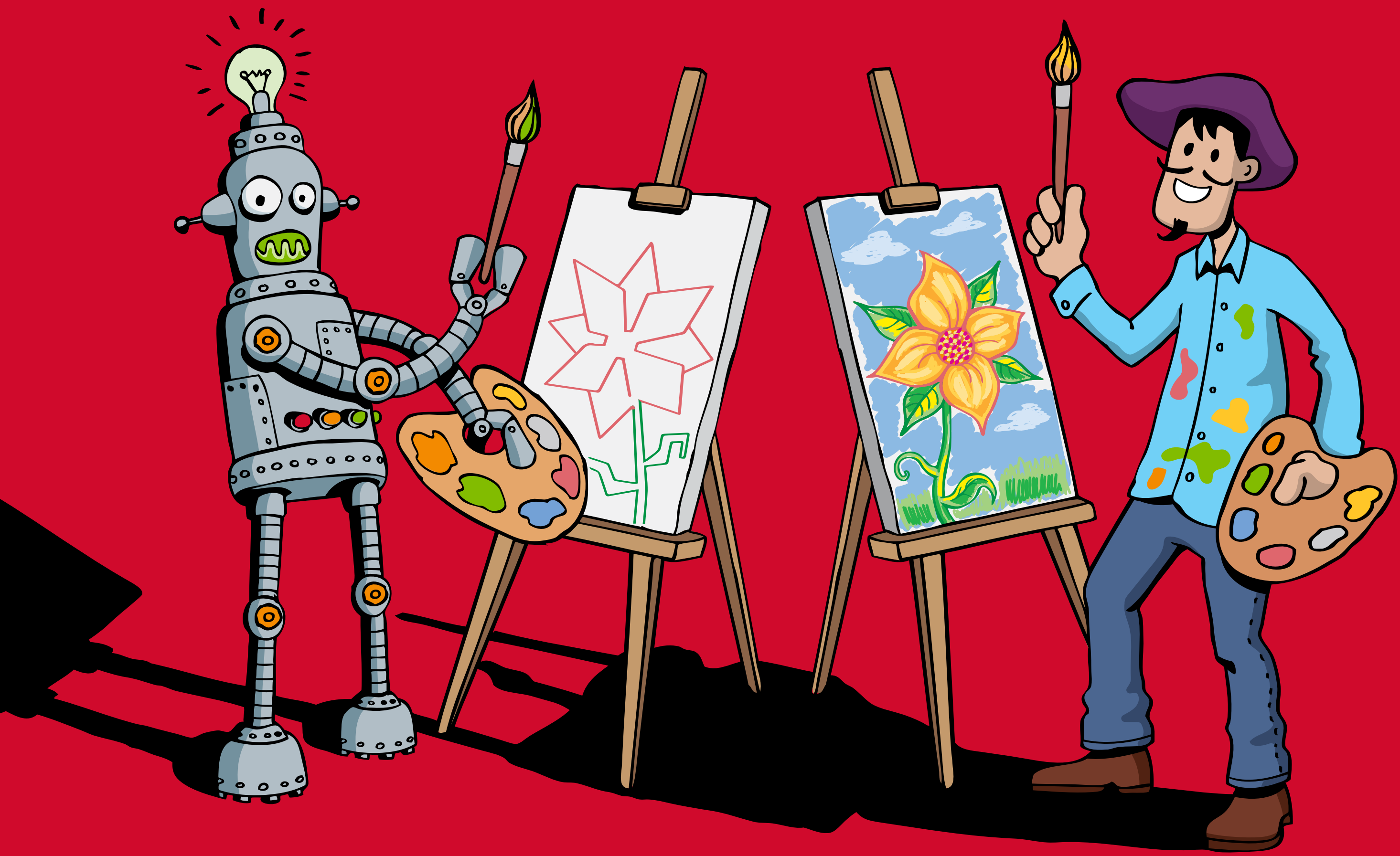
Nesta...

CREATIVITY VS. ROBOTS

THE CREATIVE ECONOMY AND THE FUTURE OF EMPLOYMENT



Hasan Bakhshi,
Carl Benedikt Frey
and **Michael Osborne**

April 2015

AUTHORS

Hasan Bakhshi is Director, Creative Economy, Nesta.

Carl Benedikt Frey is Co-Director, Oxford Martin Programme on Technology and Employment and an Oxford Martin Citi Fellow, Oxford University.

Michael Osborne, Co-Director, Oxford Martin Programme on Technology and Employment and Associate Professor in Engineering Science, University of Oxford.

ACKNOWLEDGEMENTS

We are grateful to **George Windsor** for his contributions to the project.

Nesta...

Nesta is an innovation charity with a mission to help people and organisations bring great ideas to life.

We are dedicated to supporting ideas that can help improve all our lives, with activities ranging from early-stage investment to in-depth research and practical programmes.

Nesta is a registered charity in England and Wales with company number 7706036 and charity number 1144091.
Registered as a charity in Scotland number SCO42833. Registered office: 1 Plough Place, London, EC4A 1DE.

www.nesta.org.uk

CREATIVITY VS. ROBOTS

THE CREATIVE ECONOMY AND THE FUTURE OF EMPLOYMENT

CONTENTS

1. INTRODUCTION AND SUMMARY

In October last year, Mark Riedl, Associate Professor of Computing at Georgia Institute of Technology, published a paper proposing a variant of the famous Imitation Game – Alan Turing's test to see if machines can demonstrate that they think like humans (Riedl, 2014[1]). The Turing Test involves fooling judges into thinking they are communicating with a human when in fact they're communicating with a computer. Riedl's test instead asks whether a computer can create an artefact like a poem, story, painting or architectural design that meets the requirements of a human evaluator. In fact, this test, which Riedl names the Lovelace 2.0 test, is itself an adaption of an earlier – much more demanding – Lovelace test, proposed by computer scientists in 2001, which asks whether an Artificial Intelligence (AI) can create something – a story or poem, say – in a way that the AI's programmer cannot explain how it came up with its answer.

These tests represent what is in fact humankind's longstanding obsession with expanding its engineering capabilities to allow machines to perform tasks that have previously been confined to workers. While many barriers to automation have recently been overcome, allowing sophisticated algorithms and autonomous vehicles to substitute for workers in a wider range of domains, creativity arguably still provides a big obstacle to automation. In this paper, we examine the potential quantitative impact of the expanding scope of automation on creative employment, and related implications for the demand for skills and the future of inequality.

Crucially, there is nothing inevitable about the impact of automation on jobs and skills. In fact, history suggests that the impact of new technologies on employment has been very different across time and space.[2] In 19th century England, for example, technological advances generally substituted for skilled artisans and favoured unskilled labour (Braverman, 1974,[3] Hounshell, 1985,[4] James and Skinner, 1985,[5] Goldin and Katz, 1998[6]). The tendency for technological change to raise the demand for skilled labour emerged in the late 19th/early 20th century with the shift from steam and water power to electrification and the appearance in manufacturing production of mechanised assembly lines, both developments which raised the demand for skilled manual and white collar workers.

More recently, Information and Communication Technologies have strongly augmented the returns to labour for highly skilled workers performing cognitive tasks (MacCrory et al., 2014[7]), though there is evidence that it has also led to a shift in the workforce from medium-skilled manual workers doing routine tasks to low-skilled workers in service occupations which – at least until now – have been more difficult to routinise (Autor and Dorn, 2013[8]). This polarising effect of computerisation on labour markets – jobs being either 'lousy' or 'lovely' (Goos and Manning, 2007,[9] Goos, Manning and Salomons 2009[10]) – has contributed to the historic increases in income inequality observed in countries like the US and the UK in the late 20th and early 21st centuries and is therefore of considerable political as well as economic importance (Facundo et al. 2013; Piketty, 2014[11]).

Against this backdrop it is hardly surprising that there has been an explosion of interest in what future technological trends will mean for workforce jobs and what they will imply for policy (Brynjolfsson and McAfee, 2011, 2014,[12] Mokyr, 2013,[13] Frey and Osborne, 2013,[14] Autor, 2014[15]).

In particular, the growing concern about the future of work stems from recent developments in Machine Learning and Mobile Robotics, associated with the rise of big data, which allows computers to substitute for labour across a wide range of non-routine tasks – both manual and cognitive. As McCormack and d'Inverno (2014)[16] put it, *"We now know how to build machines that can 'learn' and change their behaviour through search, optimisation, analysis or interaction, allowing them to discover new knowledge or create artefacts which exceed that of their human designers in specific contexts".*

So, looking ahead – although not so far ahead – driver-less cars may do away with non-routine manual tasks in transport and logistics (tasks seen only recently as relying critically on non-automatable human perception) (Brynjolfsson and McAfee, 2011;[17] Gordon, 2014[18] counterargues that the impacts will be limited). In the creative economy, advances in the area of Mobile Robotics may have implications for making and craft activities (as industrial robots with machine vision and high-precision dexterity become cheaper and cheaper). Data Mining and Computational Statistics where algorithms are developed which allow cognitive tasks to be automated – or become data-driven – may conceivably have significant implications for non-routine tasks in jobs as wide-ranging as content programming (Lycett, 2013[19]), distribution (Bakhshi and Whitby, 2014[20]), marketing (Mestyan, Yasseri and Kertesz, 2013[21]) and education (West, 2012[22]). More generally, jobs that are considered creative today may not be so tomorrow.

