SCIENCE POLICY RESEARCH UNIT

SPRU Working Paper Series

SWPS 2019-24 (November)

Job Composition and Its Effect on UK Firms in the Digital Era

Mabel Sánchez Barrioluengo

Energy Policy

Sustainable Development

Science and Technology Policy

Innovation and Project Management

Economics of Innovation

UNIVERSITY OF SUSSEX

BUSINESS SCHOOL

SPRU Working Paper Series (ISSN 2057-6668)

The SPRU Working Paper Series aims to accelerate the public availability of the research undertaken by SPRU-associated people, and other research that is of considerable interest within SPRU, providing access to early copies of SPRU research.

Guidelines for authors

Papers should be submitted to swps@sussex.ac.uk as a PDF or Word file. The first page should include: title, abstract, keywords, and authors' names and affiliations. The paper will be considered for publication by an Associate Editor, who may ask two referees to provide a light review. We aim to send referee reports within three weeks from submission. Authors may be requested to submit a revised version of the paper with a reply to the referees' comments to swps@sussex.ac.uk. The Editors make the final decision on the inclusion of the paper in the series. When submitting, the authors should indicate if the paper has already undergone peer-review (in other series, journals, or books), in which case the Editors may decide to skip the review process. Once the paper is included in the SWPS, the authors maintain the copyright.

Websites

UoS: **www.sussex.ac.uk/spru/research/swps**
SSRN: **www.ssrn.com/link/SPRU-RES.html**
IDEAS: **ideas.repec.org/s/sru/ssewps.html**

Job Composition and Its Effect on UK Firms in the Digital Era

Mabel Sánchez Barrioluengo

Manchester Institute of Innovation Research. Alliance Manchester Business School. University of Manchester

E-mail: msbarrioluengo@manchester.ac.uk

Abstract

This paper studies how the adoption of digital technologies has changed the employment structure of UK firms. While the scientific literature traditionally has shown inconclusive results about who is winning the race between man and machine, we argue that currently there are reasons to be less pessimistic about the effect of technology on labor. Drawing on an employer-employee panel survey in 2004 and 2011 in the UK, this study shows that the effect of the firms' routine exposure on employment and wages varies according to the skill content of occupations and by sectors. Our results suggest that firms' concentration on routine cognitive jobs does not generate outright job-losses and could even have a positive effect on overall employment at firm-level. On the other hand, firms exposed to routine manual task jobs are more at risk of generating a negative impact on firms' labor, mainly decreasing their workforce. While the concentration of routine occupations has a job-creating effect in the tertiary sector, this does not necessarily imply consistent job-losses within the secondary sector. Finally, we conclude that the investment in routine workforce without the appropriate technological adoption is not enough to generate positive effects on labor at firm-level, specifically in the manufacturing sector.

Keywords: digitalisation, employment, wages, digital technologies, routine jobs, firm, UK.

1 Introduction

There is a burgeoning literature on the relations between technology and labor and on the determinants of changes in the occupational structure and the effect on the industrial and survival of traditional business models. Literature in labor economics, including authors like Autor et al. (2003) and Goos and Manning (2007), claim that since the 1990s employment opportunities increased for high- (e.g., managers, scientists, and professionals) and low-skill (e.g., janitors, security guards, waiters, and cleaners) occupations while the demand for mid-skill jobs (e.g., clerks, production, and workers) has decreased. This phenomenon, known as the polarization of the labor markets, appears, with very few exceptions, across countries (OECD, 2017).

Information and Communication Technologies (ICT) are one of the main factors affecting 'job polarization' which, on the one hand, has accelerated the replacement of jobs intensive in routine physical and cognitive tasks while, on the other hand, has increased the productivity of occupations for which problem-solving and interaction skills are important (Levy and Murnane, 2004). While an important set of scientific papers has focused on the impact of technology and automated processes on employment and wages (Acemoglu and Restrepo, 2017), the literature is inconsistent on who is winning the race between man and machine when the analysis focuses on historical data from the last decades (see for example, Graetz and Michaels, 2018; Acemoglu and Restrepo, 2017; Bessen and Righi, 2019; Bessen, 2019), showing some differences that emerge across countries (Adermon and Gustavson, 2011; Fonseca et al., 2018; Harrigan et al., 2016; Salvatori, 2018) and sectors (Gaggl and Wright, 2017; Bessen and Righi, 2019). The current challenge is to understand if we are nowadays at a different time under the digital era and there are reasons to feel less pessimistic about the impact of technology on jobs (Balsmeier and Woerter, 2019; Bessen et al., 2019). While firms are at the heart of these labor changes (Matias-Cortes and Salvatori, 2019), very little is known about the effect of variations in the job composition and occupational (re)distribution at firm-level.

This work puts the emphasis on middle-skill routine jobs, as they are mainly at risk of being replaced by technology and automated processes (Bessen et al., 2019; Autor, 2015; Autor and Dorn, 2013), and unpacks the differences that emerge when the skill content of these routine occupations is taken into consideration. The study contributes to this special issue by providing deeper knowledge about the impact of technology on employment and wages at firm-level in the digital era and addresses the following research questions: Do changes in the skill composition of jobs affect differently firms´ overall employment and wages nowadays? Does this pattern vary across sectors? It makes contributions to two stands of the literature. On the one hand, the paper provides further insights to the debate on labour economics by disentangling the effect of firm's exposure to routine cognitive and manual jobs on labor across sectors nowadays. On the other hand, it reacts to the call for contributions in the strategic management literature on digitalisation driven changes at the business level (Loebbecke and Picot, 2015).

Drawing on data from the UK's Workplace Employment Relations Study (WERS), this paper links employers and employees information and provides evidence on the changes in the job composition (that is the occupational distribution of workers) and overall employment and wages at the firm-level. The UK is an interesting case of study due to its relatively light labor market regulations compared to other European countries (Eichhorst et al., 2010), which allows for a fast change from human labor to industrial machines. Data, provided by the Department for Business, Innovation and Skills, cover a total of 989 firms included in a panel between 2004 and 2011. We suggest that while routine occupations have exhibited notable negative growth in the last years at firm-level, changes in the occupational profile of the firm based on these middle-skill jobs does not affect equally labor. Our results show that while routine jobs are more at risk of being replaced by automation, the effect of firms' routine exposure on the overall employment and salaries varies according to the skill content of these middle-skill occupations. Specifically, exposure to routine cognitive jobs does not generate outright job-losses and could even have a positive effect on overall employment in the firm. On the other hand, firms exposed to routine manual tasks are more at risk of generating a negative impact on firms' labor, mainly decreasing total workforce. The effect of routine exposure has also a sectoral component. While concentration of routine occupations has a job-creating effect in the tertiary sector, this does not necessarily imply consistent outright job-losses within the secondary sector and could have even a positive effect on labor in the case of exposure to routine cognitive occupations. Finally, we conclude that the investment in routine workforce without the appropriate technological adoption is not enough to generate positive effects on labor at firm-level, specifically in the manufacturing sector.

The rest of the paper is structured as follows. We first introduce the relevant literature on polarization and the impact of automation on labor (Section 2). Section 3 presents the data sources, specifically the UK employer-employee survey linking the job composition of the firm with the measures of labor and the main variables used in the empirical analysis (routinization exposure and employment and wages at firm-level). Section 4 contains the empirical approach, analysing the effect of changes in the employment structure of the firm on labor. Lastly, Section 5 summarizes and concludes.

2 Literature review

2.1 Unpacking routine cognitive occupations

The task-based approach has gained traction among scholars and policymakers for many reasons. First, compared to other frameworks (i.e., skill-biased technical change) it offers a coherent account of the empirical patterns observed in the labor markets of U.S. and Europe, especially the decline in employment and wages of routine occupations that contrasts with the increment of labor in both high- and low- skilled workers (Autor et al. 2003; Acemoglu and Autor, 2011). Second, it provides a nuanced view of how disruptive forces like technology (or trade) affects selectively some work tasks (and the attendant skills) rather than causing outright job loss or worker displacement.[1] Or in other

[1] For a contrarian view, see for example Schmitt et al. (2013). Several studies have concluded that job and wage polarization are the results of other factors as well (e.g. deunionisation, government policies and institutions, investment, trade, and globalization) (Card and DiNardo, 2002; Autor, 2014; Mishel et al., 2014).

words, this approach accommodates the dual role of technology, both complementing and substituting human work. Third, it resonates with traditional labor economics by emphasizing qualitative changes in the content of occupations due to the emergence, decline or transformation of skills (Eurofound, 2015; Vona and Consoli, 2015).

The processes of computerisation and automation are a phenomenon that appears, with very few exceptions, across countries (OECD, 2017). Empirical work on polarization now covers the U.S. (Autor and Dorn, 2013), Europe (Gregory et al., 2016), individual European countries at national level (Adermon and Gustavson, 2011; Dauth, 2014; Fonseca et al., 2018; Harrigan et al., 2016; Salvatori, 2018) as well as regional economies (Consoli and Sánchez-Barrioluengo, 2019; Dauth, 2014). The UK is no exception and the projections for 2014-2024 suggest that the phenomenon of polarization will continue with a strong growth for higher level occupations (like managers or professional occupations) and non-routine manual occupations (like caring or leisure), while at the same time net job losses are projected for those occupations more sensitive to be routinized (like secretarial occupations or plant and machine operatives) (UKCES, 2016). In fact, Matias-Cortes and Salvatori (2019) show the increasing trends in Great Britain towards a workplace occupational concentration, with a particular shift towards the specialization of non-routine occupations.

In this polarization process, middle-skill routine occupations are of particular interest for understanding employment transformations because these occupations are traditionally more liable to be displaced and/or replaced by technology and automated processes (Bessen et al., 2019; Autor, 2015; Autor and Dorn, 2013). Traditionally, routine tasks are characteristic of many middle-skilled occupations covering both cognitive and manual jobs, such as bookkeeping, clerical work, repetitive production, and monitoring jobs. Because the core job tasks of these occupations follow precise, well-understood procedures, they can be (and increasingly are) codified in computer software and performed by industrial machinery (or, alternatively, they can be sent electronically -“outsourced”- often to foreign worksites) (Acemoglu and Autor, 2011). However, these routine occupations range from more cognitive tasks, that are most intensively used in clerical and sales occupations, to manual tasks that are most prevalent in production and operative positions. This distinction allows us to differentiate particular characteristics that emerge between cognitive and manual routine occupations: offshorability is highest in clerical/sales occupations and these routine cognitive tasks are strongly non-monotone in education, that is, they are used most intensively by high school and some-college workers. Routine manual tasks, in turn, reflect specialization in blue-collar production and operative occupations (Acemoglu and Autor, 2011, Matias-Cortés et al., 2016), involve less complex social interaction and are particularly vulnerable to automation (Gonzalez Vazquez, et al., 2019). In addition, routine cognitive occupations are much more predominant in services while routine manual occupations are more frequent in the manufacturing sector (Fonseca et al., 2018). Some studies even demonstrate that both types of occupations have not followed the same evolution pattern: in the US the share of the population employed in routine manual occupations declines steadily over the entire 1979-2014 period. Meanwhile, the population share of routine cognitive employment increases between 1979 and 1989 and then declines steadily until 2014 (Matias-Cortés et al., 2016). In the UK, while a decline in routine employment is entirely driven by manual occupations, the share of routine cognitive employment did not increase in the private sector (Matias-Cortes and Salvatori, 2019).

