000637	-0.00566**	0.00153	-0.0101**	-0.00725
	[0.00259]	[0.00242]	[0.00229]	[0.00509]	[0.00390]	[0.00573]
Emp. Involvement			0.617***	-0.401		-0.380
			[0.0307]	[0.417]		[0.389]
Task Discretion			0.268***	0.112		0.0292
			[0.0128]	[0.213]		[0.203]
Low Computing			0.346***		0.920**	0.931**
			[0.0241]		[0.375]	[0.381]
High Computing			0.527***		1.275***	1.277***
			[0.0305]		[0.438]	[0.449]
Observations	11549	11549	11549	68	68	68
R-squared	0.000	0.142	0.247	0.967	0.972	0.973

g. Physical Tasks

	(1)	(2)	(3)	(4)	(5)	(6)

Year	-0.00418	-0.00249	-0.00100	-0.000715	-0.00332	-0.000980
	[0.00307]	[0.00257]	[0.00259]	[0.00666]	[0.00552]	[0.00746]
Emp. Involvement			0.172***	-0.934*		-1.015*
			[0.0346]	[0.545]		[0.507]
Task Discretion			0.0616***	-0.403		-0.336
			[0.0145]	[0.279]		[0.265]
Low Computing			-0.153***		1.014*	1.091**
			[0.0272]		[0.531]	[0.496]
High Computing			-0.306***		0.203	0.360
			[0.0344]		[0.619]	[0.585]
Observations	11549	11549	11549	68	68	68
R-squared	0.000	0.312	0.319	0.981	0.981	0.985

h. Checking Tasks

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00672***	0.00670***	0.00309*	0.00557	0.000854	0.000422
	[0.00198]	[0.00188]	[0.00182]	[0.00342]	[0.00270]	[0.00397]
Emp. Involvement			0.385***	0.152		0.179
			[0.0244]	[0.280]		[0.269]
Task Discretion			0.147***	0.119		0.0577
			[0.0102]	[0.144]		[0.141]
Low Computing			0.258***		0.366	0.352
			[0.0192]		[0.260]	[0.264]
High Computing			0.372***		0.717**	0.690**
			[0.0243]		[0.302]	[0.311]
Observations	11549	11549	11549	68	68	68
R-squared	0.001	0.116	0.187	0.969	0.972	0.973

Notes:

1. In every case, columns (2) and (3) include dummy variables for 2-digit occupations. Columns (1) to (3) are estimated using OLS.
2. Columns (4) to (6) are fixed-effects estimates using the 2-digit occupation pseudo-panel. The average occupation cell size per cohort is: 106 in 1997, 166 in 2001 and 234 in 2006; minimum cell size is set to 25; the estimates are weighted by cell size.
3. Significance at 1%, 5% and 10% is indicated by ***, ** and * respectively.

Appendix Table.
Occupation-Industry Cell-Level Results.

These results are included for robustness; they are not discussed in the text.

a. Literacy

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0236***	0.0156***	0.00763***	0.0159***	0.0123***	0.0110**
	[0.00295]	[0.00253]	[0.00230]	[0.00417]	[0.00433]	[0.00472]
Emp. Involvement			0.906***	0.793**		0.731**
			[0.0313]	[0.308]		[0.303]
Task Discretion			0.242***	0.410**		0.429***
			[0.0129]	[0.158]		[0.155]
Low Computing			0.570***		0.572*	0.545**
			[0.0246]		[0.294]	[0.267]
High Computing			0.717***		0.862**	0.825**
			[0.0309]		[0.384]	[0.345]
Observations	11549	11549	11549	131	131	131
R-squared	0.006	0.304	0.434	0.981	0.977	0.982

b. Numeracy

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00932***	0.0118***	0.00373	0.0112**	0.00476	0.00450
	[0.00348]	[0.00316]	[0.00302]	[0.00558]	[0.00515]	[0.00636]
Emp. Involvement			0.285***	0.131		0.0796
			[0.0410]	[0.412]		[0.409]
Task Discretion			0.184***	0.0203		0.0324
			[0.0170]	[0.211]		[0.209]
Low Computing			0.674***		0.574	0.569
			[0.0323]		[0.351]	[0.360]
High Computing			1.220***		1.032**	1.027**
			[0.0405]		[0.458]	[0.465]
Observations	11549	11549	11549	131	131	131
R-squared	0.001	0.217	0.298	0.964	0.966	0.966

c. External Communication

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0132***	0.00806***	0.00445**	0.00655	0.00929**	0.00717
	[0.00257]	[0.00231]	[0.00218]	[0.00448]	[0.00463]	[0.00527]
Emp. Involvement			0.726***	0.739**		0.740**
			[0.0296]	[0.330]		[0.339]
Task Discretion			0.245***	0.339**		0.340*
			[0.0123]	[0.169]		[0.173]
Low Computing			0.297***		0.00523	-0.0336
			[0.0233]		[0.315]	[0.298]
High Computing			0.228***		-0.0432	-0.0835
			[0.0293]		[0.412]	[0.385]
Observations	11549	11549	11549	131	131	131
R-squared	0.002	0.238	0.331	0.961	0.954	0.961