What can we say in quantitative terms about the implications of these technological trends for the UK workforce and for the creative economy in particular?

Frey and Osborne (2013) make use of detailed task descriptions of 702 occupations from O*NET – an online service developed for the US Department of Labor – to develop a predictive model which estimates the probability of computerisation of US occupations some 10–20 years into the future.[23] They conclude that 47 per cent of jobs existing in 2010 are at high risk of computerisation. Most vulnerable are occupations related to transport, logistics, manufacturing production, construction and office administration. But also, controversially (Gordon, 2014),[24] services (e.g. household services) and a number of sales-related occupations (e.g. cashiers, telemarketers).

Knowles-Cutler, Frey and Osborne (2014)[25] extend the study to the UK (making use of crosswalks from US occupational to UK occupational classifications). Using the same approach they estimate that 35 per cent of UK jobs are at high risk of computerisation (though differences between the UK and US classifications mean that the figures are not directly comparable). The results suggest that as technological capabilities expand and costs decline, we can expect developments like Machine Learning and Mobile Robotics to gradually substitute for labour in the same wide range of occupations as in the US, spanning transport, production, construction, manufacturing production, services and sales.

In the present paper, we build predictive models for both the US and UK to assess the probabilities with which different occupations are creative or not creative, adopting an equivalent modeling strategy to that in Frey and Osborne (2013).[26]

We adopt a broad definition of creativity, taken from Oxford Dictionaries, as *"the use of imagination or original ideas to create something."*[27] This is related to, but is a broader concept of creativity than is implicit in the Department for Culture, Media and Sport's (DCMS) annual Creative Industries Economic Estimates (DCMS, 2015),[28] which is constrained by the particular focus of the Department on creative content and creative services and its need, for official measurement purposes, to treat occupations discretely as either 'creative' or not.

Using the quantitative (objective) and qualitative (subjective) task information in the O*NET data, we hand-label 120 US occupations as creative or non-creative, asking the question: does this job require the use of imagination or original ideas to create something? For classification, we develop an algorithm to estimate the individual probabilities of all 702 occupations in the US being creative given a previously unseen vector of variables derived from O*NET.

Our results suggest that 21 per cent of US employment is highly creative – that is, has a probability of more than 70 percent of being creative (which is, incidentally, a much smaller fraction of jobs in the United States than some other estimates (Florida, 2014[29]). These creative occupations include artists, architects, web designers, IT specialists and public relations professionals.

We then replicate the analysis for the United Kingdom. Relative to the United States, the UK has a higher fraction of creative employment, constituting around 24 per cent of the workforce.

As expected, given the broader concept of creativity adopted in the analysis, our estimates of creative employment are bigger than what the official estimates say. In fact, it turns out that according to our models the clear majority of all of the occupations in the DCMS list are found to be creative with a very high probability, which is reassuring for those of us who often make use of these statistics for economic analysis. However, intuitively, given our broader definition, there are a set of other occupations which the models suggest are creative with a high probability but which do not appear in the DCMS list.

The results also strongly confirm the intuition that creative occupations are more future–proof to computerisation. In the US, 86 percent of workers in the highly creative category are found to be at low or no risk of automation. In the UK, the equivalent number is 87 percent. We conclude that economies like the UK and US where creative occupations make up a large proportionate of the workforce may be better placed than others to resist the employment fallouts from future advances in computerisation.

The rest of the paper has the following structure. Section 2 details the different sources used in the study. Section 3 sets out the methodology. Section 4 presents the results, and Section 5 offers an interpretation of the findings. Section 6 concludes.

2. DATA

Our study makes use of several data sources characterising workforce occupations in both the US and the UK. In the US, we adopt the Bureau of Labor Statistics' (BLS) 2010 Standard Occupational Classification (henceforth US SOC 2010), while in the UK we use the Office for National Statistics' (ONS) 2010 Standard Occupational Classification (henceforth UK SOC 2010). This allows us to consider 702 different occupational categories in the US, and 366 in the UK (these numbers are discussed in more detail below).

To relate one to the other, we make use of an intermediary: the International Labour Organisation's 2008 International Standard Classification of Occupations (ISCO-08), of which we consider 288 occupational categories. We then make use of the ONS's crosswalk from ISCO-08 to UK SOC 2010 and the BLS's crosswalk from US SOC 2010 to ISCO-08, allowing us to perform the many-to-many mapping from the US to the UK. In doing so, our core assumption is that the skills demanded for a particular occupation are similar in both the UK and US.

We also take detailed survey data from the 2010 version of the O*NET database, an online service developed for the US Department of Labor.[30] The O*NET data was initially collected from labour market analysts, and has since been regularly updated by surveys of each occupation's worker population and related experts, to provide up-to-date information on occupations as they evolve over time. This data characterises the skills, such as 'Originality' and 'Fine Arts', required to perform 903 different occupations. Survey respondents self-report the level to which a skill is required for their job. For instance, in relation to the attribute 'Manual Dexterity', low (level) corresponds to 'Screw a light bulb into a light socket'; medium (level) is exemplified by 'Pack oranges in crates as quickly as possible'; high (level) is described as 'Perform open-heart surgery with surgical instruments'. O*NET is thus able to define the key skills required to perform an occupation as a standardised and measurable set of variables on a scale of 0 to 100. We expect these variables to be predictive of whether an occupation is or is not creative; we describe our approach to using these variables in the methodology section below.

The occupational categorisation used by O*NET closely matches that of the US SOC 2010. This allows us to link O*NET occupations to 2010 BLS employment and wage data. While the O*NET occupational classification is somewhat more detailed, distinguishing between Auditors and Accountants, for example, we aggregate (averaging over occupations thus aggregated) to correspond to the US SOC 2010 system, for which employment and wage figures are reported. In addition, we exclude the small number of six-digit US SOC 2010 occupations for which O*NET data is missing (the excluded occupations represented 4.628 million jobs, or 3.2 per cent of the overall workforce). Doing so, we end up with a final dataset consisting of 702 occupations, comprising employment equal to 138.4 million jobs. For these jobs, we use the probabilities of computerisation drawn from Frey and Osborne (2013).[31]

In the UK, we use the ONS's 2013 Annual Population Survey (APS) to provide employment and educational attainment data for 366 UK SOC 2010 occupations (this excludes three occupational categories within the armed forces for which we have no corresponding O*NET data; armed forces occupations were also excluded from Frey and Osborne's earlier study). In total, our UK dataset comprises 29.5 million jobs. We additionally make use of income data from the ONS's 2013 Annual Survey of Hours and Earnings (ASHE) to relate our measure of creative jobs to earnings. Finally, we label the 30 UK SOC 2010 occupations identified as creative by the DCMS (2013).[32] All US SOC 2010 occupations that map to the 30 DCMS creative occupations under the crosswalk are likewise labelled. There are 59 such US occupations in total. As described in detail below, providing these occupation labels to our sophisticated algorithm will permit it to learn the difference between creative and non-creative occupations.

3. METHODOLOGY

Creativity is of course notoriously difficult to define,[33] and classifying some occupations as 'creative' and others as not presents considerable challenges. The approach taken in Bakhshi, Freeman and Higgs (2013),[34] and that influenced the DCMS classification, was to manually inspect the ONS's detailed occupation coding.[35] This requires laborious expert assessment of all occupational descriptions and is sensitive to the subjective priors of experts. By contrast, inspired by the methodology of Frey and Osborne (2013),[36] work that classified occupations as to their computerisability, we employ algorithmic classification to automate this assessment in light of the occupational characteristics supplied by the O*NET variables. This provides a methodology for rapid classification of new occupations and an independent validation of the official classification.

This approach is motivated by the acknowledgement that even expert labels of creativity must be treated as noisy measurements. There is, for example, unavoidable diversity within any individual occupational category leading to uncertainty about the creativity of the occupational category as a whole, and different experts may focus on different sub-occupations. Our algorithm uses the trends and patterns it has learned from bulk data to correct for what are likely to be mistaken labels. Our non-parametric approach also allows for complex, non-linear, interactions between O*NET variables: for example, perhaps one variable is not of importance unless the value of another variable is sufficiently large. Finally, our probabilistic approach returns not just the most likely label for an occupation, but also quantifies the uncertainty in this classification given the available data. As such, our approach is robust to mislabeling and provides transparent assessment of the confidence in and justification for its classification.