We argue that a possible difference exists among workers in routine manual and routine cognitive occupations and that it relates to the skill composition that characterizes both types of jobs. Our hypothesis is that, while both routine cognitive and manual occupations are exposed to be replaced by machines due to the advance in technology -as some occupations are more susceptible of automation than others (Frey and Osborne, 2013)-, jobs requiring more social interactions and more skilled workers and, that is, those working in cognitive routine occupations, are less vulnerable to machinery adoption and can be easily reallocated to other tasks/jobs. In consequence firms do not necessarily exhibit outright job losses if they change their employment structure increasing the concentration on these occupations. However, those employees involved in manual occupations, traditionally with lower levels of education (Bessen et al., 2019) and lower skill levels will be more at risk of being displaced, generating a negative impact on firms' labor.

2.2 The effect of automotion on labor

The potential for automation to displace workers is being taken seriously in recent labor market models where the industrial machinery and workers compete in the production of different tasks and technology changes the comparative advantage of workers across those tasks (Acemoglu and Autor 2011; Benzell et al. 2016; Susskind 2017). From a theoretical point of view, on the one hand, greater penetration of technology into the economy affects wages and employment negatively because of a displacement effect (by directly displacing workers from tasks they were previously performing), while, on the other hand, the effect could be also positive because of a productivity effect (as other industries and/or tasks increase their demand for labor) (Acemoglu and Restrepo, 2017). In the case of salaries, various studies have indeed argued that technological progress has contributed to rising wage inequality in advanced countries during the past decades (e.g., Autor et al., 2003; Autor and Dorn, 2013; Goos et al., 2014).

The empirical evidence on the effects of industrial technology on labor shows, in fact, the same duality. Graetz and Michaels (2018) find that industrial robots have had positive wage effects and no employment effects across a panel of countries and industries; Acemoglu and Restrepo (2017) find that wages and employment have decreased in US regions most exposed to automation by robots, whereas Dauth et al. (2017) find evidence of positive wage effects and no changes in total employment in German regions. Other studies point out however that some differences emerge even at the sector level. In this regard, Mann and Püttmann (2017) find that automation increases jobs in services but decreases them in manufacturing. Gaggl and Wright (2017) desegregate sectors in a finer grain and find that ICT tended to raise employment in wholesale, retail, and finance industries, but had no statistically significant effect on other sectors, including manufacturing. Bessen and Righi (2019) demonstrate that jobs are lost in manufacturing, transport, and utilities while job growth following information technology shocks is robust in trade, services, and finance. Similarly, Bessen (2019) argues that technologically mature industries will tend to have lower elasticity of demand and, hence, a weaker or negative employment response.

Some of the most recent literature puts the emphasis on the effect at firm-level. For example, Koch et al. (2019) find that robot adoption generates substantial output gains reducing labor cost share by 5-7% points and leading to net job creation at a rate of 10% while revealing substantial job losses in firms that do not adopt robots. Bessen et al. (2019) conclude that automation at the firm increases the probability of workers separating from their employers and decreases days worked, leading to a 5-year cumulative wage income loss of about 8% of one year´s earnings for incumbent workers. Alternatively, Akerman et al. (2015) suggest that internet technology increased the employment of skilled workers and had no effect on unskilled ones.

What the majority of these studies have in common is the historical perspective, covering several decades that includes the most remarkable periods of industrial technology adoption in the 80s and 90s and the internet adoption and web use in the early 00s (Brynjolfsson, 2000; Autor and Dorn, 2013). Following the work from Balsmeier and Woerter (2019) analysing the process of digitalisation in Swiss firms and its influence on job creation and destruction in 2015, we argue that current times are different as we are already living in the digital era where the penetration of technology is more stable. These authors find that increased investment in digitalisation is associated with increased employment of high-skilled workers and reduced employment of low-skilled workers, with a slightly positive net effect, results that are almost entirely driven by firms that employ machine-based digital technologies. This argument is in line with the vision from Bessen (2019) who argues that, although traditionally the manufacturing sector has been more at risk of job-loss because these firms concentrate industrial machinery, the historical process of deindustrialization suggests that we are currently in a stabilization technological phase where manufacturing sector has less elastic demand than most other industries on average. In consequence, computer technology should have a relatively lighter negative impact, ceteris paribus, on employment in manufacturing industries. These arguments highlight the importance of understanding sectoral differences in the effect of technology on overall employment and wages nowadays.

We put the emphasis on firms because they are the ultimate actors deciding to replace human labor with industrial machinery rethinking their strategies and business models to face all changes related to the digital transformation. For example, firms will need to plan their investments differently to ride the robotization wave. Even if the presumed technological advances materialize, there is no guarantee that firms would choose to automate; that would depend on the costs of substituting machines for labor and this will be related, among other things, to how much wages change in response to this threat. Second, new technologies' impact on the labor market is dependent not only on where they hit but also on adjustments in other parts of the economy (Acemoglu and Restrepo, 2017). The impact of digitalisation on transaction and information costs may then in turn inform fundamental organisational strategies for using "market versus hierarchy" solutions and redefine the vertical/horizontal boundaries of the firm (Afuah, 2003), while information processing, knowledge transfer, and resource sharing will call for debates about corporate roles and responsibilities for a new allocation of internal resource (Arrfelt et al., 2015). In this regard, literature in strategic management calls for firm-centred studies contributing to understanding how digitalisation drives changes at the business level (Loebbecke and Picot, 2015).

3 Data

The main source of information is the 2004 and 2011 Workplace Employment Relations Survey (WERS) (Department for Business Innovation and Skills, 2014). WERS is a linked employer-employee survey that provides nationally representative data on workplaces[2] (35% of all workplaces) from all sectors of the economy, except agriculture and mining, in Great Britain with five or more employees[3]. The strength of the survey lies in the richness of data collected on workplace policies and practices and its

[2] We use "firm" to identify "workplaces" as they are the unit of observation in WERS and are defined as an enterprise or part thereof situated in a geographically identified place. A workplace comprises the activities of a single employer at a single set of premises. More information about the survey can be found at www.wers2011.info

[3] Matias-Cortes and Salvatore (2019) have previously used WERS to test job polarization in the UK from the demand side perspective. They conclude that overall results using this survey are in line with authors using nationally representative UK Labour Force data (Salvatori, 2018) confirming that the exclusion of smaller workplaces does not undermine the reliability of the data.

structure as a longitudinal panel.[4] The panel sample consists of 969 workplaces which had each been interviewed in the first wave of the survey in 2004 and followed up in 2011.[5] WERS provides information in three different questionnaires that are linked through the anonymised code of the firm. The three questionnaires include: a) Employee profile questionnaire answered by managers of the firm including information on the occupational structure of the workforce, b) Survey of Employees including detailed information of employee personal characteristics, wages and occupations, and c) Financial output questionnaire featuring output measures of the firm.

3.1 Measuring the job composition based on the firm´s routine exposure

Following the literature (e.g. Acemoglu and Autor, 2011; Matias-Cortes and Salvatori, 2019) we delineate occupations along two dimensions based on their task content: “cognitive" versus “manual," and “routine" versus “non-routine." The distinction between cognitive and manual occupations is based on the extent of mental versus physical activity. The distinction between routine and non-routine is based on the work of Autor et al. (2003). If the tasks involved can be summarized as a set of specific activities accomplished by following well-designed instructions, the occupation is considered routine. If instead, the job requires creativity, problem-solving, or human interaction, the occupation is non-routine.

Using the employee profile questionnaire in which managers of the 969 firms included in the panel provides information on the employment structure of the workplaces, we cluster workers as either non-routine cognitive (i.e., managers and professionals), routine cognitive (like clerks), routine manual (i.e. machine operators) or non-routine manual (capturing low-skill occupations such as cleaners and janitors) based on an aggregation of 1-digit Standard Occupation Codes.[6] Additionally, to be in line with the literature and to guarantee the comparability of this study with other reference works, we create a unique measure of routine occupations where routine cognitive and routine manual jobs are grouped together.

The main advantage of using a panel of firms is that we can capture changes in the patterns of specialization of the workplaces by looking at the distribution of occupations of their employees. Specifically, we are interested in knowing how much firms are specialized in routine jobs as they are particularly sensitive to technology adoption. To capture this change, we measure the firm´s

[4] Panel weights are used throughout the analysis to account for the stratification of the simple and differential response rates.
[5] WERS 2011 additionally includes a refreshment sample of around 1,700 workplaces that are not taken into consideration for the analysis presented here as there is not previous firm information available.
[6] See Annex I.

routinization exposure as the change in the ratio of routine occupations in each workplace over the period 2004-2011, defined as

$$\Delta ROU_{oj} = ROU_{i_{2011}} - ROU_{i_{2004}} \quad (1)$$

where for each firm j, ΔROU_{oj} is the change in the percentage of workers in routine occupation o={total, manual, cognitive} over total firm workers in the period 2004-2011. We use a relative measure (that is a ratio) of the routinization exposure because the job composition of the workplace is sensitive to firms size and this measure allows us to capture the concentration of the firm in routine jobs.

One concern with this measure of routinization exposure is that observed changes in the share of routine occupations among total employees may in part reflect demand shocks in other occupations (i.e. other than routine occupations). In order to control for this, we include in our empirical models a variable that captures the occupation mix available in the firm ($DShock_{oj}$). $DShock_{oj}$ is calculated as

$$DShock_{oj} = \sum_i S_{oj_{2004}} NG_{oi\tau} \quad (2)$$

where for each routine occupation o={total, manual, cognitive}, $S_{oj_{2004}}$ is the employment share of occupation o (o≠routine occupations) in firm j at the beginning of the period and $NG_{oi\tau}$ is the global 5-digit industry employment growth rate in the same occupation o between 2004 and 2011. The occupation mix term captures the predicted growth rate of employment in the firm if all of its occupations (except routine occupations) grow at the industry rate. This is presumed exogenous to the modelled relationships because it uses the initial occupational composition of a firm and projects firm growth based on the industry growth rate, which is unlikely to be influenced by growth dynamics of a single firm (Tsvetkova & Partridge, 2016; based on Bartik, 1991). As routine occupations (ROU) have not been included in the occupations mix, we can compare the size of this variable's coefficient to the occupation mix coefficient to ascertain whether an employment shock in middle-skill occupations has a different effect compared with an equally sized typical shock outside of the ROU occupations. We compute three different measures of the demand shock, a global measure of routine occupation mix as previously defined (DShock ROU), and two particular indicators for routine manual (DShock ROU MAN) and routine cognitive (DShock ROU COG) where the occupation mix term captures the predicted growth rate of employment in the firm if all of its occupations except routine manual and routine cognitive occupations respectively.

3.2 Employment and wages at firm-level

In line with the substantial literature on the effect of the digital transformation on local labor markets (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018a,b,c; Benzell et al., 2016; Susskind, 2017), we use two measures of labor: employment and wages of the workers. Overall employment at the workplace is measured through the number of employees in 2004 and 2011. This information is provided by the managers in the employee profile questionnaire and it includes information about the total number of employees per 1-digit occupation following the Standard Occupation Code (SOC, 2003). The variable capturing wages has been computed from the survey of employees. This survey provides information about a representative sample of employees in each firm. In this questionnaire, each employee answered the question "How much do you get paid for your job here, before tax and other deductions are taken out?". A set of fourteen intervals with weekly (also yearly) earnings (from £60 or less to £1,051 or more) were provided in the survey and employees selected the one in which they fitted in. We have assigned to each employee the middle point of the selected salary interval as their average gross weekly wage and compared this value with the national average gross weekly earnings of full-time employees[7] in the same 1-digit occupation and the correspondent year 2004 or 2011 (source: ONS). Subsequently, we have created a dichotomous variable with value 1 if the employee has a salary above the national average of wages in the same occupation and 0 if the salary is below this threshold. This allows us to calculate the percentage of employees in each firm whose salary is above/below the national average capturing firms paying employees wages above the market value. We call this variable "wage premium".

