Essays in Applied Economics
Managers, Technology and Productivity

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Essays in Applied Economics: Managers, Technology and Productivity

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ABSTRACT

This thesis aims to contribute to the economics of management and productivity. We explore some of the important linkages between managers, technology, earnings, and productivity in the United Kingdom. First, we investigate the role of managers in productivity in the context of skill-biased technical change and routinisation hypotheses. Using panel (EU KLEMS) and cross-sectional data (The Skills and Employment Survey), the empirical analyses, based on OLS, Probit, Fixed Effects, and GMM estimations, find positive and significant associations between management practices, non-routine tasks, earnings, and productivity, which introduces fresh new evidence to the literature. Second, utilising the Skills and Employment Survey, we explore the relationship between technological progress (i.e., the introduction of new technologies in the workplace), and management practices (i.e., a measure of intangible capital). The OLS and Propensity Score Matching (PSM) estimations show that the introduction of new communication technologies correlates with 'people management' practices in the workplace, but not with 'organisation management' tasks (such as resource control and planning). Additionally, the association between new computerised equipment and management practices is not significant, or at least not conclusive within the framework of this study. These results suggest that decision makers, such as CEOs and directors, must find connections between the way technology operates (e.g. social use) and the type of intangible capital intended to be shaped by managers (i.e., people management practices can be nurtured with new social channels). Third, we explore the association between computer-based numeracy tasks and earnings. For this, information about tasks, skills, earnings, and other employment conditions is taken from the Skills for Life Survey, and with an instrumental variable combined with interval-censored regression approach, it is found that ICT numeracy tasks are particularly relevant for managers and strongly correlate with earnings. The positive association between this task and earnings remains strong if the full set of occupations is considered. It is worth noting that the significance of other computerised tasks is modest. All these findings have policy implications for the United Kingdom. Notably, the formative period for managers should stress the importance of social and numeracy skills, incorporating adequate technologies into the process. This should later be reflected in the workplace, where a real potential to increase productivity is apparent. We provide avenues for developing further research. For instance, developing and exploring new panel data measures of management practices; using alternative methodologies, such as Randomised Control Trials that could be applied to the context of technological change; or studying the relationship between different management practices and their economic performance at the aggregate level.

Key words: managers, management practices, managerial skills, intangible capital, ICT investment, technological change, computer tasks, ICT numeracy tasks, earnings and productivity.

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ABBREVIATIONS

ATE	Average Treatment Effect
ATET	Average Treatment Effect on the Treated
BIS	Department for Business, Innovations, and Skills
CDF	Cumulative Distribution Function
CE	Computerised Equipment
CEO	Chief Executive Officer
CT	Communication Technologies
DfIT	Department for International Trade
e.g.	For example (exempli gratia)
et al.	And others (et alia)
EU	European Union
GfK	Gesellschaft für Konsumforschung (Society for Consumer Research)
GMM	Generalised Method of Moments
HR	Human Resources
ICT	Information and Communication Technologies
i.e.	That is (id est)
ILO	International Labour Organisation
IR	Interval Regression
IV	Instrumental Variable
KCL	King's College London
KLEMS	Capital, Labour, Energy, Material, and Service inputs
Ln	Natural Logarithm

ML	Maximum Likelihood
MLE	Maximum Likelihood Estimation
N	Number of observations
NS-SEC	National Statistics, Socio-Economic Classification
NVQ	National Vocational Qualification
OECD	Organisation for Economic Co-operation and Development
OFCOM	Office of Communications
OLS	Ordinary Least Squares
ONS	Office for National Statistics
P	Probability value
PC	Personal Computer
PCA	Principal Component Factor Analysis
PDF	Probability Density Function
Ph.D.	Doctor of Philosophy (Philosophiae Doctor)
Pp.	Pages
Pr.	Probability
PSM	Propensity Score Matching
Q	Quantile
R2	R squared
RBTC	Routine-Biased Technological Change
SBTC	Skill-Biased Technological Change
SES	Skills and Employment Survey
SfL	Skills for Life
TE	Treatment Effect

TFP	Total Factor Productivity
UK	United Kingdom
UN	United Nations
US	United States
UNCTAD	United Nations Conference on Trade and Development
Vol.	Volume
Z-score	Standardised Score that follows a normal distribution with mean 0 and standard deviation 1
2SLS	Two-Stage Least Squares

CHAPTER 1: INTRODUCTION

This chapter introduces the main topics developed in this thesis and is divided into three sections. Section 1.1. provides the background and justification for the thesis. Section 1.2. discusses the aims of this work, introduces the empirical approach taken, presents the main results and comments on the contributions made to the literature. The chapter concludes by outlining the structure of the thesis in section 1.3.

1.1 Background and justification of the study

1.1.1 Why managers?

Around 32.07 million people currently participate in the labour market in the United Kingdom (Office for National Statistics, 2017), and approximately 37% of this group corresponds to managers, professionals, and higher technical occupations[1] (ONS, 2014). Managers are an important subset of the labour force. They take responsibilities and guide employees, organisations, and nations towards social and economic success, which can ultimately translate into a better quality of life. We define managers, in accordance with the National Statistics Socio-Economic Classification (2010), as those employees in higher managerial or higher professional occupations. This group is different from, for example, supervisors that we typically find in lower managerial, lower professional, highly technical, and supervisory occupations (ONS, 2010). However, beyond these classifications, managers and supervisors have one quality in common, namely the regular use of managerial practices in the workplace.

[1] Except London, where the percentage is higher, close to 50%.

Of course, managers and supervisors emphasise different tasks, and it is on this topic that our research work begins, exploring the role of managerial tasks across different occupations.

1.1.2 Why technology?

Managers and supervisors develop their careers in environments partially characterised by globalised markets, multiculturality, interconnectivity, uncertainty, inequality, and rapid evolution, where the use of technology plays an important role. Indeed, successful technological practices are imported often from foreign countries (UNCTAD, 2014), managers benefit from communicating with peers all over the world thanks to online social networks (Garrigos-Simon et al., 2012), and the automation of repetitive tasks, under certain conditions, produces uncertainty and inequality (Goos et al., 2014). Managers and other employees must adapt to these situations and more real-world impact research is needed as guidance. Thus, in this dissertation we are interested in technological change in the workplace, i.e., cases where we observe the introductions of new technologies. We consider two different technologies, namely new communications technologies (such as texting, instant messaging, social networking, and video conferencing), and new computerised equipment (such as new hardware, printers, and machines). Additionally, given the relevance of computer use amongst managers, we also explore this technology in the workplace, paying particular attention to computer-based numeracy tasks, which are proportionally over-represented within this group of workers.

1.1.3 Brief introduction to the role of managers and technology in economics

Economists have only recently started to study the role of managers in the economy. Previous research in the fields of management, psychology, and sociology has consistently found a positive association between good management practices and firm performance[2]. However, economists did not play a major role in the discussions, since they seemed to concentrate on analysing the role of capital, labour or technology in the economy, for example, using different languages, and historically publishing in parallel academic journals. Moreover, reliable quantitative data was not available to test economic theories (Bloom et al., 2007). In this context, over the last 10-15 years, economists have developed new datasets[3], discussed corresponding problems and published a series of key papers that try to understand the link between management and economic performance (Bloom and Van Reenen, 2011; Bloom et al., 2014; ONS, 2017; Siebert and Zubanov, 2010; amongst others). The main results of these investigations suggest that management practices are positively associated with Total Factor Productivity and can explain differences across firms and countries. The interest in this area is growing, and this thesis aims to contribute to the field.

Technology, on the other hand, has been a longstanding topic in the field of economics. Several decades ago, Solow (1957) stressed the importance of technology to economic growth (i.e. the Solow residual understood as technological innovation) and, after him, several investigations have found that technology is positively associated to earnings, growth, and productivity. From

[2] What researchers mean by good practices varies according to theories and assumptions. Empirically, these practices are positively associated with the desired outcomes. Some examples are Lathan (1981), Huselid et al (1995), Huselid et al. (1997), Ichnioswki et al. (1997), Kaynak (2002), Birdi et al. (2008), and Jiang et al. (2012).

[3] For instance, the 'World Management Survey' or the 'Management Practices Survey' in Great Britain.

a macro perspective, some studies confirming these results on productivity and economic growth are Van Ark and O'Mahony (2016), Oliner and Sichel (2000), and Qiang et al., (2009). And, from a micro perspective, some examples that focus on earnings are Krueger (1993), Autor et al. (1998), Dolton and Makepeace (2004), and Dolton et al. (2007 and 2008). However, this picture is incomplete if we do not consider that other researchers have also found, with different identification strategies, that the effects of technology (for example, computer use) are negligible and highly contextual (e.g., DiNardo and Pischke, 1997; and Pabilonia and Zogui, 2005). Therefore, there is no consensus on the influence of computers on earnings, and the discussion is still open at the microeconomic level. The importance of the topic and the pressing need for more research, is clear if we consider the role of computers in popular hypotheses that have emerged to explain labour market changes and economic inequality in recent years, such as Skill-Biased Technical Change (e.g., in Autor et al., 1998; and Card and DiNardo, 2002), and Routine Biased Technical Change (e.g. in Goos et al., 2014).

1.2 Research aims, empirical approach, results, and the contribution to the literature

1.2.1 Research questions

This thesis explores important linkages between managers, technology, earnings, and productivity in the United Kingdom. In this context, several research questions motivate our work. First, what is the link between management and economic performance? Is the association between management and productivity altered by different types of managers? Second, does technological progress complement management practices in the workplace? which in more abstract terms asks whether ICT investment complements intangible capital in the workplace. And third, departing from the discussion about the returns on computer use, do computer-based numeracy tasks make a positive difference on earnings amongst managers?

For a number of reasons, the United Kingdom is a natural candidate for this analysis. Previous research has shown that the UK has relatively poor management practices and is not fully using the skills of its workforce (Bloom and Van Reenen, 2007; BIS, 2012), but at the same time it has seen relatively high ICT investment (DfIT, 2014). Therefore, it seems reasonable to assume, for instance, that new technologies could be fostering good management practices in the workplace, which may ultimately translate into higher productivity. Furthermore, the United Kingdom has developed rich datasets, with measures of management practices, skills, earnings, and productivity, amongst others which, when combined with appropriated methodologies, have the potential to add new results that can prove useful for policy.

1.2.2 Empirical approach, main results, and the contribution to the literature

We use a number of identification strategies to address our research questions and adjust these to the virtues and limitations of the observational datasets available. These techniques, the main results, and the contributions to the literature that emerge from these studies are outlined below.

First, to understand the link between management and productivity in the United Kingdom, we take advantage of two different datasets; the EU KLEMS release 2009 (O'Mahony and Timer, 2009) that corresponds to the productivity measures, and the Skills and Employment Survey SES release 2012 (Felstead et al., 2014) that contains information about skills and detailed employment conditions. We explore the returns to managerial status and to managerial tasks using OLS and Probit regressions, while considering different types of managers and supervisors, performing a significant amount of routine or non-routine tasks. Furthermore, we estimate the association between management practices and total factor productivity with several OLS, Fixed Effects, and GMM estimations. Our contribution to the literature can be described as follows. Identifying different types of managers, and complementing previous research conducted by Black and Lynch (2001; 2004), Bloom et al. (2007; 2010), and Siebert and Zubanov (2010), we consistently find a strong positive correlation between managerial tasks, non-routine tasks, and earnings, and a contribution of managers to productivity during the period 1970-2007. The results are in line with the hypotheses of Skill-Biased Technical Change and routinisation.

Then, we turn our attention to the relationship between ICT investment and intangible capital. We investigate whether technological progress is associated with more robust management practices in the workplace using data from the Skills and Employment Survey 2012. Given that a natural experiment is not possible, with observational data we try to replicate some of the characteristics of a randomised control trial, utilising a Propensity Score Matching approach. We investigate two forms of technologies, the introduction of new computerised equipment and the introduction of new communication technologies in the workplace. Also, we consider different types of management tasks, 'people management' (focused on interactions, relationships, and related to leadership skills), and 'organisation management' practices (oriented to maintaining the organisation's effective operation, for instance, through resource control or planning). The results show that the introduction of new communication technologies is associated with 'people management' practices, but not with 'organisation management'. On the other hand, the introduction of new computerised equipment is not significantly associated with management practices. This suggests that ICT capital investment (the introduction of technology) only complements intangible capital (management practices at work shaped by managers) if they share a core driver and purpose (e.g., the use of social channels). Our results complement previous research by Corrado et al. (2017) that found a complementary relationship between ICTs and intangible capital at the macro-level (i.e., intangibles have a positive impact on productivity growth in ICT-intensive industries). In this sense, our main contribution is to provide concrete examples and applications in an area that is still developing, theoretically and empirically.

Finally, we study the link between computer-based numeracy tasks and earnings, focusing on the use of spreadsheets and databases that we find to be most prevalently used by managers and higher professionals (BIS, 2012). The relevant data is taken from the Skills for Life Survey 2011. Using an instrumental variable, combined with interval regressions estimation - given that the computer task is endogenous, and the dependent variable earnings is banded - we estimate the returns to computer-based numeracy tasks, and also the probability of reaching different quintiles of the income distribution. The OLS results suggest that computer-based numeracy tasks, and no others (computer tasks), are significantly associated to earnings, and substantially increase the probability of reaching the highest quantile of the income distribution. The IV approach (which uses a measure of ICT numeracy ability as the instrument) confirms the importance of computer-based numeracy tasks amongst managers. A possible explanation is that other computers tasks have become necessities (e.g., e-mailing, the use of the internet, and word processing), but are not making a difference in the workplace today. Our contribution is in line with previous research, for example Dolton et al. (2004, 2007). And, differences can be explained by different target groups (we mainly focus on managers) and the period of analysis (our data is more recent), which indicates that the heterogeneous effects of technology evolve over time.

1.3 Structure of the thesis

This thesis explores some of the relationships between managers, technology, earnings, and productivity. But, there are differences, subtleties, and nuances among the research questions that must be addressed separately. Therefore, each of the main chapters will only be devoted to one research question, with its own literature review, dataset, empirical approach, analysis, and conclusions. In this context, the rest of the thesis is organised as follows. Chapter 2, ‘Management practices and productivity in the United Kingdom’, is how in the first instance we approach the field of the economics of management and productivity, investigating the link between management and economic performance in the United Kingdom. Then, in Chapter 3, ‘From ICT capital investment to intangible capital: Technological progress for robust management’, we look for concrete complementarities between tangible capital and intangible managerial assets, which show the potential to increase productivity. In Chapter 4, we move on to an investigation of how computer-based numeracy tasks correlate with earning, which in a sense also explores complementarities between ICT capital and economic outcomes. Chapter 5 concludes, expanding on the main findings and discussing the contributions of this work to policy making, and recommends some new avenues for further research.

CHAPTER 2: MANAGEMENT PRACTICES AND PRODUCTIVITY IN THE UNITED KINGDOM

2.1 Abstract

Human capital development is key to the good performance of organisations in modern economies. Previous research shows that a more educated workforce tends to implement better practices at work, which translates into higher productivity, efficiency, and job engagement (Black and Lynch, 2001; Bloom and Van Reenen, 2007). The role of management in this process has been less studied in economics. This paper therefore investigates the role and impact of management practices on productivity in the United Kingdom. One aim is to explore how this fluctuates when routine and non-routine managerial tasks are included in standard models. This is particularly important in the United Kingdom, a country with some degree of job polarisation, that is not using the majority of the skills of its workforce (Employers and Skills Survey, 2013), and which is in a secondary position - compared with other developed economies - regarding the use of managerial tasks (Bloom and Van Reenen, 2007; BIS, 2012). Using the Skills and Employment Survey 2012 and the EU KLEMS database release 2009, this study identifies a positive effect of managerial tasks on productivity, and significant differences between routine and non-routine jobs that are worth considering. These are robust to using several output variables and methodologies. The results may therefore contribute to academic debate and public policy making.

Keywords: Management practices, routine and non-routine tasks, earnings, productivity, and the economics of management.

2.2 Introduction

Human capital development is key to the good performance of organisations in modern economies. Previous research shows that a more educated workforce tends to perform better practices at work, which translates into higher productivity, efficiency and job engagement (Black and Lynch, 2001; Bloom and Van Reenen, 2007). These results justify the level of investment in education and training demanded by economic agents.

This paper focuses on the role of human capital, and specifically investigates the impact of managerial tasks on productivity in the United Kingdom. The topic (i.e., management as a factor determining labour productivity) has been less studied within the education and productivity literature[4], and still has areas that are under-researched, such as the impact of management practices on productivity in the context of job polarisation.

This is particularly important for the United Kingdom, because as a country it features some degree of job polarisation and does not fully utilise the skills of its workforce (under-utilization[5]), and also lags behind other developed economies, such as Germany or the US with respect to the use of managerial skills[6] (Bloom and Van Reenen, 2007; BIS, 2012). Consequently, this study undertakes a new comprehensive investigation into the role of

[4] However, the importance of management has been established in the literature, for instance in Kaldor (1934) and Bartelsman and Doms (2000).

[5] Half of the organisations report not using the full potential of the skills of their employees (Winterbotham et al. (2013). This could be a consequence of over-education that could have arisen due to polarisation.

[6] Three out of four organisations in the UK reported a shortage of administrative and leadership skills (BIS, 2012).

routinisation in explaining relatively poor management practices, thus contributing to the academic debate and informing public policy.

Managerial tasks are broadly defined as those practices only undertaken by employees with some degree of managerial responsibility[7]. Thus, they can be defined as those practices conducted by managers and/or supervisors. Examples of managerial tasks include motivating the staff, the use of coaching, the control of resources, career development of staff and strategic decision making in the organization. Questions on these tasks performed on the job are put to managers in the UK as part of the Skills and Employment Survey (SES). This survey also includes questions on other generic skills, such as numeracy, literacy and the complexity of computer use, for example. The main aim of this chapter is to quantify the associations between these tasks and earnings, and industry-level productivity. Therefore, we will first investigate the wage returns to management tasks using data taken from SES, before looking at how these tasks correlate with aggregate productivity. To do this, key productivity measures[8] made available in EU KLEMS database will be utilised.

Consequently, we first use an indirect approach that estimates the returns to management practices and managerial status (i.e., whether the employee is a manager or supervisor or, if they do not have a managerial job, perform managerial duties regularly). The dependent variables used in these models are the natural log of the gross hourly rate of pay[9], and a dummy

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[7] The literature distinguishes between management practices, and management ability (e.g., Siebert and Zubanov, 2010). We focus on management practices.

[8] Real output, real-fixed capital stock (ICT and non-ICT), labour (number of employees) and the adjusted values of intermediate inputs.

[9] Different from take home pay that includes bonuses and considers taxes.

variable that captures whether the respondent received a bonus based on own performance. If workers are paid their marginal product, it can be assumed that wages will be higher for more productive managers, and thus that the returns to management practices indicate higher productivity[10]. Second, we use a direct approach that relates the tasks of managers directly to productivity, i.e., we estimate the association between management practices and Total Factor Productivity that is derived from a Cobb-Douglas production function. This is similar to the approach used by Black and Lynch (2001), Bloom and Van Reenen (2007), and Siebert and Zubanov (2010).

Our results show a positive and significant effect of managerial tasks on productivity, with notable differences between managers in routine and non-routine jobs.

This paper is structured as follows. Section 2.3 contains the literature review and antecedents to the research question, Section 2.4 describes the methodology, section 2.5 develops the analysis and preliminary results, and the final section concludes.

[10] This is a strong assumption that requires, for instance, perfect competition, perfect mobility, perfect knowledge, and profit-maximising firms, amongst others. However, it is a useful first approximation to the problem according to the classical literature (Borjas, 2012).

2.3 Literature review

2.3.1 The relationship between human capital and productivity

One of the oldest findings in the field of labour economics is the positive relationship between human capital and economic outcomes. Previous research demonstrates that human capital development is essential for productivity, especially in a knowledge-driven economy constantly facing technological changes (De la Fuente and Ciccone, 2002; OECD, 2012; Black and Lynch, 2001).

At the microeconomic level, the empirical evidence indicates that workers who invest more in human capital enjoy better working conditions and higher wages[11]. Some findings from previous research show that school attainment is a significant predictor of wages (Ashenfelter et al., 1999); the training of workers is positively associated with wages and decreases the probability of unemployment (Heinrich and Hildebrand, 2005); literacy and numeracy skills have the potential to predict market participation and correlate positively with wages (Vignoles et al, 2011); and it has found a positive relationship between the development of human capital and productivity and competitiveness at the firm level (Blundell et al., 1999).

Interestingly, this link between human capital and wages becomes stronger in periods of rapid technological change. In the literature, this effect has been termed Skill-Biased Technical Change, which explains how a shift in production technology favours skilled over unskilled

[11] Excellent surveys about this topic are Griliches (1997), Card (1999), and De la Fuente and Ciccone (2002).

labour by increasing its relative productivity and, therefore, its relative demand (Autor et al., 1998; Violante, 2008). This effect is not central to this paper, but is worth consideration as well.

At the macro level, studies find a positive relationship between human capital and productivity, and also with innovation (see, for instance, De la Fuente and Ciccone, 2002). For example, an additional year of schooling increases the average level of aggregate productivity by around 5% on impact and by a further 5% in the long run (see De la Fuente and Ciccone, 2002). However, the magnitude of this effect is subject to a number of biases associated with measurement[12] and estimation.

2.3.2 Focusing on managerial tasks and productivity

The labour force is diverse, and so it is important to make distinctions between workers of different education levels when considering the effect of human capital on productivity, which varies greatly amongst firms and countries. In particular, it is worth investigating the productivity contribution of managers (as a subgroup of the workforce), since they tend to possess higher levels of human capital and also play a direct role when making important decisions on a daily basis.

[12] Measurement error is always an issue because the years of schooling variable used in most empirical applications is a fairly imperfect measure of human capital. Also, poor data quality is likely to be an important issue as well (De la Fuente and Ciccone, 2002).

Indeed, according to Bloom and Van Reenen (2010), management practices[13] may explain part of the differences in productivity at both the firm level and across countries. They find that firms with better management practices demonstrate superior performance across a wide range of dimensions: their firms tend to be larger, more productive, grow faster, and have higher survival rates. Black and Lynch (2001) obtained similar results by focussing specifically on firms in the US. They studied the impact on productivity of workplace practices, information technology, and human capital investments. They found that what determines higher productivity is not so much whether an employer adopts a particular work practice, but rather how that work practice is actually implemented within the establishment, and this is where managers are relevant.

Moreover, Siebert and Zubanov (2010) studied the link between management and economic performance at the establishment level in the United Kingdom, and found that middle management practices positively affect sales and productivity in a competitive profit-maximising environment. Griffiths et al. (2006) also found that differences in management account for around 40 per cent of the observed productivity spread within a major UK-based wholesaler. In other related studies, Bandiera et. al (2007) found a positive relationship between managerial performance pay and productivity. Galbraith and Nkwenti-Zamcho (2005) reported a positive impact on labour productivity of equipment maintenance, firm re-organisation and labour specialisation, and Bartel (2004) found a positive link between better communication between employees and management improving firm performance.

[13] Within and outside Human Resource Management (HRM).

Additionally, Bloom et al. (2012) undertook a management field experiment on large Indian textile firms, and found that adopting better management practices raised productivity by 17% in the first year, and within three years led to the opening of more production plants. This is quite a substantial result, although the external validity of the experiments is questionable as a consequence of the untypically poor initial conditions of the firms in the experiment. Finally, Carmeli and Tishler (2006) concluded that the managerial skills possessed by top management teams in Israel strongly affect firm performance, and in particular the skills that are required to manage people (human resources skills) are more important to firm performance than intellectual abilities. Consequently, recognising the importance of management practices, we enquire into the situation in the United Kingdom.

2.3.3 Management practices and productivity in the United Kingdom

Recent surveys in the UK indicate that a significant number of organisations have serious difficulties in finding managers with the right skills. This is either because of a shortage[14] or mismatch[15] in suitable workers (BIS, 2012; Bloom and Van Reenen, 2007 and 2010). This is costly for companies, as it affects their performance and limits their potential for growth (Winterbotham et al., 2013). Estimates made by BIS for the United Kingdom suggest that ineffective management could be costing more than £19 billion per year in lost working hours,

[14] According to BIS (2012), nearly three quarters of organisations in England reported a deficit in management and leadership skills in 2012. This means that more skills must be created through education and training.

[15] According to Winterbotham et al. (2013) half of UK employers (48 per cent) report skills under-use, and 4.3 million workers (around 15% of the total UK workforce) are reported as being over-skilled and overqualified for the jobs that they are currently performing.

and this deficit certainly contributes to the productivity gap with countries like the US, Germany and Japan.

In light of this, further research on managerial tasks/skills in the UK is needed to understand their strengths (i.e., contribution to the country's productivity) and weaknesses (i.e., where more education or training is required). This is the main purpose of this paper.

2.3.4 Management practices, productivity and job polarisation in the UK

To achieve this goal, two types of managers are considered: routine and non-routine. This distinction is based on the routinisation hypothesis and job polarisation. The routinisation hypothesis and job polarisation derives from the idea that human capital plays a key role in fostering technological change and diffusion (Goos et al., 2014; De la Fuente and Ciccone, 2002). Previous research (see for example Autor et al., 1998; Autor et al., 2006; Michaels et al., 2014) indicates that industries with faster ICT growth have also increased their demand for more educated workers. This has led to medium-skilled jobs (performing routine tasks) being replaced by computer technology. The highly-skilled workers (mainly associated with non-routine tasks) are complementary to technology adoption. As a consequence, jobs in Britain have polarised into high-quality jobs and low-quality jobs, with jobs disappearing from the middle of the distribution (See Goos et al., 2014).

In previous research, managers have been included within the category of non-routine occupations. However, we make the distinction between managers and supervisors who have a large proportion of routine tasks in their jobs, as opposed to those who are relatively more non-routine task-intensive. Therefore, we disaggregate managers depending on the type of decisions and activities that they must typically undertake in their work. The decisions that managers typically take fall into two categories. The first are the routine ones, where the process is guided by rules. The second are the non-routine ones, which are decisions made at the discretion of the decision maker (Jaimovich and Siu, 2012). Therefore, managers and supervisors who primarily perform routine tasks as opposed to intensively performing non-routine tasks should have different skills. Leading them to make different contributions to productivity, and therefore being paid accordingly.

2.4 Methodology

We use the SES 2012[16] to estimate the returns to management in the United Kingdom. As already discussed, this is an indirect approximation that investigates the relationship between management practices and productivity. This SES has been conducted every 5-6 years in the past four decades, and provides a representative sample of workers aged between 20 and 65 years[17]. We use the last three cross sections (years 2001, 2006 and 2012) because they have rich data, including several socio-economic indicators, measures of generic skills, and measures of five managerial tasks as well, namely motivating staff (motivate); coaching staff (coach); control over resources (control); developing the careers of staff (careers); and making strategic decisions for the organisation (future).

To understand the impact that managers have on productivity in the United Kingdom, we estimate two OLS regressions: the financial returns to managerial status[18] (using the whole sample) and to managerial tasks (using the sample of workers performing managerial tasks).

Empirically, the main general equation written in scalar form is:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_k x_k + \varepsilon_i \qquad \text{for } i = 1, 2 \ldots n \qquad \text{[Equation 2.1]}$$

[16] Dataset developed by Felstead et al. (2013).

[17] We use weights to take into account the differential probabilities of sample selection, the over-sampling of certain areas and some small response rate variations between groups.

[18] Whether manager, supervisor, or other.

where 'y_i' represents the natural logarithm of usual gross hourly wages (dependent variable), and 'x_i' represents all the independent variables, such as managerial status (or managerial tasks), gender, experience, education, generic skills used at work, indicators of job polarisation (dummy variable 'mainly routine tasks' = 1 versus 'mainly non-routine tasks' = 0), interaction terms between managerial status / tasks and the routinisation variable, industries, regions and time dummies[19]. We use clustered standard errors at the industry level (one-digit disaggregation).

In addition, we estimate the probability of receiving a bonus based on own performance[20], which sheds new light on the productivity of managers. We use a dummy dependent variable named 'bonus received' (y_i= 1 if receive a bonus, 0 otherwise). In mathematical notation:

$$y_i = \begin{cases} 1 \; if \; y_i * > 0 \\ 0 \; if \; y_i * < 0 \end{cases}$$

$$y_i^* = \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_k x_k + \varepsilon_i$$

Where yi* is the underlying latent propensity that y_i=1[21].

[19] Further details available in the data appendix.

[20] Data for three types of bonuses is available in SES: based on own performance, group performance, and organisational performance. All the different specifications were investigated, and the results are similar. Therefore, we only present findings for the bonus based on own performance.

[21] This crucial assumption allows us to think in a regression with normally distributed errors, and with mean 0 and variance 1, $\varepsilon \sim N(0, 1)$.

The estimated Probit model is the following:

$$\Pr(y_i = 1 \setminus x_i) = \Phi(\beta_1 x_1 + \beta_2 x_2 + \ldots \beta_k x_k) \qquad \text{[Equation 2.2]}$$

Where $y_i = 1$ represents the probability of receiving a bonus given x_i, x_i represents all the explanatory variables, and Φ is the transformation function (cumulative density function of the standard normal distribution (cdf)) that maps the linear combination into [0,1], essential for the interpretation of coefficients in terms of probabilities (Wooldridge, 2010).

To interpret the coefficients, we compute the marginal effects:

$$\frac{\partial y_i}{\partial x_k} = \frac{\partial \Phi(\beta_1 x_1 + \beta_2 x_2 + \cdots \beta_k x_k)}{\partial x_k}$$

The marginal effect of an explanatory variable (e.g., management tasks scores) is the effect of a unit change of this variable on the probability $\Pr(Y = 1 \setminus X = x_i)$, given that all other independent variables are constant.