We treat the 59 US SOC 2010 occupations with UK equivalent occupations labelled as 'creative' by the DCMS as forming a training set, which we use to train a non-parametric classifier able to provide the probability of any occupation being creative. In addition to these 59 occupations, we label a further 61 US occupations as being 'non-creative' for inclusion in the training set (which consequently comprises 120 occupations). In the selection of non-creative occupations we were guided by the detailed description of occupations made available by O*NET and the considerations of Bakhshi, Freeman and Higgs (2013).[37] Specifically, we compared the open-ended task descriptions provided by O*NET[38] against the criteria in Bakhshi, Freeman and Higgs's analysis in order to judge which occupations were most representatively non-creative. Note that it is crucial that there are examples of both creative and non-creative occupations in the training set in order to train a classifier to distinguish between the two: an algorithm that is provided only positive examples would reasonably conclude that all occupations were creative.

In the terminology of classification, the O*NET variables form a feature vector; O*NET hence supplies a complete dataset of 702 such feature vectors. A label of creative/non-creative is termed a class. The feature vectors and class labels associated with occupations form a dataset that contains information about how the class varies as a function of the features. A probabilistic classification algorithm exploits patterns existent in training data to return the probability of a new, unlabelled, test datum with known features having a particular class label. We test three probabilistic Gaussian process (Rasmussen and Williams, 2006[39]) classifiers using the GPy toolbox (GPy, 2012–2015[40]) on our data, built around exponentiated quadratic, Matérn and linear covariances. Note that the latter is equivalent to logistic regression; the former two represent more flexible models.

We also perform analysis of the sensitivity of our conclusions to the selection of occupations to include in the training set. In particular, we perform cross-validation analysis to test whether the training set is self-consistent. Specifically, we randomly select a reduced training set of 90 per cent of the available data (that is, we select 108 of the 120 occupations). The remaining data (12 occupations) form a test set. On this test set, we evaluate how closely the algorithm's classifications match the hand labels according to two metrics (Murphy, 2012[41]): the area under the receiver operating characteristic curve (AUC), which is equal to one for a perfect classifier and one half for a completely random classifier, and the log-likelihood, which should ideally be high. This experiment is repeated for ten random selections of the training set, and the average results tabulated in Table 1. The exponentiated quadratic model returns the best performance of the three[42] (outperforming the linear model corresponding to logistic regression), and is hence selected for the remainder of our testing. Note that its AUC score of nearly 0.96 represents highly accurate classification: our algorithm successfully manages to reproduce our hand labels specifying whether or not an occupation is creative. In other words, our algorithm verifies that the DCMS creative labels are systematically and consistently related to the O*NET variables. Further, none of the ten variations to the training set result in anything less than effective classification (the lowest AUC for the exponentiated quadratic covariance is 0.83). From this, we can draw some confidence that our results are not especially sensitive to the selection of the training set.

Table 1 **Results from sensitivity analysis of various classifiers**

Classifier model	AUC	Log-likelihood
Exponentiated quadratic	0.958	-61.9
Linear (logit regression)	0.945	-57.3
Matérn 3/2	0.924	-63.7

Having validated our approach, we proceed to use classification to predict the creativity for all 702 US SOC 2010 occupations (for which we have the O*NET variables). We assume that our labels are a noise-corrupted version of the unknown true creative label. We thus acknowledge that it is by no means certain that a job is indeed creative given our labelling, due to mistaken labels or within-occupation variability. Our analysis is built on an experiment in which, given all available training data (the 120 labelled occupations), we predict the true label for all 702 US occupations.

This approach firstly allows us to use the features of the 120 occupations about which we are most certain to predict for the remaining 582. But our algorithm also uses the trends and patterns it has learned from bulk data to correct for what are likely to be mistaken labels. More precisely, the algorithm provides a smoothly varying probabilistic assessment of creativity as a function of the variables. For our Gaussian process classifier, this function is non-linear, meaning that it flexibly adapts to the patterns inherent in the training data. This classifier furnishes us with probabilistic assessment of the creativity of any occupation given a measurement of its characteristics, providing a dynamic classification that can accommodate changes in the workforce.

After thus classifying the creativity of all US occupations, we use the crosswalk described above to arrive at the creative probabilities of UK SOC 2010 occupations. Given the many-to-many nature of the crosswalk, it turns out that some UK occupations are associated with multiple US occupations. In such cases, the probabilities of creativity for the UK occupations are calculated as the employment-weighted average of those for the multiple US occupations. This crosswalk methodology is identical to that adopted in Knowles-Cutler, Frey and Osborne (2014).[43]

4. RESULTS

4.1 Creative occupations

In this section, we build on previous findings examining the susceptibility of occupations to computerisation. In particular, Frey and Osborne (2013)[44] show that about 47 per cent of US employment is at risk of automation over the next decade or two, as a new wave of computer-related technologies are being adopted, potentially displacing workers in production, construction, administration and office support, transportation and logistics as well as a range of sales and service-related occupations. In the same way that these technologies will transform the US labour market, most industrial nations will be affected (e.g. Bowles, 2014[45]). Work conducted by Knowles-Cutler, Frey and Osborne (2014) shows that 35 per cent of the UK workforce is susceptible to automation. Although these findings are not directly comparable due to different levels of detail provided in occupational classifications being used – the US study was conducted for 702 occupations whereas only 369 relatively broad occupational categories are available for the UK – they nevertheless suggest a pervasive restructuring of labour markets over the decades to come.

In a similar manner, this report employs the methodology developed by Frey and Osborne (2013)[46] to examine the probability of an occupation being creative. As reported in Figures 1 and 2, we distinguish between high, medium and low probability occupations, depending on their creative content (thresholding at probabilities of 0.7 and 0.3).[47] According to our estimates, 21 percent of total US employment is in the high probability category, meaning that associated occupations involve creative tasks, such as the development of novel ideas and artefacts. When we translate our findings to the United Kingdom, we find 24 percent of the UK workforce in the creative category.

Our final classification largely extends the existing DCMS classification. While there are 30 DCMS creative occupations, our methodology shows that there are in fact as many as 47 creative occupations in terms of their task content – that is, occupations that involve work tasks that require a higher degree of originality, such as the development of novel ideas and artefacts. Furthermore, according to our findings, only seven of the DCMS creative occupations are not in the high probability of creativity category (Figure 3).

The probability of creativity of the seven DCMS occupations not in the 'high' category ranges between 23 per cent for Smiths and forge workers and 66 per cent for IT business analysts, architects and systems designers. 'Smiths and Forge Workers' in the UK correspond to 'Forging Machine Setters Operators and Tenders, Metal and Plastic' in the US, an occupation class that has a very low originality score of 27, a fine arts score of 0, and other features associated with non-creative occupations.[48] All other DCMS creative occupations not in the 'high' category are in the 'medium' creative category, corresponding to probabilities of creativity between 30 per cent and 70 per cent. Thus, while our methodology entails refinements to the DCMS classification, by far the majority of the DCMS creative occupations are indeed creative also by our definition, or exhibit above average probabilities of being creative.