The change in the measures of labor in each workplace over the period 2004-2011 ($\Delta Labor_{ij}$) is defined as the first difference in i={employment, wage premium} over the period 2004-2011 for each firm j, divided by the average employees and salaries (respectively) across the two periods 2004 and 2011.

Table 1 describes the change in both measures by 1-digit industry classification. In terms of employment, firms in the construction, accommodation and transport and communication sectors have exhibited job losses, while mainly public administration, education, other business sectors, utilities, and manufacturing sectors have gain jobs. These results are in line with the changing patterns found in UK labor markets during the recession period (UKCES, 2014), except for the positive growth described for the manufacturing sector. This difference could be explained by the fact that a) we cover both, public and private firms in this study and b) small and medium firms (SMEs) are particularly vulnerable to financial crisis as 4 in 10 SMEs experienced a fall in employment during the recession period (Cowling et al., 2015) and an important fraction of small firms is omitted in WERS. On the other hand, firms in the utilities and financial sectors have significantly increased the number of employees whose salary is above the national average, followed by the manufacturing, transport and

[7] ONS provides gross weekly earnings of full-time employees by trimester. We have used the average of the four periods in each year as the annual gross salary average.

communication and other community services sectors. All the rest (with the exception of the health sector that has almost not exhibited variation) have reduced the number of employees with salaries above the market value.

[Insert Table 1 around here]

3.3 Trends in routinization exposure and labor at firm-level

Figure 1 plots changes in the job composition in the UK with our results suggesting that the labor market has exhibited the trademark characteristics of employment polarization. In particular, between 2004 and 2011, the growth of high-skill workers in non-routine cognitive (Non-routine COG) occupations (11.35%) and low-skill non-routine manual (Non-routine MAN) occupations (0.39%) contrast with the negative growth of more routine middle-skill (ROU) occupations (-5.21%). These findings go in line with the conclusions proposed by Salvatori (2018) as there is a substantial reshuffling of employment from middle to top occupations. The explanation provided by this author is that, in contrast to the US case, the UK has exhibited an important increment of the educational attainment of the population, contributing significantly to the most prominent feature of the polarization process in this country. The lower part of Figure 1 distinguishes the employment changes between routine occupations. In general, the highest job losses have been in routine manual occupations (-7.3%) while the negative change in routine cognitive occupations is smoother (-2.5%).

However, some differences emerge across sectors. The secondary sector is the most affected by this polarization effect (5.66 and 148.2% growth in high and low skill occupations respectively and -6.0% in routine occupations), while the change in the employment structure of the tertiary sector follows a smoother curve (12.06% and 0.39% positive growth in both extremes of the skill distribution and -5.98% decrement in middle-skill occupations). Taking into account the skill content of routine occupations, firms in the tertiary sector account for the highest decrease of routine cognitive jobs (-7.67%) while the secondary sector gains routine manual jobs (1.79%) and loses workers in cognitive jobs (-4.27%).

[Insert Figure 1 about here]

Figure 2 shows the relationship between firm's routine exposure to routine occupations and our two measures of labor: employment and wages. A priori an increment in routine workforce positively correlates with outright employment ($r=0.138$; $p=0.000$) while does it negatively with wages ($r=-0.041$; $p=0.201$) at firm-level although only in the first case is significant (Figure 2 top graphs). However, when we distinguish between manual and cognitive routine occupations, some differences emerge (Figure

2 bottom graphs). Specifically, an increase in routine manual occupations positively correlates with a positive growth of overall employment (r=0.121, p-value=0.000), while there is no relation with wage premium (r=0.00, p-value=0.881). In the case of routine cognitive, there is no correlation with either employment nor wages (r=0.020, p-value=0.530 and r=-0.039, p-value=0.229 respectively).

[Insert Figure 2 around here]

4 Empirical results

In the main empirical analysis, we estimate the impact of changes in routine exposure on labor at the firm level. The baseline regression specification[8] is of the form,

$$\Delta Labor_{ij} = \propto + \beta_1 \Delta ROU_{oj} + \beta_2 DShock_{oj} + \gamma X_{j2004} + e_j \quad (3)$$

where $\Delta Labour_{ij}$ is the percentage change in the measurement of labor i={employment, wage premium} in firm j overtime period 2004-2011; ΔROU_{oj} is growth of routine exposure (in percentage points) for routine o={total, manual, cognitive} in firm j over period 2004-2011, as defined in (1); $DShock_{oj}$ is the occupation mix in firm j, as defined in (2); and X_{j2004} comprises controls for other factors that may affect the capacity of a firm to grow, including both firm-level controls for production characteristics and industry-level information on technology investment measured at the start of the period. We add a number of additional establishment characteristics, namely firm status (public/private) and region (North East, Yorkshire and Humberside, East Midlands, East Anglia, South East, South West, West Midlands, North West, Wales).

Regression models are computed using 2SLS and implemented using instrumental variables. Following previous literature (e.g. Autor and Dorn, 2013; Consoli and Sánchez-Barrioluengo, 2019) we adopt a strategy that uses the long-term pattern of employment specialization as reflected in the organisation of production across sectors. The instrumental variable is the percentage of routine occupations in each 1-digit industry in 1961, an unobserved and time-invariant attribute that captures the pattern of specialization in the UK before Thatcher labor market reforms took place in the 80s (Addison and Siesbert, 2000). The data source, in this case, is the Historic Census because this microdata disaggregates information of the labor force by industries and occupations. To compute the percentage of routine occupations in each industry we, first, assigned each occupation code name to one of the categories non-routine cognitive, routine manual, routine cognitive and non-routine manual; and second, we computed the share of routine occupations (total, manual and cognitive) on total employees by industry. Finally, we create a correspondence matrix[1] that links 1-digit industry

[8] This strategy using a standard model in differences have been frequently used in the literature (e.g. Autor et al., 2016; Balsmeier and Woerter, 2019).

codes in 1961 with those in 2004 used in WERS. In the first-stage regression of the value of the instrument on routinization exposure all the rest constant in the equation, the estimated coefficient is 18.34 and a p-value=0.010 with an F-statistic of 18.031 above the standard threshold recommended of ten (Stock and Yogo, 2005) which demonstrates the validity of the selected instrument. Finally, observations are weighted by sample design weights and the number of employees in the firm averaged over the start and end firm size. Standard errors are clustered on two-digit SIC industries.

4.1 Baseline estimates

Tables 2 and 3 give estimation results for equation (3) including all sectors (Panel A) and distinguishing between the secondary (Panel B) and the tertiary sector (Panel C). Table 2 focuses on overall employment while Table 3 includes the results for the wage premium. Model 1 (M1) presents regression specifications that include no covariates beyond the change in the employment structure and a constant term. M2 and M3 add control variables to address differences across firms and sectors. In particular, M2 includes the main independent variable capturing the occupation mix (DShock) and M3 controls for firm and industry characteristics at the beginning of the period to account for other potentially confounding factors that may affect firms' labor. Specifically, characteristics of the workplace and the following controls have been added: share of production workers in the firm, a dummy variable capturing information on whether the establishment has adopted new technologies[9] and the technology intensity of the industry measured as the volume of real gross fixed ICT formation equipment (including computing and communication equipment).[10,11]

Results for overall employment in Table 2 suggests a positive relation between the change in overall employment and the change in the routinization exposure for total ROU occupations. The results with the full set of controls for the stacked first differences of this output keeps the positive relationship. That is firms increasing their routine labor generate positive growth of the overall employment at the workplace. However, some differences emerge when the skill content of routine occupations is taken into account. Although none of the other results are significant, the signs in the coefficients differ suggesting a positive relation in the case of growth of the routine cognitive occupations while negative

---

[9] Adoption of new technologies comes from the management questionnaire and takes the value 1 if the workplace has introduced or upgraded other type of technology different from computers and 0 otherwise.

[10] The source of information for the industrial technology intensity is the EU-KLEMS database, matched with WERS at 1-digit SIC code.

[11] Annex II replicates the complete model for all sectors including an additional control variable capturing the labour productivity of the firm, measured as the turnover per employee obtained in 2004. This information is included in WERS as part of the financial outputs questionnaire. Although this is a traditionally accepted measured of firm productivity (OECD, 2013) it is important to note that the sample size in these regression models is substantively reduced due to a large number of firms (around 50%) that do not report this information. Results remain in the same direction as the ones presented here (becoming even some of them significant) when changes in productivity of the firm are included as control in the equation.

in the case of routine manual jobs. Looking at each sector separately, in tertiary industries (Panel C) concentration in routine intensity has a job-creating effect while it does not generate job-losses in the case of industry. In fact, the industry sector increases the overall employment only when there is a positive growth of the most skilled routine workers; that is those with routine cognitive occupations.

[Insert Table 2 about here]

Table 3 presents the results of the effect of changes in the employment structure on premium wages and suggests that the industry is the most benefited sector (Panel B). In this regard, the more concentration of routine and routine manual jobs in the firm, the higher the percentage of employees with salaries above the market value.

[Insert Table 3 about here]

4.2 The role of technology in the relationship between employment structure and labor

The adoption of technology at the firm level is one of the elements that has been considered as having a direct effect on the demand for different occupations or tasks within the firm (Bresnahan et al., 2002; Akerman et al., 2015; Gaggl and Wright, 2017). In order to test the complementary or supplementary role of technology in the relationship between the job composition and firms´ labor, we distinguish between workplaces that are/are not technology adopters. We define a technology adopter firm as those workplaces answering 'yes' to the question "Over the past two years management has introduced or updated other types of technology different from computers". In our sample, 56% of the workplaces are considered technology adopters in 2004.[12,13]

[12] The question specifically distinguishes between the introduction/upgrading of computers and/or other technologies. When both types of technology are taken into account to define the variable, there is no high variability in the answers provided by the firm and the majority of them (80% of the firms) have introduced at least one type of technology. For that reason, technology adopters here only take into account the introduction/upgrading of non-computer technology.

[13] Taking into account that some authors consider this question to be too vague (Cortes and Salvatori, 2019), some robustness checks have been performed using an alternative measure of technology. In particular, firms have been clustered into two groups according to the sector´s investment in industrial technology. We define high industry technology investment as those firms part of the fifty percent of the industries with the highest increment in ICT investment between 2004 and 2011, while low industry technology investment includes those firms that are part of an industry whose investment in ICT is below the median during the same period. To compute the increment in technology investment we use the information about real gross fixed ICT formation equipment between 2004 and 2011 at the 1-digit industry level (source: EU-KLEMS). According to this indicator, wholesale and retail, hotels and restaurants, transport and communication, financial series, other business services and education are the sectors whit the highest investment in ICT (called "high technology investment") in this period, while manufacturing, electricity, gas and water, construction, public administration, health, and other community services are the ones included under the category "low technology investment". Annex III presents the results for these alternative models. In general terms, results remain constant with the ones presented here when the distinction between sectors and skill intensity of routine occupations is taken into consideration.

Using WERS data, Figure 3 shows the correlation between an increment in exposure to routine jobs and firms' labor. This relationship is only significant in the case of overall employment, where the positive growth of routine exposure and the job-creating effect is even higher for those firms who adopted technology at the beginning of the studied period (Adopters: r=0.20, p-value=0.00; Non-adopters: r=0.11, p-value=0.02).

Table 4 and Table 5 include the results of the full model from equation (3) for overall employment and premium wages respectively when technology adoption of the firm is taken into account. [14] The results presented here remain significant even when the shocks in the occupation mix at the industry level are taken into consideration, as all models include the variable Dshock as main control variable (as well as all other control variables at firm and industry level).