The symbol ϕ represents the probability density function of the standard normal cdf (Φ). Thus, the marginal effect of increasing x_k results in a change in y of magnitude:

$$\phi(\beta_1 x_1 + \beta_2 x_2 + \cdots \beta_k x_k)\, \beta_k.$$

Up to this point we considered an indirect approach to achieve the purpose of the investigation. We can also continue with a more direct method, too. Following a strategy similar to Black and Lynch (2001), we first estimate a standard Cobb-Douglas production function with panel data (industry level) using both within and GMM estimators. Second, we directly check whether management practices explain some of the variation in the residuals (i.e., in total factor productivity[22]) that were obtained after the within and GMM estimations. The procedure is as follows.

We start with a general production function:

$$Y_{it} = L^{\alpha}_{it} * K^{\beta}_{it} * M^{\gamma}_{it} \qquad \text{[Equation 2.3]}$$

where Y is real output, L is for labour (number of employees), K is real fixed capital stock (later differentiated between capital ICT and non-ICT), and M is for real (adjusted) intermediate inputs. All these variables are taken from the EU KLEMS that contains industry-level measures of output, inputs and productivity from 1970 to 2007[23]. We confirm the presence of constant returns to scale[24].

Taking logs, we obtain the following linear equation for the within estimator:

[22] Total Factor Productivity (TFP) is the portion of output not explained by the amount of inputs used in production. As such, its level is determined by how efficiently and intensively the inputs are utilized in production.

[23] More details about the EU KLEMS can be found in O'Mahony et al. (2007 and 2009)

[24] The concept of constant returns to scale implies that: $\alpha + \beta + \gamma = 1$

$$y_{it} = \alpha_{ict}k_{it} + \beta_{nonict}k_{it} + \rho l_{it} + \gamma m_{it} + v_i + \varepsilon_{it} \qquad \text{[Equation 2.4]}$$

where, ε_{it} is the error term that plays a key role in the estimation, and v_i is the unobserved, time-invariant fixed effect. Note that equation 4 can be rearranged for value added, subtracting γm_{it} from y_{it}, leaving $\alpha_{ict}k_{it} + \beta_{nonict}k_{it} + \rho l_{it} + v_i + \varepsilon_{it}$ on the right-hand side.

It is worth noting that in the fixed effect estimation, we expect to have some endogeneity[25] in the sense that output can also be determined by the error term (e.g., $k_{it} = k(v_i + \varepsilon_{it})$), which will produce a bias in our estimates. In concrete terms, we expect that labour and material coefficients are biased upward and capital coefficients downward because variable materials and labour are generally considered more easily adjustable than capital. Thus, they are strongly positively correlated with the error term (Roodman, 2009). In this scenario, if the endogeneity problem (e.g., unobserved heterogeneity) is transmitted via the fixed effect, we can get rid of it by either removing it from the regression equation or from the instruments, i.e., using a GMM estimation. Therefore, the system GMM estimation emerges as a good solution to address the problem, and is the main specification discussed in the next section.

GMM estimation relies on instruments, correlated with inputs, but not with ($v_i + \varepsilon_{it}$), which are taken from the same panel data structure. This methodology has been fully developed by Arellano and Bond (1991), and Blundell and Bond (1998), and can be summarised as follows:

[25] For instance, unobserved determinants of production, such as firm-specific effects correlated with inputs.

GMM is estimated as a system of equations in level and differences:

$$y_{it} = \rho y_{i,t-1} + \alpha_{ict}k_{it} + \beta_{non\text{-}ict}k_{it} + \rho l_{it} + \gamma m_{it} + v_i + \varepsilon_{it} \qquad \text{[Equation 2.5]}$$

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \Delta(\alpha_{ict}k_{it} + \beta_{non\text{-}ict}k_{it} + \rho l_{it} + \gamma m_{it}) + \Delta\varepsilon_{it} \qquad \text{[Equation 2.6]}$$ [26]

where the instruments are obtained by imposing the following two restrictions:

1. We use lagged levels as instruments for a differenced equation.

$$E(y_{i,t-s}\Delta\varepsilon_{it}) = 0 \qquad \text{for all i,t and s = 2,}\ldots\infty$$

Thus, past levels of the dependent variable act as instruments for the current first differences of the dependent variable. This is known as difference GMM, after Arellano and Bond (1991).

2. We use differences as instruments in a levels regression:

$$E(\Delta y_{i,t-s}(v_i + \varepsilon_{it})) = 0 \qquad \text{for all i,t and s = 1,}\ldots\infty$$

[26] Taking the first difference of the linear dynamic panel regression, we remove the industry-specific unobserved effect.

Therefore, the predetermined and endogenous variables in levels are instrumented with suitable lags of their own first differences. This is known as system GMM, after Blundell and Bond (1998). Examples of previous studies using this technique are Llyang (2006), Spilimbergo (2009), and Heid et al. (2012).

We generate the predicted values of $y_{it} - \alpha_{ict}k_{it} - \beta_{non\text{-}ict}k_{it} - \rho l_{it} - \gamma m_{it} = v_i + \varepsilon_{it}$ using the within estimator and GMM estimator of α, β, ρ and γ, for the period 1970-2007. We then average those values in each period, for each industry, to get time-invariant estimates of the residual. Then, in the second step, we regress our average residuals on the management tasks scores (time-invariant average scores taken from SES for each period), human capital measures, and variables that control for routine and non-routine tasks.

$$TFP_i = \beta_1 x_1 + \beta_2 x_2 + \ldots \beta_k x_k + \varepsilon_i \qquad \text{[Equation 2.7]}$$

2.5 Results

2.5.1 Descriptive statistics

The total sample size in the Skills and Employment Survey, using three cross sections, is 15,447 individuals. This sample can be divided into managers, supervisors, and other[27]. In terms of percentages (see Table 2.1), 16.81% of the interviewees are managers (mainly higher managerial and high professional occupations), 25.31% supervisors, and 57.88% other employees[28].

Table 2.1: Percentage of managers in the samples

	Whether Manager or Supervisor (%)			
Dataset	Managers	Supervisors	Other	Total
2001	17.49	25.19	57.32	100
2006	17.73	24.51	57.76	100
2012	13.51	27.49	59	100
Total	16.81	25.31	57.88	100

Source: Skills and Employment Survey, 2012

[27] Employees in the 'other' group, by exclusion, are not supervisors or managers. In the regression analysis, this is the reference group.

[28] "Self-Employed/Business-Owners" are not included in the analysis when managerial skills are not relevant to the job (i.e. in that case they choose answer "not applicable"). This reduces a potential source of bias in our results. Further descriptive statistics are provided in the appendix.

Disaggregating the labour force by routine and non-routine tasks, we observe that managers are the group least associated with routine tasks (Table 2.2): 32% of workers in managerial occupations declare that their jobs have a strong component of repetitive tasks, which is relatively low compared with the 46.13% and 54.13% declared by supervisors and those without managerial responsibilities, respectively. However, more interestingly, we can confirm that a significant number of managers are indeed largely performing routine (repetitive) tasks, which is essential for our analysis.

Table 2.2: Labour force disaggregated by non-routine and routine tasks

	Type of Task (%)		
Whether manager or supervisor	Non-routine	Routine	Total
Managers	67.56	32.44	100
Supervisors	53.87	46.13	100
Other	45.87	54.13	100
Total	51.55	48.45	100

Source: Skills and Employment Survey, 2012

Now, we have reached a critical stage in which we need to address the key question of managers' main role in organisations. The importance of management skills amongst managers and supervisors in the United Kingdom varies from medium-high to high (note: the question in SES is: 'In your job, how important is…. (e.g., motivating)… the staff whom you manage or supervise?'. See Table 2.3 for results that uses scales from 1 to 5, where '1' means not important at all, and '5' is essential for the job). 'Making strategic decisions for the future of the organisation' and 'developing careers of the staff' get the lowest scores, but this is understandable due to the fact that these activities are less frequent in their jobs. It is worth noting that, in general, the levels and behaviour of managerial tasks are relatively similar for managers and supervisors, which means that it would be reasonable to treat them both as one group too[29].

Table 2.3: The importance of managerial tasks in the UK (Likert scale 1-5, where 5 is essential for the job) by managerial status

	Management Practices					
Category	Motivate	Control	Coach	Career	Future	Average
Manager	4.46	4.19	4.11	3.72	3.33	3.96
Supervisor	4.24	3.79	3.88	3.26	2.57	3.55

Source: Skills and Employment Survey, 2012

Also, we investigate whether the importance of management practices in the workplace change across years, classifying supervisors and managers as one group (descriptive statistics in Table 2.4), and we observe a moderate increase in the importance of managerial skills between the years 2001 and 2006, and a slight decrease between the years 2006 and 2012. Both movements are statistically significant at the 99 and 90 percent confidence levels, respectively. Furthermore, there was an increase between 2001 and 2012, and this statistic is significant at the 90 percent confidence level (see Table 2.5).

[29] Further descriptive statistics are available in the appendix.

Table 2.4: The Importance of managerial tasks across samples in the UK (Likert scales 1-5, where 5 means essential for the job)

	Management Practices					
Years	Motivate	Control	Coach	Careers	Future	Average
2001	4.28	3.93	3.90	3.38	2.86	3.67
2006	4.34	4.02	4.00	3.47	3.07	3.78
2012	4.31	3.99	3.96	3.38	3.01	3.73

Source: Skills and Employment Survey, 2012

Table 2.5: Managerial tasks' average variation across samples in the UK

Years	Tasks Variation	
2006-2001	0.11	***
2012-2001	0.06	*
2012-2006	-0.05	*

Source: Skills and Employment Survey, 2012

Finally, treating managers and supervisors as one group again, we divide them according to the type of tasks they perform (i.e., non-routine and routine tasks), and we observe a moderate increase in the importance of managerial skills between the years 2001 and 2012 (Table 2.6). This change is only statistically significant for those supervisors / managers performing mainly non-routine jobs (see Table 2.7). This can be considered as supporting the theory of job polarisation.

Table 2.6: The importance of managerial tasks amongst non-routine and routine type managers (Likert scale 1-5, where 5 means essential for the job)

	Whether Supervisor / Manager performs Non-Routine or Routine Tasks often	
Dataset	Non-routine	Routine
2001	3.70	3.63
2006	3.82	3.71
2012	3.78	3.67

Source: Skills and Employment Survey, 2012

Table 2.7: Managerial tasks average variation amongst non-routine and routine type managers

	Type of Job / Tasks Variation			
Years	Non-routine		Routine	
2006-2001	0.13	***	0.08	**
2012-2001	0.08	**	0.05	
2012-2006	-0.05		-0.03	

Source: Skills and Employment Survey, 2012

2.5.2 Empirical analysis

Our first OLS estimation takes the natural log of wages as the dependent variable and the categorical variable 'managerial status' as the main independent variable, which enters the model as two dummies (for managers and supervisors) that are compared with the reference group (employees who are neither managers nor supervisors). The last column of Table 2.8 (based on equation 2.1) shows that - after controlling for gender, experience, education, type of job, regions, industries, and time[30]- the wages of non-routine managers are, on average 30% higher than the average wage in the reference group, while the wages of routine managers are 22.5% (0.30 – 0.075) higher than the reference group, holding all else constant. Similarly, the wages of non-routine supervisors are on average 14% higher than those of the reference group, while the wages of routine supervisors are on average 8% (0.14 – 0.06) higher than the reference group[31], holding all else constant. Consequently, there is a strong positive association between non-routine tasks and wages. These coefficients are significant, support the hypothesis of job polarisation amongst managers and supervisors, and also give some idea about the marginal productivity of these groups. Furthermore, from column 4 in Table 2.8 it can be stated that - holding all else constant - the wage rate of males is 12% higher than that of females; one additional year of experience is associated with a 3% increase in wages; workers that achieve an NVQ level 4 or 5 earn on average 30% more than workers below NVQ level 4; within the generic skills, Complexity of Computer Use, Problem Solving and Literacy are all associated with higher returns. Communication skills are also positively associated, but at a lower level, and Numeracy does not show a significant effect (noting that we control for the managerial status); Financial services, Manufacturing, Construction, and Transport show the biggest gap

[30] Also, we use weights and clustered standard errors at the industry level.

[31] As a reference, the average gross hourly wage of the whole sample is £11.51.

compared to Agriculture which is the reference group (and has the highest score on routine tasks, and the lowest number of managers); and London is the region with by far higher wages (London is the reference group). The wages of most of the regions are on average 20 - 40 % lower than those in London[32/33].

Table 2.8: OLS regression - The link between managerial status and wages

	Dependent Variable: Ln wage			
	(1)	(2)	(3)	(4)
Manager	0.511***	0.335***	0.349***	0.304***
	(0.025)	(0.023)	(0.032)	(0.032)
Supervisor	0.231***	0.134***	0.165***	0.139***
	(0.025)	(0.014)	(0.018)	(0.017)
Male		0.145***	0.135***	0.117***
		(0.015)	(0.014)	(0.015)
Experience		0.028***	0.027***	0.027***
		(0.002)	(0.002)	(0.002)
Expsqdiv100		-0.053***	-0.051***	-0.049***
		(0.005)	(0.005)	(0.005)
Degree		0.372***	0.346***	0.300***
		(0.032)	(0.031)	(0.030)
Routine			-0.093***	-0.078***
			(0.015)	(0.014)
Manager*Routine			-0.065**	-0.075***
			(0.026)	(0.025)
Supervisor*Routine			-0.064**	-0.062***
			(0.022)	(0.020)
PC complexity				0.107***
				(0.021)
Literacy				0.070***
				(0.015)
Numeracy				0.003
				(0.012)
Communication				0.031*

[32] Industry and regional dummies are omitted in Table 2.8 for presentation purposes.
[33] We also tried a version of this model including the indicator variable "sector" (private vs public), and the main coefficients remain unchanged. However, further research could investigate these two sectors in more detail in order to understand subtle differences.

Table 2.8 continued:

				(0.016)
Problem Solving				0.094***
				(0.017)
Industries	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes
Adjusted R-squared (N = 9292)	0.359	0.490	0.503	0.526

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills and Employment Survey, 2012

In our second set of regressions, based on equation 2.1 (Table 2.9), we use the sub-sample of managers and supervisors. We regress the natural log of wages on managerial tasks, with the same control variables as in equation 2.1. As is shown in the last column of Table 2.9, the correlation between strategic decisions about the future of the organisation (future) and wages varies between routine and non-routine jobs[34]. This is after controlling for industries and region, and using clustered standard errors at the industry level. In terms of interpretation, we could say that, *ceteris paribus*, those managers and supervisors placing more importance on non-routine tasks earn on average 12.7% higher wages than those who assign less importance to this particular task (future). On the other hand, amongst routine managers and supervisors, we observe lower returns (2.6% = 12.7 – 10.1) when comparing those that give more importance to strategic decision making about the future of the organisation and those who declare that it is less relevant for the job.

[34] Here we are exploring associations. An individual that exercises strategic decisions is endogenous in the pay determination system. In other words, an omitted third factor ("ability") could determine whether an individual is selected to make strategic decisions, and his/her earnings. The next section tries to address endogeneity with a GMM approach.

Table 2.9: OLS regression - The link between managerial tasks and wages

	Dependent Variable: Ln wage			
	(1)	(2)	(3)	(4)
Motivate	0.022	0.032	0.029	0.020
	(0.023)	(0.021)	(0.018)	(0.017)
Control	-0.002	-0.005	0.005	-0.007
	(0.022)	(0.015)	(0.030)	(0.031)
Coach	-0.030***	-0.001	-0.019	-0.029
	(0.007)	(0.013)	(0.026)	(0.026)
Future	0.203***	0.138***	0.156***	0.127***
	(0.032)	(0.024)	(0.033)	(0.033)
Career	0.110***	0.063**	0.075**	0.066*
	(0.022)	(0.023)	(0.030)	(0.031)
Male		0.154***	0.140***	0.119***
		(0.022)	(0.020)	(0.019)
Experience		0.036***	0.034***	0.034***
		(0.002)	(0.002)	(0.002)
Expsqdiv100		-0.068***	-0.064***	-0.063***
		(0.006)	(0.005)	(0.005)
Degree		0.391***	0.355***	0.314***
		(0.032)	(0.031)	(0.030)
Routine			-0.170***	-0.147***
			(0.033)	(0.031)
Motivate*Routine			0.015	0.017
			(0.039)	(0.036)
Control*Routine			-0.020	-0.023
			(0.052)	(0.051)
Coach*Routine			0.049	0.038
			(0.041)	(0.039)
Future*Routine			-0.089*	-0.101*
			(0.049)	(0.052)
Career*Routine			-0.026	-0.037
			(0.041)	(0.044)
PC complexity				0.090***
				(0.020)
Literacy				0.058**
				(0.023)
Numeracy				-0.014
				(0.014)
Communication				0.061***
				(0.019)
Problem Solving				0.121***
				(0.022)

Table 2.9 continued:

Industries	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
Adjusted R-squared (N = 4226)	0.239	0.402	0.424	0.446

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills and Employment Survey, 2012

Additionally, using equation 2.2, we estimate the probability of receiving a bonus based on own performance, which is thus another proxy for productivity. The interpretation of the marginal effects of the regressors, in the context of a Probit model, is how much the conditional probability of the outcome variable changes when we change the value of a regressor, holding all other regressors constant. In our case (interpreting column 4 in Table 2.10), managers are approximately 11% more likely to get a bonus, compared with the reference group, and supervisors are 6% more likely than the reference group (employees who are not managers or supervisors) to receive a bonus based on their performance. As a robustness test, we run the same model, but remove the finance industry (well-known for a higher frequency of bonuses), and the results remain unchanged[35]. In addition, we observe that there is no significant difference between routine and non-routine tasks, but that the marginal effects of the complexity of computer use, problem solving, and communication are positive and highly significant, which reflects the importance of technology, analytics, and social skills at work, respectively.

[35] The output is in the appendix.

Table 2.10: Probit regression - Conditional probability of 'receiving a bonus' based on managerial status

	Dependent Variable: Whether Received Bonus			
	(1)	(2)	(3)	(4)
Manager	0.146***	0.140***	0.126***	0.108***
	(0.020)	(0.019)	(0.027)	(0.027)
Supervisor	0.080***	0.079***	0.068***	0.057***
	(0.013)	(0.016)	(0.021)	(0.021)
Male		0.043***	0.043***	0.039***
		(0.014)	(0.014)	(0.013)
Experience		0.002	0.002	0.002
		(0.003)	(0.003)	(0.003)
Expsqdiv100		-0.010*	-0.010*	-0.009*
		(0.005)	(0.005)	(0.005)
Degree		0.009	0.008	-0.006
		(0.012)	(0.011)	(0.010)
Routine			-0.018	-0.011
			(0.014)	(0.014)
Supervisor*Routine			0.022	0.022
			(0.025)	(0.025)
Manager*Routine			0.035	0.030
			(0.029)	(0.028)
PC complexity				0.032***
				(0.012)
Literacy				0.012
				(0.013)
Numeracy				-0.003
				(0.012)
Communication				0.048***
				(0.018)
Problem Solving				0.034***
				(0.009)
Industries	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
(N = 9292)				

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills and Employment Survey, 2012

In our second probit regression (Table 2.11), based on equation 2.2, we use a sub-sample of managers and supervisors, and regress the dummy variable bonus based on own performance (i.e. bonus received = 1, zero otherwise) on our managerial tasks variables, plus controls. The interpretation of the last column of Table 2.11 states that, *ceteris paribus*, focusing on 'motivating' and 'coaching' the staff increases the probability of receiving a bonus (these are 'people management' practices). However, 'coaching' is almost double the probability of 'motivating', which is important to consider when making policy. Also, it is worth noting that we did not find differences between non-routine and routine jobs, and that computer use is positive and highly significant, which supports the hypothesis of skill-biased technical change. We try this model without the finance industry again and arrive at the same conclusion. The output of this model has been attached in the appendix.

Table 2.11: Probit regression – Conditional probability of 'receiving a bonus' based on management practices

	Dependent Variable: Whether Received Bonus			
	(1)	(2)	(3)	(4)
Motivate	0.038***	0.041***	0.048***	0.042***
	(0.013)	(0.013)	(0.017)	(0.016)
Control	-0.029**	-0.027*	-0.020	-0.024
	(0.014)	(0.015)	(0.016)	(0.017)
Coach	0.085***	0.087***	0.084***	0.085***
	(0.013)	(0.014)	(0.026)	(0.024)
Future	0.037	0.029	-0.006	-0.013
	(0.033)	(0.036)	(0.036)	(0.037)
Career	0.019	0.016	0.027	0.024
	(0.023)	(0.024)	(0.031)	(0.032)
Male		0.062***	0.064***	0.061***
		(0.015)	(0.014)	(0.014)
Experience		0.001	0.001	0.002
		(0.003)	(0.003)	(0.003)

Table 2.11 continued:

Expsqdiv100		-0.007	-0.007	-0.008
		(0.005)	(0.005)	(0.005)
Degree		0.013	0.016	0.003
		(0.020)	(0.018)	(0.019)
Routine			0.014	0.019
			(0.035)	(0.036)
Motivate*Routine			-0.017	-0.012
			(0.043)	(0.041)
Control*Routine			-0.018	-0.019
			(0.034)	(0.033)
Coach*Routine			0.005	-0.001
			(0.047)	(0.046)
Future*Routine			0.099*	0.095
			(0.055)	(0.058)
Career*Routine			-0.029	-0.030
			(0.036)	(0.037)
PC complexity				0.060***
				(0.019)
Literacy				0.018
				(0.018)
Numeracy				-0.010
				(0.018)
Communication				0.084
				(0.053)
Problem Solving				0.001
				(0.020)
Industries	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
(N = 4226)				

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills and Employment Survey, 2012

Previously, we estimated the effect of management on productivity using an indirect approach (i.e., using the natural log of wages or bonuses as dependent variables that we assume to proxy productivity under certain conditions). Now, our second approach is direct, and here we adopt a two-stage procedure.

First, we estimate a classic Cobb-Douglas production function using the OLS, Fixed Effects and GMM estimators[36]. The dependent variable in our model is the natural logarithm of real output, and the explanatory variables are the log of real fixed capital stock ICT, the log of real fixed capital stock non-ICT, and the log of the adjusted intermediate inputs[37]. All variables are per capita / worker adjusted, and the control variables are included in the second step. We observe some changes from the Fixed Effects to the GMM estimations. This is due to endogeneity in the within estimation, where the coefficients of capital are biased downward, and the coefficient of intermediate inputs are biased upward, as is shown in Table 2.12.

Second, we take the residuals from the within and GMM estimations, and average those values over the period 1970-2007 for each industry[38] to get a time-invariant estimate of the residuals. Then, we regress the average TFP per industry on the average managerial skills taken from SES, controlling for gender, experience, education, and routine tasks (equation 2.7). Following this procedure, we find in Table 2.12 (in the second stage) a positive and significant effect of management practices on productivity: after controlling for the full set of covariates, using the within estimation, the coefficient is 0.05, while with the GMM regression it is 0.02. Considering this, it could be said that managerial tasks have a positive effect on having higher-than-average productivity over the period 1970-2007[39], but the effect is less pronounced -and

[36] These estimations are based in equations 2.3, 2.4, 2.5 and 2.6. Here, we use clustered standard errors at the 2-digit industry level.

[37] All these variables were transformed using the natural logarithm, and were originally measured in millions of British Pounds.

[38] EU KLEMS provides detail at the 2-digit level.

[39] As a robustness test we also estimated the model using the EU KLEMS release 2017 (that offers adjusted value added instead of real output), finding the same results for the period 2001-2006. However, the clearly significant relationship disappears during the recession and years immediately after (2007-2012), which could relate to the problems and effects of the financial crisis. Further analyses of the recession, however, go beyond the scope of

more accurate- in the GMM estimation after correcting part of the endogeneity problem[40]. Regarding non-routine and routine tasks performed by the entire labour force, we note that during the period 1970-2007, non-routine tasks have had, on average, an important role in productivity (variable 'non-routine/routine tasks industry ratio' in Table 2.12). This is also consistent with the hypothesis of job polarisation, because ICT investment has consistently increased during this period. Additionally, it is worth noting that industries working with a larger ratio of non-routine managers over routine managers tend to be more effective and productive during the same period[41].

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this study. Tables with First and Second stages for this period, and regressions in differences, have been added to the appendix.

[40] The moment conditions of the GMM estimator are valid if there is no serial correlation in the idiosyncratic errors. Because the first difference of white noise is necessarily autocorrelated, we focus on the second and higher autocorrelation. Effectively, we reject the hypothesis of no-autocorrelation in the Arellano-Bond test for AR(2) in first differences, with a z-value of 0.05. Furthermore, we fail to reject the Sargan Test of over-identifying restrictions with a p-value of 0.08, which suggests that the instruments are valid.

[40] The coefficients of "problem-solving" and "experience" are virtually zero in the best specification (GMM). The negative sign of "experience" can be understood in the context of rapid technical change that is adopted by younger generations. In addition, "problem solving" strongly correlates with other covariates, such as managerial status/tasks (our main predictors in this regression) and non-routine tasks, and that affects the sign and magnitude of the coefficient.

Table 2.12: Managerial tasks and productivity. First stage (production functions), and Second stage (regressions of TFP on managerial tasks)

	First Stage			Second Stage							
	OLS	FE	GMM	Dependent Variable: TFP FE				Dependent Variable: TFP GMM			
Log of ICT Capital per worker	0.035***	0.017*	0.006								
	(0.010)	(0.009)	(0.020)								
Log of Non-ICT Capital per worker	0.112***	0.155***	0.168**								
	(0.025)	(0.042)	(0.068)								
Log of Intermediate Inputs per worker	0.707***	0.748***	0.722***								
	(0.031)	(0.053)	(0.077)								
Average Managerial Tasks				0.035***	0.027***	0.023***	0.053***	0.025***	0.019***	0.020***	0.020***
				(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Non-Routine / Routine managers ratio					0.061***	0.066***	0.076***		0.011***	0.010***	0.011***
					(0.006)	(0.006)	(0.007)		(0.001)	(0.001)	(0.001)
Non-Routine / Routine Tasks industry ratio					0.045***	0.054***	0.013*		0.009***	0.009***	0.006***
					(0.005)	(0.005)	(0.007)		(0.001)	(0.001)	(0.001)
Male / Female ratio						0.014***	0.018***			0.004***	0.004***
						(0.004)	(0.004)			(0.001)	(0.001)
Experience						-0.045***	-0.060***			-0.006***	-0.009***
						(0.004)	(0.004)			(0.001)	(0.001)
Literacy							0.060***				0.007***
							(0.006)				(0.001)
Numeracy							0.063***				0.008***
							(0.006)				(0.001)
Computer Use							0.014*				0.003**
							(0.007)				(0.001)
Problem Solving							0.023***				-0.002*
							(0.006)				(0.001)
Communication							0.068***				0.011***
							(0.006)				(0.001)
Adjusted R-squared	0.973	0.963		0.039	0.122	0.240	0.389	0.064	0.168	0.240	0.363
(N First stage/Second stage= 1064/84)											

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ / Sources: EUKLEMS release 2009 and SES 2012

2.6 Conclusions

Managers and supervisors get higher wages compared to the rest of the labour force in the UK, and the use of managerial tasks –especially amongst those performing non-routine tasks- is rewarded with an increase in wages too. Within the set of managerial skills, 'making strategic decisions' (future), motivating staff and coaching seem to have a larger impact on productivity. These findings, plus the fact that computer use is strongly associated with an increase in productivity, reveal the importance of developing human capital / managerial skills, and support the hypothesis of job polarisation.

We also estimated standard Cobb-Douglas production functions (following the two-step technique previously used by Black and Lynch (2001)) to understand the impact of management practices on aggregate productivity, and found a positive and significant association in the long run (managerial tasks have a positive effect on having higher-than-average productivity over the period 1970-2007). Furthermore, non-routine tasks have been crucial for productivity during the past four decades, and we found that the higher the ratio of non-routine managers over routine managers, the higher the productivity, which is expected and consistent with the hypothesis of job polarisation.

Some estimation problems still arise, mainly due to the difficulty in finding panel data measures of managerial tasks. This data is not yet available because this is a relatively new field at the intersection of management and economics. Also, further research regarding the role and impact of managerial tasks and their interactions with other skills seems appropriate (at both the micro and aggregated levels), and more disaggregation of non-routine tasks could be explored.

Managerial tasks are key to the country's productivity, and this study confirms that the United Kingdom now has the unique opportunity to improve its performance by boosting human capital and the skills of managers. This study is thereby presented as a contribution to academic discussion and public policy making.