Figure 1 **Employment by occupation category and creative probability, US**

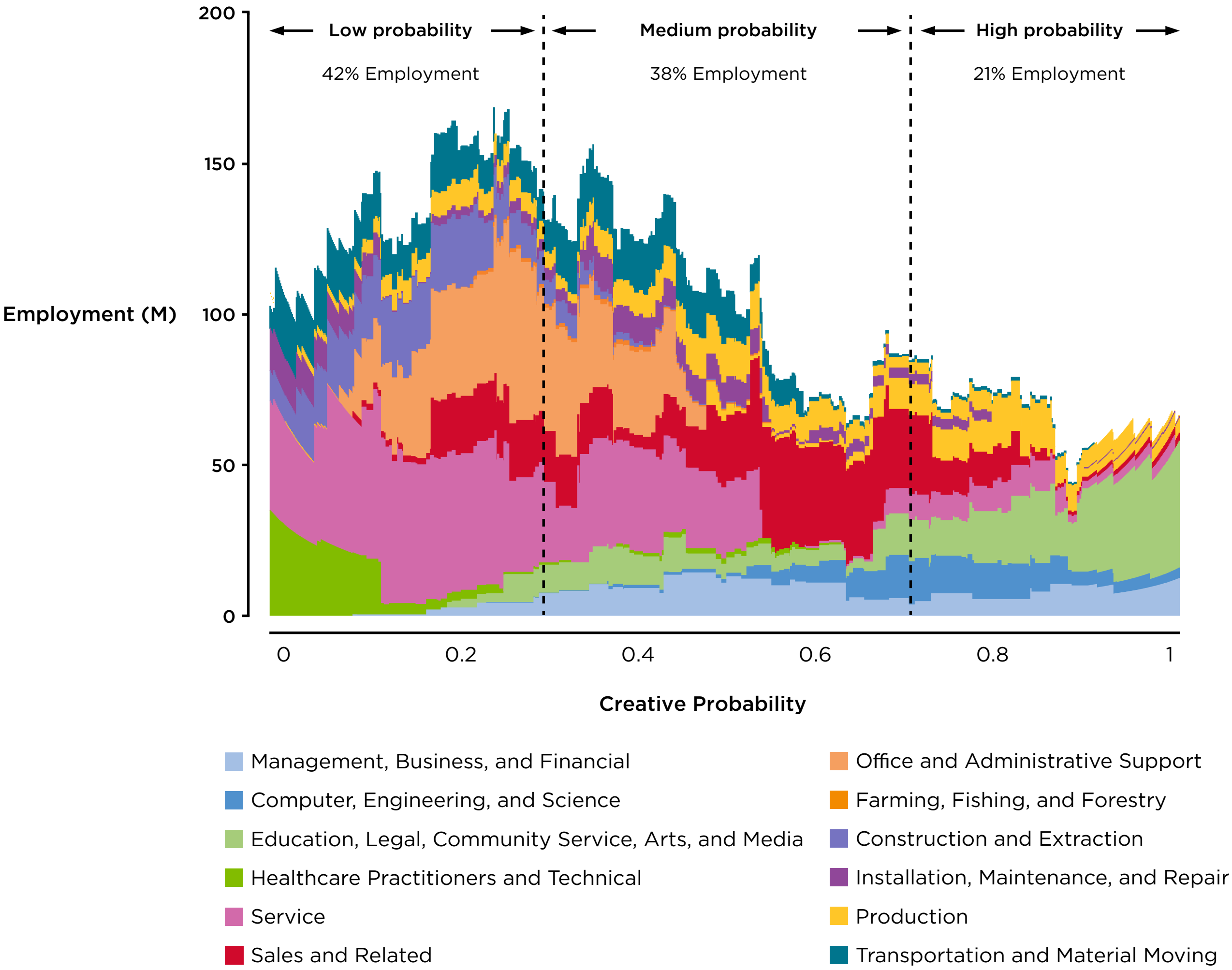
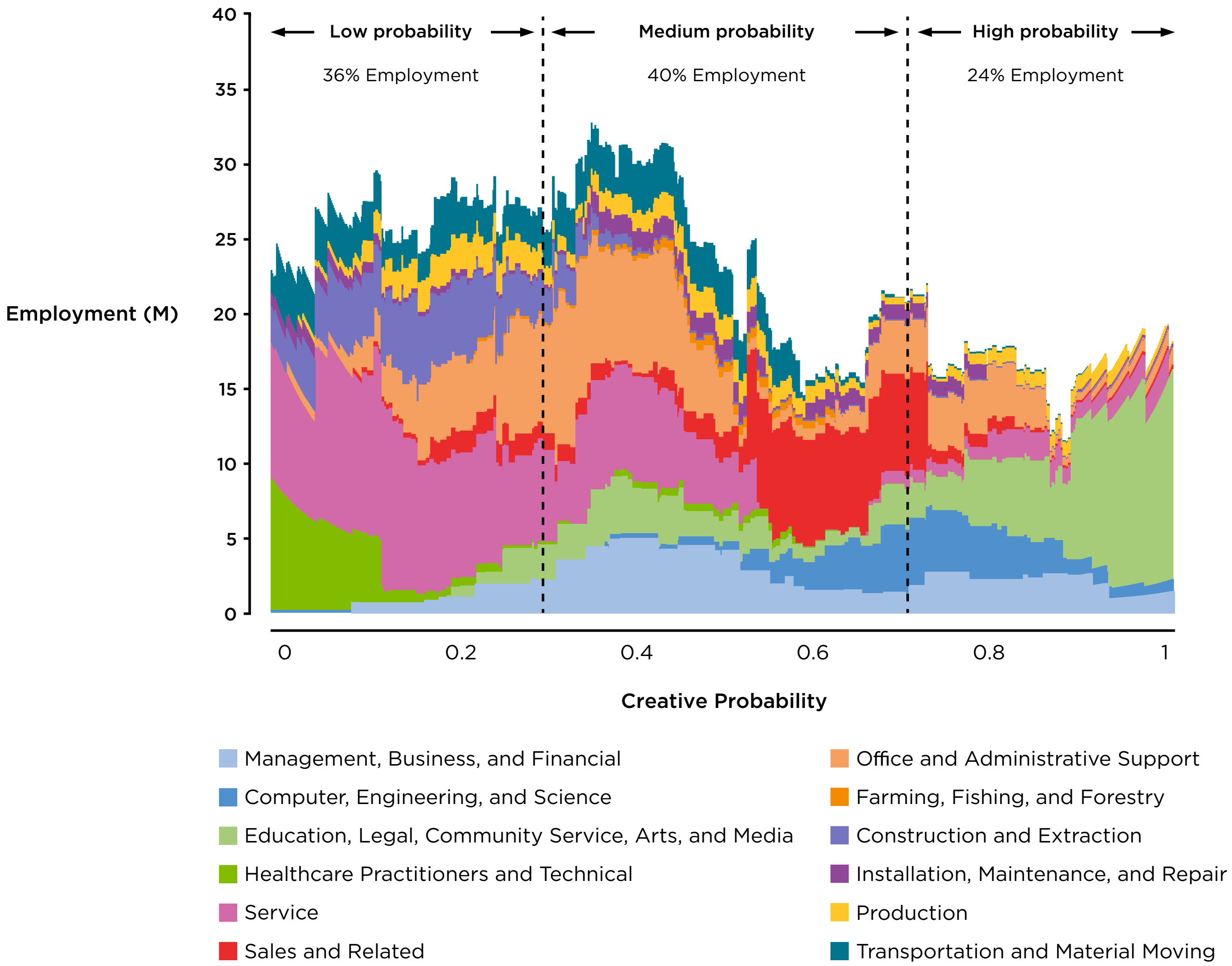


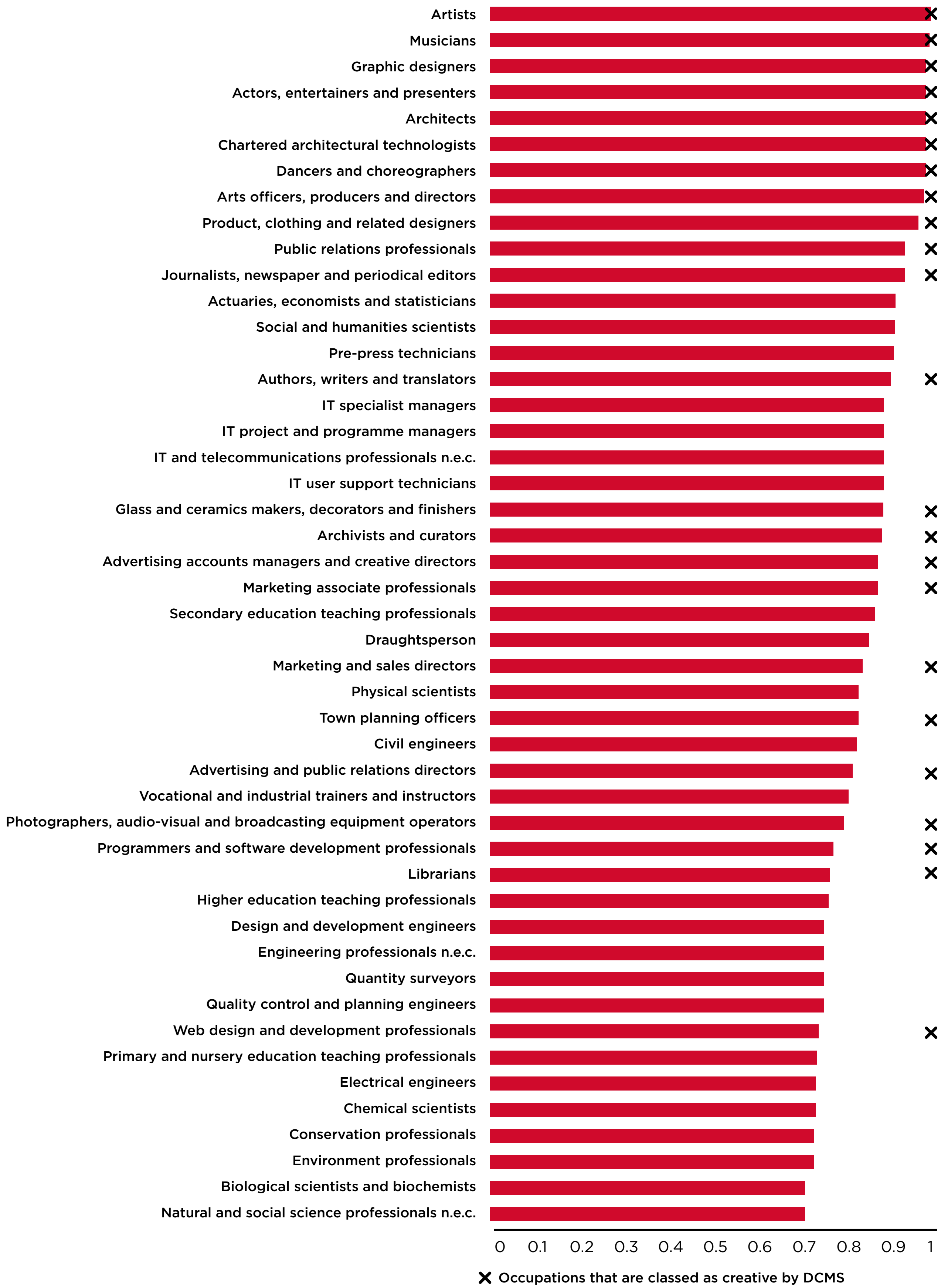
Figure 2 **Employment by occupation category and creative probability, UK**