Results in Panel A of Table 4 confirm the importance of disentangling routine occupations, as its effect differ depending on the skill content of jobs. In this case, while in technology adopter firms, routine manual labor increases overall employment, the impact on non-adopters generates job-losses. On the contrary, there is no effect of routine cognitive occupations on technology adopters, while it is positive in the case of non-adopters. This general beneficial pattern of routine jobs is reproduced in the tertiary sector (Panel C), while some job-losses are evident in the secondary sector (Panel B). For those firms investing in routine jobs, mainly routine manual jobs, they have exhibited a reduction in total employment if this investment was not complemented by the adoption of technology. However, those places investing in technology and routine occupations (cognitive and/or manual) have seen an increment in the overall employment figures.

Differences in technology adoption do not make substantial differences between the results presented in Table 3 and those presented in Table 5 in the relationship between changes in the employment structure and wages. As in the previous case, the secondary sector is the most benefited with a positive effect of routine and routine manual jobs on premium wages regardless of the adoption of technology (Panel B).

[Insert Table 4 and 5 around here]

[14] This full model does not include the dummy variable "introduction of technology in the firm" as this has been used to distinguish between technology adopter and non-adopter firms.

5 Summary and conclusions

In spite of the widespread anxiety about job destruction driven by, among other things, technological change for workers in occupations highly vulnerable to automation, last scenarios invite to be less pessimistic about the impact of technology on jobs. The most recent estimations from OECD suggests that a sharp decline in overall employment is unlikely: while certain jobs may disappear (14% are at high risk of automation in OECD countries), others will emerge. Overall, employment has been growing because while technological progress makes some occupations obsolete, it also creates new jobs (OECD, 2019a). Similarly, conclusions from the European Commission's report on the changing nature of work suggest that digital technologies do not simply create and destroy jobs: they also change what people do on the job, and how they do it (Gonzalez Vazquez et al., 2019).

By unpacking differences in routine occupations and sectors, this paper articulates the convergence of two research strands in the digitalisation era through the analysis of current changes in the job composition of firms on two measures of labor (employment and wages). On the one hand, this study complements studies in labor economics by emphasising the occupation mix of the employment structure at firm-level. In particular, we capture the firm's routinization exposure as a measure of the specialization of a workplace in routine tasks, assuming that they have a higher risk of replacing human labor triggered by the progressive spread of labor-saving technologies (Autor and Dorn, 2013). On the other hand, by developing a firm-centred study, this work provides insights into the strategic management literature on digitalisation driven changes at the business level (Loebbecke and Picot, 2015). We expect that by gaining a thorough comprehension of how changes (increasing/decreasing) in particular occupations affect the workplace, managers could make better decisions when investing in technology to complement or replace human labor.

The analysis makes several contributions. First, it highlights the importance of the understanding of the effect of digital transformation on labor at firm-level. While there is burgeoning literature on the relationship between technology and labor (Autor et al., 2003; Autor and Dorn, 2013; Goos et al., 2014, Adermon & Gustavson, 2011; Dauth, 2014; Fonseca et al., 2018; Harrigan et al., 2016; Salvatori, 2018), the majority of these studies put the emphasis on aggregate sectors and labor markets. There are a few recent exceptions that focus on the firm-level (Bessen, 2019; Bessen et al., 2019; Koch et al., 2019; Autor et al., 2016). Our results confirm the worldwide phenomenon of polarization (OECD, 2017) taking place in the UK at firm-level as well, with a positive growth of occupations at both ends of the skill distribution (high- and low-skill occupations), while there is negative growth of middle-skill routine jobs. Routine occupations are then particularly interesting because these jobs are more exposed to replacement by automated processes (Bessen et al., 2019) and have been the centre of the debate in the analysis of the impact of automation on employment and wages (Acemoglu and Restrepo, 2017).

Second, the treatment of routine occupations as a whole hides the differences that emerge between cognitive and manual jobs. This work disentangles these middle-skill occupations and our results suggest that, while routine jobs are more at risk of being replaced by automated processes (Frey and Osborne, 2013), the effect of the firms' routine exposure on the outright employment and salaries vary according to the skill content of these occupations. In general terms, the exposure to routine cognitive jobs does not generate outright job-losses and could even have a positive effect on overall employment in the firm. Routine cognitive tasks require more complex social interaction and are usually performed by high school and some-college workers (Bessen et al., 2019) whose skills and capacities become a valuable asset for the firm preventing from a negative impact on labor. On the contrary, firms concentration on routine manual tasks, most prevalent in production and operative positions, reflecting specialization in blue-collar production and operative occupations (Acemoglu and Autor, 2011, Matias-Cortés et al., 2016) and with lower levels of education, are more at risk of exhibiting a negative impact of overall employment and wages, mainly the first case, at firm-level.

Third, the effect of routine exposure on labor has also a sectoral component. The historical process of deindustrialization suggests that the effect of automated processes has mainly affected negatively the secondary sector, not only because industries in this sector are more exposed to automated processes due to the higher concentration of routine tasks (Acemoglu and Rastrepo, 2017), but also because mature industries will tend to have on average lower elasticity of demand and, hence, a weaker or negative employment response (Bessen, 2019). In this regard, Mann and Püttmann (2017) find that automation increases jobs in services but decreases them in manufacturing. Our findings only partially confirm previous results. While the concentration on routine occupations has a job-creating effect in the tertiary sector, this does not necessarily imply job-losses within the secondary sector and could have even a positive effect on firms' labor in the case of exposure to routine cognitive occupations. Although a priori it could seem contradictory, we explain this absence of job-losses in the secondary sector based on the time frame covered in our study under the digitalisation era. In fact, to better explain this we need to take into account how demand plays a key role to understand whether major new technologies will decrease or increase employment proposed by Besset (2019). According to his argument, there is a life cycle explanation for the inverted-U pattern of industrialization/deindustrialization seen in manufacturing employment. While the highest introduction of industrial machinery in firms took place in the 80s and 90s, this study covers the period 2004-2011 where firms have moved along the life cycle towards maturity with less elastic demands and, in consequence, labor-saving technology has a weaker impact on employment nowadays. So, our study is in line with the recent positive views on the impact of digitalisation on labor (OECD, 2019a; Gonzalez Vazquez et al., 2019; Balsmeier and Woerter, 2019; Bessen et al., 2019).

Fourth, the role of technology is the last element of importance in the relationship between employment structure and firms' labor. Although the UK is one of the OECD countries that have experienced the fastest growth in ICT use in the workplace over the past two decades, jobs are at a lower risk of automation than the OECD average (OECD, 2019b). Our results reconcile some of the differences highlighted in the literature revelling substantial job losses in firms that do not adopt robots (Koch et al., 2019), while Akerman et al. (2015) suggest that internet technology increased employment of skilled workers and had no effect on unskilled ones. In our case, results show that investment in the workforce without the appropriate technological adoption is not enough to generate positive impacts in the firm, specifically for the secondary sector. Our results suggest that an increment in less-skilled routine manual jobs in firms that have not adopted technology recently has a negative effect on overall employment. On the contrary, the adoption of technology complements the routine exposure of workplaces, and technology adopter firms increasing routine occupations raise outright employment as well. An investment in routine cognitive jobs is a safe bet factor because even in the absence of technology, routine cognitive firms raise overall employment. In the case of wages, technology does not play a particular role in the relationship between employment structure and wage premium employees.

In addition to the managerial conclusions, the paper derives some policy implications as well. First, as some workers are more at risk of being displaced, it is important to keep workers constantly upskilled, retrained and adapted to emerging skill needs, even more taken into account the fast-changing jobs landscape. That is way the education systems should be updated in order to be able to adapt to the diversified amount of knowledge needed. Second, as digitalization is increasing the positive returns from firms to labour markets, it is important that those profits are also reflected in the income of the workers, something that this research is not properly capturing. Therefore, policies should guarantee a social transition needs to ensure that everyone benefits of technological advancements.

In sum, this paper studies how UK firms have responded to the changes in their employment structure due to the digital transformation. While the scientific literature shows inconclusive statements about the impact of digitalisation on job creation and destruction, we highlight the importance of the skill content of middle occupations by showing that changes in routine manual and routine cognitive occupations affect differently firm's labor. Using a UK employer-employee panel survey between 2004 and 2011, our results suggest that while firms' routine exposure may eliminate jobs in some cases, it creates jobs in others. The effect on salaries tends to be mainly unaffected. If unemployment is not the main consequence of the current labor-saving technology because there is not only a job-creation and/or job-destruction phenomenon, this study opens up stimulating avenues for further research. First, this study is based on a panel of firms that are "survivors" to the financial crisis. Future analysis could take into consideration changes in the employment structure of a broader range of firms using administrative data in order to include survival rates characterizing periods of economic fluctuations. Second, a new policy challenge is to understand how jobs have changed, what the new tasks at hand are and how to make these transitions easier to workers. Third, if firms are already exhibiting an occupational transformation due to the adoption of technology, it could be interesting to understand how these changes in the nature and composition of jobs are affecting firms' financial outputs such us productivity, value-added or their organisational and financial strategies. Finally, if there are specific jobs that require key attributes of human labor like sociability, creativity or full autonomy that are currently beyond the capabilities of the automated process (Gonzalez Vazquez, et al., 2019), this study opens up questions related to the role of digitalisation on firms' innovation process, strategies and outputs.

Acknowledgments

I would like to thank Davide Consoli, Silvia Massini, Ian Miles, Jonatan Pinkse, Barbara Ribeiro, Bruce Tether and Elvira Uyarra for their valuable comments, which led to a substantial improvement of the manuscript. I also thank to the anonymous SWPS reviewer for the comments received. An earlier version of the paper was presented at the EMAEE Conference (Brighton, June 2019) and BAM Symposium on "Artificial Intelligence and Data – Disruptions to Society, Organisations and People" (London, November 2019) were insightful comments were received from the participants. Any remaining errors are my responsibility.

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. *Handbook of Labour Economics*, 4: 1043–1171.

Acemoglu, D. and Restrepo, P. (2017). Robots and Jobs: Evidence from US Labour Markets. NBER working paper series 23285. Available at: https://www.nber.org/papers/w23285

Acemoglu, D. and Restrepo, P. (2018a). Artificial Intelligence, Automation and Work. NBER Working Paper 24196. Available at: https://www.nber.org/papers/w24196.pdf

Acemoglu, D. and Restrepo, P. (2018b). Modeling automation. *AEA Papers and Proceedings*, 108: 48–53.

Acemoglu, D. and Restrepo, P. (2018c). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review*, 108(6): 1488–1542.

Adermon, A., and Gustavson, M. (2011). Job polarisation and task-biased technological change: Evidence from Sweden, 1975–20. The Scandinavian Journal of Economics, 117(3): 878–917.

Addison, J.T. and Siebert, W.S. (2000). Labour Market Reform in the United Kingdom : From Thatcher to Blair. *Journal of Private Enterprise,* The Association of Private Enterprise Education, vol. 15(Spring 20): 1-34.

Afuah, A. (2003). Redefining Firm Boundaries in the Face of the Internet: Are Firms Really Shrinking? *Academy of Management Review*, 28: 34-53.

Agrawal, A. K., Gans, J., and Goldfarb, A., (2017) *The Economics of Artificial Intelligence*. University of Chicago Press.

Arrfelt, M., Wiseman, R. M., McNamara, G. and Hult, G. T. M. (2015). Examining a Key Corporate Role: The Influence of Capital Allocation Competency on Business Unit Performance. *Strategic Management Journal*, 36: 1017-34.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, 29(3): 3–30.

Autor, D. H., and Dorn, D. (2013). The growth of low-skill service jobs and the polarisation of the US labour market. *American Economic Review*, 103(5): 1553–1597.