2.7 Appendix

A. Data description

Table A2.1: Detailed description of variables

Variable	Description
Motivate	Importance for managers / supervisors of motivating the staff (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Control	Importance of keeping close control over resources (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Future	Importance of making strategic decisions about the future of the organisation (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Career	Importance for managers / supervisors of developing the careers of the staff (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Coach	Importance for managers / supervisors of coaching the staff (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Motivate (dummy)	Importance for managers / supervisors of motivating the staff (1 if essential, 0 otherwise)
Control (dummy)	Importance of keeping close control over resources (1 if essential, 0 otherwise)
Future (dummy)	Importance of making strategic decisions about the future of the organisation (1 if essential, 0 otherwise)
Career (dummy)	Importance for managers / supervisors of developing the careers of the staff (1 if essential, 0 otherwise)
Coach (dummy)	Importance for managers / supervisors of coaching the staff (1 if essential, 0 otherwise)
Management	z-scores of the computed average managerial tasks
Manager	1 if respondent is a manager, 0 otherwise
Supervisor	1 if respondent is a supervisor, 0 otherwise
Other	1 if respondent is not a manager / supervisor (baseline category)
Ln income	Natural logarithm of gross hourly wage
Bonus	1 if respondent receive bonus based on own performance, 0 otherwise
Male	1 if respondent is male, 0 if female
Experience	Number of years in paid work since leaving fulltime education
Experience Squared	Number of years in paid work since leaving fulltime education squared
Degree (Education)	1 if respondent achieved NVQ level 4/5, 0 otherwise
Routine tasks (Likert scale)	How often work involves short / repetitive tasks (1: never, 2: rarely, 3 : sometimes, 4 : often, 5 : always)
Routine tasks (dummy)	1 if work involves short / repetitive tasks often or always, 0 otherwise
Non-routine/routine ratio	Ratio of non-routine / routine types of workers per industry
Manager/Non-manager ratio	Ratio of manager/non-manager types of workers per industry
PC complexity	Complexity level of computer use (1: straightforward, 2: moderate, 3: complex, 4: advanced)
Literacy	Importance of writing long documents (1: not at all important, 2: not very important, 3: fairly important, 4: very important: 5: essential)
Numeracy	Importance of advanced mathematics / statistics (1: not at all important, 2: not very important, 3: fairly important, 4: very important: 5: essential)
Communication	Importance of dealing with people (1: not at all important, 2: not very important, 3: fairly important, 4: very important: 5: essential)
Problem Solving	Importance of analysing complex problems in depth (1: not at all important, 2: not very important, 3: fairly important, 4: very important: 5: essential)
PC complexity (dummy)	1 if advanced level of computer use, 0 otherwise
Literacy (dummy)	1 if importance of writing long documents is: very important or essential, 0 otherwise
Numeracy (dummy)	1 if importance of advanced mathematics / statistics is: very important or essential, 0 otherwise
Communication (dummy)	1 if importance of dealing with people is: very important or essential, 0 otherwise
Problem Solving (dummy)	1 if importance of analysing complex problems in depth is: very important or essential, 0 otherwise
North East	1 if respondent resides in North East, 0 otherwise
North West	1 if respondent resides in North West, 0 otherwise
Yorkshire and the Humber	1 if respondent resides in Yorkshire and the Humber, 0 otherwise

Table A2.1 continued:

East Midlands	1 if respondent resides in East Midlands, 0 otherwise
West Midlands	1 if respondent resides in West Midlands, 0 otherwise
East of England	1 if respondent resides in East of England, 0 otherwise
London	1 if respondent resides in London, 0 otherwise
South East	1 if respondent resides in South East, 0 otherwise
South West	1 if respondent resides in South West, 0 otherwise
Wales	1 if respondent resides in Wales, 0 otherwise
Scottish Lowlands	1 if respondent resides in Scottish Lowlands, 0 otherwise
Highlands and Islands	1 if respondent resides in Highlands and Islands, 0 otherwise
Northern Ireland	1 if respondent resides in Northern Ireland, 0 otherwise
Ln Output 1	Natural logarithm of real output per capita
Ln Output 2	Natural logarithm of real adjusted value added per capita
Ln Capital ICT	Natural Logarithm of real fixed capital ICT
Ln Capital non-ICT	Natural Logarithm of real fixed capital (except ICT)
Ln Labour	Natural Logarithm of number of employees in the economy
Ln intermediate inputs	Natural Logarithm of adjusted Intermediate Inputs
TFP	Total Factor Productivity
Time Dummies	1 if year 2001, 2 if year 2006 (baseline category), and 3 if year 2012.
Agriculture, Forestry, and Fishing	1 if respondent works in this industry Agriculture, Forestry, and Fishing, 0 otherwise
Mining and Quarrying	1 if respondent works in this industry Mining and Quarrying, 0 otherwise
Food products, beverages, and tobacco	1 if respondent works in this industry Food products, Beverages, and Tobacco, 0 otherwise
Textiles, wearing apparel, leather, and related products	1 if respondent works in this industry Textiles and related products, 0 otherwise
Wood and paper products; printing and reproduction of recorded media	1 if respondent works in this industry Wood, Paper and related, 0 otherwise
Coke and refined petroleum products	1 if respondent works in this industry Coke and petroleum, 0 otherwise
Chemicals and chemical products	1 if respondent works in this industry Chemicals, 0 otherwise
Rubber and plastics products, and other non-metallic mineral products	1 if respondent works in this industry Rubber, Plastics, and related, 0 otherwise
Basic metals and fabricated metal products, except machinery and equipment	1 if respondent works in this industry Metals, 0 otherwise
Electrical and optical equipment	1 if respondent works in this industry Electrical and Optical Equipment, 0 otherwise
Machinery and equipment n.e.c.	1 if respondent works in this industry Machinery and Equipment, 0 otherwise
Transport equipment	1 if respondent works in this industry Transport Equipment, 0 otherwise
Other manufacturing; repair and installation of machinery and equipment	1 if respondent works in this industry Other Manufacturing, 0 otherwise
Electricity, Gas and Water Supply	1 if respondent works in this industry Electricity, Gas, and Water Supply, 0 otherwise
Construction (baseline category)	1 if respondent works in this industry Construction, 0 otherwise
Wholesale and retail trade and repair of motor vehicles and motorcycles	1 if respondent works in this industry Wholesale and retail of motor vehicles and motorcycles, 0 otherwise
Wholesale trade, except of motor vehicles and motorcycles	1 if respondent works in this industry Wholesale trade, 0 otherwise
Retail trade, except of motor vehicles and motorcycles	1 if respondent works in this industry Retail Trade, 0 otherwise
Transport and storage	1 if respondent works in this industry Transport and Storage, 0 otherwise
Postal and courier activities	1 if respondent works in this industry Postal and Courier Activities, 0 otherwise
Accommodation and Food Services Activities	1 if respondent works in this industry Accommodation and Food Services, 0 otherwise
Information and Communication	1 if respondent works in this industry Information and Communication, 0 otherwise
Financial and Insurance Activities	1 if respondent works in this industry Financial and Insurance Services, 0 otherwise
Real Estate Activities	1 if respondent works in this industry Real Estate Activities, 0 otherwise
Professional, Scientific, Technical, Administrative and Support Service Activities	1 if respondent works in this industry Professional, Scientific, and related, 0 otherwise
Community Social and Personal Services	1 if respondent works in this industry Community Social, and Personal Services, 0 otherwise
Public administration and defence; compulsory social security	1 if respondent works in this industry Public Administration, defence, social security, 0 otherwise
Education	1 if respondent works in this industry Education, 0 otherwise
Health and social work	1 if respondent works in this industry Health and Social Work, 0 otherwise
Arts, entertainment and recreation	1 if respondent works in this industry Arts, Entertainment, and recreation, 0 otherwise
Other service activities	1 if respondent works in this industry Other Services Activities, 0 otherwise

B. Data transformation

In the Skills and Employment Survey 2012, the questions associated with managerial tasks take the following general form: 'In your job, how important is…. (e.g. motivating)… the staff whom you manage or supervise?' Interviewees answered the questions using a Likert scale 1 to 5, where 5 = essential for the job, 4 = very important, 3 = fairly important, 2 = not very important, and 1 = not important at all. In this chapter, five types of management practices are investigated:

- Coaching the staff whom you manage (coaching)
- Developing the careers of the staff whom you manage (career)
- Motivating the staff whom you manage or supervise (motivate)
- Keeping close control over resources (control)
- Making strategic decisions about the future of your organisation (future)

With this information, we created five indicator variables (one per management task). In the empirical section, each new dummy variable takes value 1 when the original score is 5 (i.e., if the management practice is essential for the job), or 0 (less important for the job) otherwise.

In addition, the question linked to routine tasks is: 'How often does your work involve carrying out short, repetitive tasks...?' And, answers use a Likert scale with potential values ranging from 1 to 5, where 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, and 5 = Always. For the empirical analysis, an indicator variable was created that takes value 1 (i.e., of high importance for the job) when the original score is 4 or 5, and 0 (less important) otherwise.

Furthermore, generic skills are measured as the 'Importance of…(the skill)..for the job' in scales from 1 (Not at all important) to 5 (Essential for the job). Five generic skills are considered:

- Computer use: the importance of complexity of computer use.
- Literacy: the importance of writing long documents with correct spelling and grammar.
- Numeracy: the importance of calculations using more advanced mathematical or statistical methods.
- Problem solving: the importance of analysing complex problems in depth.
- Communication: the importance of dealing with people.

These variables were transformed and entered the models as indicator variables that take value 1 (i.e., of high importance for the job) when the original score is 4 or 5, or 0 (less important for the job) otherwise.

C. Further descriptive statistics:

Figure A2.1: Association between wages and management tasks (SES 2012).

Figure A2.1 shows a positive relationship between wages and management practices, which will be tested by conducting the empirical analysis.

Table A2.2: Percentage of managers in the sample by gender

	Gender (%)		
Whether Supervisor or Manager	Female	Male	Total
Manager	40.4	59.6	100
Supervisor	49.09	50.91	100
Other	56.67	43.33	100
Total	52.02	47.98	100

Source: Skills and Employment Survey, 2012

Who are the managers and supervisors? A gender analysis reveals that a higher percentage of males work in managerial positions, while a higher percentage of females are concentrated in lower occupations. As is shown in Table A2.2, 59.6% of all managers are males. Interestingly, this difference between males and females decreases amongst supervisors, while the gap appears again in reference group 'Other'.

Table A2.3: Percentage of managers in the sample by qualification level held (NVQ).

	Whether Supervisor or Manager (%)			
Qualification Level Held (NVQ)	Other	Supervisor	Manager	Total
Below 4	74.61	55.44	41.22	64.14
4 or 5	25.39	44.56	58.78	35.86
Total	100	100	100	100

Source: Skills and Employment Survey, 2012

As expected, managers are on average more educated than non-managers. Using the National Vocational Qualification (NVQ) as a tool of measurement, we observe that 58.8% of managers reached at least level 4, which is high compared to the 44.6% of supervisors and 25.4% of employees who not managers or supervisors (see Table A2.3). This evidence suggests a positive and solid association between educational investment and better jobs / promotions.

Table A2.4: Percentage of managers in the sample by occupation

	Whether Supervisor or Manager (%)			
ISCO - 1 digits	Other	Supervisor	Manager	Total
Armed forces	0.13	0.7	0.48	0.33
Legislators, senior occupations	2.88	13.93	50.73	13.72
Professionals	10.67	17.06	18.51	13.61
Technicians and assoc.	10.77	19.19	13.85	13.42
Clerks	18.65	12.32	6.73	15.04
Service workers	22.25	13.58	3.65	16.93
Skill agricultural	0.5	0.47	0.13	0.43
Craft and related works	8.81	9.17	2.95	7.91
Plant and machine operators	10.79	6.07	1.14	7.97
Elementary occupation	14.57	7.51	1.85	10.64
Total	100	100	100	100

Source: Skills and Employment Survey, 2012

Furthermore, grouping the data using the International Standard Classification of Occupations - ISCO[42] revealed that the category managers is mainly concentrated amongst Legislators, Senior Occupations, Professionals and Technicians. It is worth noting that this pattern is less pronounced between supervisors, and is not present in the rest of the labour force.

[42] List and detailed definitions available on the International Labour Organization website: www.ilo.org/public/english/bureau/stat/isco.

Table A2.5: Percentage of managers in the sample by industry

	Whether Supervisor or Manager (%)			
Industry	Other	Supervisor	Manager	Total
Agriculture	61.11	25.40	13.49	100
Mining	45.90	37.70	16.39	100
Manufacturing	59.26	25.86	14.89	100
Electricity	57.14	20.95	21.90	100
Construction	54.65	27.73	17.62	100
Wholesale	62.00	22.03	15.96	100
Hotels	61.40	26.08	12.53	100
Transport	65.56	19.17	15.27	100
Financial	55.03	21.70	23.27	100
Real Estate	55.54	23.67	20.79	100
Public Adm.	54.45	25.89	19.66	100
Education	56.90	25.39	17.71	100
Health	55.14	31.06	13.81	100
Other services	58.54	24.58	16.89	100
Total	57.87	25.34	16.79	100

Source: Skills and Employment Survey, 2012

Some industries have more managers than others, which seems to be related to the type of activity that they predominantly perform. Table A2.5 shows that Agriculture, Hotels and Health Services are the three industries with the lowest percentage of managers. On the other hand, the three industries with the highest percentage of managers are Electricity, Financial Services and Real Estate. It is also worth noting how the category ‘manager’ is complemented with ‘supervisors’, as shown in Table A2.5. The sum of the percentage of managers plus the percentage of supervisors is close to 42% for all industries, with the unique exemptions of Mining and Transport.

Table A2.6: Percentage of managers in the sample by region in the UK

	Whether Supervisor or Manager (%)			
Region	No	Supervisor	Manager	Total
North East	58.98	28.6	12.42	100
North West	59.2	26.08	14.72	100
Yorkshire and the Humber	59.2	23.98	16.81	100
East Midlands	60.04	21.44	18.51	100
West Midlands	57.48	24.08	18.44	100
East of England	56.24	23.06	20.69	100
London	53.85	28.05	18.1	100
South East	50.91	28.41	20.68	100
South West	57.39	24.97	17.64	100
Wales	60.54	26.49	12.97	100
Scottish Lowlands	59.6	26.35	14.05	100
Highlands and Islands	63.67	23.06	13.27	100
Northern Ireland	61.06	23.08	15.87	100
Total	57.88	25.31	16.81	100

Source: Skills and Employment Survey, 2012

Regarding the geographical distribution, we observe that the proportion of managers is relatively constant across all the regions in the UK. This is also true for supervisors. In this context, it is perhaps more important to see which regions have the highest percentage of employees who are not managers or supervisors because they could be at a 'managerial disadvantage' (see Table A2.6). These regions are Wales (60.5%), Highlands and Islands (63.7%), and Northern Ireland (61.1%), and indeed the regression analysis confirms that this produces negative consequences for productivity.

Table A2.7: The importance of managerial tasks by gender and educational level

	Gender		Qualification level held	
Category	Female	Male	Below 4	4 or 5
Supervisor	3.57	3.52	3.48	3.63
Manager	3.96	3.96	3.91	4.00

Source: Skills and Employment Survey, 2012

Among managers, the descriptive statistics show no difference between males and females, and female supervisors assign more importance to the use of managerial skills than males (see Table A2.7 which uses a Likert scale from 1 to 5, where 5 means 'tasks essential for the job'). As is also expected, those managers and supervisors with NVQ level 4 or 5 report using more managerial tasks than those with an NVQ qualification below 4.

Table A2.8: The importance of managerial tasks by industry, Likert scales 1 - 5

	Whether Supervisor or Manager	
Industry	Supervisor	Manager
Agriculture	3.76	3.69
Mining	3.40	3.86
Manufacturing	3.42	3.95
Electricity	3.12	3.88
Construction	3.50	3.95
Wholesale	3.57	4.06
Hotels	3.64	4.00
Transport	3.54	3.71

Table A2.8 continued:

Financial	3.55	3.88
Real Estate	3.44	3.93
Public Adm.	3.52	3.91
Education	3.67	4.10
Health	3.61	4.00
Other services	3.67	3.95

Source: Skills and Employment Survey, 2012

The analysis by industry shows that managerial tasks are relevant across all industries (see Table A2.8 above). The industries that stand out with the highest scores are Wholesale, Hotels[43], Education and Health Services. Agriculture seems to be a special case, where supervisors use more managerial tasks than managers, which could be related to the intrinsic nature of the agriculture activity (it requires less technology, for example).

Table A2.9: The Importance of routine tasks in the UK, Likert scales 1 - 5

	Managerial Status		
Dataset	Supervisors	Managers	Other
2001	3.29	2.86	3.44
2006	3.28	2.95	3.46
2012	3.34	3.03	3.53

Source: Skills and Employment Survey, 2012

[43] "Hotels" have the lowest share of managers amongst all sectors in this sample. Yet, managerial tasks are highly appreciated in that sector. We interpret this as scarcity of managerial tasks in that sector.

Table A2.10: Routine tasks average variation across samples in the UK

	Managerial Status		
	Supervisors	Managers	Other
2006-2001	-0.01	0.09**	0.02
2012-2001	0.05	0.17***	0.09***
2012-2006	0.06	0.09	0.07**

Source: Skills and Employment Survey, 2012

One additional dimension that is worth considering is the importance of routine and non-routine tasks amongst managers (Note: the question in SES is: ‘How often does your work involve carrying out short, repetitive tasks...?’. See Table A2.9 for results that use Likert scales from 1 to 5, where 5 means ‘use repetitive tasks always’). Routine jobs saw surprising increases between 2001 and 2012. For managers, the scores go up from 2.86 to 3.03, while for supervisors they also increase from 3.29 to 3.34, and for the rest of the labour force (neither managers nor supervisors) the scores also increased from 3.44 in 2001 to 3.53 in 2012. Among managers, these changes are statistically significant at the 95% confidence level (see Table A2.10), and we reject the null hypothesis of no variation across time.

D. Further tests

Table A2.11: Probit regression – conditional probability of receiving a bonus based on own performance linked to managerial status (excluding the Finance industry)

	Dependent Variable: Whether a bonus was received			
	(1)	(2)	(3)	(4)
Manager	0.144***	0.139***	0.121***	0.102***
	(0.021)	(0.019)	(0.027)	(0.027)
Supervisor	0.080***	0.079***	0.069***	0.058***
	(0.014)	(0.017)	(0.021)	(0.021)
Male		0.046***	0.046***	0.043***
		(0.014)	(0.014)	(0.013)
Experience		0.001	0.001	0.001
		(0.003)	(0.003)	(0.003)
Expsqdiv100		-0.008	-0.008	-0.007
		(0.005)	(0.005)	(0.005)
Degree		0.011	0.010	-0.005
		(0.012)	(0.011)	(0.011)
Routine			-0.019	-0.012
			(0.015)	(0.015)
Manager*Routine			0.046*	0.041
			(0.027)	(0.026)
Supervisor*Routine			0.019	0.018
			(0.026)	(0.025)
PC complexity				0.030**
				(0.013)
Literacy				0.017
				(0.012)
Numeracy				-0.000
				(0.013)
Communication				0.047**
				(0.019)
Problem Solving				0.033***
				(0.010)
Industries	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
(N = 8897)				

Source: Skills and Employment Survey 2012

Table A2.11 shows marginal effects calculated after the Probit regression. This model does not include the Finance industry (where bonuses are common). Notwithstanding this, the results are fully consistent with the model that also controls for the industry Finance.

Table A2.12: Probit regression – conditional probability of receiving a bonus based on own performance linked to managerial tasks (excluding the Finance industry)

	Dependent Variable: Whether a bonus was received			
	(1)	(2)	(3)	(4)
Motivate	0.039***	0.042***	0.051***	0.044***
	(0.013)	(0.014)	(0.018)	(0.017)
Control	-0.026*	-0.023	-0.019	-0.024
	(0.015)	(0.016)	(0.017)	(0.018)
Coach	0.088***	0.091***	0.090***	0.091***
	(0.013)	(0.015)	(0.027)	(0.025)
Future	0.034	0.026	-0.007	-0.016
	(0.034)	(0.036)	(0.038)	(0.037)
Career	0.014	0.011	0.018	0.014
	(0.024)	(0.025)	(0.032)	(0.032)
Male		0.062***	0.064***	0.061***
		(0.016)	(0.015)	(0.015)
Experience		-0.000	0.000	0.000
		(0.002)	(0.003)	(0.003)
Expsqdiv100		-0.004	-0.005	-0.005
		(0.005)	(0.005)	(0.005)
Degree		0.016	0.020	0.002
		(0.020)	(0.018)	(0.020)
Routine			0.014	0.022
			(0.037)	(0.038)
Motivate*Routine			-0.019	-0.014
			(0.045)	(0.043)
Control*Routine			-0.011	-0.012
			(0.035)	(0.034)
Coach*Routine			-0.001	-0.009
			(0.049)	(0.047)
Future*Routine			0.094*	0.088
			(0.056)	(0.060)
Career*Routine			-0.019	-0.020
			(0.035)	(0.037)
PC complexity				0.066***
				(0.020)
Literacy				0.031**
				(0.013)
Numeracy				-0.002
				(0.017)
Communication				0.087

Table A2.12 continued:

				(0.054)
Problem Solving				-0.006
				(0.020)
Industries	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes
(N = 4057)				

Source: Skills and Employment Survey 2012

Again, this regression is consistent with the model that includes the Finance industry, and we present this output as a robustness check.

Table A2.13: Production functions in differences. Robustness tests

	ΔLn Output	
	2001-2006	2007-2012
	(1)	(2)
ΔLn ICT Capital	0.038	0.070
	(0.068)	(0.062)
ΔLn non-ICT Capital	0.456***	0.451***
	(0.094)	(0.097)
ΔLn Labour	0.362***	0.320***
	(0.074)	(0.084)
ΔManagement	0.211**	-0.017
	(0.098)	(0.074)
Adjusted R2	0.840	0.843
N	61	62

Source: Skills and Employment Survey 2012

Table A2.13 shows a production function estimated in differences for the periods 2001-2006 and 2007-2012. This is a version of equation 2.3, where we include management practices directly into the regression. Considering these estimations, we conclude that an increase in managerial tasks is positively associated with an increase in output during the period 2001-2006, but no clear association is found for the period 2007-2012, *ceteris paribus*.

Table A2.14: First Stage (Cobb-Douglas production functions), and Second Stage (association between TFP and management practices)

	First Stage – Dep. Var: Ln Output p/w				Second Stage (OLS) - Dependent Variable: Total Factor Productivity											
	Fixed Effects		GMM		Stage 2: Fixed Effects			Stage 2: GMM			Stage 2: Fixed Effects			Stage 2: GMM		
	2001-06	2007-12	2001-06	2007-12	Period 2001 - 2006						Period 2007 - 2012					
Ln ICT	0.036	0.073*	0.128	0.187***												
	(0.047)	(0.038)	(0.132)	(0.033)												
Ln Non-ICT	0.584***	0.517***	0.471*	0.471***												
	(0.047)	(0.047)	(0.282)	(0.056)												
Management					0.042**	0.053***	0.038***	0.042***	0.054***	0.029***	0.018	0.019	0.005	0.008	0.007	0.002
					(0.018)	(0.017)	(0.012)	(0.015)	(0.015)	(0.010)	(0.012)	(0.012)	(0.009)	(0.036)	(0.036)	(0.027)
Non-Routine/rou ratio						0.053***	0.034**		0.151***	0.058***		0.018*	0.049***		0.012	0.052***
						(0.019)	(0.016)		(0.020)	(0.013)		(0.009)	(0.013)		(0.011)	(0.019)
Manager/Non-mag. Ratio						0.034***	0.031***		0.006	0.006*		-0.032***	-0.045***		0.007	-0.005
						(0.006)	(0.004)		(0.005)	(0.003)		(0.006)	(0.005)		(0.007)	(0.006)
Male/Female ratio							0.063***			0.029***			-0.115***			-0.081***
							(0.010)			(0.009)			(0.011)			(0.014)
Experience							-0.067***			-0.059***			-0.050***			-0.124***
							(0.011)			(0.009)			(0.011)			(0.014)
Literacy							0.197***			0.179***			0.060***			0.020
							(0.016)			(0.013)			(0.017)			(0.036)
Numeracy							0.123***			0.143***			0.096***			0.043
							(0.015)			(0.013)			(0.018)			(0.042)
Computer Use							0.082***			-0.010			-0.024			-0.036
							(0.019)			(0.016)			(0.020)			(0.023)
Problem Solving							0.158***			0.043***			-0.007			0.063**
							(0.017)			(0.014)			(0.020)			(0.027)
Communication							0.063***			0.034***			-0.081***			0.015
							(0.011)			(0.009)			(0.012)			(0.015)
Adjusted R-squared	0.618	0.609			0.012	0.155	0.650	0.004	0.078	0.502	0.017	0.167	0.654	0.003	0.001	0.453
(N = 372)																

Sources: EUKLEMS release 2017, and SES 2012

Finally, using data for the period 2001-2012, we estimate classic Cobb-Douglas production functions using the within Fixed Effects and GMM estimators[44]. The dependent variable in our model (output) is the natural log of adjusted value added[45] in per-capita terms (i.e., divided by the number of employees), while the explanatory variables are the natural log of real fixed capital stock ICT, as well as the natural log of real fixed capital stock non-ICT[46] per worker. Control variables are included in the second step.

Secondly, the values of the residuals from the within and GMM estimations were averaged over the periods 2001-2006 and 2007-2012, for each industry to get time-invariant estimates of the residuals. Then, we regress the average TFP per industry on the average managerial tasks taken from SES (pre-and post-recession), controlling for gender, experience, education, managerial status, and non-routine / routine tasks. Following this procedure, we find (in the second stage) a positive and significant effect of managerial tasks on productivity in the period 2001-2006 (see Table A2.14). For instance, after controlling for the full set of covariates in Table A2.14, the coefficients using the within and GMM estimations are 0.038, and 0.029, respectively. Both are statistically significant. Considering this, we could say that managerial tasks have a positive effect on having higher-than-average productivity over the period 2001-2006, a result that is consistent in both within and GMM estimations. Regarding routine and non-routine tasks, we note that during the period 2001-2006, industries with a higher ratio of non-routine / routine tasks tend to be more productive. This is also consistent with the hypothesis of job polarisation.

[44] Here, we also use clustered standard errors at the 2-digits industry level.

[45] In the context of a Cobb-Douglas production function, adjusted value added is equal to real gross output minus adjusted intermediate inputs.

[46] All these variables are measured in millions of British Pounds.

Figures A2.2 and A2.3: Mean Ln adjusted value added (output - left), and mean Ln adjusted value added per worker (productivity measure - right) in the period 2001-2012

The same analysis is conducted for the period 2007-2012 as can be seen in Table A2.14. And, as expected, we did not find significant results. The financial crisis and the years immediately after it represent an abnormal economic period wherein the failures of the financial system (Stiglitz, 2010) heavily impacted output and productivity in the United Kingdom (as shown in the Figures A2.2 and A2.3). Further analyses of the recession, however, are beyond the scope of this study.

CHAPTER 3: FROM ICT CAPITAL INVESTMENT TO INTANGIBLE CAPITAL: TECHNOLOGICAL PROGRESS FOR ROBUST MANAGEMENT

3.1 Abstract

In chapter 2, a positive link between management practices and productivity was identified. Now we analyse the association between management practices and technological change, which shows potential to increase productivity. More precisely, we investigate whether the introduction of new technologies in the workplace has an influence on management. Two technologies are considered; communication technologies and computerised equipment. The key variables are taken from the Skills and Employment Survey, conducted in the United Kingdom in the years 2001, 2006 and 2012. The empirical analyses, based on OLS and Propensity Score Matching (PSM) estimations, consistently find a positive relationship between the introduction of communication technologies and ‘people management’ practices (linked to interactions, social and leadership skills). Other associations explored between technologies and management practices are not statistically significant. The results suggest that the way the technology operates (e.g., social use) must be considered while it is being applied in the workplace (in line with Back and Lynch, 2001) and must share some characteristics with management practices in order to facilitate complementarities. The contributions made by this chapter are twofold. First, it shows a practical way to foster robust management. Second, it is an original area of exploration within the new economics of management and productivity.

Keywords: ICT capital investment, technological change, intangible capital, managerial tasks, management practices, productivity, and propensity score matching.

3.2 Introduction

This introduction is divided into two sections. Section 3.2.1. provides the background and justification for the study. Then, Section 3.2.2. makes explicit the research questions, explains how the problem is conceived, and states the relevance of the study.

3.2.1 Background and motivation for the study

Technological change is a dynamic process at the centre of economic growth that involves the application of new knowledge to the productive process (Solow, 1957). It has many facets and, depending on key assumptions and purposes, can be defined as an exogenous or endogenous variable in econometric models. Researchers that model technology as an exogenous variable argue that economic activities and policies have no impact on research, development, and the diffusion of new technologies (as in the Solow-Swan model). The emphasis here is placed upon showing the mere effect of technical change, but not on how technological development occurs. On the other hand, those who think of technology as an endogenous variable state that it cannot be simply defined outside the model, but to an important degree, induced by needs and socio-economic pressures (Romer, 1990).

The literature on technological change has shown interest on wage inequality, job polarisation and labour effects:

The ‘Skill-Biased Technological Change’ hypothesis (SBTC) is today a well-known explanation of technology-driven effects and inequality in labour markets. This model arose from the observation that demand is shifting in favour of more educated workers, thanks in part to technological change that complements skilled labour while substituting unskilled labour in the labour market (see for instance Machin, 1995; Berman, Bound and Machin, 1998; Autor et al., 1998; Card et al., 2002; Violante, 2008; Goldin and Katz, 2010; Acemoglu and Autor, 2011). Notwithstanding its usefulness, the early version of the SBTC hypothesis cannot explain one of the most important trends in modern labour markets, which is the recent phenomenon of job polarisation, where employment has shifted from occupations in the middle of the skill distribution towards those in the tails associated with non-routine tasks.

The main hypotheses put forward to explain job polarisation are that recent technological change is biased towards replacing labour in routine tasks, i.e., Routine-Biased Technological Change (RBTC) and that there is task offshoring, itself partially influenced by technological change (Goos et al., 2014). Both new machine technologies and overseas labour substitute for middle-skill jobs and are, in turn, complementary to high-skill cognitive jobs and low-skill manual jobs. This phenomenon has been documented in the United States (Autor et al., 2006, 2008; Autor and Dorn, 2013), the United Kingdom (Goos and Manning, 2007), Germany (Spitz-Oener, 2006; Dustmann et al., 2009), and other European countries (Goos et al., 2009; Michaels et al., 2014).

Technological change has the potential to produce, at the same time, labour complementarities and substitution effects for different types of workers, such as those mentioned above in relation to the SBTC and RBTC hypotheses. There are multiple effects, and the impact of technology on skill levels seems indeed to be highly contextual (ILO, 2001). On the one hand, technological change tends to reduce skill levels (for instance, deskilling routine workers that do not receive appropriate training while being ‘replaced’ by technology), but can also lead to skill upgrading (for instance, Acemoglu (1998) and Autor et al. (2003) found strong complementarities between high skill workers and ICTs in the United States), and both views are correct. Because no firm conclusion is possible, it is reasonable to say that the introduction of new technologies does not guarantee positive outcomes. This underlines the importance for organisations of creating fertile grounds to actively implement new technologies at work.