As shown in Figures 1 and 2, the higher share of creative employment in the United Kingdom largely stems from its higher proportion of jobs in the Education, Legal, Community Service, Arts and Media category, which constitutes 11.2 percent of the total UK workforce relative to 9.6 percent in the United States. In particular, the share of the UK workforce in Arts and Media is more than twice that of the US (2.1 and 1 percent, respectively).

Nevertheless, our findings show that creative jobs span a broad range of occupational categories. While many occupations in Arts and Media – such as artists, musicians, dancers and choreographers, actors and entertainers – are in the high probability category, several Management occupations, including marketing and sales directors, as well as advertising account managers, are also highly creative. The same is true of a range of Computer, Engineering and Science occupations, such as civil engineers, IT specialist managers, and chemical scientists. Thus, our findings suggest that many of the occupations that are intensive in creative tasks are jobs that are directly associated with the arrival of new technologies – echoing the analysis in Bakhshi, Freeman and Higgs (2013)[49] and Bakhshi et al., (2015).[50]

Figure 3 Creative probability and DCMS creative occupations



The wide range of creative occupations implies that the originality involved in the development of novel ideas and artefacts manifests in many different forms, and is thus characterised by very different work tasks. For example, according to O*NET, an essential part of the work of choreographers is to 'develop ideas for creating dances.' While still only a relative minority of those employed in this occupation have been affected by recent technological change, arguably the work of many more musicians has been significantly altered. This is highlighted by their O*NET work tasks, which include 'experimenting with different sounds, and types and pieces of music, using synthesizers and computers as necessary to test and evaluate ideas.' Yet, although the task content of the work conducted by musicians has clearly changed in response to technological progress, the creative aspect of their work has not. Instead, many musicians today have learned how to work with computers in creative ways.

The creative content of occupations beyond Arts and Media is well captured by the occupational description of software developers, which 'design, develop and modify software systems, using scientific analysis and mathematical models to predict and measure outcome and consequences of design.' Examples of other new creative jobs resulting from technological progress include occupations associated with biotechnology. A crucial task of biochemical engineers, for example, is 'the development of methodologies for transferring procedures or biological processes from laboratories to commercial-scale manufacturing production.' Although much of the creative work of these occupations may not be directly perceived by the consumer, the cognitive processes involved in software development and biochemical engineering are arguably similar to those of choreographers in that they involve an element of originality.

Occupations in the medium probability category mainly relate to Management and Financial occupations, as well as jobs in Sales and Services. A common characteristic of these occupations is that they are intensive in generalist tasks requiring social intelligence, but are not necessarily as intensive in creative work, which often requires specialist knowledge – that is, creative jobs tend to be non-routine and thus not susceptible to automation according to the task model (Autor et al., 2003).[51] To be sure, many creative occupations also require social skills. The O*NET tasks of actors, for example, involve 'performing humorous and serious interpretations of emotions, actions, and situations, using body movements, facial expressions, and gestures', and 'learning about characters in scripts and their relationships to each other in order to develop role interpretations.' Nevertheless, while a range of creative jobs may require social skills, many jobs that involve social interactions are not creative. The work of human resource managers provides such an example, involving 'serving as a link between management and employees by handling questions, interpreting and administering contracts and helping resolve work-related problems.' While such work requires a high degree of social intelligence, many questions human resource specialists handle are of routine nature, and does typically not demand the same level of originality as, say, the work of musicians or software developers.

4.2 Creative occupations and automation

Crucially, we find that creativity is inversely related to computerisability. Drawing upon the probabilities of computerisation from Frey and Osborne (2013)[52] and Knowles-Cutler, Frey and Osborne (2014),[53] we are able to relate the probability of a job being computerised to that of it being creative (see Figures 4 and 5). The Figures should be interpreted as follows - in the UK over 2.4 million jobs are in occupations with a creative probability between 0.2 and 0.3 and a probability of computerisation of over 0.9. In the US, over 10.5 million jobs are in occupations with a creative probability between 0.2 and 0.3 and a probability of computerisation of over 0.9.

In the United Kingdom, 12 percent of employment in the medium probability of creativity category is susceptible to automation, relative to 13 percent in the United States. By contrast, most jobs in the low probability category are highly susceptible to automation, reflecting that these jobs are also less intensive in tasks requiring social intelligence – a finding that is suggestive of creativity and social intelligence often going hand-in-hand.

Crucially, for both the UK and the US, none of the jobs at all in the highly creative category are at high risk of automation. This supports the hypothesis of Frey and Osborne (2013) that creativity is a key bottleneck to computerisation: the skills required to innovate are not readily replaceable by a machine. While many creative occupations have undoubtedly been affected by computers, our findings show that computer-controlled equipment is unlikely to substitute for labour in creative domains. Rather, computers serve as a complement to most creative professions, making creative skills more productive.