d. Influencing

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0263***	0.0173***	0.0105***	0.0171***	0.0155***	0.0144***
	[0.00249]	[0.00209]	[0.00180]	[0.00328]	[0.00407]	[0.00378]
Emp. Involvement			1.078***	0.950***		0.909***
			[0.0245]	[0.242]		[0.243]
Task Discretion			0.295***	0.586***		0.599***
			[0.0101]	[0.124]		[0.124]
Low Computing			0.304***		0.365	0.338
			[0.0192]		[0.277]	[0.214]
High Computing			0.419***		0.517	0.473*
			[0.0242]		[0.361]	[0.276]
Observations	11549	11549	11549	131	131	131
R-squared	0.010	0.334	0.517	0.985	0.975	0.986

e. Self-planning

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.0207***	0.0142***	0.0135***	0.0160***	0.0119**	0.0130**
	[0.00258]	[0.00232]	[0.00210]	[0.00442]	[0.00450]	[0.00507]
Emp. Involvement			0.556***	0.510		0.431
			[0.0285]	[0.326]		[0.326]
Task Discretion			0.490***	0.459***		0.488***
			[0.0118]	[0.167]		[0.166]
Low Computing			0.220***		0.536*	0.546*
			[0.0224]		[0.306]	[0.287]
High Computing			0.297***		0.639	0.624*
			[0.0282]		[0.400]	[0.371]
Observations	11549	11549	11549	131	131	131
R-squared	0.006	0.234	0.385	0.964	0.959	0.966

f. Problem-solving

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00163	0.000209	-0.00500**	-0.00187	-0.00825*	-0.00816
	[0.00259]	[0.00245]	[0.00232]	[0.00484]	[0.00462]	[0.00548]
Emp. Involvement			0.633***	0.410		0.366
			[0.0315]	[0.357]		[0.352]
Task Discretion			0.260***	0.298		0.308*
			[0.0130]	[0.183]		[0.180]
Low Computing			0.364***		0.511	0.508
			[0.0248]		[0.314]	[0.310]
High Computing			0.565***		0.962**	0.946**
			[0.0311]		[0.410]	[0.401]
Observations	11549	11549	11549	131	131	131
R-squared	0.000	0.147	0.252	0.923	0.923	0.929

g. Physical Tasks

	(1)	(2)	(3)	(4)	(5)	(6)
Year	-0.00418	-0.000643	-0.000294	-0.00568	-0.00342	-0.00455
	[0.00307]	[0.00258]	[0.00260]	[0.00590]	[0.00554]	[0.00680]
Emp. Involvement			0.212***	0.0643		-0.0515
			[0.0353]	[0.435]		[0.437]
Task Discretion			0.0400***	-0.230		-0.181
			[0.0146]	[0.223]		[0.223]
Low Computing			-0.121***		0.566	0.551
			[0.0278]		[0.377]	[0.385]
High Computing			-0.202***		0.188	0.186
			[0.0349]		[0.492]	[0.497]
Observations	11549	11549	11549	131	131	131
R-squared	0.000	0.329	0.333	0.965	0.966	0.966

h. Checking Tasks

	(1)	(2)	(3)	(4)	(5)	(6)
Year	0.00672***	0.00707***	0.00351*	0.00785**	0.00702**	0.00628*
	[0.00198]	[0.00189]	[0.00183]	[0.00321]	[0.00325]	[0.00376]
Emp. Involvement			0.389***	0.411*		0.412*
			[0.0249]	[0.237]		[0.242]
Task Discretion			0.146***	0.246**		0.243*
			[0.0103]	[0.121]		[0.123]
Low Computing			0.268***		0.0798	0.0643
			[0.0196]		[0.221]	[0.213]
High Computing			0.385***		0.222	0.202
			[0.0246]		[0.289]	[0.275]
Observations	11549	11549	11549	131	131	131
R-squared	0.001	0.135	0.205	0.939	0.932	0.940

Notes:

1. In every case, columns (2) and (3) include dummy variables for 1-digit occupation-industry cells. Columns (1) to (3) are estimated using OLS
2. Columns (4) to (6) are fixed-effects estimates using the 1-digit occupation-industry pseudo-panel. The average occupation cell size per cohort is: 52 in 1997, 74 in 2001 and 91 in 2006; minimum cell size is set to 25; the estimates are weighted by cell size.
3. Significance at 1%, 5% and 10% is indicated by ***, ** and * respectively.