The impact of technological change on management practices has not yet been explored in the field of economics[47]. In fact, research on management practices (or managerial skills) from an economic point of view is relatively new, and the relatively small number of academic papers available indicates that this area is in its early stages of development. A series of key papers (e.g., Bloom et al, 2007 and 2010; Bloom et al., 2012; Bloom et al., 2013) investigate what factors are associated with better management practices and found that US firms are better managed in general because of the higher levels of competition in their domestic markets and the more limited involvement of primogeniture family firms (family-owned firms where, in the second generation or beyond, the CEO is the eldest son). Also, they found a larger supply of human capital (measured as the intensity of graduate level employees) in the United States that is strongly associated with better people-management practices, and that lower levels of labour

[47] The management literature has investigated this topic both theoretically, and empirically. For example, Utterback (1994), Bruggeman and Slagmulder (1995), Taylor and Helfat (2009), and Benner (2009). Empirical studies mostly rely on cases studies, and some quantitative investigations embrace management theories and concepts.

market regulation (labour flexibility) are significantly and positively correlated with better people-management across countries.

3.2.2 Research questions, approach, and the relevance of the study

Drawing on previous research, we continue with the general questions that motivate this chapter: does technological change correlate positively with management practices? Are there complementarities? In the empirical framework utilised here, five key managerial tasks represent the role of managers (the same variables analysed in chapter 2), and we explore whether their importance in the workplace is altered after the introduction of new communication technologies and computerised equipment, which are proxies for technological change[48]. It is worth noting that the two variables measuring technological change are retrospective variables (i.e., they indicate if the technology was implemented 3-5 years ago in the workplace), and managerial tasks are measured at the current period (i.e., date of the cross section). Therefore, given the characteristics of the data and the research question, technological change is modelled as an exogenous variable. The data taken from the Skills and Employment Survey (2001, 2006 and 2012) and the econometric approach used in this chapter explore only one direction of the association between technology and managerial tasks, and we have tried to eliminate the problem of endogeneity / double causality in all the decisions taken during this research. In this context, further investigation within the field of economics could examine the other side of the research question: what is the role of managers in technological change?

[48] In the sense that new production processes require new capital equipment.

The selection of these proxies for technological change is not arbitrary. Both types of technology have revolutionised the way we live, and have impacted modern economies. Examples of communication technologies include the use of e-mail, texting, instant messaging, twitting, and video conferencing. All these technologies usually involve devices (for example, mobile phones) and software / applications. Examples of computerised equipment are personal computers, printers, servers, and other machines, which can be associated with the concept of automation (related literature explore the idea of RBTC, mentioned above). These technologies are increasingly popular and have become ubiquitous[49].

The initial hypotheses are that communication technologies foster those managerial tasks that are intrinsically social (i.e., people management practices), such as motivating staff or coaching[50], and that the introduction of new computerised equipment is positively associated with other 'organisation management' practices, such as resource control and strategic decision-making. The main argument behind these hypotheses is that ICT capital investment could be nurturing the production of intangible capital shaped by managers (i.e., management practices). According to Corrado et al (2009), intangible capital / assets are those that do not have a physical or financial embodiment. Forms of intangible assets include computerised information (software and databases), design, and economic competencies (such as firm-specific human capital, networks, management practices, and organisational know-how). Then, managers would benefit from technological progress in cases where this change supports the development of economic competencies, such as management practices. From a macro

[49] The literature reveals that 91% of British households have mobile phones (Dutton and Blank, 2013). Furthermore, 72% of adults in Great Britain used a computer every day (ONS, 2015), and 83% of the adult population in the United Kingdom use the internet (Ofcom, 2014), with 73% doing so on a daily basis (Office for National Statistics, 2015).

[50] Therefore, in the econometric analysis, we expect to reject the null hypothesis of no significant effect.

perspective, a recent study by Corrado et al. (2017) found that productivity in ICT-intensive industries is stronger in countries with relatively fast-growing intangible capital, suggesting complementarity between ICTs and intangible capital. The present study also identifies complementarities, but from a micro perspective. Thus, we add new insights to the field.

We acknowledge that results at the microeconomic level in this area of research can be highly contextual. Therefore, we focus on the United Kingdom, where managers seem to be under performing (Bloom et al., 2007) and there is a relatively high level of ICT investment (DfIT, 2014). This paper does not fully examine the mechanisms through which technological change potentially alters skill levels amongst managers, leaving it for further research.

The structure of this chapter continues as follows. Section 3.3 describes the pooled cross-sectional dataset used for the analysis. The empirical framework is explained and justified in section 3.4. The results are presented in section 3.5, and section 3.6 offers some concluding remarks, including some possible topics for further research.

3.3 Data

The Skills and Employment Survey is a national study of people aged 20-65 who are in paid work. It collects data on what people do at work, what skills they use, and how they work (Feldstein et al., 2013; GfK, 2013). The key variables taken for the analysis are those measuring the importance of managerial tasks and technological change in the workplace. Five different managerial tasks are available for the years 2001, 2006 and 2012, and they measure the importance for managers of motivating staff, coaching staff, keeping close control over resources, making strategic decision about the future of the organisation, and developing the careers of staff[51]. All these variables are measured on Likert scales from 1 to 5, where 1 means that the task is not important at all, and 5 means that it is essential for the job. Even though these are clearly categorical variables, it can be argued that the scale (level of importance) is based on a latent continuous variable.

As a first step, we use a statistical method of data reduction to explore relationships between the managerial tasks available. The method is called Principal Component Factor Analysis (Jolliffe, 2002), which can reduce a large number of variables into a smaller number of factors/components, extracting the maximum variance from the dataset with each factor/component (Tabachnick and Fidell, 2007). The association between the original variables and the estimated factors is measured by factor loadings, which can be interpreted as

[51] Example of a question in SES is (GfK, 2013): 'In your job, how important is motivating the staff whom you manage or supervise?'.

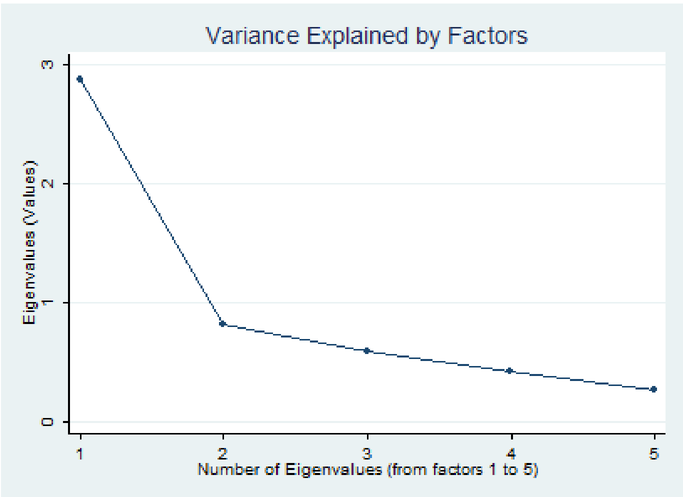
standardized regression coefficients[52]. We present the results of the factor analysis in the table below.

Table 3.1: Principal Component Factor Analysis 1. Finding the number of factors

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.876	2.056	0.575	0.575
Factor2	0.820	0.221	0.164	0.739
Factor3	0.599	0.170	0.120	0.859
Factor4	0.429	0.154	0.086	0.945
Factor5	0.275	.	0.055	1.000

Source: Skills and Employment Survey, 2012

Figure 3.1: Graphical depiction of eigenvalues (source: SES, 2012)



[52] Similar results are obtained with the principal factor and principal component factor analysis (Jollife, 2002). Here, the outcome obtained from Principal Component Factor Analysis is presented.

Table 3.1 shows the factors (i.e., components) and their eigenvalues, a measure of how much of the variance of managerial tasks is explained by a factor. The output shows that Factor 1 explains as much variance as 2.88 managerial tasks. Other eigenvalues are very small and do not capture the fundamental part of other managerial tasks. Therefore, Factor 1 is retained for the analysis. A graphical representation of the eigenvalues can be observed in Figure 3.1.

Table 3.2: Factor loadings (associations between the managerial tasks and factor 1).

Variable	Factor1	Uniqueness
Motivate	0.791	0.374
Control	0.704	0.505
Future	0.610	0.628
Career	0.817	0.332
Coach	0.846	0.284

Source: Skills and Employment Survey, 2012

However, upon reaching this point more distinctions can be made. The Principal Component Factor Analysis shows (see Factor 1 in Table 3.2) that there is a strong relationship between 'motivating staff', 'coaching', 'developing the careers of staff' and Factor 1. It is worth noting that they represent one dimension, which will be referred to as 'people management practices'[53]. Each of these variables, with a factor loading value above 0.79, has a high correlation with Factor 1[54]. On the other hand, the variables 'control over resources' and

[53] These tasks are related to social, communication and leadership skills. This dimension could also have been named 'Human Resource Management Practices' (HR). However, HR practices represent a broader concept and more items are needed for a more robust measure.

[54] Factor loading is a measure of the association between computed factors and the original variables.

‘strategic decisions about the future of the organisation’ have relatively high factor loadings, but also a higher level of uniqueness (variance not shared with other variables in Factor 1). Therefore, they seem to be different. ‘control over resources’ embodies an important administrative task, which is related to supervisory and accounting tasks, while ‘strategic decisions about the future of the organisation’ indicates more about the art of strategy, planning, and the general vision of business. These two variables are also relevant for the analysis and will represent ‘organisation management practices’[55] in this analysis.

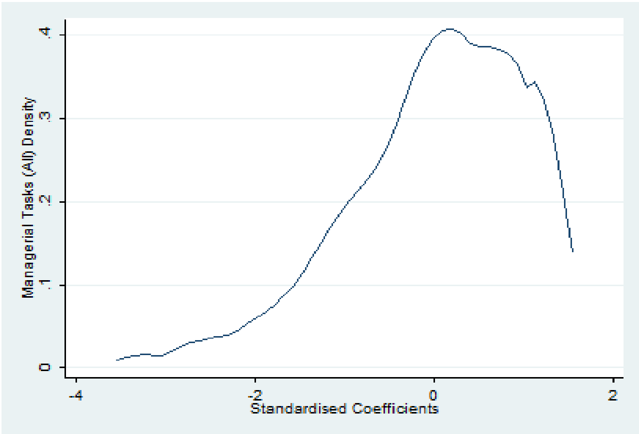
Consequently, for the econometric analysis we consider three dependent variables created with the Principal Component Factor Analysis technique. First, a composite measure considers all managerial tasks. This variable receives an Alpha Cronbach scale reliability coefficient of 0.8, which can be interpreted as very good internal consistency. In factor analysis, the values of the new variable ‘managerial tasks’ are computed as the predicted values of Factor 1, taking the information from the eigen-decomposition of the covariance matrix, and can be represented by the following multiple linear regression[56]:

$$\textit{All Manag. Tasks}_i = \alpha + \beta_1 \textit{Motivate}_i + \beta_2 \textit{Coaching}_i + \beta_3 \textit{Career}_i + \beta_4 \textit{Control}_i + \beta_5 \textit{Future}_i + \varepsilon_i$$

[55] An alternative name in the literature is ‘Operations Management Practices’.

[56] The first principal component is the linear combination of the variables that has maximum variance (amongst all linear combinations), so it accounts for as much variation in the data as possible. It takes its information (i.e., eigenvectors) from the first (largest) eigenvalue.

Figure 3.2: Managerial tasks density distribution (source: SES, 2012)



Second, following the same procedure, we create a variable that condenses the information of 'people management practices' ('motivating the staff', 'coaching', and 'developing career of the staff'). Again, only the first factor is retained. The Alpha Cronbach coefficient of internal consistency is of 0.82, which confirms the excellent coherence between variables.

$$People\ Management\ Practices_i = \alpha + \beta_1 Motivate_i + \beta_2 Coaching_i + \beta_3 Career_i + \varepsilon_i$$

And, finally, we create a new variable to represent 'organisation management practices'[57] (i.e., the first factor retained between 'control over resources' and 'strategic decision making'). The

[57] More details about how these variables were created (i.e., table with eigenvalues, factor loadings, and linear predictions) are available in the appendix.

Alpha Cronbach coefficient is of 0.56, which is acceptable considering that organisational practices have many facets[58].

$$\textit{Organisation Management Practices}_i = \alpha + \beta_1 \textit{Control}_i + \beta_2 \textit{Future}_i + \varepsilon_i$$

Two indicator variables are created to represent the introduction of new technologies (i.e., variables used as proxy measures for technological change). One variable corresponds to communication technologies and another to computerised equipment. These variables take value '1' if the technology was introduced in recent years, or '0' otherwise[59]. It is worth noting that current levels of management practices cannot affect past decisions about the introduction of new technologies at work (that took place 3-5 years before). Therefore, the introduction of technology in this scenario can be considered an exogenous variable, which reduces the chance of double causality.

In addition, several key explanatory variables are included as controls. Gender (dummy variable that takes value 1 or 0, if male or female, respectively); Experience at work (in years); Education (indicator variable equals 1 if the worker has a degree, and 0 if not); use of computers at work (dummy with value 1 if the worker uses a computer regularly at work); Socioeconomic

[58] A more robust measure of organisation management practices includes more items to represent the management of the entire production system. These variables, unfortunately, were not available in this data.

[59] Question wording in questionnaire: '(Section: your job 3-5 years ago), did any of the following changes occur at your workplace? 1) Introduction of new computerised or automated equipment; 2) Introduction of new communication technologies equipment; 3) Other new equipment was introduced.'

Categories based on the National Statistics Socio-Economic Classification[60] (ONS, 2010); Regions in the UK[61]; a set of 14 Industries[62]; and Time indicator variables for the years 2001, 2006 and 2012.

The analysis focuses on all those workers in managerial positions or who regularly perform managerial tasks at work. The total sample size in the Skills and Employment Survey is 6,272 workers. This group can be categorised as follow: 1,032 in higher managerial jobs, 2,992 in lower managerial positions and 2,248 in other positions, but also performing managerial tasks. Further details of the sample are displayed in Table 3.3, below.

---

[60] Higher managerial occupations include managers, employers in large establishments, administrative occupations, and higher professional occupations. Lower managerial occupations include lower professional and higher technical occupations, lower managerial, administrative occupations, and higher supervisory occupations. Intermediate occupations are clerical, sales, technical and auxiliary, as well as intermediate engineering occupations. Small employers are employers in small organisations, and own account workers. Lower supervisory occupations are lower technical craft and lower technical process operative occupations. Semi-routine occupations are sales, service, technical, operative, agricultural, clerical and childcare. Finally, routine occupations include sales and service, production, technical, operative and agriculture workers.

[61] North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scottish Lowlands, and Highlands and Islands.

[62] Agriculture, Mining, Manufacturing, Electricity, Construction, Wholesale, Hotels, Transport, Financial, Real Estate, Public Administration, Education, Health, and Other Services.

Table 3.3: Sample stratification by occupation. Pooled (raw data) sample

NS-SEC	Freq.	Percent	Cum.
Higher managerial	1,032	16.45	16.45
Lower managerial	2,992	47.7	64.16
Intermediate	399	6.36	70.52
Small employers	431	6.87	77.39
Lower supervisory	810	12.91	90.31
Semi-routine occupations	402	6.41	96.72
Routine occupations	206	3.28	100
Total	6,272	100	

Source: Skills and Employment Survey, 2012

3.4 Empirical framework

3.4.1 Ordinary Least Squares

The first approach to answering the question, 'Is technological change related to management practices?' is based on OLS estimations. The statistical relationship between key variables is explored using multiple regression models that describe how a single response variable y_i (i.e., predicted standardised value of managerial task) depends linearly on a set of predictor variables (i.e., the introduction of new technologies, and the control variables), X_i. The general OLS model can be mathematically summarised as follows:

[Equation 3.1]

$$\begin{aligned} \textit{Managerial Tasks}_i = \beta_0 + \beta_1 \textit{NewTech}_i + \beta_2 \textit{UsePC}_i + \beta_3 \textit{Male}_i + \beta_4 \textit{Experience}_i + \beta_5 \textit{ExperienceSq}_i + \\ \beta_6 \textit{Education}_i + \beta_7 \textit{Occupation}_i + \beta_8 \textit{Regions}_i + \beta_9 \textit{Industries}_i + \beta_{10} \textit{Year}_i + u_i \end{aligned}$$

The dependent variable 'Managerial Tasks' measures the level of importance of 'all managerial tasks', 'people management practices', or 'organisation management practices', while 'NewTech' represents the introduction of new technologies to the workplace (new communication technologies or new computerised equipment). Several multiple regression models are discussed using the three managerial tasks variables[63], and the two types of technologies. The full set of covariates[64] and the error term, *u,* complete the models.

The key parameter, β_1, that represents the relationship between managerial tasks and technological change, can be interpreted as the difference in average importance of managerial tasks between managers exposed and not exposed to new technologies at work, *ceteris paribus*[65].

3.4.2 Propensity Scores Matching

The objective here is to measure the effect of an intervention, the introduction of new technologies in the workplace. One problem that arises is that the allocation between workers exposed to technologies (participants), and those who were not exposed (non-participants) is not random, which means that the two groups are not fully comparable[66]. As a solution, participants could be matched to non-participants with the same observed characteristics. In doing so, the difference in the outcome variable (management practices) between the two

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63 'People management practices', 'organisation management practices', or 'all managerial tasks'.

64 'UsePC': dummy that takes value 1 if a computer is used at work, 0 otherwise; Male: indicator variable that equals 1 if male, and 0 otherwise; Experience: continuous variable (years of experience); 'Education': indicates whether the worker has a degree '1', or '0' if not; 'Occupation': categorical variable that distinguishes between different occupations; 'Region': categorical variable that includes geographical regions of the United Kingdom; 'Industries': categorical variables in which all 1-digit industries are included; 'Year': time dummies, where the reference group is the year 2006 (vs 2001, and vs 2012).

65 $\beta 1$ is the difference in expected values, when NewTech changes from 0 to 1: E(M.Task\NewTech = 1, *ceteris paribus*) - E(M.Task\NewTech = 0, *ceteris paribus*) = $\beta 1$.

66 Some workers will be more likely to participate in the intervention than other.

groups should only be due to the treatment status. However, with a large number of characteristics determining selection, it is difficult to find comparable individuals. Specifically, an enormous amount of information would be needed. Then, an alternative would be to match on a single index (i.e., the propensity score that summarises the relevant information contained in the list of covariates), which reflects the probability of participation. If this technique is properly implemented (i.e., considering relevant known and observed covariates), it could yield consistent estimates of the treatment effect in the same way as matching on all covariates.

Propensity Score Matching (PSM) is an econometric technique originally proposed by Rosenbaum and Rubin (1983). Its main purpose is to estimate the effect of an intervention (introduction of new technologies) by accounting for the covariates that predict receiving the treatment. Under certain circumstances, PSM could reduce bias due to confounding variables in the estimation of treatment effects with observational datasets.

The theory behind the Propensity Score Matching technique is described as follows[67]. Consider a binary treatment indicator (Rosebaum and Rubin, 1983; Angrist and Pischke, 2009; Imbens and Rubin, 2015),

$$D_i = \begin{cases} 1 \text{ if worker i is exposed to the new technology} \\ 0 \text{ if worker i is not exposed to the new technology} \end{cases}$$

[67] The model is also useful for explaining other techniques, such as Instrumental Variables. An example of this presentation in an IV context is Angrist (2004).

where $Y_i (D_i)$ is the potential outcome for individual *i*. In this model, a simple treatment effect would be:

$$\varsigma_i = Y_i (1) - Y_i (0)$$

However, this estimation suffers from the fundamental problem of causal inference, which is that only $Y_i (1)$ or $Y_i (0)$ is observed, but never both outcomes. A solution to this is to estimate the Average Treatment Effect on the Treated (ATET)[68], which puts more weight on those workers more likely to be treated.

$$ATET = E [\varsigma \mid D = 1] = E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1]$$

The Average Treatment Effect on the Treated is defined as the difference between expected outcome values with and without treatment for those who actually participate in treatment (Leuven and Sianesi, 2003). The first term of the formula ($E[Y(1) \mid D = 1]$) corresponds to the treatment group and the second ($E[Y(0) \mid D = 1]$) is the unobserved counterfactual. In the context of this research, the parameter of interest (Average Treatment Effect on the Treated) shows the average difference in managerial tasks scores between workers exposed to new

[68] Alternatively, we could have estimated the Average Treatment Effect, $E[Y(1) – Y(0)]$, or the Average Treatment Effect on the Untreated, $E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1]$. The former answer the question 'what is the expected effect of the outcome if individuals in the population were randomly assigned to treatment?', which includes unintended the effects on individuals. The latter is uninteresting because it represents treatment effects for the untreated subjects.

technologies and matched control individuals (i.e., with similar propensity scores when PSM is used).

The key assumptions of the Propensity Score Matching estimator are Conditional Independence and Common Support (Caliendo and Kopeinig, 2008).

The Conditional Independence Assumption (also known as selection on observables) says that there exists a set of observable and relevant covariates X, such that after controlling for these, the potential outcomes are independent of the treatment status. The Conditional Independence Assumption implies that after controlling for X, the assignment of units to treatment is 'as good as random'. This assumption requires that all variables relevant to the probability of receiving treatment may be observed and included in X, allowing the untreated units to be used to construct an unbiased counterfactual for the treatment group.

$$(Y(1),Y(0) \perp D \mid X$$

The Common Support assumption (also known as the overlap assumption) states that for each value of observable covariates X, there is a positive probability of being both treated and untreated. This implies that the probability of (not) receiving treatment for each possible value of the vector X is strictly within the unit interval. This assumption guarantees that there is sufficient overlap in the characteristics of treated and untreated units to find adequate matches (therefore, a comparison is made between similar individuals). In both groups, we expect to have individuals with similar propensity scores and, therefore, the matching process becomes feasible.

$$0 < \Pr(D = 1|X) < 1$$

Subsequently, the Propensity Score Matching technique attempts to replicate some features of randomisation, relying on two steps. First, the calculation of propensity scores that refer to the probability of participating in the 'intervention' (here, the exposition of new technologies) conditional on the characteristics, X*i*. The propensity score is computed as the conditional probability that a subject belongs to the treatment group, given the observed covariates X*i*, p(x) = Pr [D = 1 | X = x][69]. Second, the matching method is the technique used to find participants and non-participants with similar propensity scores. Thus, if the Conditional Independence Assumption holds, and assuming in addition that there is overlap between both groups, the PSM estimator for the Average Treatment Effect on the Treated can be written as follows (Caliendo et al., 2008):

$$\varsigma^{PSM\text{-}ATET} = E_{[P(X)|D=1]}\{E[Y(1)|D = 1,P(X)] - E[Y(0)|D = 0,P(X)]\} \quad \text{[Equation 3.2]}$$

That is, the PSM estimator computes the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

[69] In practice, the propensity scores are computed as the predicted values of a probit (or logit) model:
Propensity Score = $\hat{\Pr}(Di = 1 \setminus Xi) = \Phi(\hat{\alpha} + \hat{\rho}Xi)$.
Where Di = 1 represents the probability of receiving the treatment given the set of covariates, Xi represents all the explanatory variables, and Φ is the transformation function (cumulative density function of the standard normal distribution (cdf)) that maps the linear combination into [0 , 1] (Wooldridge, 2010).

3.5 Results

3.5.1 Descriptive statistics:

The rate of introduction of new technologies in the workplace is characterised in Table 3.4, and four key aspects are worth considering. First, the rate of introduction of technological change is substantial. For example, regarding the introduction of new computerised equipment 66.11%, 64.46%, and 56.95%, respectively reported having been exposed to this change at work in the years 2001, 2006 and 2012. Secondly, the proportion of managers exposed to technological change is larger than the proportion not exposed to it in every year, and this is valid for both technologies investigated. Considering the pooled sample, we test the equality of proportions between workers exposed and not exposed to a new technology and reject the null hypothesis[70] in both cases. For new computerised equipment, the one sample test shows a z-statistic of 17.00, while for new communication technologies the z-value is 11.63. Third, the rate of introduction decreases over time. These changes are statistically significant at the 99% confidence level for the period 2001-2012 (the test of proportions calculates a z-value of 4.03 for 'new computerised equipment', and 4.08 for 'new communication technologies'). Fourth, the overall introduction of new computerised equipment has been slightly more frequent than that of new communication technology, which could reflect the needs of firms at every point in time. Testing on the equality of proportions, we obtain a z-value of 3.89, with which the null hypothesis is rejected at the 99% level of confidence.

[70] H_0: Workers exposed and not exposed to new technologies are in the same proportions (0.5). Weights are used to work with a representative sample.

Table 3.4: Rate of introduction of technologies in the workplace in the years 2001, 2006 and 2012

Year	New Computerised Equipment			New Communication Technology		
	No	Yes	Total	No	Yes	Total
2001	33.89	66.11	100	36.94	63.06	100
2006	35.54	64.46	100	40.63	59.37	100
2012	43.05	56.95	100	46.33	53.67	100
Pooled sample	36.67	63.33	100	40.87	59.13	100

Source: Skills and Employment Survey, 2012

Table 3.5: The average importance of managerial tasks by occupation and year. Each score represents the average importance of the task at work, using the original scale from 1 to 5, where 5 and 1 mean 'essential' and 'not important', respectively

	The Importance of Managerial Tasks			
Occupation	2001	2006	2012	Average
Higher Managerial	3.87	3.83	3.85	3.85
Lower Managerial	3.69	3.93	3.79	3.82
Other[71]	3.49	3.6	3.56	3.55

Source: Skills and Employment Survey, 2012

[71] The higher managerial category includes managers, employers in large establishments, administrative occupations, and higher professional occupations. Lower managerial occupations include lower professional and higher technical occupations, lower managerial, administrative, and higher supervisory occupations. Intermediate occupations, smaller employers, lower supervisory, semi-routine occupations, and routine occupations.

Table 3.5 shows how the role of managers fluctuates on average across years. As expected, managers in higher and lower positions ascribe more importance to managerial tasks than other workers in lower-ranked positions who are also performing managerial tasks. These differences are tested using the pooled sample, revealing statistically significant differences between higher managerial jobs and other occupations (excluding lower managerial jobs) exhibit a t-test of 8.55. Furthermore, differences between lower managerial jobs and other occupations (excluding higher managerial jobs) with a t-test of 8.55. However, no significant differences between higher managerial and lower managerial jobs were apparent, with a t-test 0.78.

There are different types of managerial tasks and they behave in slightly different ways (see Table 3.6). Comparing (testing) average levels of managerial tasks between higher managerial and lower managerial jobs, we find that there is no significant difference in ‘people management practices’ (t-value 1.46), ‘organisation management practices’ (t-value 1.88), and in ‘all managerial tasks’ (t-value 0.23), with at least a 95% confidence level. However, if any of these groups (higher or lower managerial positions) are compared with the reference group ‘other’ (i.e., workers in other positions that also perform managerial duties), we find statistically significant differences at the 99% level of confidence (the smallest t-value is of 6.18, when comparing the average level of people management practices between the groups ‘higher managerial’ and ‘other’). These results suggest that, first, notably higher managerial and lower managerial workers split responsibilities associated with managerial tasks, and secondly that some tasks are used more frequently than others, in accordance with different types of positions.

Table 3.6: The importance of different tasks by occupation. Each score uses the original scale from 1 to 5, where 5 and 1 mean 'essential' and 'not important' to the job, respectively

	The Importance of Managerial Tasks		
Occupation	People	Organisation	All
Higher Managerial	3.93	3.65	3.79
Lower Managerial	3.97	3.55	3.76
Other	3.71	3.34	3.53

Source: Skills and Employment Survey, 2012

Table 3.7: The importance of management practices in the context of technological change. The scores presented in the table below use the original scale 1 - 5, where 5 and 1 denote 'essential' and 'not important', respectively

		The Importance of Managerial Tasks		
		People	Organisation	All
New computerised equipment	No	3.79	3.45	3.67
	Yes	3.93	3.53	3.79
New communication technology	No	3.78	3.43	3.65
	Yes	3.95	3.55	3.81

Source: Skills and Employment Survey, 2012

Table 3.7 displays the differences in means between workers exposed and not exposed to technological change and considering all different tasks. We find that new communication technologies always make a difference with respect to the average level of importance of ‘people’, ‘organisation’, and ‘all management practices’. These variables are, on average, statistically significant at the 99% confidence level, comparing the group exposed to technological change with the group not exposed to it. Additional test statistics suggest that new computerised equipment is positively associated with ‘organisation’, and ‘people management practices’ too[72]. However, the t-values tend to be lower[73]. To expand on this result, we continue with the econometric analysis.

[72] All these t-values ranking between 2.5 and 5.

[73] For instance, the t-test values of the difference in means (tasks) amongst those workers exposed to new communication technologies, and new computerised equipment, are equal to 3.63 and 2.34, respectively.

3.5.2 Econometric analysis:

3.5.2.1 OLS estimations

The econometric analysis explores the linkages between the importance (role) of managerial tasks and technological change[74] in the workplace. Table 3.8 presents the OLS estimations based on equation 3.1, where the dependent variable corresponds to a standardised measure of the managerial tasks (all, people, or organisation management practices), previously computed using the Principal Component Factor Analysis technique. The coefficients in this table represent marginal effects. The introduction of new communication technologies (CT) is positively associated with 'people management practices' (.102) and 'organisation management practices' (0.06) too, all else being held constant. These results are statistically significant at the 99% confidence level. However, the magnitude of the association differs. In this sense, it is possible to state that the association between this type of technology is stronger when we consider people management tasks, which is consistent with the initial hypothesis. On the other hand, the statistical association between new computerised equipment (columns 4-6) and managerial tasks is also positive, but the coefficients shrink, and in all cases the level of significance associated with people / organisation management tasks decreases.

In addition, controlling for a set of covariates, it is found that the use of computerised equipment (Use PC) is positively and significantly associated with all managerial tasks; males

[74] Models 1-3 explore the association between new communication technologies and managerial tasks, and models 4-6 investigate the link between new computerised equipment and the same tasks.