Figure 4 **Computerisable vs. Creative, UK**

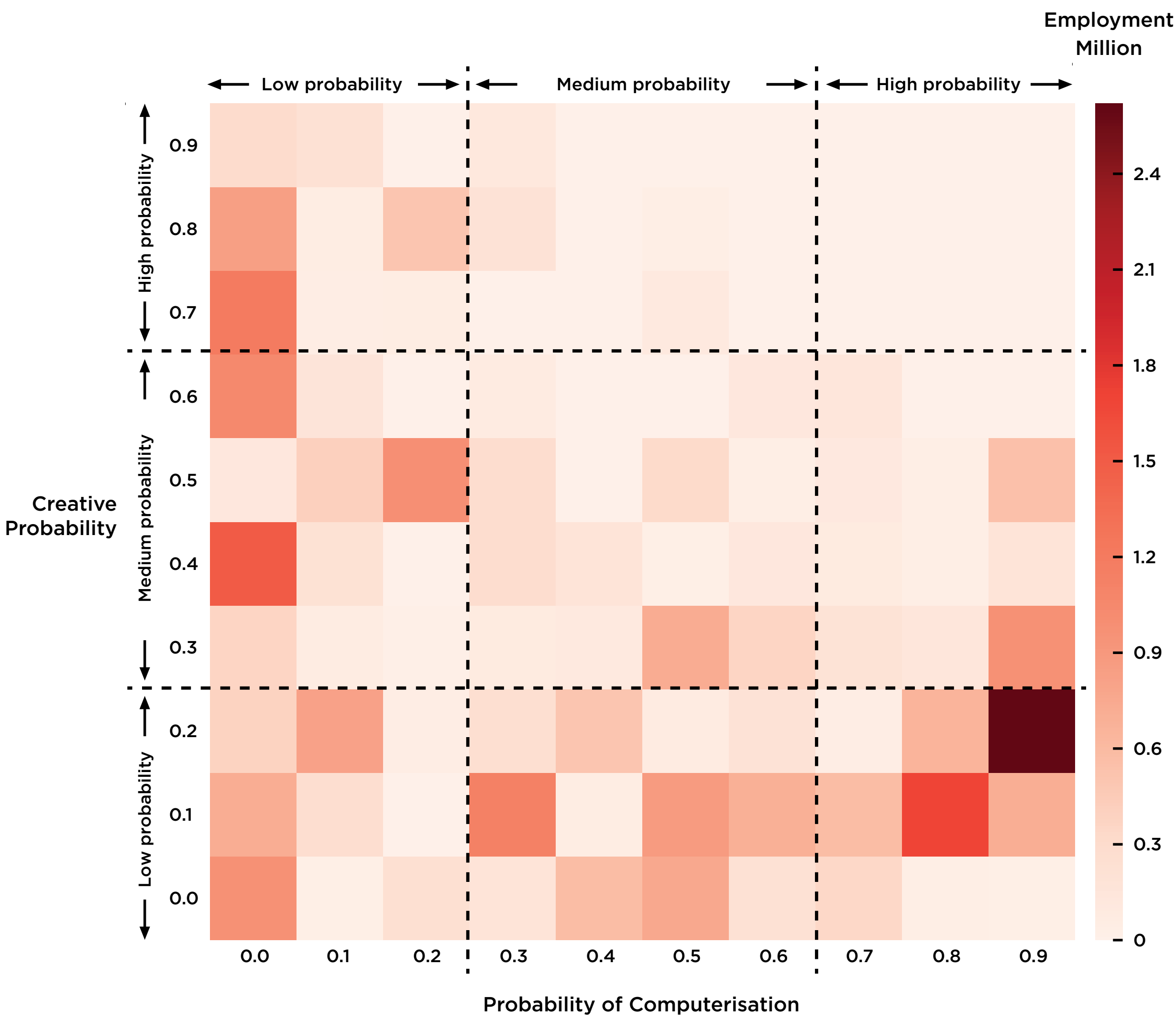
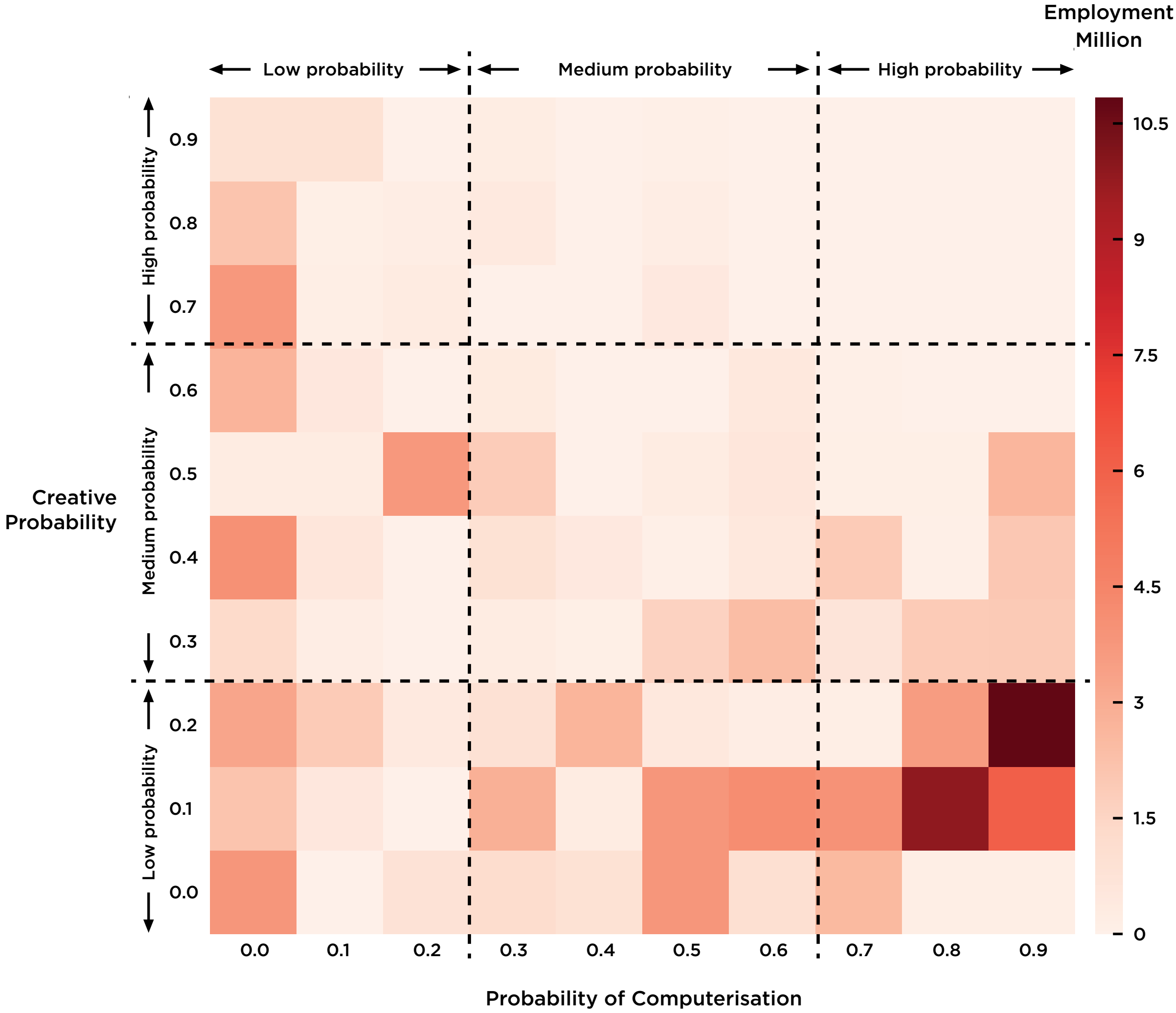


Figure 5 **Computerisable vs. Creative, US**



4.3 Creative occupations, earnings and education

To further examine the characteristics of creative jobs, we plot the average median wage of occupations by their probability of being creative. We do the same for skill level, measured by the fraction of workers having obtained a bachelor's degree, or higher educational attainment, within each occupation.

Figures 6 and 7 reveal that while workers in creative occupations on average earn higher wages than individuals in the medium and low probability category, the relationship between the probability of an occupation being creative and the average income of people in such jobs has an inverse U–shape (look at the wages of occupations in the high creative probability segment). This relationship holds in both the United Kingdom and the United States, and reflects that some of the most obviously creative occupations, such as musicians, actors and artists, earn relatively low wages to occupations characterised by only high to average creativity – including IT specialist managers, barristers and judges, financial managers, and management consultants. For example, in the United Kingdom, the ASHE reports average annual income for musicians and actors as £16,796 and £5,091, respectively. By contrast, IT specialist managers on average earn £49,128, while financial managers exhibit an average annual income of £64,424. Figures 6 and 7 illustrate the mean income of all workers with a given probability of creativity. Explicitly, the figures plot employment-weighted average incomes within windows of width 1/1000 in probability. Musicians, for example, sit to the right of the plot, but their low income is offset by other workers with the same high probability of creativity but much higher income. This aggregation eliminates excessive volatility from the plot.

A similar pattern holds in the relationship between education and the probability of an occupation being creative, again in both the United Kingdom and United States: creative occupations are typically characterised by higher levels of education, but some of the most creative jobs are less so. The implication is that wages are seemingly more related to levels of education rather than an occupation's creative content – a topic worthy of further research.