Autor, D. Dorn, D., Hanson, G, Pisano, G and Shu, P. (2016) Foreign Competition and Domestic Innovation: Evidence from U.S. Patents. *NBER Working Paper* No. 22879. Available at: https://www.nber.org/papers/w22879

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content Of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*, 118(4): 1279–1333

Autor, D., (2014). Polanyi's Paradox and the Shape of Employment Growth. *NBER Working Paper* no. 20485. Available at: https://www.nber.org/papers/w20485

Balsmeier, B. and Woerter, M. (2019) Is this time different? How digitalization influences job creation and destruction. *Research Policy*, 48(8): 1-10

Bartik, T.J. (1991). *Who Benefits from State and Local Economic Development Policies?* Books from Upjohn Press.

Bessen, J. E. (2019) Automation and Jobs: When Technology Boosts Employment. Boston Univ. School of Law, Law and Economics Research Paper No. 17-09. Available at SSRN: http://dx.doi.org/10.2139/ssrn.2935003

Bessen, J E and C Righi (2019), Shocking technology: What happens when firms make large IT investments*? Boston University School of Law, Law and Economics Research Paper* 19-6.

Bessen, J.E., Goos, M., Salomons, A. and Van den Berge, W. (2019) Automatic Reaction - What Happens to Workers at Firms that Automate?. *Boston Univ. School of Law, Law and Economics Research Paper*. Available at: http://dx.doi.org/10.2139/ssrn.3328877

Bresnahan, T.; Brynjolfsson, E. and Hitt, L.M. (2002) Information Technology, Workplace Organization, and the Demand for Skilled Labour: Firm-level evidence*. The Quaterly Journal of Economics*, 117(1): 339-376.

Brynjolfsson, Erik (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance*. Journal of Economic Perspectives*, 14: 23-48.

Card, D., and DiNardo, J. (2002) Skill-biased technological change and rising wage inequality: some problems and puzzles. *Journal of Labour Economics* 20 (4): 733–783.

Consoli D. and Sánchez-Barrioluengo M. (2019) Polarization and the growth of low-skill service jobs in Spanish local labour markets. *Journal of Regional Science,* 59: 145–162.

Benzell, S. G., Kotlikoff, L. J., LaGarda, G., and Sachs, J. D. (2016). Robots Are Us: Some Economics of Human Replacement. *NBER Working Paper* 20941. Available at: https://www.nber.org/papers/w20941

Cowling, M, Liu, W, Ledger, A & Zhang, N (2015) 'What really happens to small and medium-sized enterprises in a global economic recession? UK evidence on sales and job dynamics', *International Small Business Journal* 33 (5): 488-513.

Dauth, W. (2014). *Job polarisation on local labour markets* (Technical Report 18). Nuremberg, Germany: Institute for Employment Research.

Dauth, W., Findeisen, S., Südekum, J., and Wößner, N. (2017). *German Robots – The Impact of Industrial Robots on Workers*. Technical report, Institute for Employment Research, Nuremberg, Germany.

Department for Business, Innovation and Skills, Advisory, Conciliation and Arbitration Service and National Institute of Economic and Social Research (2014) *Workplace Employee Relations Survey, 2011* [computer file]. 6th Edition. Colchester: UK Data Service [distributor]. SN: 7226, http://dx.doi.org/10.5255/UKDA-SN-7226-4

Eichhorst, W.; Escudero, V.; Marx, P. and Tobin, S. (2010) *The Impact of the crisis on employment and the role of labour market institutions*. ILO. Available at: https://www.ilo.org/wcmsp5/groups/public/---dgreports/---inst/documents/publication/wcms_192839.pdf

European Foundation for the Improvement of Living and Working Conditions (Eurofound) (2015). *Upgrading or polarisation? Long-term and global shifts in the employment structure. European Jobs Monitor 2015.* Available at: https://www.eurofound.europa.eu/es/publications/report/2015/labour-market/upgrading-or-polarisation-longterm-and-global-shifts-in-the-employment-structure-european-jobs

Fonseca, T., Lima, F., & Pereira, S. C. (2018). Job polarisation, technological change and routinization: Evidence for Portugal. *Labour Economics*, 51, 317–339.

Frey, C.B. and Osborne M.A. (2013) *The future of Employment: How susceptible are jobs to computerisation?* Mimeo, Oxford Martin School.

Gaggl, P. and Wright, G.C. (2017) A short-run view of what computers do: evidence from UK tax incentive. *Amercian Economics Journal*, 9(3):262-294

Gonzalez Vazquez, I., Milasi, S., Carretero Gomez, S., Napierala, J., Robledo Bottcher, N., Jonkers, K., Goenaga, X. (eds.), Arregui Pabollet, E., Bacigalupo, M., Biagi, F., Cabrera Giraldez, M., Caena, F., Castano Munoz, J., Centeno Mediavilla, C., Edwards, J., Fernandez Macias, E., Gomez Gutierrez, E., Gomez Herrera, E., Inamorato Dos Santos, A., Kampylis, P., Klenert, D., López Cobo, M., Marschinski, R., Pesole, A., Punie, Y., Tolan, S., Torrejon Perez, S., Urzi Brancati, C., Vuorikari, R. (2019) *The changing nature of work and skills in the digital age*, EUR 29823 EN, Publications Office of the European Union, Luxembourg. ISBN 978-92-76-09206-3, doi:10.2760/679150, JRC 117505.

Goos, M., & Manning, A. (2007). Lousy and lovely jobs: The rising polarisation of work in Britain. *The Review of Economics and Statistics*, 89(1), 118–133.

Graetz, G. and Michaels, G. (2018). Robots at Work. *Review of Economics and Statistics*, 100: 753-768

Gregory, T., Salomons, A., & Zierahn, U. (2016). Racing with or against the machine? Evidence from Europe. Evidence from Europe. *ZEW-Centre for European Economic Research Discussion Pape*r, 16-053.

Harrigan, J., Reshef, A., and Toubal, F. (2016). The march of the techies: Technology, trade, and job polarisation in France, 1994-2007. *NBER Working Paper* 22110.

Koch, M., Manuylov, . and and Smolka, M.(2019) Robots and Firms (2019). *CESifo Working Paper* No. 7608. Available at SSRN: https://ssrn.com/abstract=3377705

Levy, F., & Murnane, R. (2004). *The new division of labour: How computers are creating the next job market.* Princeton, NJ: Princeton University Press

Loebbecke, C. and Picot, A. (2015) Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *Journal of Strategic Information Systems*, 24: 149–157.

Mann, K. and Püttmann, L. (2018) Benign Effects of Automation: New Evidence from Patent Texts. Available at SSRN: http://dx.doi.org/10.2139/ssrn.2959584

Matias Cortes, G., Jaimovich, N. and Siu H.E. (2016) Disappearing routine Jobs: Who, How and Why? *NBER Working paper Series* 22918. Available at: http://www.nber.org/papers/w22918

Matias-Cortes G. and Salvatori, A. (2019) Delving into the demand side: Changes in workplace specialization and job polarization. *Labour economics*, 57: 164-176

Mishel, L., Schmitt, J., and Shierholz, H., (2014). *Wage Inequality: a Story of Policy Choices, New Labour Forum*. The Murphy Institute, City University of New York, pp. 1–6.

Office for National Statistics (2015) *Business Structure Database, 1997-2014: Secure Access.* [data collection]. Colchester: UK Data Service [distributor]. SN:6697, http://doi.org/10.5255/UKDA-SN-6697-9

OECD (2013) Measuring total factor productivity at the firm level using OECD-ORBIS. Economics department working papers No. 1049. ECO/WKP(2013)41

OECD (2017) Getting Skills Right: Good Practice in Adapating to Changing Skill Needs: A perspective on France, Italy, Spain, South Africa and the United Kingdom. OECD Publishing. Paris. Available at: http://dx.doi.org/10.1787/9789264277892-en

OECD (2019a) OECD Employment Outlook 2019.

OECD (2019b) OECD Employment Outlook 2019. UK Country note.

Salvatori, A. (2018) The anatomy of job polarisation in the UK. *Journal for Labour Market Research* 52: 8. https://doi.org/10.1186/s12651-018-0242-z

Schmitt, J., Shierholz, H., Mishel, L., (2013). Don't Blame the Robots: Assessing the Job Polarization Explanation of Growing Wage Inequality. *Economic Policy Institute*.

Stock, J. and Yogo, M., (2005). *Testing for weak instruments in linear IV regression. Andrews DWK Identification and Inference for Econometric Models*. Cambridge University Press, New York.

Susskind, D. (2017). A Model of Technological Unemployment. *Economics Series Working Papers* 819, University of Oxford, Department of Economics.

UKCES (2014) Working Futures 2012–2022. Evidence Report 83. UK Commission for Employment and Skills, Wath-upon-Dearne. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/298510/working-futures-2012-2022-main-report.pdf

UKCES (2016*) UKCES Employer Skills Survey 2015: UK report*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/704104/Employer_Skills_Survey_2015_UK_Results-Amended-2018.pdf

Tsvetkova, A., and Partridge, M. D. (2016). Economics of modern energy boomtowns: Do oil and gas shocks differ from shocks in the rest of the economy. *Energy Economics*, 59, 81–95.

Vona, F., and Consoli, D. (2015). Innovation and skill dynamics: A life-cycle approach. *Industrial and Corporate Change,* 24(6), 1393–1415.

Annex I. Classification of occupations

Occupation	Tasks	Occupational group
Managers, DIRECTORS and senior officials	Planning, directing and coordinating resources to achieve the efficient functioning of organisations and businesses.	NON-ROUTINE COGNITIVE
professionals	Practical application of an extensive body of theoretical knowledge, increasing the stock of knowledge by means of research and communicating such knowledge by teaching methods and other means.	NON-ROUTINE COGNITIVE
associate professional and technical	Operation and maintenance of complex equipment; legal, business, financial and design services; the provision of information technology services; providing skilled support to health and social care professionals; serving in protective service occupations; and managing areas of the natural environment.	NON-ROUTINE COGNITIVE
administrative and secretarial	Retrieving, updating, classifying and distributing documents, correspondence and other records held electronically and in storage files; typing, word-processing and otherwise preparing documents; operating other office and business machinery; receiving and directing telephone calls to an organisation; and routing information through organisations.	ROUTINE COGNITIVE
skilled trades	Apply specific technical and practical knowledge and skills to work with metal, textiles and wooden, metal, and other articles; set machine tools or make, fit, maintain and repair machinery and equipment.	ROUTINE COGNITIVE
caring, leisure, and other personal service	Care of the sick, the elderly and infirm; the care and supervision of children; the care of animals; and the provision of travel, personal care, and hygiene services.	NON-ROUTINE MANUAL
sales and customer service	Sell goods and services, accept payment in respect of sales, replenish stocks of goods in stores, provide information to potential clients and additional services to customers after the point of sale.	ROUTINE COGNITIVE
process, plant and machine operatives and drivers	Operate and monitor industrial plant and equipment; to assemble products from component parts according to strict rules and procedures and to subject assembled parts to routine tests; and to drive and assist in the operation of various transport vehicles and other mobile machinery.	ROUTINE MANUAL
routine unskilled	Using hand-held tools and physical effort to construct and maintain buildings; drive and operate trains, motor vehicles, and mobile machinery.	ROUTINE MANUAL

Source: Task information from Standard Occupational Classification (ONS, 2010) and International Standard Classification of Occupations (ILO, 2012)

Annex II. Robustness check. The effect of routinization exposure on firm-level outputs controlling by workplace productivity.