(compared to females) are strongly associated to ‘organisation management practices’; ‘Experience’ showing a modest, but significant, positive association with all tasks; ‘Higher managerial positions’ more positively associated with ‘organisation tasks’ (compared with the reference group other[75]), and ‘lower managerial positions’ showing higher levels of ‘people’ and ‘organisation tasks’ compared to the reference group. In addition, we control for a full set of industries, and regions, and include time dummies to complete the models.

Table 3.8: Managerial task functions. OLS estimations

	OLS Estimations					
	All	People	Organisation	All	People	Organisation
	(1)	(2)	(3)	(4)	(5)	(6)
New CT	0.111***	0.102***	0.061**			
	(0.034)	(0.030)	(0.027)			
New CE				0.080**	0.073**	0.044*
				(0.031)	(0.031)	(0.023)
Computer Use	0.230***	0.172***	0.218***	0.238***	0.180***	0.222***
	(0.034)	(0.028)	(0.052)	(0.034)	(0.026)	(0.052)
Male	0.062*	-0.027	0.213***	0.068**	-0.022	0.217***
	(0.029)	(0.029)	(0.038)	(0.027)	(0.027)	(0.038)
Experience[76]	0.019**	0.015**	0.016*	0.019**	0.016**	0.017*
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)	(0.009)
Higher Managerial	0.276***	0.185***	0.296***	0.284***	0.192***	0.300***
	(0.060)	(0.032)	(0.094)	(0.060)	(0.033)	(0.093)
Lower Managerial	0.279***	0.217***	0.239***	0.284***	0.221***	0.242***
	(0.047)	(0.045)	(0.052)	(0.047)	(0.045)	(0.052)
Industries	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.055	0.046	0.065	0.053	0.045	0.065
(N = 4008)						

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills and Employment Survey, 2012

[75] Workers performing managerial duties, but without a Higher or Lower Managerial Position. For example, they can be small employers, or workers in intermediate positions.

[76] “Experience squared” has been omitted in the table. The coefficient is close to zero, and statistically not significant.

3.5.2.2 Propensity Score Matching estimations

Matching attempts to replicate experimental conditions, when the Conditional Independence Assumption holds[77], by ensuring that all determinants of outcomes (other than treatment status) are similar between the treated group and its matched controls. The benefit of using the Propensity Score Matching technique compared to the Ordinary Least Squares estimation is that, with matching based on similar propensity scores, more weight is placed on those most likely to be treated. This section, first, evaluates the key assumptions underlying the estimation, and then presents the PSM results.

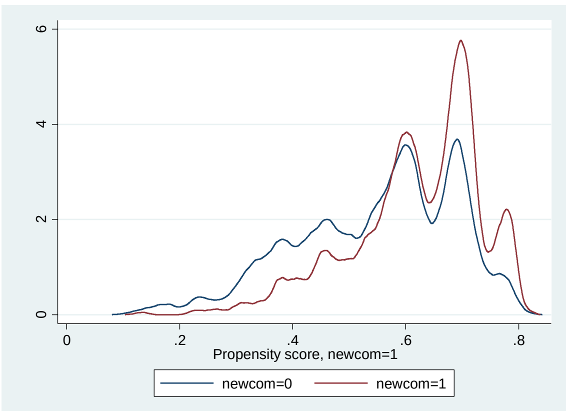
First, regarding the 'selection on observables', we use a set of relevant covariates to estimate the propensity scores. The same set of variables is used to estimate the Average Treatment Effect on the Treated (ATET). The full list of covariates includes gender, work experience (and its squared term), level of education, computer use, occupations based on the National Statistics Socio-Economic Classification, geographical regions of the United Kingdom, a full set of 15 industries in the UK, and time dummies for the years 2001 and 2012, where the reference year is 2006. All these variables have the potential to significantly affect the probability of treatment and the outcome of the model as well. It is worth noting that the results rely on the Conditional Independence Assumption to hold, which would be the case if the control variable fully captures all potential confounders.

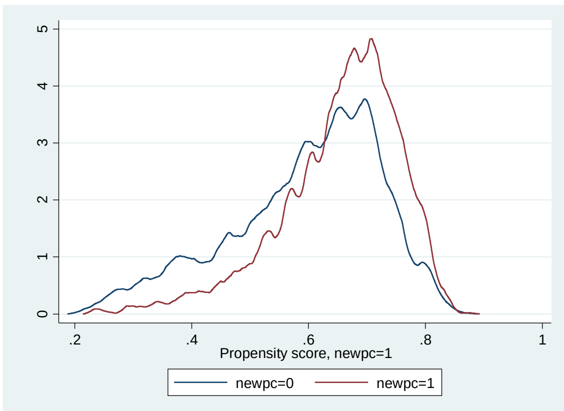
Secondly, regarding the assumption of Common Support, graphical analysis is used to test it. The overlap assumption is satisfied when there is a chance of seeing observations in both the

[77] This is difficult to achieve in practice.

control and treatment groups at each combination of the covariate values. Additionally, the overlap assumption is violated when an estimated density has too much mass around 0 or 1 (Busso et al., 2011). Graphs 3.3 and 3.4 below display the estimated density of the predicted probabilities that a manager not exposed to technical change is exposed to it and the estimated density of the predicted probabilities that a manager exposed to technical change is exposed to it. Neither plot indicates much probability mass near 0 or 1, and the two estimated densities have most of their respective masses in regions in which they overlap one another. Furthermore, the expected propensity scores tend to be higher for the treated than the controls. In this data, the probability of receiving the treatment is higher amongst male workers, higher educated, computer users, which tends to correlate highly with managerial and intermediate occupations. This should not be a major concern, given that the largest overlap is still in the middle-right side of the distribution. Thus, this reassures that there may be sufficient common support.

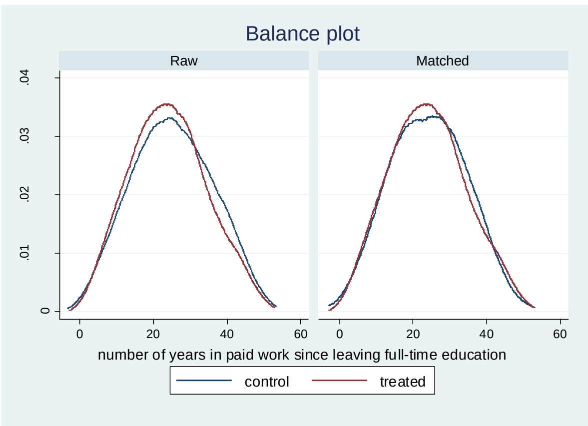
Figures 3.3 and 3.4: Propensity score histograms (estimated densities of the predicted probabilities) by treatment status. Introduction of new communication technologies (left), and new computerised equipment (right). Source: SES (2012).

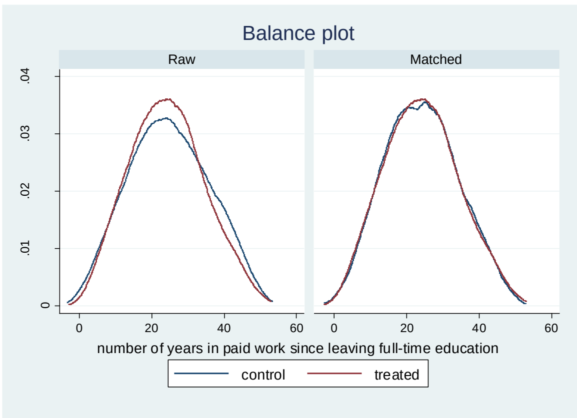




Additionally, the post-match balance tests provide information on how well matching has 'replicated' the experimental benchmark. The density plots for both matched samples are nearly indistinguishable, implying that matching on the estimated propensity score balanced the covariates (Figures 3.5 and 3.6). Performing the balance test, it can be observed that all covariates are balanced. We do not reject the null hypothesis of no differences between the two groups in all cases (p-values are larger than 0.05, and t-values are larger than critical values at the 95% confidence level). Furthermore, the R-squared statistics associated with this test are close to zero (0.001 and 0.002), which suggests no role for the covariates in explaining the differences between the treated and control groups. Moreover, the Likelihood Ratio Chi-squared test statistics are not significant (8.54 and 15.39). Therefore, again we do not reject the hypothesis of balance across matched samples[78].

Figures 3.5 and 3.6: Density plots for the matched samples. New computerised equipment (left) and new communication technologies (right). Source: SES (2012).





[78] Tables are included with all the relevant statistics, for all covariates, in the appendix.

Propensity Score Matching balance[79] has been achieved across matched samples using: (1) matching with replacement; (2) reducing the distance (caliper) between the propensity scores of the treated and controls from 0.02 to 0.01; (3) increasing the nearest neighbour to 10[80] and; (4) limiting the analysis to regions of common support. With these specifications, we increased the balance, and the difference between the matched samples has decreased. The control groups consist of 1,645 observations for new communication, and 1,477 for new computerised equipment, which can be considered reliable numbers.

Table 3.9: Managerial tasks functions. Propensity Score Matching estimations

Treatment	Outcome	Treated	Controls	Difference (ATET)	S.E.	T-Stat
New Communication Technologies	All	0.082	-0.013	0.095	0.037	2.58
	People	0.073	-0.013	0.086	0.033	2.64
	Organisation	0.050	-0.007	0.056	0.037	1.52
New Computerised Equipment	All	0.059	-0.008	0.067	0.038	1.75
	People	0.055	-0.002	0.057	0.034	1.67
	Organisation	0.031	-0.017	0.048	0.038	1.26

Source: Skills and Employment Survey, 2012 / N = 3,986 observations on support

[79] Alternatively, other matching methods that can be used are Mahalanobis distance matching or Coarsened Exact Matching (King et al, 2011).

[80] Nearest neighbour refers to the number of observations of the control group than can be compared with 1 observation from the treated group.

Table 3.9 shows the Average Treatment Effects (ATET) estimated by Propensity Score Matching. The PSM-ATET estimator based on equation 3.2 computes the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants[81]. In the first model, the dependent variable is 'managerial tasks' (all tasks), in the second 'people management practices', and in the third 'organisation management practices'. The introduction of new technologies is called 'treatment' in the PSM framework, and the same dependent and control variables as in previous models are included[82].

First, we analyse the introduction of new communication technologies. Table 3.9 shows a positive link between the composite measure of managerial tasks (all) and the introduction of new communication technologies. This is in line with the OLS estimation presented in Table 3.8. Furthermore, 'new communication technologies' are positively associated to 'People Management Practices' (0.086 score difference), which is significant at the 99% confidence level and consistent with the OLS estimation too. However, a more robust measure of organisation management practices after the introduction of communication technologies is not observed (the t-statistic in this case is only 1.52, much lower than 1.96 that is expected at the 95% confidence level). In general, it is worth noting that Propensity Score Matching estimates are smaller than those obtained by OLS, as a result of an improved balance amongst the groups compared.

[81] This estimation is possible because if each treated individual is matched to one or more control individuals (i.e., comparing workers with similar propensity scores).

[82] The model estimated includes a vector of observed variables (gender, experience, education, regions, industries, and occupations) that is used to predict the probability of experiencing the event, such as exposure to new technologies at work, and also to create a counterfactual group.

Now, considering the introduction of new computerised equipment as the treatment, we observe that the magnitude of the coefficients is similar to those found in OLS estimations. However, the level of significance has decreased in all cases, and so it is not possible to state that the introduction of this technology is positively associated with more robust management in the workplace.

The OLS and PSM estimations confirm that the technology purpose, and the way the technology operates (e.g., centred on social aspects of work) play an important role in the workplace. This is in line with previous research conducted by Black and Lynch (2001)[83]. Hence, if ICT capital investment is centred on interactions with employees, it will likely promote people management practices, but not organisation tasks. This is our most consistent result, and ultimately suggests that ICT capital investments are not always correlated with intangible capital.

[83] They found that the way of implementing technology in the workplace is relevant.

3.6 Conclusions

This chapter explored the link between the introduction of new technologies (a proxy for technological change) and the importance of managerial tasks in the workplace.

Using OLS and Propensity Score Matching estimations we consistently found a positive and significant association between new communication technologies and ‘people management practices’. This result is good news for companies and CEOs in the United Kingdom. Communication technologies are relatively cheap, and now ubiquitous, which means opportunities for improved management if the technology is successfully implemented. This represents a practical way to foster the production of intangible capital from ICT capital investment, and also better management practices in the United Kingdom.

On the other hand, using propensity score matching estimations, no statistically significant associations between communication technologies and ‘organisation management practices’ were verified. This suggests that managers must carefully consider the type of technology to be implemented, which must share some characteristics with the predominant type of management.

Furthermore, the Propensity Score Matching estimation shows that there is no clear association between the introduction of new computerised equipment and machines and the role of managerial tasks at the workplace. A plausible interpretation is that computers and machines have become a necessity, and are therefore not strongly related to higher-order skills.

This chapter aims to contribute to the relatively unexplored area of the economics of management and productivity. The results complement previous findings at the macro level by Corrado et al. (2017) and further research at the micro level could consider co-investments in training and organisational change, given that the link between ICT adoption, intangible capital, and productivity growth is complex (Bresnahan et al., 2002).

3.7 Appendix

A. Data

Table A3.1 Detailed description of variables

Variable	Description
Motivate	Importance for managers / supervisors of motivating the staff (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Control	Importance of keeping close control over resources (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Future	Importance of making strategic decisions about the future of the organisation (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Career	Importance for managers / supervisors of developing the careers of the staff (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Coach	Importance for managers / supervisors of coaching the staff (1: not at all important, 2: not very important, 3: fairly important, 4: very important, 5: essential)
Factor All	Factor (standardised coefficients) that considers all managerial tasks
Factor 'People Management Practices'	Factor (standardised coefficients) that considers variables motivate, coach and career
Factor 'Organisation Management Practices'	Factor (standardised coefficients) that considers variables future, and control
NewCom	Introduction of New Communications Technologies (indicator of technological change)
NewCE	Introduction of New Computerised Equipment and Machines (indicator of technological change)
Computer Use	1 if respondent use computers at work, 0 otherwise
Manager	1 if respondent is a manager, 0 otherwise
Supervisor	1 if respondent is a supervisor, 0 otherwise
Male	1 if respondent is male, 0 if female
Experience	Number of years in paid work since leaving fulltime education
Experience Squared	Number of years in paid work since leaving fulltime education squared
Higher managerial	1 if respondent is in a higher managerial occupation, 0 otherwise
Lower managerial	1 if respondent is in a lower managerial occupation, 0 otherwise
Intermediate	1 if respondent is in an intermediate occupation, 0 otherwise
Small employers	1 if respondent is a small employer, 0 otherwise
Lower supervisory	1 if respondent is in a lower supervisory occupation, 0 otherwise
Semi-routine occupations	1 if respondent is in a routine occupation, 0 otherwise
Routine occupations	1 if respondent is in a routine occupation, 0 otherwise
North East	1 if respondent resides in North East, 0 otherwise
North West	1 if respondent resides in North West, 0 otherwise
Yorkshire and the Humber	1 if respondent resides in Yorkshire and the Humber, 0 otherwise
East Midlands	1 if respondent resides in East Midlands, 0 otherwise
West Midlands	1 if respondent resides in West Midlands, 0 otherwise
East of England	1 if respondent resides in East of England, 0 otherwise
London	1 if respondent resides in London, 0 otherwise
South East	1 if respondent resides in South East, 0 otherwise
South West	1 if respondent resides in South West, 0 otherwise
Wales	1 if respondent resides in Wales, 0 otherwise
Scottish Lowlands	1 if respondent resides in Scottish Lowlands, 0 otherwise
Highlands and Islands	1 if respondent resides in Highlands and Islands, 0 otherwise
Northern Ireland	1 if respondent resides in Northern Ireland, 0 otherwise
Time Dummies	1 if year 2001, 2 if year 2006 (baseline category), and 3 if year 2012.
Agriculture, Forestry, and Fishing	1 if respondent works in this industry Agriculture, Forestry, and Fishing, 0 otherwise
Mining and Quarrying	1 if respondent works in this industry Mining and Quarrying, 0 otherwise
Manufacturing	1 if respondent works in this industry Food products, Beverages, and Tobacco, 0 otherwise
Electricity, Gas and Water Supply	1 if respondent works in this industry Electricity, Gas, and Water Supply, 0 otherwise
Construction (baseline category)	1 if respondent works in this industry Construction, 0 otherwise
Wholesale and retail	1 if respondent works in this industry Wholesale and retail of motor vehicles and motorcycles, 0 otherwise
Transport and storage	1 if respondent works in this industry Transport and storage, 0 otherwise
Accommodation and Food Services Activities	1 if respondent works in this industry Accommodation and Food Services, 0 otherwise
Financial and Insurance Activities	1 if respondent works in this industry Financial and Insurance Services, 0 otherwise
Real Estate Activities	1 if respondent works in this industry Real Estate Activities, 0 otherwise
Public administration and defence; compulsory social security	1 if respondent works in this industry Public Administration, defence, social security, 0 otherwise

Table A3.1 continued:

Education	1 if respondent works in this industry Education, 0 otherwise
Health and social work	1 if respondent works in this industry Health and Social Work, 0 otherwise
Other service activities	1 if respondent works in this industry Other Services Activities, 0 otherwise

Source: Skills and Employment Survey 2012

B. Principal Component Factor Analysis (PCA)

Table A3.2: Principal Component Factor Analysis 2. Generating variable ‘people management practices’

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.242	1.766	0.747	0.747
Factor2	0.475	0.192	0.158	0.906
Factor3	0.283	.	0.094	1.000

Source: Skills and Employment Survey 2012

Table A3.2 shows how we create the variable ‘people management tasks’ departing from the original variables ‘motivating the staff’, ‘coaching’, and ‘developing the careers of the staff’. The eigenvalue greater than 1 confirms that only one factor must be retained (see column Eigenvalue).

Table A3.3: Factor loadings (association between 'motivating the staff', 'coaching', and 'developing careers of the staff' and factor 'people management tasks')

Variable	Factor1	Uniqueness
Motivate	0.848	0.281
Coach	0.906	0.180
Career	0.838	0.298

Source: Skills and Employment Survey 2012

Table A3.3 above shows excellent correlations amongst 'people management' variables. The factor captures this, which is directly related to the low levels of uniqueness.

Table A3.4: Principal Component Factor Analysis 3. Generating variable 'organisation management practices' of managers

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.409	0.817	0.704	0.704
Factor2	0.591	.	0.296	1.000

Source: Skills and Employment Survey 2012

The new variable 'organisation management tasks' uses the information of 'control over resources' and 'strategic decision about the future of the organisation'. As a method of data reduction, factor analysis is effective in this case because only one factor (with an eigenvalue greater than 1) explains the co-variance between the two variables.

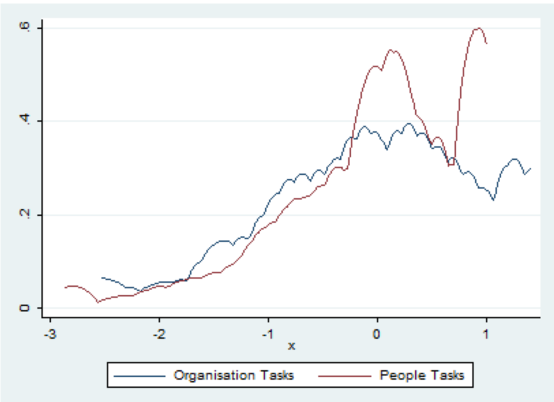
Table A3.5: Factor loadings (association between 'control over resources', 'strategic decisions about the future of the organisation' and created factor 'organisation management tasks')

Variable	Factor1	Uniqueness
Control	0.8393	0.2956
Future	0.8393	0.2956

Source: Skills and Employment Survey 2012

The new 'organisation management tasks' variable has strong correlations with the original variables and the level of uniqueness is low, as expected.

Figure A3.1: Predicted values of 'people management tasks' and 'organisation management tasks' (standardised coefficients). Source: SES 2012



The standardised values for People and Organisation tasks have a mean of zero, and standards deviation of 1. As expected, the density of the two variables differs (they represent different dimensions), as is shown in Figure A3.1

C. Propensity Score Matching

The Propensity Score Matching general procedure (Stata Corp, 2013; Baum, 2013) adapted for this analysis can be described as follows: first, the propensity scores were estimated, which refers to the predicted probabilities associated with the treatment, running a probit or logistic regression. The dependent variable (‘treatment’ in this case) can take two values: Y(1), if participating, or Y(0), otherwise. Choosing appropriate confounders (variables hypothesized to be associated with both the treatment and outcome) is key for the estimation. Second, we ensure that the propensity scores are balanced across treatment and comparison groups and that the set of covariates is balanced across treatment and the counterfactual. Third, a matching algorithm that uses the estimated propensity scores to match untreated units to treated units was selected. The nearest neighbour was chosen whose matching is equal to 10, decreasing the caliper matching limit to 0.01, and limiting the estimation to the area of common support. Given these specifications, the covariates are balanced across treatment and comparison groups in the matched sample. Finally, the econometric analysis is based on the new sample, with the t-statistics associated to the Average Treatment Effect on the Treated observed.

Table A3.6: Extent of balancing of the variables between the two matched groups. Treatment: Introduction of new communication technologies

Variable	Treated	Control	%bias	t	p>t
Use PC	0.794	0.793	0.100	0.020	0.983
Male	0.581	0.578	0.400	0.150	0.878
Experience	24.083	24.076	0.100	0.020	0.982
Experience Squared	681.920	680.880	0.200	0.070	0.945
Degree	0.517	0.522	-0.900	-0.320	0.751
Higher Managerial	0.179	0.179	-0.200	-0.070	0.941
Lower Managerial	0.516	0.517	-0.200	-0.060	0.951
Intermediate	0.082	0.081	0.500	0.150	0.884
Small Employers	0.051	0.047	1.300	0.570	0.569
Lower Supervisory	0.103	0.105	-0.800	-0.290	0.773
North West	0.091	0.094	-0.900	-0.300	0.767
Yorkshire and the Humber	0.075	0.067	2.900	1.030	0.301
East Midlands	0.103	0.099	1.200	0.410	0.681
West Midlands	0.071	0.069	0.800	0.290	0.770
East of England	0.086	0.089	-1.300	-0.410	0.679
London	0.070	0.075	-1.600	-0.530	0.596
South East	0.130	0.130	0.000	0.000	0.999
South West	0.065	0.064	0.500	0.170	0.863
Wales	0.065	0.067	-0.900	-0.340	0.736
Scottish Lowlands	0.138	0.131	2.100	0.720	0.471
Highlands and Islands	0.032	0.039	-3.700	-1.330	0.184
Northern Ireland	0.038	0.038	0.300	0.110	0.910
Mining	0.005	0.004	1.100	0.410	0.685
Manufacturing	0.147	0.149	-0.700	-0.230	0.818
Electricity	0.008	0.008	-0.100	-0.050	0.960
Construction	0.048	0.046	1.000	0.400	0.689
Wholesale	0.111	0.118	-2.100	-0.740	0.459
Hotels	0.014	0.012	1.200	0.640	0.521
Transport	0.051	0.046	2.100	0.710	0.476
Financial	0.040	0.041	-0.800	-0.230	0.819
Real Estate	0.115	0.115	0.100	0.030	0.974
Public Administration	0.122	0.122	0.000	0.010	0.994
Education	0.126	0.129	-0.800	-0.260	0.793

Table A3.6 continued:

Health	0.160	0.162	-0.600	-0.210	0.830
Other services	0.042	0.038	2.000	0.750	0.454
Year 2012	0.191	0.195	-1.000	-0.360	0.722
Year 2001	0.261	0.250	2.500	0.840	0.398

Source: Skills and Employment Survey 2012

Table A3.6 shows how the treated and control groups differ after using propensity scores. It is worth noting that in all cases we do not reject the null hypothesis of balance across samples.

Table A3.7: Extent of balancing of the variables between the two matched groups. Treatment: Introduction of new computerised equipment

Variable	Treated	Control	%bias	t	p>t
Use PC	0.779	0.783	-0.9	-0.37	0.714
Male	0.559	0.571	-2.5	-0.9	0.367
Experience	23.951	24.000	-0.5	-0.17	0.866
Experience Squared	678.100	680.090	-0.4	-0.14	0.891
Degree	0.502	0.514	-2.3	-0.82	0.411
Higher Managerial	0.159	0.169	-2.8	-0.98	0.328
Lower Managerial	0.519	0.523	-0.9	-0.31	0.755
Intermediate	0.079	0.079	-0.2	-0.06	0.954
Small Employers	0.052	0.049	1.2	0.55	0.583
Lower Supervisory	0.110	0.103	2	0.79	0.432
North West	0.090	0.097	-2.3	-0.82	0.415
Yorkshire and the Humber	0.074	0.064	3.8	1.43	0.154
East Midlands	0.106	0.109	-1	-0.34	0.735
West Midlands	0.071	0.070	0.2	0.06	0.952
East of England	0.089	0.095	-2.3	-0.75	0.454
London	0.068	0.068	0.2	0.07	0.942
South East	0.128	0.124	1.2	0.42	0.675
South West	0.064	0.062	0.7	0.25	0.799
Wales	0.070	0.075	-1.9	-0.71	0.48

Table A3.7 continued:

Scottish Lowlands	0.137	0.135	0.5	0.16	0.87
Highlands and Islands	0.033	0.034	-0.4	-0.14	0.886
Northern Ireland	0.035	0.036	-0.2	-0.08	0.935
Mining	0.004	0.005	-0.3	-0.13	0.899
Manufacturing	0.147	0.158	-3.1	-1.08	0.279
Electricity	0.008	0.007	0.6	0.23	0.821
Construction	0.040	0.039	0.3	0.14	0.886
Wholesale	0.123	0.132	-2.8	-0.96	0.337
Hotels	0.019	0.017	1.1	0.52	0.602
Transport	0.048	0.047	0.4	0.15	0.879
Financial	0.037	0.038	-0.3	-0.11	0.912
Real Estate	0.102	0.108	-1.7	-0.63	0.529
Public Administration	0.119	0.117	0.4	0.14	0.885
Education	0.131	0.119	4	1.29	0.197
Health	0.167	0.164	1	0.34	0.731
Other services	0.041	0.038	1.7	0.68	0.494
Year 2012	0.187	0.188	-0.1	-0.02	0.981
Year 2001	0.263	0.249	3.1	1.11	0.269

Source: Skills and Employment Survey 2012

In Table A3.7 (case: introduction of new computerised equipment) we observe that all covariates are balanced. We do not reject the null hypothesis of no differences between the two groups in all cases (p-values larger than 0.05, and t-values larger than the critical values at 95% confidence level).

Furthermore, the R-squared statistics associated with Tables A3.6 and A3.7 are close to zero (0.001 and 0.002), which suggests no role for the covariates in explaining differences between the treated and control groups, and the Likelihood Ratio Chi-squared tests statistics are not significant (8.69 and 15.39, respectively). Thus, we do not reject the null hypothesis of balance across matched samples.

CHAPTER 4: COMPUTER-BASED NUMERACY TASKS AND EARNINGS IN ENGLAND

4.1 Abstract

This chapter continues to explore the link between ICT and economic indicators. It addresses the association between computer-based numeracy tasks (e.g. the use of spreadsheets and databases) and earnings. The data are taken from the Skills for Life Survey 2011 (BIS, 2012), which contains detailed information about computer use, computer use intensity, computer tasks, and ICT skills in England. The variable 'earnings', which is key to the analysis, is measured in bands (interval-censored coded) in the dataset. Therefore, interval censored regressions are used to explore the association between ICT numeracy tasks and wages. The variable 'computer-based numeracy tasks' is endogenous due to unobserved heterogeneity. Thus, we address endogeneity with an instrumental variable approach, estimated via the control function and maximum likelihood procedures, utilising an actual measure of the ability to perform numeracy tasks on a computer as the instrument. The econometric analysis is presented for the population of England and also for the sub-group of managers. The analysis suggests that computer-based numeracy tasks, and no other computer tasks, are positively and significantly linked to income, and that their use significantly increases the probability of reaching the highest quintile of the income distribution.

Key words: Computer use, computer tasks, ICT numeracy tasks, ICT numeracy skills, earnings functions, instrumental variable, and interval regression analysis.

4.2 Introduction

This chapter continues to explore the role of Information and Communications Technologies (ICTs) in the workplace, focusing again on managerial occupations. The diffusion of ICTs is an important characteristic of modern labour markets. Hardware, software, the internet, and connectivity have become popular terms in the last decades, and as will be seen below, much academic research has been conducted in this area.

The link between ICTs[84] and economic performance, notably promoted by Solow (1957) in the field of economics, has been studied from both macro and micro perspectives and using different methodologies, such as growth accounting[85] and econometric models.

From a macro perspective, estimates of the impact on economic growth suggest that about 20% of GDP growth can be attributed to ICTs (Van Ark and O'Mahony, 2016). More precisely, using growth accounting methodology, the estimated contribution to labour productivity growth from ICT capital in the US is 0.4 percentage points, and 0.3 percentage points in the European Union for the period 2008-2014 (Van Ark and O'Mahony, 2016). With a similar methodology, Timmer et al. (2010) found a positive effect for the period 1995-2005 in the US, but the evidence for Europe was less clear-cut due to heterogeneity across countries. Empirical

[84] ICTs are usually represented by proxies, such as investments in hardware, software or broadband connectivity, for instance.

[85] Growth accounting is a dynamic approach that tries to capture the contributions of different types of assets to output or labour productivity growth. This is usually calculated using aggregate data at the country or industry level. Examples of growth accounting studies include Jorgenson and Stiroh, 2000, Oliner and Sichel, 2000, and Barro, 1999.

studies -for instance, O'Mahony and Vecchi (2005) in the context of estimating a production function using industry data for the US and the UK- find even larger impacts, suggesting excess returns to ICT on output growth. There is a vast list of studies reasserting or adding to earlier contributions, including Oliner and Sichel (2000), Crepon and Heckel (2002), Van Ark et al. (2002), and Qiang et al., (2009).