Figure 6 Mean income and creative probability, UK

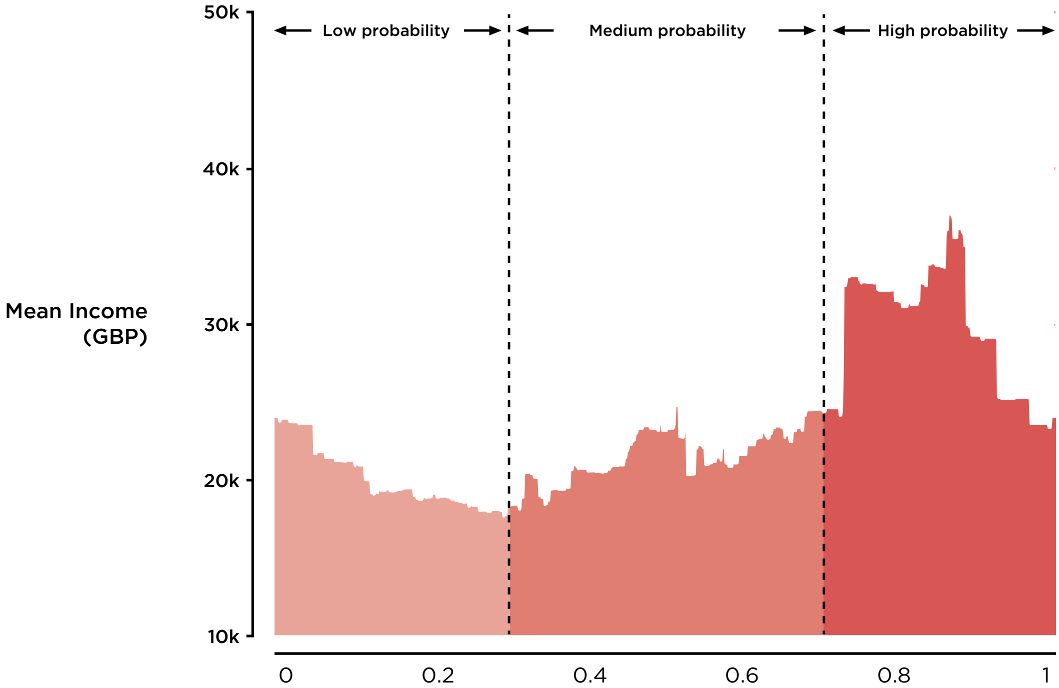
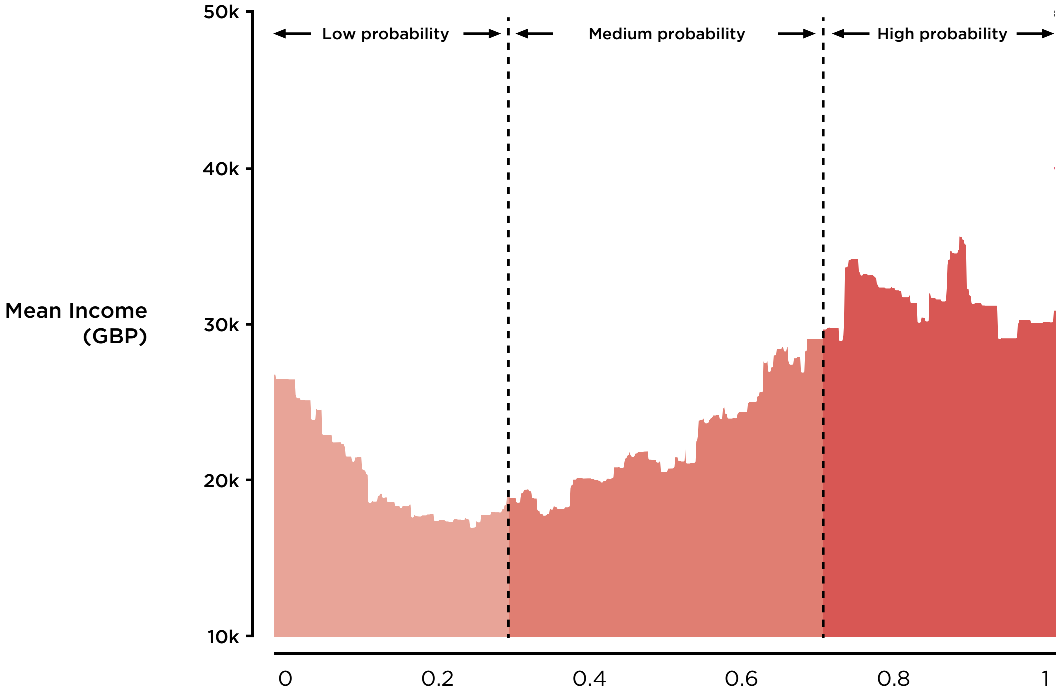


Figure 7 **Mean income and creative probability, US**



4.4 Creative industries and disruption from automation

In addition, we map our findings to UK industries, allowing us to examine the susceptibility to automation of the creative industries as a group – as defined by the DCMS – relative to other industries, as well as the potential scope of automation within various creative sub-sectors, reflecting the fact that many employ significant numbers of workers in non-creative occupations too.

Unsurprisingly, we find that the DCMS creative industries are on average much less susceptible to automation than other industries: while only 15 per cent of jobs in creative industries are in the high risk category, 32 per cent of employment in non-creative industries is at high risk of being automated. At the same time, 64 per cent of employment in creative industries is in the low probability category, while the equivalent figure for non-creative industries is 38 per cent.

Among the creative industries, Computer programming activities exhibits the highest fraction of employment in the low probability category (85 per cent), followed by PR and communication activities (84 per cent), Computer consulting activities (83 per cent), and Cultural education (82 per cent). The creative industries with the highest share of employment at risk, on the other hand, include Motion picture projection activities (75 per cent), Publishing of directs and mailing lists (69 per cent), and Manufacturing jewellery and related articles (67 per cent). These results reflect the fact that not all creative industries are equally intensive in creative occupations: the work of motion picture projectionists, for example, has a 97 per cent probability of automation over the next decade or two.

4.5 The geography of creativity

Finally, we perform a regional analysis of the creative fraction of the UK workforce. The results principally reveal a marked contrast between London and the UK as a whole: specifically, 31 per cent of London employment is assessed as having a high creative probability, relative to only 24 per cent of total UK employment. The disproportionate importance of creative work in London's workforce has been documented in previous work (Chapain et al., 2010;[54] Bakhshi et al, 2015).[55] It also echoes the findings of Knowles–Cutler, Frey and Osborne (2014),[56] showing that the probability of computerisation for UK employment unambiguously distinguishes London from the remainder of the UK: 30 per cent of London employment is found to be at high risk of computerisation, against a figure of 35 per cent for the UK as a whole. These findings lend further credence to our hypothesis that creativity is a crucial barrier to computerisation, with London's creative workforce being more secure compared with other parts of the UK as a consequence.

5. INTERPRETATION

The key finding that creative occupations are much more resistant to automation should not be surprising when one considers that computers will most successfully be able to emulate human labour when a problem is well specified – that is, when performance can be straightforwardly quantified and therefore evaluated (Acemoglu and Autor, 2011)[57] – and when the task environment is sufficiently simple to enable autonomous control (Autor, 2014).[58] By contrast, they will struggle when tasks are highly interpretive (tacit), geared at 'products whose final form is not fully specified in advance' (Bakhshi, Freeman and Higgs, 2013), and where task environments are complex and cannot be simplified.

According to Frey and Osborne (2013), there are in general three 'bottlenecks' to computerisation of non–routine tasks – even when there is enough big data to enable pattern recognition. In each of these cases there are strong reasons for thinking that they arise in creative occupations:

> When perception and manipulation are important in complex and unstructured environments e.g. think of artist spaces or film sets, where multiple, irregular objects must be identified and tight spaces inhibit the mobility of robots, or of crafts occupations, where Richard Sennett has written eloquently on the difficulties of automating human manipulation tasks. (Sennett, 2009)[59]
>
> Where novelty is valued. Generating novelty per se is not difficult to automate; automating the creation of novel products which are of *value* is, however, much harder to do. This is because automation requires creative values to be sufficienly well articulated in quantitative terms that they can be encoded in a computer programme (Boden, 1994).[60] One need only think of the longstanding and unresolved issues about whether one can at all, let alone how, measure cultural value to see the challenges in automating evaluation of creative work. (Bakhshi, 2012)[61]

> Where tasks involve high degrees of social intelligence: the challenge of emulating real–time recognition of natural human emotion that is fundamental to tasks such as negotiation, motivation and persuasion means that automation of tasks involving socially intelligent tasks remains a distant prospect. Often working in project–based environments, creative workers have been described as forming 'motley crews' – in that creative projects require a diversity of inputs, a mix of highly creative and more humdrum tasks, that complicates the organisation of creative activity. (Caves, 2000).[62] In order to shoot a film or record a piece of music, for example, every performer along with every technician has to perform at some minimum level at the same time to produce a valuable outcome. Team members must coordinate and sequence their activities, and maintain their cooperation to ensure successful collaboration.

Understood this way, it becomes clear why creative occupations like musicians, architects and artists emerge as those with some of the highest probabilities of being resistant to automisation.

In fact, the greater resilience of creative jobs is, if anything, understated by the approach we have taken in this paper, as we consider the potential of computers to simulate and replicate human labour. We do not look at the significance of computers in enabling and giving rise to new forms of creativity and collaborative relationships of the types that, not coincidentally, creative practitioners are at the vanguard in developing (and in the same way that they pioneered in the use of earlier technologies) (McCormack and d'Inverno, 2014).[63] Whether this is designers and programmers that are building virtual reality gaming environments, artists and programmers building performance capture technologies or jazz musicians jamming with robots.

6. CONCLUSIONS

In this paper, we develop a novel methodology for measuring the creative content of occupations, to examine the implications of the expanding scope of automation for the creative economy. Building on DCMS's official statistics and the manual classification of occupations in Bakhshi, Freeman and Higgs (2013), we employ an 'algorithmic classification' based on detailed survey data about the creative content of jobs. In doing so, we go beyond the DCMS classification of creative occupations, confirming that creativity extends well beyond the arts and culture. It turns out that the work of software developers and biochemical engineers requires about the same degree of creativity as many jobs in Arts and Media.