				PANEL A. Employment					
	Total			**Manufacturing**			**Tertiary**		
Δ ROU	**5.659*****			**-3.184*****			**3.923*****		
	[1.87]			**[0.50]**			**[1.08]**		
Dschock ROU	**0.000***			**-0.000*****			**0.000*****		
	[0.00]			**[0.00]**			**[0.00]**		
Δ ROU MAN		-1.206			**-2.238*****			0.405	
		[1.35]			**[0.61]**			[0.74]	
Dschock ROU MAN		**0.000***			-0.000			**0.000*****	
		[0.00]			[0.00]			**[0.00]**	
Δ ROU COG			1.487			**4.086****			0.559
			[1.19]			**[1.77]**			[0.80]
Dschock ROU COG			**0.000***			**0.000*****			**0.000*****
			[0.00]			**[0.00]**			**[0.00]**
Observations	349	358	352	79	79	79	270	279	273
				PANEL B. Wage premium					
	Total			**Manufacturing**			**Tertiary**		
Δ ROU	-3.27			**5.380*****			**3.923*****		
	[2.31]			**[1.45]**			**[1.08]**		
Dschock ROU	0.000			-0.000			**0.000*****		
	[0.00]			[0.00]			**[0.00]**		
ROU MAN		2.046			**3.601*****			0.405	
		[1.37]			**[0.74]**			[0.74]	
Δ Dschock ROU MAN		0.000			0.000			**0.000*****	
		[0.00]			[0.00]			**[0.00]**	
ROU COG			-2.081			-1.575			0.559
			[1.40]			[2.03]			[0.80]
Dschock ROU COG			0.000			**-0.000*****			**0.000*****
			[0.00]			**[0.00]**			**[0.00]**
Observations	349	358	352	79	79	79	270	279	273

Note: Significant results in bold. Each regression model captures the relative change in employment and wages at firm-level on the change of the firm routinization exposure. The relative change in employment is defined as the first difference in employment over the period 2004-2011, divided by the average number of employees across the two periods 2004 and 2011. The relative change in wages is defined as the first difference in wage premium over the period 2004-2011, divided by the average number of employees above the market salary across the two periods 2004 and 2011. M3 includes a set of firm and industry controls (share of production workers, introduction of technology in the firm, workplace characteristics and the industry technology investment). All models are weighted by the sample design weights and number of employees in a firm averaged over employees at the start and end of a period, and stand errors are clustered on 2-digit SIC industries. *p-value<0.1; **p-value<0.05; ***p-value<0.01.

Annex III. Robustness check. An alternative measure of technology adoption

PANEL A1. Employment

	High tech. investment	**Low tech. investment**	**High tech. investment**	**Low tech. investment**	**High tech. investment**	**Low tech. investment**
Δ ROU	**2.646*** **	-1.668				
	[0.82]	[1.95]				
Dschock ROU	0	**0.000*** **				
	[0.00]	**[0.00]**				
Δ ROU MAN			0.749	-2.026		
			[0.79]	[1.50]		
Dschock ROU MAN			0	0		
			[0.00]	[0.00]		
Δ ROU COG					1.193	2.034
					[0.94]	[1.43]
Dschock ROU COG					0	0
					[0.00]	[0.00]
Observations	565	365	573	380	572	374

PANEL B1. Employment in Secondary sector

	High tech investment	**Low tech investment**	**High tech investment**	**Low tech investment**	**High tech investment**	**Low tech investment**
ΔROU	**2.570*** **	**-6.057*** **				
	[0.61]	**[1.43]**				
Dschock ROU	0.00	0.00				
	[0.00]	[0.00]				
ΔROU MAN			**2.429***	**-5.277*** **		
			[1.38]	**[1.40]**		
Dschock ROU MAN			**0.001*** **	0.00		
			[0.00]	[0.00]		
ΔROU COG					**2.809*** **	5.027
					[0.79]	[3.31]
Dschock ROU COG					0.00	0.000**
					[0.00]	[0.00]
Observations	42	129	43	130	43	129

PANEL C1. Employment in Tertiary sector

	High tech investment	**Low tech investment**	**High tech investment**	**Low tech investment**	**High tech investment**	**Low tech investment**
ΔROU	**3.361** **	**2.346*** **				
	[1.71]	**[0.59]**				
Dschock ROU	0.00	0.00				
	[0.00]	[0.00]				
ΔROU MAN			**1.446***	**1.846** **		
			[0.79]	**[0.89]**		
Dschock ROU MAN			0.00	0.00		
			[0.00]	[0.00]		
ΔROU COG					1.763	0.207
					[1.94]	[1.16]
Dschock ROU COG					0.00	0.00
					[0.00]	[0.00]
Observations	465	294	471	309	471	303

Note: Significant results in bold. Each regression model captures the relative change in employment at firm-level on the change of the firm routinization exposure. The relative change in this measure of labor is defined as the first difference in employment over the period 2004-2011, divided by the average number of employees across the two periods 2004 and 2011. M3 includes a set of firm and industry controls (share of production workers, introduction of technology in the firm, workplace characteristics and the industry technology investment). All models are weighted by the sample design weights and number of employees in a firm averaged over employees at the start and end of a period, and stand errors are clustered on 2-digit SIC industries. *p-value<0.1; **p-value<0.05; ***p-value<0.01.

PANEL A2. Wage premium						
	High tech. investment	**Low tech. investment**	**High tech. investment**	**Low tech. investment**	**High tech. investment**	**Low tech. investment**
ΔROU	1.671	**4.974*** **				
	[1.75]	**[1.51]**				
Dschock ROU	0.000	0.000				
	[0.00]	[0.00]				
ΔROU MAN			1.356	**3.275***		
			[1.54]	**[1.88]**		
Dschock ROU MAN			0.000	-0.000***		
			[0.00]	[0.00]		
ΔROU COG					0.39	-1.001
					[1.24]	[1.72]
Dschock ROU COG					0.000	0.000
					[0.00]	[0.00]
Observations	565	365	573	380	572	374

PANEL B2. Wage premium in Secondary sector						
	High tech investment	**Low tech investment**	**High tech investment**	**Low tech investment**	**High tech investment**	**Low tech investment**
ΔROU	**3.459*** **	**7.510*** **				
	[1.29]	**[2.27]**				
Dschock ROU	**-0.001*** **	0.000				
	[0.00]	[0.00]				
ΔROU MAN			**3.207*** **	**7.192*** **		
			[0.76]	**[2.36]**		
Dschock ROU MAN			0.000	0.000		
			[0.00]	[0.00]		
ΔROU COG					3.559	-9.852
					[2.76]	[6.33]
Dschock ROU COG					**-0.001*** **	0.000
					[0.00]	[0.00]
Observations	42	129	43	130	43	129

PANEL C2. Wage premium in Tertiary sector						
	High tech investment	**Low tech investment**	**High tech investment**	**Low tech investment**	**High tech investment**	**Low tech investment**
ΔROU	-1.055	1.563				
	[2.42]	[1.02]				
Dschock ROU	0.000	0.000				
	[0.00]	[0.00]				
ΔROU MAN			0.718	0.02		
			[1.83]	[1.53]		
Dschock ROU MAN			0.000	**-0.000*** **		
			[0.00]	**[0.00]**		
ΔROU COG					-1.245	0.961
					[1.70]	[0.99]
Dschock ROU COG					0.000	0.000
					[0.00]	[0.00]
Observations	465	294	471	309	471	303

Note: Significant results in bold. Each regression model captures the relative change in wages at firm-level on the change of the firm routinization exposure. The relative change in this measure of labor is defined as the first difference in wage premium over the period 2004-2011, divided by the average number of employees above the market salary across the two periods 2004 and 2011. Columns 3 includes a set of firm and industry controls (share of production workers, introduction of technology in the firm, workplace characteristics and the industry technology investment). All models are weighted by the sample design weights and number of employees in a firm averaged over employees at the start and end of a period, and stand errors are clustered on 2-digit SIC industries. *p-value<0.1; **p-value<0.05; ***p-value<0.01.

Table 1. Change in labor between 2004 and 2011 by 1-digit industry.

	Employment			Wage Premium		
	Mean	**SD**	**N**	**Mean**	**SD**	**N**
Manufacturing	18.32	48.64	117	6.51	141.15	118
Electricity, gas and water	22.12	40.95	16	40.79	122.92	16
Construction	-4.87	52.73	43	-54.39	119.60	43
Wholesale and retail	8.13	37.82	100	-35.84	141.44	100
Hotels and restaurants	-4.17	31.43	48	-10.80	89.37	48
Transport and Communication	-2.17	46.72	69	8.27	118.37	69
Financial services	6.17	45.49	26	45.79	149.28	26
Other business services	24.95	67.38	105	-10.61	148.31	105
Public administration	30.43	80.51	91	-23.27	129.02	91
Education	26.77	45.79	117	-6.18	128.52	117
Health	18.51	52.56	187	0.34	138.00	190
Other community service	-1.47	43.57	64	5.08	113.41	64

Note: Survey design weights applied. Employment refers to the increment in the firm size. Wage premium measures the number of employees in the firm whose salary is above the national average.

Table 2. The effect of routinization exposure on employment at firm-level.

	PANEL A. Employment								
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
ΔROU	**4.227***	**4.164***	**5.427*****						
	[2.23]	**[2.48]**	**[2.04]**						
Dschock ROU		0.000	0.000						
		[0.00]	[0.00]						
ΔROU MAN				-1.1	-1.183	-0.753			
				[1.71]	[1.80]	[1.48]			
Dschock ROU MAN					0.000	0.000			
					[0.00]	[0.00]			
ΔROU COG							3.402	3.408	2.604
							[2.43]	[2.49]	[1.68]
Dschock ROU COG								0.000	0.000
								[0.00]	[0.00]
Observations	960	930	930	963	954	953	960	946	946
	PANEL B. Employment in Secondary sector								
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
ΔROU	-2.268	-2.253	-0.398						
	[2.75]	[2.78]	[2.05]						
Dschock ROU		0.000	**0.000*****						
		[0.00]	**[0.00]**						
ΔROU MAN				-2.743	-2.935	-2.388			
				[1.94]	[1.98]	[1.95]			
Dschock ROU MAN					0.000	0.000			
					[0.00]	[0.00]			
Δ ROU COG							**3.925***	**3.669****	**5.329*****
							[2.06]	**[1.73]**	**[1.95]**
Dschock ROU COG								**0.000***	**0.000****
								[0.00]	**[0.00]**
Observations	173	171	171	174	173	173	**173**	**172**	**172**
	PANEL C. Employment in Tertiary sector								
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
ΔROU	**4.155*****	**4.468*****	**3.287*****						
	[1.43]	**[1.59]**	**[0.97]**						
Dschock ROU		0.000	0.000						
		[0.00]	[0.00]						
ΔROU MAN				0.051	0.021	-0.143			
				[1.07]	[1.09]	[1.25]			
Dschock ROU MAN					0.000	0.000			
					[0.00]	[0.00]			
Diff ROU COG							1.349	1.353	0.961
							[1.11]	[1.12]	[0.99]
Diff Dschock ROU COG								0.000	0.000
								[0.00]	[0.00]
Observations	787	759	759	789	781	780	787	774	774

Note: Significant results in bold. Each regression model captures the relative change in employment at firm-level on the change of the firm routinization exposure. The relative change in this measure of labor is defined as the first difference in employment over the period 2004-2011, divided by the average number of employees across the two periods 2004 and 2011. M3 includes a set of firm and industry controls (share of production workers, introduction of technology in the firm, workplace characteristics and the industry technology investment). All models are weighted by the sample design weights and number of employees in a firm averaged over employees at the start and end of a period, and stand errors are clustered on 2-digit SIC industries. *p-value<0.1; **p-value<0.05; ***p-value<0.01.

Table 3. The effect of routinization exposure on wages at firm-level.