From a micro perspective, a series of studies have mostly focused on the returns to computerisation, and the results are not conclusive[86]. Some economists have found positive effects of computer use on earnings using cross-sectional data. Notably, Krueger (1993), using data from the United States, concluded that computer users earned a 15–20% wage premium over non-users during the 1980s. Autor et al. (1998), analysing the same data, found a positive effect of close to 20%. In Britain, Borghans and ter Weel (2001), examining the Skills Survey, found a 17-21% wage premium, with Arabsheibanin et al. (2004) also reporting similar returns, and Dolton and Makepeace (2004) finding a 10-13% wage premium as well (but, OLS estimates decreased after controlling for more variables)[87]. Dolton et al. (2007 and 2008) also investigate what workers use a computer for and their frequency of use, finding that there are clear returns to computer use intensity, and the use of e-mail and the Internet. However, this is far from being the whole picture, and the direct link between computer use and earnings (as a causal relationship) has been criticised from a methodological point of view. DiNardo and Pischke (1997), in an influential paper, argue that the wage premium observed is not picking the effect of computer use, but the effect of unobserved heterogeneity between workers.

[86] We focus on the returns to computerisation. However, it is worth noting that other researchers have also been interested on the impact of the Internet (Crandall et al., 2007, Czernich et al., 2009 and Koutroumpis, 2009), for instance, suggesting that the Internet might indeed have had some causal effect on growth.

[87] Similar results were found by Liu et at (2004) using micro-data in Taiwan.

According to this argument, the use of computers is positively correlated with skilful workers, which represent a source of bias[88]. In view of this problem, and using panel data to control for unobserved characteristics (fixed effects), other researchers, such as Entorf et al. (1999), Entorf and Kramaz (1997), and Pabilonia and Zogui (2005), find only little or negligible effects of computer use on income.

In this study, using micro data, the focus is on the association between computer-based numeracy tasks and earnings, and we explore the likelihood of reaching different quintiles of the income distribution when spreadsheets and databases (i.e., computer tasks that stress the importance of maths and statistics) are used on a regular basis. The use of spreadsheets and databases is one of the most common computer tasks amongst workers in England, together with word processing, accessing and browsing the internet, the use of e-mails, and education and learning, and it is concentrated amongst higher managerial and professional occupations (BIS, 2012).

The data is taken from the Skills for Life Survey (SfL) 2011, which contains detailed information about computer use, the level of intensity / frequency of use, different types of computer tasks and the associated Information and Communication Technologies skills. The sample is relatively large (6,183 observations), and representative of the population in England[89]. Moreover, the data set is rich and flexible enough to explore different econometric specifications.

[88] The same reasoning is found in Oosterbeek (1997).

[89] We also use weights, which are effectively the inverse of the sampling probability.

The dependent variable ‘earnings’ is originally measured in brackets in the dataset. Therefore, we use interval regressions to explore the association between computer-based numeracy tasks and interval-coded variable earnings. The interval-censored regression, originally devised by Stewart (1983), is a generalisation of the Tobit Model (Wooldridge, 2010) and can be estimated by Maximum Likelihood[90]. A problem that arises in the estimation is that ‘computer-based numeracy tasks’ may be correlated with unobserved characteristics, such as ability, that also generate a wage return[91]. Thus, potential endogeneity due to omitted variable bias is addressed with an instrumental variable approach that follows procedures developed by Smith and Blundell (1986), Rivers and Vuong (1988), and Bettin and Lucchetti (2012). Here, we take a good proxy for the ability to work using mathematical and statistical functions on a computer as the instrument. The instrument - ICT numeracy skills - has been designed in the Skills for Life Survey 2011 to operate only through ICT numeracy tasks. Thus, we try to control for the effects of unobserved characteristics with this variable that has been tested in the Skills for Life Survey 2011[92]. The instrument is positively associated with the use of spreadsheets and databases (first stage), and its values are unrelated to the error term in the structural equation of interest (further analyses are presented in next sections). We discuss in some details the conditions under which the instrument is a valid one.

[90] OLS estimation is not adequate when the dependent variable is categorical.

[91] There is a positive covariance between the skill and the task, which can be inferred, for instance, from software characteristics. It is well known that the language of math computer programs can be often abstract and complex.

[92] Details about the instrument can be found in the appendix, section D. Examples of tasks used to measure the underlying ICT numeracy skill are: the capacity to create simple graphs, and the ability to sort data and use simple formulas in a spreadsheet.

In addition, we also estimate the probability of reaching quantile '*x*'[93] associated with the use of computer-based numeracy tasks. Consistently, we find statistical evidence pointing out that there is a positive and significant association between using spreadsheets and databases and earnings. Thus, this task increases (decreases) the probability of reaching the highest (lowest) quantile of the income distribution. The same results do not hold true with other computer tasks.

It is worth noting that the present chapter differs from previous research in several dimensions. First, the data is more recent, which is important given the massive diffusion of computers in recent years. This phenomenon should reduce the source of bias (i.e., more skilful workers use computers), in the sense that computers are now more accessible to all. Second, it extends the notion of computer use, exploring computer tasks, which allows for a more detailed analysis. Five computer tasks are initially considered. Then, we focus on the role of spreadsheets and databases using a sub-sample of managers. This group shows higher levels of computer use, and ICT numeracy skills, compared to other occupations. Third, the key question in this chapter not only concerns the association between ICT tasks and earnings, but also the relationship between computer tasks and the probabilities of reaching different sections of the income distribution (quintiles of income). It is apparent that endogeneity can still be a problem here, because unobserved heterogeneity/ability can produce upward biased results. Then, we try to overcome this issue with an instrumental variable approach that uses a good proxy for the underlying ability, i.e., a measure of the ICT numeracy skills taken from SfL 2011.

[93] Where '*x*' goes from quintile 1 to 5.

The remainder of the paper is organised as follows. Section 4.3 describes the Skills for Life Survey 2011 dataset. Section 4.4 presents the econometric approach based on interval regressions and the instrumental-variable strategy. Next, section 4.5 discusses the results, with concluding remarks advanced in section 4.6.

4.3 Data

The Skills for Life 2011 Survey was commissioned by the Department for Business, Innovation, and Skills, and designed to measure basic skills amongst people aged between 16 and 65 in England (BIS, 2012). In large part, the survey replicated a previous similar survey conducted in 2003; however, the measurement of ICT skills differs in theory and practice. Given that a reliable comparison is not possible and that the latest measurement of ICT skills is more suitable for this analysis, we decided to use the 2011 cross section. The total sample size available contains 6,183 observations, which is relatively large and suitable for the econometric analysis. The sample is a probability sample and intended to be representative of the population (BIS, 2012). The sampling probability is known for all survey respondents, so a sampling weight (effectively the inverse of the sampling probability) has been used for each respondent in all our empirical investigations.

The key explanatory variables in this analysis are 'computer use', 'intensity of computer use' (frequency), 'computer tasks', and 'ICT skills'. 'Computer use' is a binary response variable that takes value 1 if the worker uses a computer at work, 'intensity of computer use' is a dummy variable that equals 1 if the worker uses the computer daily, and the five most common[94] computer tasks in England at the time of the survey were included as indicator variables with value 1 if the worker performs the task with their computer, or 0 otherwise. The tasks are: (1) word processing; (2) processing spreadsheets and databases; (3) using the e-mail; (4) accessing the Internet and; (5) the use of the computer for educational and learning purposes. Moreover, ICT skills, i.e., the underlying ability tested in the survey and related to word processing,

[94] According to their frequency in this sample.

spreadsheets and database use, accessing and browsing the Internet, e-mail use, and general ICT knowledge, are operationalised as indicator variables, which are equal to 1 if the level achieved is entry level 3 or above (which will be considered an adequate level), or 0 if the result of the test is below this threshold.

The set of control variables contains 'age' (continuous variable measured in years), 'educational level' (= 1 if worker has a degree), 'occupation' (= 1 if worker is in managerial position), 'region' (categorical variable that includes the regions of England), and 'industry' at the 1 level digit of aggregation (categorical variable). A full list of occupations (based on the national statistics socio-economic classification 2010), regions, and industries (based on the current Standard Industrial Classification 2007) is available in the appendix[95].

The variable 'annual gross earnings' is measured in bands in the Skills for Life Survey 2011. This data type gives an indication of where the respondent lies in the income distribution; however, exact figures are not available for estimation purposes (Von Fintel, 2006). There are 32 income categories in the dataset[96], with the first band corresponding to left-censored data, the last band to right-censored data, and all others to interval-censored data. It is worth noting that earnings brackets help to maintain sufficient response rates, particularly in cases in which the interviewee does not want to provide an exact figure, or when the level of income (for instance, household income) is not entirely clear (Von Fintel, 2006).

[95] Tables in the appendix contain frequencies and analyses of the distributions.

[96] The frequency table is also available in the appendix.

4.4 Descriptive analysis

The level of computer use in managerial occupations in England is relatively high[97] (Table 4.1). The proportion of workers using computers at work is higher in jobs that require more abstract tasks, such as higher managerial, lower managerial and intermediate jobs. For example, the use of computers is key for higher managerial jobs (95.71%) and their penetration is very high amongst lower managerial positions as well (87.76%). Hypothesis testing (independent sample t-test) suggests that there is a significant mean difference in computer use between managers (higher or lower managerial) and non-managers (with a t-value of 5.23). In addition, hypothesis testing (independent sample t-test) is also conducted to see if there is a significant mean difference between male and female workers regarding the use of computers (using pooled data), and we fail to reject the null of no difference[98] with a t-statistics of 0.7, concluding that there is no statistically significant difference between the two groups.

Table 4.1: Computer use at work. Proportion of workers by occupation in 2011

	Computer Use at Work 2011 (%)		
Occupation	All	Males	Females
Higher managerial	95.71	96.29	94.60
Lower managerial	87.76	87.11	88.36
Intermediate	83.53	86.66	82.01
Small employers	53.23	51.50	57.13
Lower supervisory	63.21	63.61	62.35
Semi-routine occupations	46.47	47.26	45.90
Routine occupations	22.73	24.01	20.75

Source: Skills for Life Survey 2011

[97] This is in line with measures published by the Office for National Statistics (2015).

[98] Ho: mean of male workers = mean of female workers.

Figures in Table 4.2 correspond to the sub-sample of workers using a computer (3,487 observations). It is clear that the intensity of computer use (the proportion of workers using a computer on a daily basis) is high across all occupations. Even amongst routine workers, around 70 percent use a computer daily. The t-test shows that there is a significant mean difference between males and females regarding average computer use intensity (we reject the null with a t-statistic of 3.98). This means that among all workers using a computer, the proportion of males using them daily is higher compared to that of females. Also, as expected, the null hypothesis of no difference in means (proportions) of intensity of computer use between managers and non-managers is rejected, with a t-statistic of 3.51.

Table 4.2: Computer use intensity. Proportion of workers, disaggregated by gender

Occupation	Computer Use on a Daily Basis (%)		
	All	Males	Females
Higher managerial	96.67	97.3	95.45
Lower managerial	90.39	93.26	87.81
Intermediate	88.79	87.66	89.35
Small employers	76.69	77.43	75.2
Lower supervisory	74.07	74.61	72.91
Semi-routine occupations	71.65	80.18	65.38
Routine occupations	69.65	72.58	64.49

Source: Skills for Life Survey 2011

The number of workers using a computer and the intensity of use will give an incomplete picture if computer tasks are not included in the analysis. The benefit of using the Skills for Life Survey 2011 is that this level of detail can be reached. The five most common uses of the computer[99] are addressed, namely word processing, accessing the internet, using e-mail, the use of spreadsheets and databases (ICT numeracy tasks), and education and learning. Table 4.3 displays the most common uses, across all occupations, which are accessing the internet and using e-mail. The proportion of workers using word processors is higher than those using spreadsheets and databases, again across all occupations (we reject the null of equal mean use between the tasks with a two-sample paired test, and a t-statistic of 24.1). Also, it is worth noting that more than half of all managers (both higher and lower managerial) tend to use the computer for education and learning purposes as well. A further analysis of this data can be found in the econometric analysis section.

Table 4.3: Most common uses of the computer. Proportion of workers by occupation

	Most Common Uses of the Computer				
Occupation	Word	Internet	E-mail	Spreadsheet	Education
Higher managerial	89.7	95.91	97.24	80.87	60.92
Lower managerial	81.84	95.36	96.25	67.23	55.14
Intermediate	72.93	91.92	90.97	52.51	36.02
Small employers	59.95	93.12	83.41	43.88	31.43
Lower supervisory	56.85	89.85	83.66	40.09	34.61
Semi-routine occupations	49.05	92.3	80.17	24.7	31.82
Routine occupations	38.43	88.37	70.51	18.78	32.49

Source: Skills for Life Survey 2011

There is a dual connection between tasks and skills. On the one hand, skills help to complete tasks successfully (i.e., skills equal to the ability to performs tasks). However, tasks also have the potential to foster and develop skills (i.e. learning by doing). In this analysis, priority is

[99] Other less common uses are not included in this analysis, such as drawing, gaming or photography.

assigned to tasks, given that the starting point is the use and intensity of use of the computers[100]. However, ICT skills will be brought into the analysis as well, as part of the instrumental variable approach in the econometric section. Table 4.4 shows the proportion of workers reaching an adequate level (entry level 3 or above) in each of the ICT skills measured in the Skills for Life Survey 2011. There are four different skills associated with word processing, e-mail use, spreadsheet and database processing, and basic ICT knowledge. The latter gets the best results[101], especially in jobs in which abstract tasks must be performed on a regular basis. Regarding the distribution of ICT skills, it is worth mentioning that the skills variance is large between occupations, but there is a certain concordance within occupations. This suggests that there can be occupations intrinsically more prone to developing the skills associated with computers than others (where higher managerial jobs are a good example). Interestingly, the proportion of workers reaching an adequate level of the skill is higher -across all occupations- in e-mail tasks than word processing, and in spreadsheets tasks than word processing. Both findings are statistically significant, with t-values of 12.4 and 4.03, respectively. This is surprising considering that the word processing task is more common than the use of spreadsheets and databases (see Table 4.3). However, it is interesting to note that the picture changes if we adopt a stricter definition of 'adequate level'. That is, if the adequate level is defined with a different threshold, for instance as level 2 or above (instead of entry level 3 or above), then the proportion of workers reaching the adequate level is higher for word processing tasks than for spreadsheet and database processing tasks[102].

[100] Furthermore, the same approach has been used in the literature before.

[101] For instance, two samples paired t-test of 'ICT knowledge' and 'e-mail' rejects the null with a t-statistics of 18.7, which indicates that there is a statistically significant difference in mean results between these skills.

[102] A table with more detail is available in the appendix.

Table 4.4: ICT skills. Proportion of workers reaching an adequate level by occupation

Occupations	ICT Skills			
	Email	Word	Spreadsheet	ICT Knowledge
Higher managerial	86.36	80.31	80.46	99.31
Lower managerial	86.68	74.60	76.28	96.71
Intermediate	82.11	69.01	73.57	96.43
Small employers	52.71	38.55	51.51	88.72
Lower supervisory	59.87	44.70	51.11	88.97
Semi-routine occupations	61.54	47.31	53.26	89.32
Routine occupations	42.91	34.92	38.84	76.41

Source: Skills for Life Survey 2011

The following section explores how a multivariate analysis can shed light on the main research questions. Accordingly, we estimate the returns to computer-based numeracy tasks, and also, the probability of reaching different quintiles of the income distribution associated with these tasks.

4.5 Econometric approach

To estimate earnings functions with interval-censored income observations we use an interval regression procedure that is a generalisation of the popular Tobit model (Wooldridge, 2010). An interval regression is estimated via maximum likelihood, and is characterised as follows:

There is an underlying latent variable y*, such that

$$y_i^* = x_i'\beta + u_i \qquad i = 1,\ldots,n$$

$$u_i \mid x_i \sim N(0, \sigma^2) \qquad i = 1,\ldots,n$$

where x_i contains the key variable 'computer-based numeracy tasks', and the error term, u_i, follows a normal distribution. The variable y_i^* is not fully observed, and we only have access to limited information, as is described below:

$y_i = y_{Li}$ if $y_i^* \leq y_{Li}$	y_{Li} is the upperbound of the first category[103]
$y_i = y_{Ri}$ if $y_i^* \geq y_{Ri}$	y_{Ri} is the lowerbound of the top category[104]
$y_i = y_i^*$ if $y_{li} \leq y_i^* \leq y_{ri}$	y_{1i} is the lowerbound of the $_i$th category
	y_{2i} is the upperbound of the $_i$th category[105]

[103] Likelihood contribution of individual in this category is $\Pr(y_i^* \leq y_{Li})$.

[104] Likelihood contribution of $\Pr(y_i^* \geq y_{Ri})$.

[105] Likelihood equals to $\Pr(y_{li} \leq y_i^* \leq y_{ri})$

Therefore, working with this type of data implies the incorporation of the interval-coded information into the log-likelihood function for the interval regression (Daniels and Rospabé, 2005; Wik et al., 2004; StataCorp, 2013). This model assumes a lognormal distribution of variable earnings, and is estimated by maximum likelihood[106].

$$\log L = -\frac{1}{2}\sum_{i \in C} w_i \left[\left(\frac{yi - \beta' x_i}{\sigma}\right)^2 + log 2\pi\sigma^2\right] + \sum_{i \in L} w_i \, log\Phi\left(\frac{y\mathrm{Li} - \beta' x_i}{\sigma}\right)$$

$$+ \sum_{i \in R} w_i \, log\left[1 - \Phi\left(\frac{yRi - \beta' x_i}{\sigma}\right)\right] + \sum_{i \in I} w_i \, log\left[\Phi\left(\frac{yri - \beta' x_i}{\sigma}\right) - \Phi\left(\frac{yli - \beta' x_i}{\sigma}\right)\right]$$

[Equation 4.1]

Where,

$i \in$ C = point data
$i \in$ L = left-censored data
$i \in$ R = right-censored data
$i \in$ I = interval-censored data

and w_i are the sampling weights.

A complication that arises with the estimation of this model is that the variable 'computer-based numeracy tasks' is endogenous which means that the estimated parameters may not be consistent. In particular, numeracy tasks may be correlated with unobserved characteristics, such as ability, that also generate a wage return. In this context, the model is improved with an instrumental variable, using an actual measure of ICT numeracy skills as the instrument, and we estimate the parameters via control function and full maximum likelihood procedures.

[106] We also estimate a similar model based on ordered probit regressions (in the appendix) that do not assume the normality of variable earnings. The results of both models are consistent.

Smith and Blundell (1986) and Rivers and Vuong (1988) proposed the control function procedure in the context of endogeneity, using Tobit and Probit models, respectively[107]. We adapt this technique to modelling the endogeneity as follows:

$y_{1i}* = x_{1i}'\beta + \gamma y_{2i} + u_{1i}$ [Equation 4.2] Structural equation of interest

$y_{2i} = z_i'\pi_2 + v_{2i}$ [Equation 4.3] Reduced form for endogenous variable y_2

where $y_{1i}*$ is the latent model for the interval-coded variable income, and y_{2i} is the binary endogenous regressor, namely 'computer-based numeracy tasks'. The error terms, u_1 and v_2 are correlated, and $z_i' = (x_{1i}', x_{2i}')$ contains the excluded instrument x_{2i}' from the equation for y_{1i} *.

Using the orthogonal decomposition for u_1 (Wooldridge, 2010), yields:

$$u_{1i} = \rho v_{2i} + \varepsilon_{1i} \qquad \text{, and } E(\varepsilon_{1i} \mid v_{2i}) = 0$$

where y_2 is uncorrelated with u_1, conditional on the control function v_2. Now, we define the augmented model as,

$$y_{1i}* = x_{1i}'\beta + \gamma y_{2i} + \rho v_{2i} + \varepsilon_{1i} \qquad \text{[Equation 4.4]}$$

$$y_{2i} = z'_i\pi_2 + v_{2i} \qquad \text{[Equation 4.5]}$$

107 For the linear case, and when y_i is fully observed, a Two-Stage Least Squares (2SLS) approach is possible.

Which can be solved in two steps. First, a linear probability model estimation[108] to obtain the residuals of equation (4.5) $\hat{v}_{2i} = y_{2i} - \hat{\pi}_2\text{'}z_i$. Second, we use $\hat{v}_{2i}$ as a control function in the model for y_1*, and estimate (4.4) by the interval regression method. The exogeneity test in this procedure is analogous to test H_0: $\rho = 0$, which will be rejected with a t-value of 1.85. That is, the t-test suggests that ρ does not significantly differ from zero, which indicates that the instrument is indeed exogenous.

In addition, we estimate the model by full maximum likelihood (Steward, 1983; Bettin and Lucchetti, 2012), which is an alternative to the control function approach presented above in two steps. The data generating process is the same, and it is assumed that the error terms follow a joint normal distribution:

$$y_{1i}{}^* = x_i\text{'}\beta + \gamma y_{2i} + u_{1i}$$

$$y_{2i} = z_i\text{'}\pi_2 + v_{2i}$$

$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim N\,(0, \Sigma)$$

where Σ is the covariance matrix. The covariance between u and v may be non-zero, and therefore the vector of explanatory variables y_2 becomes endogenous, and the ordinary interval regression does not provide consistent estimates of β and γ (Bettin and Lucchetti, 2012).

[108] A linear approximation of a non-linear function is appropriated in the context of a binary response endogenous regressor because we only need a consistent estimation of the marginal effects (Angrist, 2001).

The estimation of the model relies on the joint normal distribution of (y_{1i}*,y_{2i}) given z that is found by using the following formula (Wooldridge, 2010),

$$f\,(y_{1i}^*, y_{2i} \mid z) = f\,(y_{1i}^* \mid y_{2i}, z)\, f\,(y_{2i} \mid z)$$

Because y_{1i}* is not observed, the log-likelihood for one observation can be written as follows (Bettin and Lucchetti, 2012):

$$\ln f\,(u_i, v_i; \psi) = \ln\,[f\,(u_i \mid v_i; \psi)] + \ln f\,(v_i; \psi) \qquad \text{[Equation 4.6]}$$

where ψ is a vector containing all the parameters.

The first term of the right-hand side is a conditional component, and corresponds to the contribution to the log-likelihood from an interval data observation:

$$\ln\,[f\,(u_i \mid v_i; \psi)] = \ln \mathrm{P}\,(l_i < y_i^* < r_i \mid v_i)$$

where, l_i and r_i are the lower and upper limits of an interval, respectively.

The second term, ln f (v_i; ψ), is a marginal component, that is characterised as an ordinary multivariate Gaussian loglikelihood[109]:

$$\ln f(v_i; \psi) = -\frac{1}{2}[n \ln(2\pi)] + \ln|\Sigma| + (y_{2i} - z_i'\pi_2)'\, \Sigma^{-1} (y_{2i} - z_i'\pi_2)$$

where n is the number of parameters, and $|\Sigma|$ and Σ^{-1} the determinant and the inverse of the covariance matrix, respectively.

The next section presents the results obtained via interval regressions, where the control function and maximum likelihood techniques produce consistent and unbiased estimates of the key paraments studied.

[109] Commonly named Probability Density Function (PDF), or simply density.

4.6 Results and discussion

This section presents and discusses the results of the interval regressions. The dependent variable in these models is the natural logarithm of income (banded), with age, gender, educational level, occupation, region, and industry work as control variables. Each model presented explores different aspects of ICTs on the job. First, we present a model investigating the role of computer use. Second, we explore the intensity of computer use. Third, the role of different computer tasks. And, fourth, we implement our instrumental variable approach, where the variable 'computer-based numeracy' is instrumented with a measure of the underlying 'ICT numeracy ability', available in the SfL survey. We analyse two weighted samples[110], one for the whole population, and the other for the population of managers in England. Clustered standard errors at the industry level are set, given that observations could be correlated within each industry[111]. All the coefficients in the tables represent marginal effects.

4.6.1 Computer use, and computer use intensity

The key independent variable in the first interval regression model (column 1 in Table 4.5) is the dummy variable 'computer use', which is equal to 1 if the worker uses a computer at work, and zero otherwise. The results in this table refer to equation 4.1. Table 4.5 shows a positive association between this variable and income that is statistically significant at the 99% confidence level, with a β coefficient of 0.226 (log points) and standard error of 0.037. A constructive feature of the interval regression is that it can be interpreted in the same way as an OLS regression. Therefore, we observe that workers using computers at work earn on average

[110] Weights based on the inverse of the sampling probability.

[111] i.e., the i.i.d. assumption is violated.

23% more than those not using them, holding all else constant. This result is consistent with Krueger (1993) and Autor et. al. (1998). Column 2 (Table 5) considers a sub-sample of workers who use computers at work to explore how the ‘intensity of computer use’ (frequency of use) is associated with income. The intensity is measured as a dummy variable that takes value 1 if the computer is used daily, or 0 if the use is less frequent. The marginal effect of ‘frequency of computer use’ is also large (0.232 log points), and the magnitude is comparable to that obtained for ‘computer use’. These results suggest that the returns to computer use primarily tend to increase when this technology is an essential tool for the job. Other explanatory variables are also statistically significant in these specifications, and their interpretation is standard in the context of log earnings functions[112]. The final two columns in Table 5 refer to a sample that only includes managers. This shows similar results. We observe that the magnitude of the coefficient for ‘computer use’ is higher (0.28 log points). This suggests, on average, larger returns for this sample. And, the marginal effect of ‘frequency of use’ still shows a strong positive association with earnings (even though it decreases from column 2 to column 4, in Table 5). Finally, as expected it is apparent that those workers in higher managerial positions have on average 18.3% higher income (column 4), compared with other employees performing managerial duties in other positions (lower managerial and other positions), all else constant.

[112] For example, in model 2, the coefficient on ‘Degree’ states that those workers with a degree have on average 17.6% higher income than those without a degree, *ceteris paribus*. Also, lower managerial positions earn 25% more than those workers in routine occupations (which is the reference group), holding all else constant. Analogous interpretations can be made for the rest of the occupations.

Table 4.5: Interval regressions. Computer Use, and the intensity of computer use, in log earnings functions

	Dependent Variable: Ln income			
	Full sample		Sample managers	
	(1)	(2)	(3)	(4)
Computer Use	0.226***		0.288***	
	(0.037)		(0.059)	
Computer freq. of use		0.232***		0.201***
		(0.047)		(0.063)
Age	0.009***	0.007***	0.010***	0.010***
	(0.001)	(0.001)	(0.002)	(0.002)
Male	0.252***	0.215***	0.184***	0.173***
	(0.029)	(0.034)	(0.040)	(0.043)
Degree	0.215***	0.176***	0.264***	0.233***
	(0.034)	(0.037)	(0.042)	(0.044)
Higher Managerial	0.437***	0.401***	0.196***	0.183***
	(0.067)	(0.101)	(0.048)	(0.049)
Lower Managerial	0.272***	0.246***		
	(0.057)	(0.095)		
Intermediate Occ.	0.001	-0.066		
	(0.066)	(0.102)		
Small Employers	-0.073	-0.001		
	(0.069)	(0.116)		
Lower Supervisory	0.137**	0.117		
	(0.061)	(0.100)		
Semi-Routine Occ.	-0.051	-0.105		
	(0.058)	(0.103)		
Industries	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes
N	3276	2486	1950	1743

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Tables 4.6 and 4.7: Most common ICT computer tasks in log earnings functions, using the full (4.6) and managers (4.7) samples

Table 4.6: Full sample

	Dependent Variable: Ln Earnings				
	(1)	(2)	(3)	(4)	(5)
ICT Numeracy	0.118***	0.121***	0.118***	0.133***	0.129***
	(0.035)	(0.035)	(0.036)	(0.038)	(0.038)
ICT Internet		-0.045	-0.055	-0.045	-0.052
		(0.070)	(0.074)	(0.074)	(0.074)
ICT Email			0.034	0.054	0.051
			(0.072)	(0.073)	(0.073)
ICT Literacy				-0.056	-0.066
				(0.047)	(0.048)
ICT Education					0.043
					(0.035)
Controls*	Yes	Yes	Yes	Yes	Yes
N	2486	2486	2486	2486	2486

Controls: Age, Gender, Educational Level, Occupations, Industries, and Regions.
Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Table 4.7: Managers sample

	Dependent Variable: Ln Earnings				
	(1)	(2)	(3)	(4)	(5)
ICT Numeracy	0.112**	0.113**	0.103**	0.113**	0.103**
	(0.046)	(0.046)	(0.046)	(0.049)	(0.050)
ICT Internet		-0.017	-0.074	-0.065	-0.082
		(0.097)	(0.103)	(0.104)	(0.105)
ICT Email			0.185*	0.197*	0.198*
			(0.111)	(0.113)	(0.113)
ICT Literacy				-0.038	-0.056
				(0.063)	(0.063)
ICT Education					0.085*
					(0.044)
Controls*	Yes	Yes	Yes	Yes	Yes
N	1743	1743	1743	1743	1743

*Controls: Age, Gender, Educational Level, Occupations, Industries, and Regions.
Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Tables 4.6 and 4.7 show the relationships between the most frequent computer tasks and earnings by estimating versions of equation 4.1. Computer tasks enter the models as dummy variables, taking value 1 if the task is used or 0 otherwise. Table 4.6 considers the full sample, and Table 4.7 refers to the restricted sample of managers. First, in Table 4.6, we include all the different tasks stepwise, controlling for age, gender, educational level, occupations, industries, and geographical region[113]. The econometric analysis (interval regressions) shows that 'computer-based numeracy tasks' are always positively and significantly associated with income. In column 1 (Table 4.6), the estimate indicates that workers using spreadsheets and databases (i.e., ICT numeracy tasks) earn 11.8% more than other workers not using this task, holding all else constant. This interpretation is valid at the 99% confidence level, with a standard error of 0.035. It is worth noting that a very similar wage return (0.12 log points) is obtained in column 5, after controlling for all other relevant computer tasks. This suggests that the main effect of 'ICT numeracy' is robust, over and above any potential interaction effects with the other computer inputs. Furthermore, Table 4.6 shows that accessing the Internet, the use of e-mails, word processing (ICT literacy), and using the computer for educational purposes are not significant (we do not to reject the null hypothesis of no effect in all cases). A similar result holds for the sample of managers (Table 4.7), where ICT numeracy tasks are positively associated with income. Also, the use of e-mail, and computer-based education and learning show significant results now (which is closer to Dolton et al., 2007), which suggests that managers are able to take advantage from technological progress in the workplace.

[113] Also, we tried several other specifications, adding each task one at a time. The results remain unchanged, and the output is included in the appendix.

4.6.2 Instrumental variable combined with interval regression approach: ICT numeracy tasks

The models examined previously suffer from endogeneity because the ability associated with ICT numeracy tasks is not observed. In labour economics, this type of endogeneity has been named 'omitted variable bias'. However, the Skills for Life Survey (2011) actually tests the ability associated with ICT numeracy tasks in a probability sample. That is, the survey contains an ICT assessment section focused on numeracy tasks. In practice, respondents familiar or partially familiar with computers tried (in a computer) a substantial number of items at the required level in order to make an accurate assessment of their skills standards (BIS, 2012)[114]. This variable, ICT numeracy skill level, is designed to operate only through ICT numeracy tasks. Therefore, we can correct part of the endogeneity problem using that good proxy for ability as an instrument. The model now has one endogenous regressor (the use of ICT numeracy tasks), and one instrument (the ability associated with ICT numeracy tasks), which means that it is just identified.

[114] The ICT assessment is a minimum competence test. Descriptive statistics, such as the distribution of skills by occupation, can be found in sections Descriptive Statistics, and with more detail in the appendix (section D).

Table 4.8: Analysis of the instrument

	Full Sample			Managers Sample		
	Ln Earnings	ICT Numeracy	Ln Earnings	Ln Earnings	ICT Numeracy	Ln Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Instrument (Ability)	0.087**	0.280***	0.058	0.107**	0.343***	0.061
	(0.043)	(0.022)	(0.044)	(0.048)	(0.033)	(0.050)
ICT Numeracy Tasks			0.118***			0.145***
			(0.041)			(0.046)
Age	0.004**	0.001	0.004***	0.003*	-0.002*	0.003*
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Male	0.246***	-0.015	0.248***	0.192***	0.024	0.194***
	(0.037)	(0.022)	(0.037)	(0.041)	(0.030)	(0.040)
Degree	0.110***	0.080**	0.108***	0.176***	0.100***	0.166***
	(0.041)	(0.032)	(0.041)	(0.043)	(0.032)	(0.043)
Occupation	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
N	2486	2486	2486	1743	1743	1743

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

In the previous section, the causal / structural relationship[115] of interest was defined with equation 4.2, and the task-reduced form (first stage)[116] with equation 4.3. We can also define an income-reduced equation as a version of equation 4.1, substituting ICT tasks with ICT skills (the instrument). Table 4.8 reports a set of regressions[117], using both the full and managers' samples that help to reveal how the instrument operates. The income-reduced forms are in columns 1 and 4. Then, the task-reduced forms (first stages) are in columns 2 and 5. Finally,

[115] The structural equation, i.e., regression of Ln Earnings on ICT numeracy tasks.

[116] Regression of ICT numeracy tasks on ICT numeracy skills.

[117] We also tried these models using OLS and Linear Probability Model regressions, and obtained similar results. The Adjusted R2 ranged from 0.22 to 0.33.

the structural equations of interest with the instrument also added to the models are in columns 3 and 6. We find similar results in the two samples. In columns 4 and 5, we observe a positive and significant association between the instrument (ICT numeracy ability) and both income and ICT numeracy tasks. It is worth noting the strength of the first stage. Then, column 6 shows how the instrument becomes insignificant when the computer task is also added to the model, i.e., it does not appear as a separate regressor in the structural equation of interest. In addition, the F-statistics in columns 2 and 5 are 16.62 and 10.81, respectively, which according to Stock et al. (2002) is evidence against a weak instrument problem (they suggest that F-statistics above 10 indicate that you do not have a weak instrument problem). This evidence is supporting the validity of our instrument.

Table 4.9: IV and interval regression estimates

	Dependent Variable: Ln Earnings					
	Full Sample			Sample Managers		
	IR	IV-CF	IV-MLE	IR	IV-CF	IV-MLE
	(1)	(2)	(3)	(4)	(5)	(6)
ICT Numeracy	0.110***	0.122***	0.124***	0.103**	0.155***	0.158***
	(0.035)	(0.036)	(0.036)	(0.045)	(0.046)	(0.047)
Age	0.006***	0.007***	0.007***	0.008***	0.008***	0.008***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male	0.234***	0.265***	0.265***	0.195***	0.193***	0.192***
	(0.034)	(0.036)	(0.036)	(0.042)	(0.034)	(0.034)
Degree	0.203***	0.237***	0.236***	0.263***	0.304***	0.303***
	(0.037)	(0.035)	(0.035)	(0.044)	(0.035)	(0.035)
Higher Managerial	0.427***	0.519***	0.517***	0.163***	0.163***	0.163***
	(0.101)	(0.078)	(0.078)	(0.050)	(0.034)	(0.034)
Lower Managerial	0.283***	0.375***	0.374***			
	(0.094)	(0.067)	(0.067)			
Intermediate Occ.	-0.014	0.108	0.107			
	(0.100)	(0.093)	(0.093)			
Small Employers	-0.084	-0.087	-0.088			
	(0.116)	(0.108)	(0.109)			
Lower Supervisory	0.144	0.230***	0.229***			
	(0.101)	(0.043)	(0.043)			
Semi-Routine Occ.	-0.123	-0.015	-0.015			
	(0.103)	(0.090)	(0.090)			
Industries	Yes	Yes	Yes	Yes	Yes	Yes
Regions	Yes	Yes	Yes	Yes	Yes	Yes
N	2486	2486	2486	1743	1743	1743

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Table 4.9 contains the results of the instrumental variable estimations, again using the Skills for Life Survey (2011). Models 1 - 3 refer to the whole sample, and models 4 - 6 are limited to the sample of managers. In each case, the first model (in columns 1 and 4) corresponds to an ordinary interval regression (equation 4.1), the second model (in columns 2 to 5) refers to the control function procedure (based on equations 4.2-4.5), and finally the third model presents the estimates of the full-maximum likelihood instrumental variable estimation (based on equation 4.6). The variable used to instrument ICT numeracy tasks is the ability to perform numeracy tasks using a computer. This variable is a dummy variable that equals 1 if the worker/manager has reached an adequate level (entry level 3 and above) in the ICT numeracy test, or zero otherwise[118]. The results of 'ICT numeracy tasks' are consistent across models. The main interpretation is that there is a positive and significant association between ICT numeracy tasks and income, which is significant at the 99% confidence level. For example, in column 6, managers using spreadsheets and databases earn, on average, 15.8% more than other workers in managerial positions not using this task, holding all else constant. The magnitude of the coefficients is similar to those found by Dolton et al (2004, 2007 and 2008) who estimated the effect of computer use and programming in Great Britain[119]. We find slightly larger returns to ICT numeracy tasks using IV approaches. The existing literature that uses IV estimation to correct for omitted ability bias in estimating the effect of education often finds substantially higher IV estimates relative to the OLS estimates (Card, 1995; Butcher and Case 1994; and Ashenfelter and Zimmerman 1997). In these cases, the attenuation bias caused by

[118] The ICT assessment tool produces a computer numeracy score for the participants. These raw scores are, unfortunately, not available in the dataset. In this context, the variable ICT numeracy skill is recorded in levels, clearly stating which is the threshold (adequate level) used for policy in the UK.

[119] However, their coefficients tended to decrease with the use of more covariates, and / or using panel data. For instance, the coefficient associated to computer use (any use) decreased from 0.21 to 0.03 log points, and the 'effect' of programming on earnings decreased from 0.1 to 0.05 log point, in Dolton et al (2008). Notwithstanding these changes, the level of significance remained unchanged.

the measurement error of schooling reduces OLS estimates (Griliches, 1997; and Angrist and Krueger, 1991). Accordingly, potential sources of measurement error in the present study[120], and different understandings about what numeracy tasks really mean could explain the difference between estimations.

4.6.3 Analysis by quintiles

The analyses based on interval regressions presented above suggest that using measures of banded income does not necessarily serve as a disadvantage. In fact, the interpretation is similar to an OLS regression using the midpoints of the band. The next section presents an analysis by quintiles to investigate whether the relationship still holds at different points of the distribution of earnings.

The dependent variable for income (originally banded) in this section is re-categorised into quintiles. Consequently, Quintile 1 includes earnings under £10,000, Quantile 2 between £10,000 and £16,000, Quantile 3 between £16,000 and £23,000, Quintile 4 between £23,000 and £36,000, and Quintile 5 at £36,000 or above. Table 4.10 shows the frequencies associated with each income quintile in the sample, where each quintile gets roughly 20 percent of the sample (not exactly 20% because original data are banded). We observe only subtle differences between the raw and weighted data. Given this categorisation, the following econometric

[120] Such as respondent confusion, carelessness or dishonesty.

analysis[121] explores how the explanatory variables affect the probabilities associated with reaching different quintiles of the income distribution.

Table 4.10: Quintiles of variable earnings

		Raw data		Weighted data	
Quintiles	Freq.	Percent	Cum.	Percent	Cum.
Q1 (Left censored data)	702	21.43	21.43	21.53	21.53
Q2 (interval data)	691	21.09	42.52	21.44	42.97
Q3 (interval data)	559	17.06	59.58	17.24	60.21
Q4 (interval data)	746	22.77	82.36	22.58	82.79
Q5 (right censored data)	578	17.64	100.00	17.21	100
Total	3276	100		100	

Source: Skills for Life Survey 2011

Table 4.11 shows the predicted probabilities associated with the use of computer-based numeracy tasks at different quintiles of income (estimated with equations 4.1 and 4.6). The estimates are derived from interval regressions (conditioning on the same set of controls as those used in Tables 5 - 7). The final row corresponds to equation 4.6 which is the IV specification estimated using maximum likelihood. First, it is worth mentioning that ICT numeracy is once again a significant predictor of the worker quintile of earnings. Second, this quintile analysis shows that ICT numeracy tasks have more influence at the extremes of the

[121] Here, we present the Interval Regression analysis. As a robustness test, we have included in the appendix a detailed discussion of an alternative version based on Ordered Probit regressions.

income distribution. For example, if the first quintile[122] is analysed, workers performing ICT numeracy tasks are roughly 8% less likely to be in quintile 1, compared to those not using spreadsheets and databases at work, on average. In contrast, workers familiar with numeracy tasks, are on average 7% more likely[123] to reach quintile 5[124] compared to others not using ICT numeracy tasks. Interestingly, quintiles 2, 3 and 4 demonstrate small coefficients that are close to zero. This is likely to be related to the heterogeneity of occupations in these groups.

Table 4.11: Predicted probabilities of computer-based numeracy tasks by quintiles of income

	Interval Regressions – Predicted probabilities				
	< £10,000	£10,000 and under £16,000	£16,000 and under £23,000	£23,000 and under £36,000	£36,000 or above
Quintile	Q1	Q2	Q3	Q4	Q5
ICT - Numeracy	-0.0792***	-0.0190***	-0.00446***	0.00930***	0.0933***
	(0.0145)	(0.00359)	(0.00112)	(0.00232)	(0.0172)
ICT - Numeracy (IV MLE)	-0.0836***	-0.00441***	0.00392***	0.0126***	0.0715***
	(0.0210)	(0.00107)	(0.000960)	(0.00291)	(0.0183)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Figure 4.1 shows the linear predictions of the quintiles of income for workers that use and do not use computer-based numeracy tasks. This clearly shows two very different distributions.

122 Semi-routine occupations represent 30% of this category.

123 Taking the IV estimation as an example.

124 Higher managerial and professional occupations represent 40% of this category.

The left-side of Figure 1 refers to workers who do not perform ICT numeracy tasks, while the right-side refers to workers who do perform these tasks. It can be observed that both distributions seem to be normal, and that the mean of income is significantly higher when workers include the task as part of their set of actions (this estimation predicts an average of 3.4 quantiles when workers use spreadsheets and databases, and 3.0 quintiles if they don't use them, where quintile 3 ranges from £16,000 to £23,000). This predicted average difference is statistically significant at the 99% confidence level, with a t-ratio of 19.7.

Figure 4.1: Linear predictions of the income quintiles. Histograms showing frequency densities when workers perform numeracy tasks (left) and when they don't (right). Source: Skills for Life Survey 2011

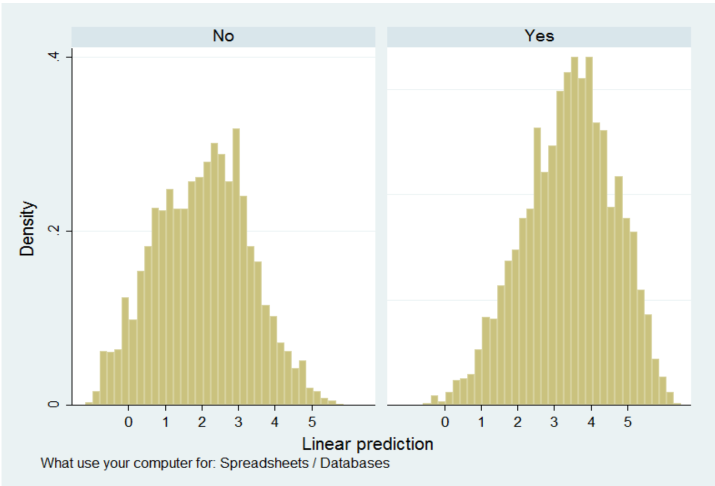


Table 4.12: Marginal effects (linear predictions) of computer-based numeracy tasks

	Interval Regressions – Linear predictions				
	< £10,000	£10,000 and under £16,000	£16,000 and under £23,000	£23,000 and under £36,000	£36,000 or above
Quintile	Q1	Q2	Q3	Q4	Q5
ICT - Numeracy	0.0668***	0.00742***	0.00442***	0.00685***	0.0794***
	(0.0128)	(0.00142)	(0.000871)	(0.00132)	(0.0157)
ICT - Numeracy (IV MLE)	0.0896***	0.00798***	0.00473***	0.00727***	0.0658***
	(0.0245)	(0.00210)	(0.00125)	(0.00191)	(0.0182)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Finally, we compare the expected values by quintile according to the use of spreadsheets and databases (see Table 4.12). Again, we find larger mean differences at the extremes of the distribution. The IV interval regression shows that, in quintile 1, the marginal effect associated with ICT numeracy task use is 8.96%, while in quintile 5 the coefficient is 6.58%. These results make sense when it is considered that 45% of workers in quintile 1 range between 16-25 years of age (i.e., we compare this emergent group against routine and semi-routine workers who do not engage in ICT numeracy tasks), and 47% of quintile 5 corresponds to Higher managerial positions, since these workers tend to take advantage of computerised and communication technologies, as was seen also in chapter 2 and 3.

4.7 Conclusions

The empirical analysis of cross-sectional data (year 2011) suggests a positive overall effect of computer use and computer use intensity on earnings. This is in line with existing empirical research. Krueger (1993) and Dolton et al. (2004, 2007) also find high returns to computer use using cross sectional data, in the US and UK, respectively. Furthermore, our study finds that workers using a computer (vs non-users) and those using them more frequently have higher (lower) probabilities of reaching the top (bottom) of the income distribution. However, these results must be attenuated by the fact that, in line with DiNardo and Pischke (1997), the use of computers still seems to be more prevalent amongst professionals and higher managerial jobs, which represent a more skilful group.

The results from the interval regression analysis for the full sample suggests that using spreadsheets and databases, and no other computer tasks, increases the probability of reaching the highest quintile of the income distribution. This result differs from previous research. Dolton et al. (2007) found that e-mailing and the use of the Internet were highly rewarded, although they used data from the early 2000s. This suggests that the returns to different types of computer use evolve over time. This is understandable, given that technology has had explosive development at all levels during the last few years. Focusing on a sample of managers provides similar conclusions regarding the use of computer-based numeracy tasks. It was also found that the use of e-mail (communication skills) and the use of the computer for educational and learning purposes are relevant for managers, which indicates that computer use intensity (i.e., more relevant tasks generating positive complementarities) is key for such workers.

This chapter reveals a positive and significant correlation between computer-based numeracy tasks and earnings using an Instrumental Variable approach to address the potential endogeneity of computer-based numeracy tasks. Therefore, this study suggests that investment in computer-based numeracy tasks (involving the use of spreadsheets and databases) should be encouraged, for instance, among medium income and risk groups. These findings have policy relevance, since they contribute to the understanding of how ICTs affect productivity, inequality and, ultimately, economic growth.

Finally, we suggest new avenues for further research using panel data measures to eliminate other sources of unobserved heterogeneity (such as effort, or genetics) among managers. These studies should be carried out often, considering the changing nature and the heterogeneous effects of technology.

4.8 Appendix

A. Data: Detailed description of variables

Table A4.1: List of variables. Variable name (left) and brief description (right)

Variable	Description
Computer Use	1 if respondent use computers at work, 0 otherwise
Computer Frequency of use	1 if computer is used daily, 0 otherwise
Word	1 if respondent is familiar with word processing tasks (writing letters and documents in computers), 0 otherwise
Excel	1 if respondent is familiar with ICT numeracy tasks (spreadsheets and databases), 0 otherwise
Internet	1 if respondent is familiar with the use of the internet, 0 otherwise
Email	1 if respondent is familiar with e-mailing tasks, 0 otherwise
Education (computer based)	1 if respondent is familiar with ICT education and learning activities, 0 otherwise
Word Skill	1 if respondent scored entry level 3 or above in the test, 0 otherwise
Spreadsheet Skill	1 if respondent scores entry level 3 or above in the test, 0 otherwise
Email Skill	1 if respondent scores entry level 3 or above in the test, 0 otherwise
ICT knowledge	1 if respondent scores entry level 3 or above in the test, 0 otherwise
Manager	1 if respondent is a manager, 0 otherwise
Supervisor	1 if respondent is a supervisor, 0 otherwise
Other	1 if respondent is not a manager / supervisor, 0 otherwise
Ln Earnings	Natural Logarithm of variable earning (interval-censored coded - 32 categories)
Q1	1 if respondent is in 1st quintile of the income distribution (lower bound), 0 otherwise
Q2	1 if respondent is in 2nd quintile of the income distribution, 0 otherwise
Q3	1 if respondent is in 3rd quintile of the income distribution, 0 otherwise
Q4	1 if respondent is in 4rth quintile of the income distribution, 0 otherwise
Q5	1 if respondent is in 5th quintile of the income distribution, 0 otherwise
Male	1 if respondent is male, 0 if female
Age (continuous)	Age of the respondent
Age 1	if Age of respondent is between 16-19 years, 0 otherwise
Age 2	if Age of respondent is between 20-24 years, 0 otherwise
Age 3	if Age of respondent is between 25-34 years, 0 otherwise
Age 4	if Age of respondent is between 35-44 years, 0 otherwise
Age 5	if Age of respondent is between 45-54 years, 0 otherwise
Age 6	if Age of respondent is between 55-65 years, 0 otherwise
Higher managerial	1 if respondent is in a higher managerial occupation, 0 otherwise
Lower managerial	1 if respondent is in a lower managerial occupation, 0 otherwise
Intermediate	1 if respondent is in an intermediate occupation, 0 otherwise
Small employers	1 if respondent is a small employer, 0 otherwise
Lower supervisory	1 if respondent is in a lower supervisory occupation, 0 otherwise
Semi-routine occupations	1 if respondent is in a routine occupation, 0 otherwise
Routine occupations	1 if respondent is in a routine occupation, 0 otherwise
North East	1 if respondent resides in North East, 0 otherwise
North West	1 if respondent resides in North West, 0 otherwise
Yorkshire and the Humber	1 if respondent resides in Yorkshire and the Humber, 0 otherwise
East Midlands	1 if respondent resides in East Midlands, 0 otherwise
West Midlands	1 if respondent resides in West Midlands, 0 otherwise
East of England	1 if respondent resides in East of England, 0 otherwise
London	1 if respondent resides in London, 0 otherwise
South East	1 if respondent resides in South East, 0 otherwise
South West	1 if respondent resides in South West, 0 otherwise
Wales	1 if respondent resides in Wales, 0 otherwise
Scottish Lowlands	1 if respondent resides in Scottish Lowlands, 0 otherwise
Highlands and Islands	1 if respondent resides in Highlands and Islands, 0 otherwise
Northern Ireland	1 if respondent resides in Northern Ireland, 0 otherwise
Time Dummies	1 if year 2001, 2 if year 2006 (baseline category), and 3 if year 2012.
Agriculture, Forestry, and Fishing	1 if respondent works in this industry Agriculture, Forestry, and Fishing, 0 otherwise
Mining and Quarrying	1 if respondent works in this industry Mining and Quarrying, 0 otherwise
Manufacturing	1 if respondent works in this industry Food products, Beverages, and Tobacco, 0 otherwise

Table A4.1 continued:

Electricity, Gas and Water Supply	1 if respondent works in this industry Electricity, Gas, and Water Supply, 0 otherwise
Construction (baseline category)	1 if respondent works in this industry Construction, 0 otherwise
Wholesale and retail	1 if respondent works in this industry Wholesale and retail of motor vehicles and motorcycles, 0 otherwise
Transport and storage	1 if respondent works in this industry Transport and storage, 0 otherwise
Accommodation and Food Services Activities	1 if respondent works in this industry Accommodation and Food Services, 0 otherwise
Financial and Insurance Activities	1 if respondent works in this industry Financial and Insurance Services, 0 otherwise
Real Estate Activities	1 if respondent works in this industry Real Estate Activities, 0 otherwise
Public administration and defence; compulsory social security	1 if respondent works in this industry Public Administration, defence, social security, 0 otherwise
Education	1 if respondent works in this industry Education, 0 otherwise
Health and social work	1 if respondent works in this industry Health and Social Work, 0 otherwise
Other service activities	1 if respondent works in this industry Other Services Activities, 0 otherwise

Source: Skills for Life Survey 2011

B. Further descriptive statistics

Table A4.2: Censored-coded variable earnings

Banded Annual Earnings	Freq.	Percent	Cum.
Less than £520	94	2.66	2.66
£520 less than £1,040	23	0.65	3.32
£1,040 less than £1,560	29	0.82	4.14
£1,560 less than £2,080	33	0.94	5.07
£2,080 less than £2,600	35	0.99	6.06
£2,600 less than £3,120	42	1.19	7.25
£3,120 less than £3,640	20	0.57	7.82
£3,640 less than £4,160	29	0.82	8.64
£4,160 less than £4,680	33	0.94	9.58
£4,680 less than £5,200	83	2.35	11.93
£5,200 Less than £6,240	118	3.34	15.27
£6,240 Less than £7,280	83	2.35	17.63
£7,280 Less than £8,320	71	2.01	19.64
£8,320 less than £9,360	91	2.58	22.22
£9,360 less than £10,400	102	2.89	25.11
£10,400 less than £11,440	83	2.35	27.46
£11,440 less than £12,480	123	3.49	30.94
£12,480 less than £13,520	98	2.78	33.72
£13,520 less than £14,560	121	3.43	37.15
£14,560 less than £15,600	96	2.72	39.87
£15,600 less than £16,640	125	3.54	43.41

Table A4.2 continued:

£16,640 less than £17,680	105	2.98	46.39
£17,680 less than £18,720	112	3.17	49.56
£18,720 less than £19,760	73	2.07	51.63
£19,760 less than £20,800	101	2.86	54.49
£20,800 less than £23,400	214	6.06	60.56
£23,400 less than £26,000	204	5.78	66.34
£26,000 less than £28,600	156	4.42	70.76
£28,600 less than £31,200	196	5.55	76.31
£31,200 less than £33,800	99	2.81	79.12
£33,800 less than £36,400	145	4.11	83.22
£36,400 or more	592	16.78	100
Total	3,529	100	

Source: Skills for Life Survey 2011

The variable 'earnings' is the dependent variable in the econometric models. It is measured in bands in the Skills for Life Survey dataset 2011. There are 32 bands (showed in Table A4.2), where the first band corresponds to left-censored data, the last band to right-censored data, and all other bands to interval-censored data.

Table A4.3: List of occupations in the sample (raw data)

Occupation	Freq.	Percent	Cum.
Higher managerial	645	13.89	13.89
Lower managerial	1,526	32.85	46.74
Intermediate	537	11.56	58.3
Small employers	433	9.32	67.62
Lower supervisory	498	10.72	78.34
Semi-routine	614	13.22	91.56
Routine occupations	392	8.44	100
Total	4,645	100	

Source: Skills for Life Survey 2011

Table A4.3 tabulates workers aged 16-65 from the 2011 Skills for Life Survey by occupation, using the National Statistics Socio-Economic Occupational Classification (rebased on SOC 2010). The higher managerial category includes managers, employers in large establishments, administrative occupations, and higher professional occupations. Lower managerial occupations include lower professional and higher technical occupations, lower managerial, administrative occupations, and higher supervisory occupations. Intermediate occupations contain clerical, sales, technical and auxiliary, and intermediate engineering occupations. Small employers consist of workers in small organisations, and own account workers. Lower supervisory occupations contain lower technical craft and lower technical process operative occupations. Semi-routine occupations are sales, service, technical, operative, agricultural, clerical and childcare workers. Finally, routine occupations consist of sales and service, production, technical, operative and agriculture workers.

Table A4.4 ICT Skills. Proportion of workers with level 2 or above by occupation

	ICT Skills			
Occupation	Awareness	Word	Spreadsheet	Email
Higher managerial	82.2	42.86	42.57	73.58
Lower managerial	72	31.51	23.05	66.49
Intermediate	68.78	25.41	14.07	57.41
Small employers	39.54	13.99	5.24	34.94
Lower supervisory	39.47	12.31	6.93	39.43
Semi-routine occupations	47.97	20.62	11.03	43.6
Routine occupations	30.03	9.32	2.88	25.89

Source: Skills for Life Survey 2011

Table A4.4 tabulates workers aged 16-65 and with level 2 ICT skills or above by occupation, again drawing on the 2011 Skills for Life Survey. This shows higher proportions of workers reaching level 2 or above in ICT awareness (ICT basic general knowledge), and e-mail use. Furthermore, workers in higher and lower managerial occupations tend to perform better in these tests compared to the other occupations.

Table A4.5: Occupational composition by quantile of income

Quintile	Q1	Q2	Q3	Q4	Q5	Total
Higher managerial	6.45	6.51	9.46	29.63	47.94	100
Lower managerial	10.76	16.97	20.9	30.8	20.58	100
Intermediate	25.14	36.15	20.2	13.05	5.46	100
Small employers	32.36	18.09	11.33	23.77	14.46	100
Lower supervisory	18.48	27.7	21.93	23.43	8.47	100
Semi-routine occupations	45.24	31.88	14.33	6.26	2.29	100
Routine occupations	41.16	25.41	16.92	13.58	2.92	100

Source: Skills for Life Survey 2011

Table A4.5 shows that the extremes of the earnings distribution are dominated by higher managerial jobs (quintile 5) and semi-routine and routine occupations (quintile 1). Additionally, it is observed that Intermediate occupations, Small Employers, and Lower Supervisory Occupations are much more evenly distributed across all five quintiles.

Table A4.6: Age composition by quintile

Quintile	Q1	Q2	Q3	Q4	Q5	Total
16-19	79.00	14.00	6.00	0.00	1.00	100.00
20-24	37.85	37.85	17.29	5.61	1.40	100.00
25-34	16.91	20.97	22.02	27.65	12.45	100.00
35-44	20.45	18.52	12.73	25.91	22.39	100.00
45-54	16.43	23.54	16.56	22.77	20.70	100.00
55-65	20.50	17.60	20.89	23.02	17.99	100.00
Total	21.62	21.28	17.22	22.98	16.91	100.00

Source: Skills for Life Survey 2011

Table A4.6 shows how different age bands are classified in terms of income quintiles. Not surprisingly, there are more older workers in the higher quintiles, although this tends to fall slightly for the oldest group, which is likely to be a consequence of higher retirement rates amongst the most wealthy.

Table A4.7: Regions in England (raw data)

Region	Freq.	Percent	Cum.
North East	741	12.86	12.86
North West	1,860	32.29	45.15
Yorkshire	684	11.87	57.02
East Midlands	497	8.63	65.65
West Midlands	611	10.61	76.25
East	830	14.41	90.66
London	538	9.34	100
South East	634	19.53	88.97
South West	358	11.03	100
Total	5,761	100	

Source: Skills for Life Survey 2011

The regions in England considered for the analysis are: The North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, Est, London, the South East and South West. We use weighting (effectively the inverse of the sampling probability) to make each of these regions representative of England.

Table A4.8: Set of industries according to the Standard Industrial Classification (2007)

Industries	Freq.	Percent	Cum.
Agriculture, Forestry, Fishing and Mining	42	0.73	0.73
Manufacturing	561	9.79	10.52
Utilities supply, sewage and waste management	45	0.79	11.3
Construction	307	5.36	16.66
Wholesale and Retail Trade	807	14.08	30.74
Transport and Storage	255	4.45	35.19
Accommodation and Food Service Activities	326	5.69	40.88
Information and Communication	219	3.82	44.7
Financial and Insurance Activities	232	4.05	48.74
Real estate activities	56	0.98	49.72
Professional, Scientific, and Technical	362	6.32	56.04
Administrative and Support Services Activities	283	4.94	60.97
Public Administration and Defence	432	7.54	68.51
Education	653	11.39	79.9
Human Health and Social Work Activities	849	14.81	94.71
Other activities	303	5.29	100
Total	5,732	100	

Source: Skills for Life Survey 2011

Table A4.8 above is based on the current Standard Industrial Classification (SIC, 2007) used in classifying business establishments and other statistical units by the type of economic activity in which they are engaged. 16 industries are included in the empirical analysis (1-digit aggregation). Again, weights (the inverse of the sampling probability) help to make each of these industries representative of the England labour market.