	M1	M2	M3	M1	M2	M3	M1	M2	M3
PANEL A. Wage premium									
ΔROU	0.765	1.095	1.125						
	[3.53]	[3.67]	[2.98]						
Dschock ROU		0.000	0.000						
		[0.00]	[0.00]						
ΔROU MAN				**2.891****	**3.070****	**2.783***			
				[1.43]	**[1.50]**	**[1.44]**			
ΔDschock ROU MAN					0.000	0.000			
					[0.00]	[0.00]			
ROU MAN							-2.98	-2.996	-2.001
							[2.99]	[3.07]	[2.24]
ΔDschock ROU COG								0.000	0.000
								[0.00]	[0.00]
Observations	960	930	930	963	954	953	960	946	946
PANEL B. Wage premium in Secondary sector									
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
ΔROU	**6.218*****	**6.232*****	**5.768*****						
	[1.42]	**[1.38]**	**[1.57]**						
Dschock ROU		0.000	0.000						
		[0.00]	[0.00]						
ΔROU MAN				**5.321*****	**5.764*****	**7.141*****			
				[1.27]	**[1.35]**	**[1.68]**			
Dschock ROU MAN					0.000	0.000*			
					[0.00]	[0.00]			
ΔROU MAN							-0.04	-0.042	0.464
							[1.40]	[1.42]	[1.12]
Dschock ROU COG								0.000	**-0.000***
								[0.00]	**[0.00]**
Observations	173	171	171	174	173	173	173	172	172
PANEL C. Wage premium in Tertiary sector									
	M1	**M2**	**M3**	**M1**	**M2**	**M3**	**M1**	**M2**	**M3**
ΔROU	-0.297	-0.326	1.087						
	[2.64]	[2.78]	[2.06]						
Dschock ROU		0.000	0.000						
		[0.00]	[0.00]						
ΔROU MAN				1.023	1.375	1.232			
				[1.14]	[1.19]	[1.44]			
Dschock ROU MAN					0.000	0.000			
					[0.00]	[0.00]			
ΔROU MAN							-0.04	-0.042	0.464
							[1.40]	[1.42]	[1.12]
Dschock ROU COG								0.000	0.000
								[0.00]	[0.00]
Observations	787	759	759	789	781	780	787	774	774

Note: Significant results in bold. Each regression model captures the relative change in wages at firm-level on the change of the firm routinization exposure. The relative change in this measure of labor is defined as the first difference in wage premium over the period 2004-2011, divided by the average number of employees above the market salary across the two periods 2004 and 2011. Columns 3 includes a set of firm and industry controls (share of production workers, introduction of technology in the firm, workplace characteristics and the industry technology investment). All models are weighted by the sample design weights and number of employees in a firm averaged over employees at the start and end of a period, and stand errors are clustered on 2-digit SIC industries. *p-value<0.1; **p-value<0.05; ***p-value<0.01.

Table 4. The effect of routinization exposure employment by technology adoption.

	PANEL A. Employment					
	Technology adopters	**Non-adopters**	**Technology adopters**	**Non-adopters**	**Technology adopters**	**Non-adopters**
ΔROU	1.36	**5.655*** **				
	[1.02]	**[1.84]**				
Dschock ROU	0.000	**0.000*** **				
	[0.00]	**[0.00]**				
ΔROU MAN			**1.383** **	**-6.951** **		
			[0.66]	**[3.41]**		
Dschock ROU MAN			0.000	**0.000*** **		
			[0.00]	**[0.00]**		
ΔROU COG					-1.902	**4.794*** **
					[1.77]	**[1.58]**
Dschock ROU COG					0.000	**0.000*** **
					[0.00]	**[0.00]**
Observations	507	423	514	439	374	511
	PANEL B. Employment in Secondary sector					
	Technology adopters	**Non-adopters**	**Technology adopters**	**Non-adopters**	**Technology adopters**	**Non-adopters**
ΔROU	**2.566*** **	**-3.777** **				
	[0.81]	**[1.87]**				
Dschock ROU	**0.000*** **	**-0.000** **				
	[0.00]	**[0.00]**				
ΔROU MAN			2.315	**-3.201** **		
			[1.41]	**[1.48]**		
Dschock ROU MAN			**0.000*** **	0.001		
			[0.00]	[0.00]		
ΔROU COG					**3.427***	1.185
					[1.87]	[1.27]
Dschock ROU COG					**0.000*** **	**0.001** **
					[0.00]	**[0.00]**
Observations	109	62	110	63	109	63
	PANEL C. Employment in Tertiary sector					
	Technology adopters	**Non-adopters**	**Technology adopters**	**Non-adopters**	**Technology adopters**	**Non-adopters**
ΔROU	0.963	**3.480*** **				
	[1.21]	**[0.97]**				
Dschock ROU	0	**0.000*** **				
	[0.00]	**[0.00]**				
ΔROU MAN			**0.865** **	-0.522		
			[0.42]	[2.41]		
Dschock ROU MAN			0	**0.000*** **		
			[0.00]	**[0.00]**		
ΔROU COG					-0.816	**2.990*** **
					[0.72]	**[0.64]**
Dschock ROU COG					0	**0.000*** **
					[0.00]	**[0.00]**
Observations	398	361	404	376	402	372

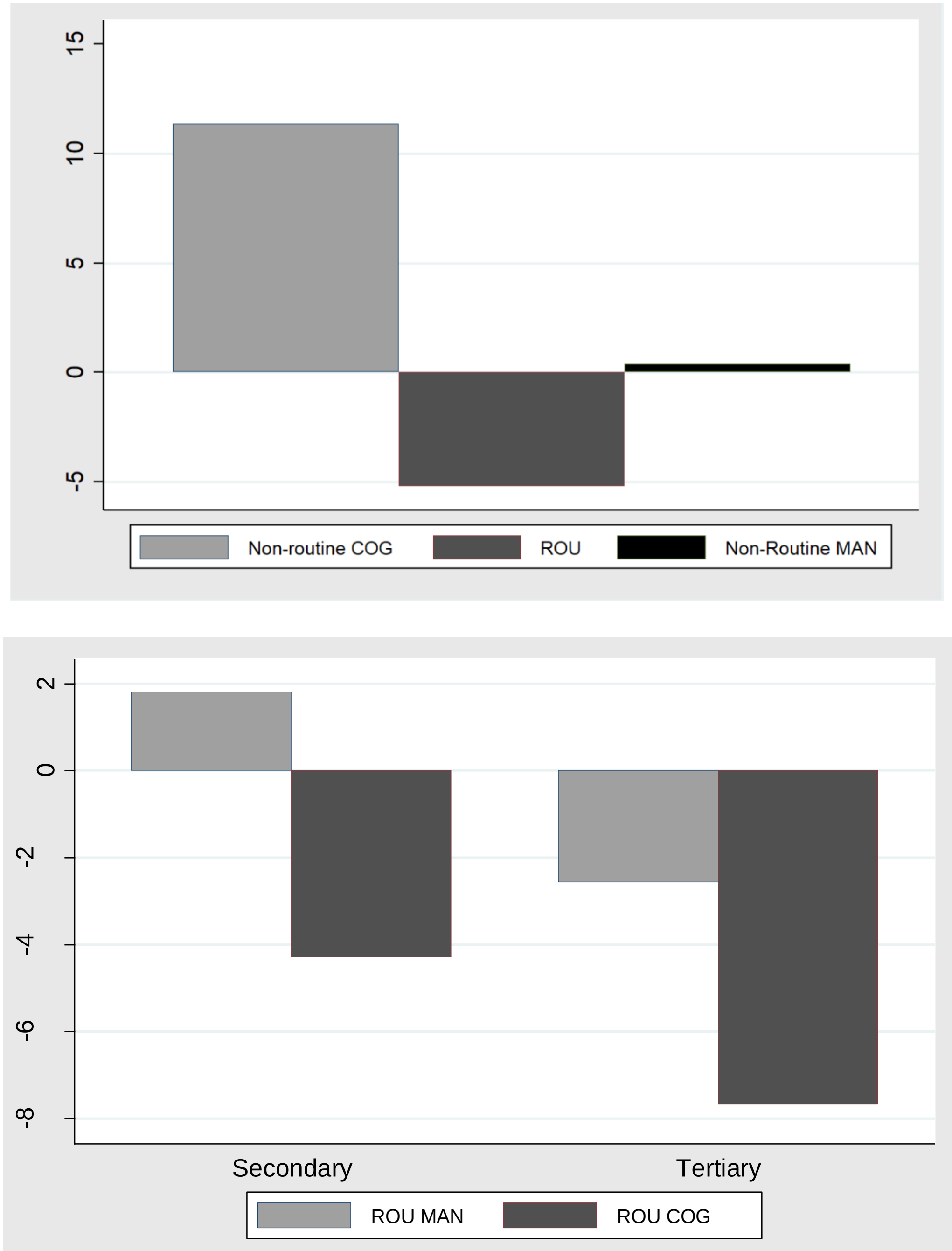
Note: Significant results in bold. Each regression model captures the relative change in employment at firm-level on the change of the firm routinization exposure. The relative change in this measure of labor is defined as the first difference in employment over the period 2004-2011, divided by the average number of employees across the two periods 2004 and 2011. M3 includes a set of firm and industry controls (share of production workers, workplace characteristics and the industry technology investment). All models are weighted by the sample design weights and number of employees in a firm averaged over employees at the start and end of a period, and stand errors are clustered on 2-digit SIC industries. *p-value<0.1; **p-value<0.05; ***p-value<0.01.

Table 5. The effect of routinization exposure on wages by technology adoption.

			PANEL A. Wage premium			
	Technology adopters	**Non-adopters**	**Technology adopters**	**Non-adopters**	**Technology adopters**	**Non-adopters**
ΔROU	2.97	-3.701				
	[2.04]	[2.82]				
Dschock ROU	0.000	0.000				
	[0.00]	[0.00]				
ΔROU MAN			**2.439****	0.249		
			[1.19]	[4.50]		
Dschock ROU MAN			**0.00**	0.000		
			[0.00]	[0.00]		
ΔROU COG					-2.398	-2.259
					[2.59]	[2.52]
Dschock ROU COG					0.000	0.000
					[0.00]	[0.00]
Observations	507	423	514	439	511	435
			PANEL B. Wage premium in Secondary sector			
	Technology adopters	**Non-adopters**	**Technology adopters**	**Non-adopters**	**Technology adopters**	**Non-adopters**
ΔROU	**3.572*****	**6.428***				
	[1.14]	**[3.43]**				
Dschock ROU	**0.00**	**0.00**				
	[0.00]	**[0.00]**				
ΔROU MAN			**5.781*****	**4.436***		
			[1.99]	**[2.54]**		
Dschock ROU MAN			**0.000***	**-0.002***		
			[0.00]	**[0.00]**		
ΔROU COG					1.45	2.582
					[2.86]	[2.56]
Dschock ROU COG					0.00	**-0.001*****
					[0.00]	**[0.00]**
Observations	109	62	110	63	129	109
			PANEL C. Wage premium in Tertiary sector			
	Technology adopters	**Non-adopters**	**Technology adopters**	**Non-adopters**	**Technology adopters**	**Non-adopters**
ΔROU	0.326	-1.296				
	[2.11]	[2.03]				
Dschock ROU	0.00	0.00				
	[0.00]	[0.00]				
ΔROU MAN			0.716	-6.515		
			[0.81]	[4.95]		
Dschock ROU MAN			0.00	0.00		
			[0.00]	[0.00]		
ΔROU COG					-1.287	-0.235
					[1.24]	[1.53]
Dschock ROU COG					0.00	0.00
					[0.00]	[0.00]
Observations	398	361	404	376	402	372

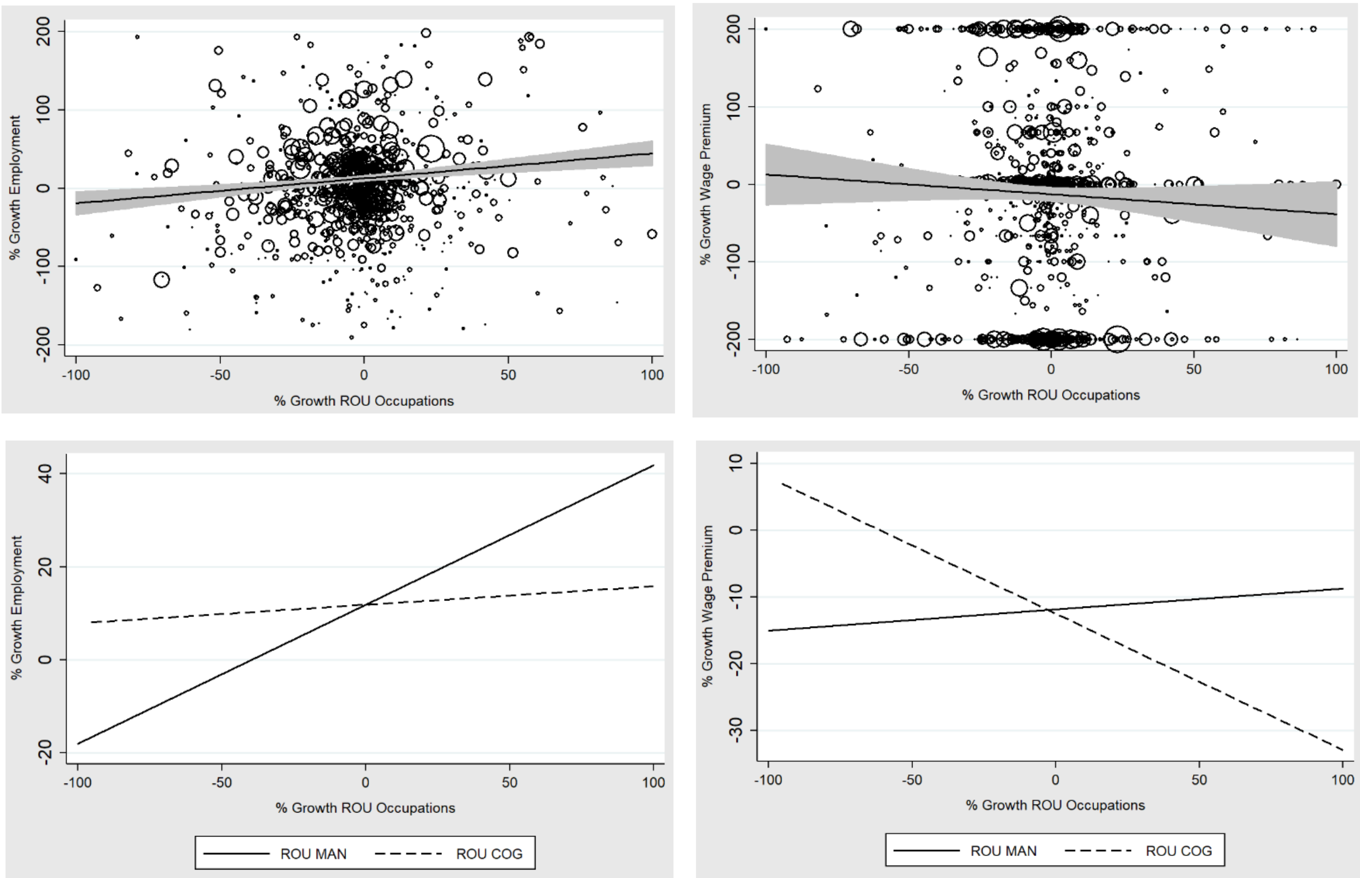
Note: Significant results in bold. Each regression model captures the relative change in wages at firm-level on the change of the firm routinization exposure. The relative change in this measure of labor is defined as the first difference in wage premium over the period 2004-2011, divided by the average number of employees above the market salary across the two periods 2004 and 2011. Columns 3 includes a set of firm and industry controls (share of production workers, workplace characteristics and the industry technology investment). All models are weighted by the sample design weights and number of employees in a firm averaged over employees at the start and end of a period, and stand errors are clustered on 2-digit SIC industries. *p-value<0.1; **p-value<0.05; ***p-value<0.01.

Figure 1. Employment polarization in UK (2004-2011)



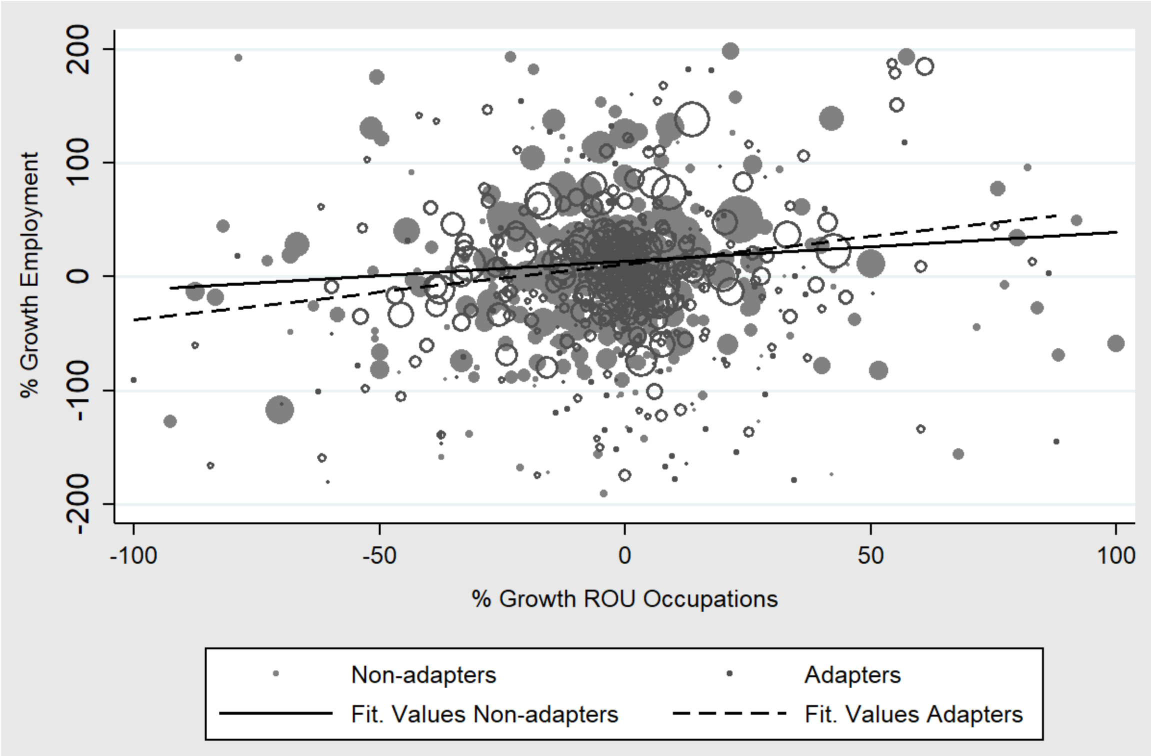
Source: Panel WERS 2004-2011.

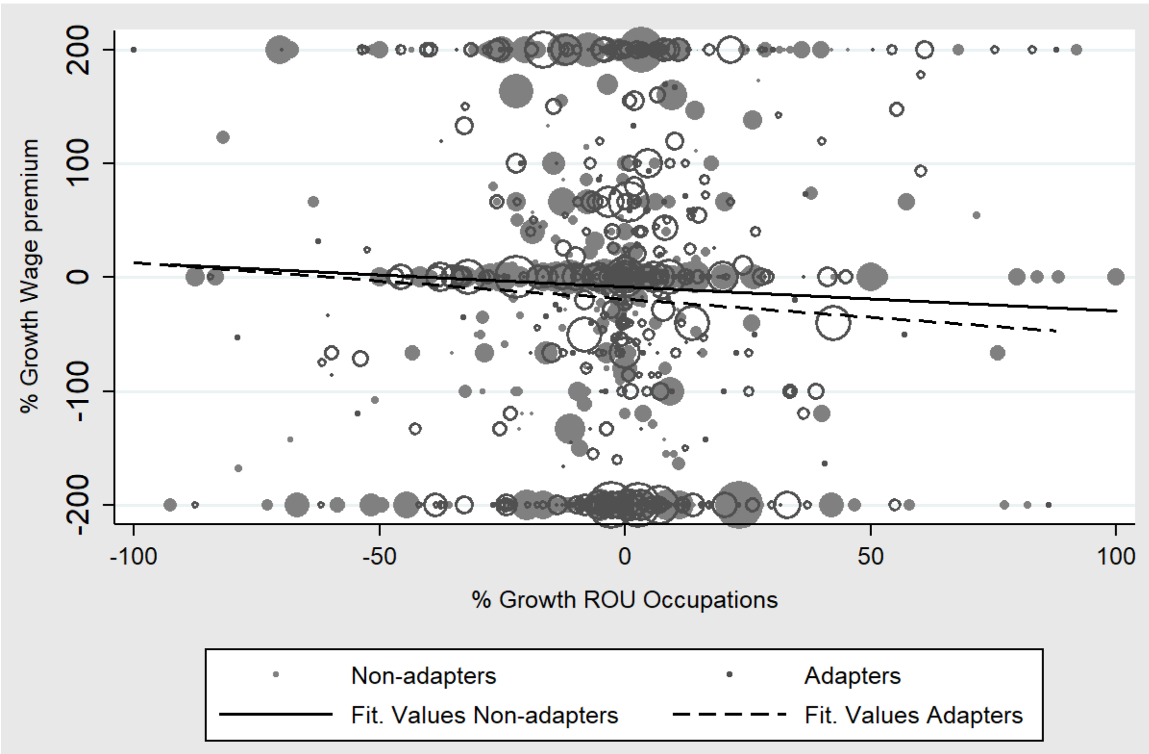
Figure 2. Correlation between routine exposure and labor at firm-level



Source: Panel WERS 2004-2011

Figure 3. Correlation between routine exposure and labor at firm-level by technology adoption





Recent papers in the SPRU Working Paper Series:

November

2019-23. Start-up Subsidies: Does the Policy Instrument Matter? *Hanna Hottenrott and Robert Richstein*

2019-22. Organised Crime and Technology. *Mustafa Caglayan, Alessandro Flamini and Babak Jahanshahi*

October

2019-21. The Value of Data: Towards a Framework to Redistribute It. *Maria Savona*

September

2019-20. Teaming up with Large R&D Investors: Good or Bad for Knowledge Production and Diffusion? *Sara Amoroso and Simone Vannuccini*

2019-19. Experimental Innovation Policy. *Albert Bravo-Biosca*

August

2019-18. Relating Financial Systems to Sustainability Transitions: Challenges, Demands and Dimensions. *Chantal P. Naidoo*

2019-17. Innovation and Self-Employment. *Tommaso Ciarli, Mattia Di Ubaldo and Maria Savona*

2019-16. Integration in Global Value Chains and Employment in Europe. *Filippo Bontadini, Rinaldo Evangelista, Valentina Meliciani and Maria Savona*

Suggested citation:
Mabel Sánchez Barrioluengo (2019). Job Composition and Its Effect on UK Firms in the Digital Era. SPRU Working Paper Series (SWPS), 2019-24: 1-34. ISSN 2057-6668. Available at: www.sussex.ac.uk/spru/swps2019-24

Science Policy Research Unit
University of Sussex, Falmer
Brighton BN1 9SL
United Kingdom

SPRU website: **www.sussex.ac.uk/business-school/spru**
SWPS website: **www.sussex.ac.uk/business-school/spru/research/swps**
Twitter: **@spru**

US UNIVERSITY OF SUSSEX | BUSINESS SCHOOL