C. Further empirical analysis: Log earning functions

Table A4.9: ICT tasks in log earnings functions (full sample)

	Dependent Variable: Ln Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
ICT Numeracy	0.118***					0.129***
	(0.035)					(0.038)
ICT Internet		-0.018				-0.052
		(0.070)				(0.074)
ICT Email			0.054			0.051
			(0.068)			(0.073)
ICT Literacy				0.006		-0.066
				(0.042)		(0.048)
ICT Education					0.050	0.043
					(0.034)	(0.035)
Controls*	Yes	Yes	Yes	Yes	Yes	Yes
N	2486	2486	2486	2486	2486	2486

*Controls: Age, Gender, Educational Level, Occupations, Industries, and Regions.
Standard errors in parentheses / * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Table A4.9 contains several specifications, adding different ICT tasks to the models, and using the full sample. We find a positive and significant correlation between ICT numeracy tasks and earnings. After controlling for other ICT tasks and covariates, we find that users of ICT numeracy tasks have 12.9% higher wages on average compared to non-users.

Table A4.10: ICT tasks in log earnings functions (managers sample)

	Dependent Variable: Ln Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
ICT Numeracy	0.112**					0.103**
	(0.046)					(0.050)
ICT Internet		0.013				-0.082
		(0.097)				(0.105)
ICT Email			0.195*			0.198*
			(0.104)			(0.113)
ICT Literacy				0.034		-0.056
				(0.056)		(0.063)
ICT Education					0.095**	0.085*
					(0.042)	(0.044)
Controls*	Yes	Yes	Yes	Yes	Yes	Yes
N	1743	1743	1743	1743	1743	1743

*Controls: Age, Gender, Educational Level, Occupations, Industries, and Regions.
Standard errors in parentheses / * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Using the managers sample, Table A4.10 shows a positive and significant correlation between ICT numeracy tasks and earnings. In addition, columns 3 and 5 show a positive relationship between e-mail tasks, the use of the computer for educational and learning purposes, and earnings. Furthermore, after controlling for the set of covariates and other tasks in column 6, we identify, once more, strong complementarities between these tasks. Thus, this result suggests that there are more complementarities between ICT tasks and the higher-order skills of managers.

D. Skills for Life assessment in information and communication technologies: measurement of ICT numeracy skills - The instrument (ability)

The ICT assessment used in the Skills for Life Survey is a minimum competence test. Respondents familiar or partially familiar with computers would be expected to undertake a substantial number of items at the required level in order to make an accurate assessment of their skills standards. Whilst each assessment was partially designed with the intention of measuring skills in a topic (e.g., spreadsheet and database use), the priority was the reliable production of a level per topic within the time available for the test (approximately 25 minutes), noting the potentially very wide range of skills that respondents might have. Hence, for all topic areas, the number of items on which the skill assessment is based is limited, and respondents are presented with items across a range of levels so that a judgement (based on a degree of compensation) can be made as to the skill level for a topic (BIS, 2012). Table A4.11 shows how the ICT numeracy skills were evaluated (source: BIS, 2012).

Table A4.11: ICT numeracy skills assessment – Skills for Life Survey 2011

Task	Question	Spreadsheet Task Curriculum References Spreadsheet	Level
Task 1	1	Enter a specified value into a specified cell	Entry 3
Task 2	1	Edit a date	Entry 3
	2	Select and format the content of a range of cells	Entry 3
	3	Use the auto-sum button to sum values in a vertical range of cells	Entry 3
Task 3	1	Format the values in a range of cells to display a specified number of decimal places	Level 1
	2	Enter a formula containing a single arithmetic operator, e.g. =C11*D11 into a specified cell	Level 1
Task 4	1	Enter a formula using a single arithmetic operator	Level 1
	2	Sort a block of data in a spreadsheet on one column heading	Level 1
	3	Create a simple chart in a spreadsheet	Level 1

Table A4.11 continued:

Task 5	1	Use the mouse to adjust the width of a column or the height of a row	Level 2
	2	Use an absolute cell reference in a formula	Level 2
	3	Replicate a formula to a specified range	Level 2

Source: Skills for Life Survey 2011

Table A4.12: ICT numeracy skills assessment – Level achieved (%) by occupation

Occupation	Entry Level 2 or below	Entry Level 3	Level 1	Level 2 or above	Total
Higher managerial	18.33	22.5	16.25	42.92	100
Lower managerial	25.30	33.45	18.02	23.22	100
Intermediate	28.50	32.37	24.64	14.49	100
Small employers	38.97	37.50	17.65	5.88	100
Lower supervisory	46.00	30.50	15.50	8.00	100
Semi-routine	45.24	32.94	13.49	8.33	100
Routine	53.85	31.36	11.83	2.96	100
Total	33.63	31.56	17.01	17.8	100

Table A4.12 shows the 'ICT numeracy skills' levels achieved in the Skills for Life Survey 2011 by occupation (in percentages). The performance is low across all occupations, which means that an important group of participants failed to complete relatively simple tasks. This is surprising, considering that the use of spreadsheets and databases is one of the most frequent computer tasks (as shown in section 4.4). This information will be used to create the instrumental variable utilised in the IV section. This instrument takes value 1 if the participants reaches Entry level 3 or above (adequate level according to relevant policy reports, such as BIS, 2012) or zero otherwise.

E. Computer-based numeracy tasks and the distribution of earnings: an ordered probit approach

The dependent variable, income (originally banded) can be categorised into quintiles. Quintile 1 includes earnings under £10,000, Quantile 2 between £10,000 and £16,000, Quantile 3 between £16,000 and £23,000, Quintile 4 between £23,000 and £36,000, and Quintile 5 at £36,000 or above. Table A4.13 shows the frequencies associated with each income quintile in the sample. Each quintile accounts for roughly 20% of the sample, and there are only subtle differences between the raw and weighted data.

Table A4.13: The variable income (quintiles) contains, left-censored data, interval data, and right-censored data

Quantiles	Interval	Type of data
Q1	Under £10.000	Left-censored
Q2	£10.000 and under £16.000	Interval
Q3	£16.000 and under £23.000	Interval
Q4	£23.000 and under £36.000	Interval
Q5	£36.000 or above	Right-censored

Source: Skills for Life Survey 2011

Ordered probit regressions were used, as an alternative method, to understand how the probability of reaching quantile '*x*'[125] is associated with the use of spreadsheets and databases (i.e., computer-based numeracy tasks), controlling for a set of other key explanatory variables. The ordered probit regression is a generalisation of the probit model (Long, 1997; Wooldridge, 2010), and is estimated by Maximum Likelihood[126]. Endogeneity due to omitted variable bias (ability associated to computer tasks is not observed in task functions) is addressed with an instrumental variable approach (following Angrist, 2001; Arellano, 2008; and Blundell and Powell, 2003). We take the ability (skill level) to use spreadsheets and databases in a computer as an instrument. This variable (as tested in the Skills for Life Survey 2011) is highly correlated with the use of spreadsheets and databases and, as seen in Chapter 4, meets the criteria of a valid instrument.

E.1 Empirical approach

The econometric theory behind ordered probit models departs from a latent variable model (Wooldridge, 2010), which is not observed:

$$y^* = x'\beta + \varepsilon, \quad \text{where } \varepsilon \sim N(0,1)$$

[125] Where '*x*' goes from quintile 1 to 5.

[126] OLS estimation is not possible when the dependent variable is categorical.

The latent variable (here, the continuous variable income) is not available[127] and so we can only work with limited information / categories, which for this analysis are the quintiles of income:

$y = 1$ (quintile 1) if $x'\beta + \varepsilon \leq \alpha 1$

$y = 2$ (quintile 2) if $\alpha 1 < x'\beta + \varepsilon \leq \alpha 2$

$y = 3$ (quintile 3) if $\alpha 2 < x'\beta + \varepsilon \leq \alpha 3$

$y = 4$ (quintile 4) if $\alpha 3 < x'\beta + \varepsilon \leq \alpha 4$

$y = 5$ (quintile 5) if $x'\beta + \varepsilon > \alpha 4$

The probability of observing a determined outcome, for instance $y = 5$ (quintile 5), is given by:

$$\Pr(y = 5 / x) = \Pr(x'\beta + \varepsilon > \alpha 4)$$

$$\Pr(y = 5 / x) = \Pr(\varepsilon > \alpha 4 - x'\beta)$$

$$\Pr(y = 5 / x) = 1 - \Phi(\alpha 4 - x'\beta)$$

$$\Pr(y = 5 / x) = \Phi(x'\beta - \alpha 4)$$

where Φ is the cumulative density function of the normal distribution.

The full ordered probit model is estimated by Maximum Likelihood, and the interpretation of the coefficients (i.e., marginal effects) is understood as the change in probabilities when the explanatory / indicator variable[128] fluctuates from 1 to 0. Taking again the example of quintile

[127] In the Skills for Life Survey income (continuous variable) is, indeed, not observed. In this dataset, the variable income is banded.

[128] Ie. Computer use (yes or no), intensity of computer use (daily or not) or computer task (performed or not)

5, the marginal effect of the use of spreadsheets and databases (represented by, e.g., x_2) is calculated as follows:

$$\Delta Pr(y = 5 / x) = \Phi[\beta_0 + x_1\beta_1 + \beta_2 + x_3\beta_3 +..\ x_k\beta_k] - \Phi[\beta_0 + x_1\beta_1 + x_3\beta_3 +..\ x_k\beta_k]$$

capturing the change in the probabilities when $x_2 = 1$ and $x_2 = 0$.

The estimation of the key explanatory variable in this analysis, ICT numeracy, can be subject to endogeneity problems due to unobserved heterogeneity. To address this problem, an instrumental variable approach is taken, where the instrument is the capacity of processing spreadsheets and databases in a computer, as tested in the Life for Skills Survey 2011.

To estimate an ordered probit model with endogeneity, we follow Arellano (2008), Blundell and Powell (2003). Note that the ordered probit model (described above) with five categories can be transformed into a system of four probit regressions, as follows:

i) $E(y5 \mid x) = 1 – \Phi(\alpha4 - x'\beta)$

$E(y5 \mid x) = \Phi(-\alpha4 + x'\beta)$

ii) $E(y4 + y5 \mid x) = [\Phi(\alpha4 - x'\beta) - \Phi(\alpha3 - x'\beta)] + [1 – \Phi(\alpha4 - x'\beta)]$

$E(y4 + y5 \mid x) = 1 - \Phi(\alpha3 - x'\beta)$

$E(y4 + y5 \mid x) = \Phi(-\alpha3 + x'\beta)$

iii) $E(y3 + y4 + y5 \mid x) = [\Phi(\alpha3 - x'\beta) - \Phi(\alpha2 - x'\beta)] + [\Phi(\alpha4 - x'\beta) - \Phi(\alpha3 - x'\beta)] + [1 – \Phi(\alpha4 - x'\beta)]$

$E(y3 + y4 + y5 \mid x) = 1 - \Phi(\alpha 2 - x'\beta)$

$E(y3 + y4 + y5 \mid x) = \Phi(-\alpha 2 + x'\beta)$

iv) $E(y2 + y3 + y4 + y5 \mid x) = [\Phi(\alpha 2 - x'\beta) - \Phi(\alpha 1 - x'\beta)] + [\Phi(\alpha 3 - x'\beta) - \Phi(\alpha 2 - x'\beta)] + [\Phi(\alpha 4 - x'\beta) - \Phi(\alpha 3 - x'\beta)] + [1 - \Phi(\alpha 4 - x'\beta)]$

$E(y2 + y3 + y4 + y5 \mid x) = 1 - \Phi(\alpha 1 - x'\beta)$

$E(y2 + y3 + y4 + y5 \mid x) = \Phi(-\alpha 1 + x'\beta)$

These estimates, (α1, α2, α3, α4, β), are consistent and asymptotically normal. But, not as efficient as ordered probit Maximum Likelihood because they are maximizing a pseudo-likelihood as opposed to the full-likelihood (Arellano, 2003). The advantage is that they can be obtained from a binary probit routine while enforcing the constraint on β across groups[129].

Using the same bivariate probit strategy and adding an instrument to the model, the ordered probit regressions with dummy endogenous explanatory variable can be estimated. Now, the initial model is,

i) $y1 = 1(x\alpha + z_1'\gamma + u \leq \alpha 1)$

ii) $y2 = 1(\alpha 1 < x\delta + z_1'\gamma + u \leq \alpha 2)$

iii) $y3 = 1(\alpha 2 < x\delta + z_1'\gamma + u \leq \alpha 3)$

iv) $y4 = 1(\alpha 3 < x\delta + z_1'\gamma + u \leq \alpha 4)$

v) $y5 = 1(x\delta + z_1'\gamma + u > \alpha 4)$

vi) $z = 1(z'\pi + v > 0)$

[129] The constraint is that all β coefficients must be the same across groups.

vii) $\begin{pmatrix} u \\ v \end{pmatrix} \mid Z \sim N\left(0, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$

with $z = (z_1', z_2')'$, where z_1 are exogenous controls, and z_2 is the excluded instrument.

Rearranging the system to estimate the probit regressions, the full model now becomes:

i) $y5 = 1(x\delta + z_1'\gamma + u > \alpha 4)$

ii) $y4 + y5 = 1(x\delta + z_1'\gamma + u > \alpha 3)$

iii) $y3 + y4 + y5 = 1(x\delta + z_1'\gamma + u > \alpha 2)$

iv) $y2 + y3 + y4 + y5 = 1(x\delta + z_1'\gamma + u > \alpha 1)$

v) $z = 1(z'\pi + v > 0)$

vi) $\begin{pmatrix} u \\ v \end{pmatrix} \mid Z \sim N\left(0, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$

Again, taking the example of quintile 5, the estimator ($\delta.\ \gamma, \alpha, \rho, \pi$) is consistent, and can be estimated as a standard probit model with equations i), v) and vi). A similar strategy is used to calculate the rest of the coefficients.

E.2 Ordered probit estimations

The tables below show results from several ordered probit regressions. The different outputs presented have a similar structure, with the quantiles of the income distribution as the dependent variable, and age, gender, educational level, occupation, region, and industry as control variables. Each model explores different aspects of the ICTs on the job. The first model investigates the effect of computer use. The second, the intensity of computer use. And the third, the role of different computer tasks. In the last part of this section, we present an instrumental variable approach for the variable 'computer-based numeracy tasks' (i.e., the use of spreadsheets and databases), which is the main point of the analysis. Sample weights are used to work with a representative sample, and clustered standard errors are set at the industry level, given that observations could be correlated within each industry[130]. All the coefficients in the tables represent marginal effects.

The key independent variable in the first ordered probit regression (Table A4.14) is the dummy variable 'computer use' (UsePC), which is equal to 1 if the worker uses a computer at work, and zero otherwise. The association between this variable and income is statistically significant in each quantile. For example, in quantile 5, the coefficient of the variable 'computer use' indicates that on average, workers using a computer at work are 12.6% more likely than workers that do not use one, to reach the highest quintile of the distribution of income. In contrast, the negative coefficient in quantile 1 means that on average, workers using a computer at work are 10.8% less likely than workers that do not use one to be at the bottom of the distribution.

[130] i.e., the i.i.d. assumption is violated.

Table A4.14: Ordered probit estimation. Computer use

			Ordered Probit		
Quintiles	Q1	Q2	Q3	Q4	Q5
UsePC	-0.108***	-0.0275***	-0.00952***	0.0197***	0.126***
	(0.0172)	(0.00419)	(0.00173)	(0.00264)	(0.0204)
Age	-0.00378***	-0.000957***	-0.000332***	0.000686***	0.00438***
	(0.000570)	(0.000166)	(0.0000503)	(0.000110)	(0.000675)
Male	-0.150***	-0.0381***	-0.0132***	0.0273***	0.174***
	(0.0152)	(0.00488)	(0.00232)	(0.00436)	(0.0179)
Degree	-0.103***	-0.0261***	-0.00905***	0.0187***	0.119***
	(0.0112)	(0.00279)	(0.000965)	(0.00189)	(0.0130)
Manager	-0.156***	-0.0396***	-0.0137***	0.0284***	0.181***
	(0.0104)	(0.00386)	(0.00115)	(0.00318)	(0.0119)
Region	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
N	3247	3247	3247	3247	3247

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

Taking the sub sample of workers who use a computer at work, we explore how the 'intensity of computer use' (OftenPC) relates to each quintile of income. Table A4.15 shows that the use of computers on a daily basis significantly increases the probability of reaching quintile 5 and decreases the probabilities of reaching quintiles 1, 2 and 3, compared to those workers who use the computer less frequently on the job. At the same time, the effect is close to zero in quintile 4. This suggests that workers using computers daily tend to be concentrated at the top of the income distribution, where they earn on average at least £36,000 per year (gross income).

Table A4.15: Ordered probit estimation. Frequency of computer use

			Ordered Probit		
Quintiles	Q1	Q2	Q3	Q4	Q5
OftenPC	-0.114***	-0.0456***	-0.0269***	0.00593***	0.181***
	(0.0193)	(0.00823)	(0.00461)	(0.00137)	(0.0311)
Age	-0.00300***	-0.00120***	-0.000708***	0.000156***	0.00475***
	(0.000414)	(0.000190)	(0.000104)	(0.0000426)	(0.000670)
Male	-0.122***	-0.0485***	-0.0286***	0.00631**	0.192***
	(0.0119)	(0.00519)	(0.00402)	(0.00222)	(0.0178)
Degree	-0.0817***	-0.0326***	-0.0192***	0.00424**	0.129***
	(0.0116)	(0.00629)	(0.00309)	(0.00161)	(0.0191)
Manager	-0.129***	-0.0515***	-0.0304***	0.00670***	0.204***
	(0.0111)	(0.00443)	(0.00261)	(0.00176)	(0.0160)
Region	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
N	2471	2471	2471	2471	2471

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

The next regression includes the computer tasks the ordered probit model. We explore the five most common tasks, namely ‘word processing’ (Word), ‘access to the internet’ (Internet), the ‘use of e-mails’ (Email), ‘spreadsheet and databases processing’ (Spreadsheet), and the use of the computer for ‘educational purposes’ (Education). All of them enter the model as independent variables. Table A4.16 shows that the only one that gets significant coefficients is the ‘use of spreadsheet and databases’, which on average increase the probability of reaching at least quantile four of the income distribution, holding all else constant. The main effects[131] of ‘word processing’, the ‘access to the internet and browsing’, and the ‘use of e-mails’ are not

[131] Interactions in these models are not included because they are not related to the main objective of the chapter.

significant, probably because they are widespread, and today necessary conditions for modern jobs and the modern economy (thus, they are not making a difference in these equations). On the other hand, the use of the computer for educational and learning purposes seems not to be frequent enough, and the impact is difficult to measure with this dataset.

Table A4.16: Ordered probit estimation. Computer tasks

	Ordered Probit				
Quintiles	Q1	Q2	Q3	Q4	Q5
Word	0.0131	0.00512	0.00297	-0.000804	-0.0203
	(0.0154)	(0.00589)	(0.00360)	(0.00100)	(0.0238)
Internet	0.0232	0.00910	0.00528	-0.00143	-0.0361
	(0.0224)	(0.00911)	(0.00523)	(0.00146)	(0.0353)
Email	-0.0288	-0.0113	-0.00655	0.00177	0.0449
	(0.0208)	(0.00806)	(0.00499)	(0.00139)	(0.0324)
Spreadsheet	-0.0573***	-0.0225***	-0.0130***	0.00353**	0.0893***
	(0.0144)	(0.00597)	(0.00365)	(0.00114)	(0.0227)
Education	-0.0174	-0.00682	-0.00396	0.00107	0.0271
	(0.0121)	(0.00461)	(0.00257)	(0.000711)	(0.0185)
Age	-0.00329***	-0.00129***	-0.000749***	0.000203***	0.00513***
	(0.000498)	(0.000219)	(0.000113)	(0.0000444)	(0.000772)
Male	-0.123***	-0.0484***	-0.0281***	0.00761***	0.192***
	(0.0116)	(0.00548)	(0.00417)	(0.00199)	(0.0180)
Degree	-0.0809***	-0.0317***	-0.0184***	0.00498***	0.126***
	(0.0110)	(0.00599)	(0.00302)	(0.00151)	(0.0180)
Manager	-0.133***	-0.0523***	-0.0303***	0.00822***	0.208***
	(0.0130)	(0.00479)	(0.00275)	(0.00138)	(0.0181)
Region	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
N	2471	2471	2471	2471	2471

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Skills for Life Survey 2011

The last part of this section presents the instrumental variable results. The ‘use of spreadsheets and databases’ is instrumented with ICT math and stats processing skills (i.e., the capacity to use spreadsheets and databases in a computer), as tested in the Skills for Life Survey. Table A4.17 shows the results of regressing the quintiles of income on computer tasks, age, gender, educational level, occupation, region, and industry, in an ordered probit model and in an IV-ordered probit model, too. Consistently, we observe in both models, that the use of spreadsheets and databases increases the probability of reaching higher quintiles of the distribution. For instance, regarding quintile 5, the IV ordered probit model shows that workers using spreadsheets and databases on their computers are on average 9.9% more likely to be at the right extreme of the distribution, holding all else constant. A similar coefficient is obtained in the simple ordered probit model.

Table A4.17: Instrumental variable ordered probit estimation. Computer-based numeracy tasks

		Quintiles of Earnings				
		Q1	Q2	Q3	Q4	Q5
Ordered Probit	ICT Numeracy	-0.055^{***}	-0.022^{***}	-0.013^{***}	0.0032^{**}	0.086^{***}
		(0.0133)	(0.00579)	(0.00348)	(0.00102)	(0.0216)
IV-Ordered Probit	ICT Numeracy	-0.053^{***}	-0.038^{**}	-0.023^{**}	0.013^{**}	0.099^{***}
		(0.0147)	(0.0125)	(0.00786)	(0.00450)	(0.0302)

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, N: 2471 observations
Source: Skills for Life Survey 2011

CHAPTER 5: CONCLUSION

The last chapter of this thesis is divided into two sections. Section 5.1 presents a summary of the findings and its original contributions to the literature. Then, section 5.2 describes the limitations of the study and outlines new avenues for further research.

5.1 Summary of findings, and the original contributions to the literature

This thesis investigates some of the important linkages between managers, technology, earnings, and productivity in the United Kingdom. The summary of findings and the contributions to the economics of management and productivity are presented below.

In chapter 2, we explore a central question of the economics of management and productivity, which is looking at the role of managers in productivity in the United Kingdom. Taking into account different types of managers (e.g., managers and supervisors, performing routine or non-routine tasks) this study complements previous research conducted by Black and Lynch (2001), Bloom et al (2007; 2010), and Siebert and Zubanov (2010). We repeatedly observe a strong positive correlation between managerial tasks, non-routine tasks, and earnings, and a contribution of managers to productivity during the period 1970-2007, which is in line with the Skill-Biased Technical Change (SBTC) (Autor et al., 1998; Card and DiNardo, 2002) and the routinisation hypotheses (Goos et al, 2014). The contributions to the literature are twofold. First, this study uses different measures of management practices, which brings credibility to the subject in terms of internal validity[132]. Second, this chapter distinguishes between non-routine and routine task-intensive types of managers, which is particularly relevant in a country that suffers from some degree of job polarisation. The empirical analysis suggests that both routine and non-routine managers make contributions to productivity. However, the contribution of routine managers is limited in the context of SBTC.

In chapter 3, we investigate complementarities between ICT capital investment and intangible capital that show potential to increase productivity. More precisely, we explore whether technological progress correlates with more robust management in the workplace. Two technologies are considered; the introduction of new computerised equipment and the introduction of new communication technologies. We also analyse different tasks, such as 'people management tasks' (focused on interactions, relationships, and related to leadership skills), and 'organisation management' practices (oriented to maintaining the effective running of the organisation, such as planning and resource control). The empirical analyses show that the introduction of new communication technologies is consistently associated with 'people management' practices, but not with 'organisation management'. However, the introduction of new computerised equipment is not significantly associated with management practices. These results suggest that ICT capital investment (the introduction of technology) only complements intangible capital (management practices at work shaped by managers) if they share key characteristics (e.g., if the technology operates using social channels, then it will likely connect with people management practices). The thesis contributes to the existing literature by shedding

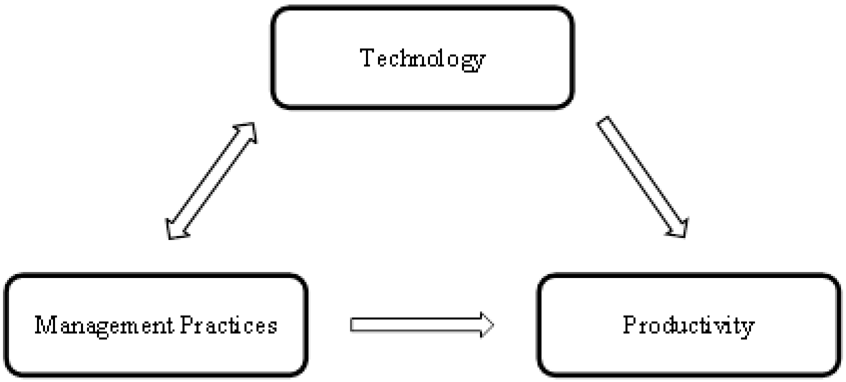
[132] The measurement of management practices can suffer from internal validity issues, as discussed by Bloom et al. (2007). Internal validity refers to whether one can validly draw the inference that within the context of the study the differences in the dependent variables were caused by differences in the relevant explanatory variables (Meyer, 1995). Common threats to interval validity are mismeasurements, omitted variables, and simultaneity, among others.

light on the black box of management practices, and by demonstrating that not all managerial tasks utilise the same skills. We distinguish between people and organisation management practices, and relate these to the concept of intangible capital that is expanding the limits of the economics literature. We found clear examples indicating that the *modus operandi* of a technology (for instance, centred on interactions between employees and managers) is crucial to understanding how it matches the higher-order skills of managers. This last result supports the previous findings by Corrado et al. (2017), who look at the topic from a macro-perspective.

Finally, chapter 4 explores aspects of modern technology that have the potential to affect productivity and economic growth, namely the relationship between computer-based numeracy tasks and earnings. The focus here is on the use of spreadsheets and databases, since these are more common among managers and higher professionals (BIS, 2012). We present estimates for the returns to computer-based numeracy tasks, but we investigate the extent to which the probabilities of reaching different quintiles of the income distribution are associated with such tasks. Using the full sample, the results show that computer-based numeracy tasks, and no other tasks, are significantly associated with earnings, and substantially increase the probability of reaching the highest quantile of the income distribution. A possible explanation is that other computer tasks have become general purpose technologies (e.g., e-mailing, the use of the internet, and word processing) and are not making a difference in the workplace today. However, if the sample is restricted to managers (a more skilled group, on average), heterogenous effects are observed. We find that computer-based numeracy tasks, e-mailing, and the use computers with educational and learning purposes are also important. Thus, there are more technology-skill complementarities for this group of workers. Compared with Dolton et al, (2004 and 2007), we identify relatively similar results only in our restricted sample. This suggests that the effects of computer use evolve over time, given that our data are more recent.

These results complement existing empirical evidence (for example, Krueger, 1993; Borghans and ter Weel, 2001; Dolton et. al., 2004, 2007 and 2008; DiNardo and Pischke, 1997; Entorf et al., 1997 and 1999; and Pabilonia and Zogui, 2005), and make a contribution to the controversial topic on the returns to computer tasks.

Figure 5.1: Key variables and relationships studied



To conclude, our contribution to the economics of management and productivity is depicted in Figure 5.1 that shows the key relationships studied and our main conclusion, i.e. we find clear complementarities between management practices and technology (Chapter 3 and 4), which are associated with a positive effect on productivity (Chapter 2 and 4). The limitations of the study and new avenues for further research are presented below.

5.2 Limitations and further work

5.2.1 Limitations of the study

The limitations of this thesis mainly relate to data availability. Further contributions to the literature could be made by adopting panel data techniques. Ideally, this should be in the context of Randomised Control Trials or difference-in-difference approaches that can potentially find causal relationships. Richer datasets could also offer more robust measures of people management and organisational management practices.

5.2.2 Further research

The limitations of this study could be addressed by future work. One example is the 'Management Practices Survey 2016', which is currently under development by the Office for National Statistics (ONS). The 'World Management Database' (shaped by Bloom, Van Reenen, and collaborators) is also growing fast. Therefore, more panel data estimates should be available within a couple of years.

In addition, further research could focus on the development of managerial skills outside higher education institutions. This thesis has shown that there are different types of managers, and also that there are many workers in non-managerial occupations, such as intermediate occupations, and owners of small businesses, who regularly perform managerial tasks. They make different contributions to productivity that can be maximised if researchers and policymakers recognise their roles and their different leadership responsibilities. Therefore, further research focusing on technical institutions, primary and secondary schools seems to be appropriate and relevant.

Furthermore, our findings suggest that studies on technology and technological change should be conducted as often as possible. Continual research in this area is strongly recommended. Technology is highly contextual. It evolves fast and, has heterogeneous effects, whilst having a substantial impact on the way we live and work. In particular, further investigation could focus on the skills needed to perform ICT numeracy tasks, because these are likely to boost the careers of employees/managers.

Another topic that emerges is workplace training for ICT numeracy skills. Their importance has already been established, but unfortunately some employees have strong barriers that must be overcome, such as lack of confidence, lack of competence, and lack of access to resources (Bingimlas, 2009). Moreover, ICT numeracy programmes and software evolve fast, which justifies continuous training in this area. In this context, the implementation and evaluation of different training programmes is also strongly recommended.

Finally, our results yield new insights that are closely related to the field of labour economics. Further investigation could also be useful to macroeconomics. For example, further study on the relationship between management practices and their economic performance at the aggregate level, would be useful for reducing uncertainty during times of financial turmoil.

6. References

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