According to our estimates, as many as 24 percent of jobs in the United Kingdom, and 21 percent in the United States, have a high probability of being creative, including a wide range of occupations in Education, Management, Computers, Engineering and Science in addition to Arts and Media. We also report that creative skills receive higher wages in the labour market: with the important exception of some Arts and Media jobs, creative professions on average earn relatively high wages.

Our findings relate to a growing literature, showing that the potential scope of automation has recently expanded and will inevitably continue to expand (Frey and Osborne 2013;[64] Brynjolfsson and McAffee, 2014).[65] Nevertheless, despite the expanding scope of automation, Frey and Osborne (2013) shows that creativity remains a key bottleneck to computerisation. In line with these findings, we show that creative jobs are the least susceptible to automation: none of the occupations we find to be creative are at high risk of displacement. By contrast, while the next wave of computer-related technologies is likely to displace a wide range of occupations, they are also likely to complement creative workers. The work of musicians, for example, increasingly involves working with computers to test new creative ideas, and today's architects rely on sophisticated software to visualise their development plans.

More generally, the digitisation of the economy is likely to further increase the demand for creative skills. A key challenge for governments is thus to help workers that are made redundant to transition into novel creative professions. As Ada Lovelace – one of the pioneers of the early mechanical general-purpose computer – famously noted already during the nineteenth century: *"The Analytical Engine has no pretensions whatever to originate anything"* (Isaacson, 2014).[66] While the scope of potential computerisation has expanded enormously since then, and will inevitably continue to expand, human labour still holds the comparative advantage in creative work, involving valued originality, and is likely to continue to do so for some time yet.

Thus, as technology progresses creative skills will become more important, meaning that places that have specialised in creative work will most likely be the main beneficiaries of the digital age. The United Kingdom is thus seemingly in a relatively good position to take advantage of new technologies becoming available. However, as other countries e.g. in Asia and the Americas prioritise their creative economies for development, the United Kingdom will have to continuously create jobs in new creative professions if it is to retain its competitive edge.

APPENDICES

Appendix 1

Note that all results are estimates made in the face of substantial uncertainty, so probabilities for individual four-digit occupations should be treated with caution..

Sic	Industry name	Creative probability %	Probability of computerisation %
70.21	PR & communication activities	65.6	11.9
73.11	Advertising agencies	50.9	19.9
73.12	Media representation	56.5	12
71.11	Architectural activities	60.3	7.1
32.12	Manu jewellery & related articles	7.5	67.5
74.10	Specialised design activities	60.7	28.4
59.11	Motion pic, video & tv prog prod actv	67.9	8
59.12	Motion pic, video & tv prog po-pro activities	57.9	19.8
59.13	Motion pic, video & tv prog dist activities	37.1	32.8
59.14	Motion picture projection activities	5.1	74.6
60.10	Radio broadcasting	72.5	7.7
60.20	Tv programming & broadcasting activities	54.3	12.7
74.20	Photographic activities	82.5	10.6
58.21	Publishing of computer games	35.5	26.6
58.29	Other software publishing	53.1	14.7
62.01	Computer programming activities	66.3	7.7
62.02	Computer consultancy activities	58.8	8.6
58.11	Book publishing	46.8	18.9
58.12	Publ of directs & mailing lists	17.6	69.4
58.13	Publishing of newspapers	47.4	29.6
58.14	Publishng of journls & periodicls	66.6	5.7
58.19	Other publishing activities	42.1	22.5
74.30	Transltion and interpretation activities	88.3	5.8
91.01	Library and archive activities	26.1	49.1
91.02	Museum activities	22.1	24.3
59.20	Sound recording & music publ activities	56.5	18.1
85.52	Cultural education	34.7	7.8
90.01	Performing arts	80.1	7
90.02	Support activities to performing arts	48	14.6
90.03	Artistic creation	89.7	3.5
90.04	Operation of arts facilities	43.2	30.3

01.11	Growing of cereals, except rice	0	91.2
01.13	Growing veg & melons, roots & tubers	4.7	54.3
01.15	Growing of tobacco	0	0
01.16	Growing of fibre crops	0	100
01.19	Growing of othr non-perennial crops	0	46.8
01.21	Growing of grapes	0	66.5
01.22	Growing of trop & subtrpical fruits	0	0
01.24	Growing of pome fruits & stone fruit	0	100
01.25	Growing othr tree, bush fruit & nuts	0	8.2
01.28	Growing spices, drug & pharm crops	0	0
01.29	Growing of other perennial crops	0	54
01.30	Plant propagation	4.7	35.9
01.41	Raising of dairy cattle	0.1	89.3
01.42	Raising other cattle and buffaloes	0.4	85.8
01.43	Raising horse and other equines	0	17.8
01.45	Raising of sheep and goats	0	89.3
01.46	Raising of swinepigs	2.2	65.1
01.47	Raising of poultry	0	61.5
01.49	Raising of other animals	7.6	39
01.50	Mixed farming	0.4	84.6
01.61	Support activities for crop production	8.7	65.1
01.62	Support activities for animal prod	0	59.5
01.63	Post-harvest crop activities	0	37.3
01.64	Post-harvest crop activities	42.9	19.4
01.70	Hunting, trappng & reltd serv activities	0	15
02.10	Silviculture & other forestry activities	3.5	79.7
02.20	Logging	9.3	66.4
02.30	Gathring wild grwing non-wood prod	0	79.6
02.40	Support services to forestry	8.5	72.6
03.11	Marine fishing	0	81.6
03.12	Freshwater fishing	0	31.9
03.21	Marine aquaculture	1.5	49.6
03.22	Freshwater aquaculture	9.5	42.3
05.10	Mining of hard coal	16.8	21
05.20	Mining of lignite	0	100
06.10	Extraction of crude petroleum	23.2	18.1
06.20	Extraction of natural gas	43	21
07.10	Mining of iron ores	100	0
07.29	Mining other non-ferrous metal ores	0	46.4
08.11	Quarry ornamental & building stone	0	45.5

08.12	Operation of gravel & sand pits	9.3	56.1
08.91	Mining chem & fertiliser minerals	15.2	8.1
08.92	Extraction of peat	0	100
08.93	Extraction of salt	0	49.5
08.99	Other mining and quarrying n.e.c.	22.8	48.6
09.10	Supp actvities petrol & nat gas extracn	19.8	25.9
09.90	Supp actvivities other mining & quarrying	15.4	11.8
10.11	Processing and preserving of meat	0	54.6
10.12	Proc & preserving of poultry meat	0.9	63.6
10.13	Productn meat & poultry meat prod	2.4	53.4
10.20	Proc fish, crustaceans & molluscs	1.3	57.9
10.31	Proc and preserving of potatoes	0	51.4
10.32	Manu of fruit & vegetable juice	0	70.3
10.39	Other proc & presvg of fruit & veg	0.8	45.1
10.41	Manufacture of oils and fats	20.1	37.2
10.42	Manu margarine & sim edible fats	0	100
10.51	Operation dairies & cheese making	1.5	45.1
10.52	Manufacture of ice cream	0	55.7
10.61	Manufacture of grain mill products	1.5	43.9
10.62	Manu of starches & starch products	0	16.4
10.71	Man bread, fresh pastry gds & cake	2.4	61.3
10.72	Man ruskbiscpres pastry gdscake	1.8	50.1
10.73	Man mac, nood, couscous & sim prod	0	88.7
10.81	Manufacture of sugar	15.2	13.5
10.82	Man cocoa, chocolate & sugar conf	6.9	52.5
10.83	Processing of tea and coffee	14.6	35.5
10.84	Manu of condiments & seasonings	6.6	35.5
10.85	Manu of prepared meals & dishes	6.3	45.5
10.86	Man homogen food preps & diet food	22.6	31.2
10.89	Manu other food products n.e.c.	3.6	58.3
10.91	Manu preprd feeds for farm animals	0	36.5
10.92	Manufacture of prepared pet foods	6.7	41.3
11.01	Distil, rectifyg & blending spirit	14.8	27.4
11.02	Manufacture of wine from grape	17.5	22.7
11.03	Manuf of cider & other fruit wines	0	0
11.04	Man other non-distil fermentd bev	0	100
11.05	Manufacture of beer	3.7	38.2
11.06	Manufacture of malt	0	31.7
11.07	Manu soft drinks & mineral waters	3.9	24.6
12.00	Manufacture of tobacco products	8.7	39.3

13.10	Prep & spinning of textile fibres	4	61.1
13.20	Weaving of textiles	1.7	40.1
13.30	Finishing of textiles	11.9	37.2
13.91	Manu knitted & crocheted fabrics	0	35.1
13.92	Man made-up textile art, exc appl	5.3	54.3
13.93	Manufacture of carpets and rugs	7	42.8
13.94	Man cordage, rope, twine & netting	6.7	64
13.96	Manuf of other tech & ind textiles	7.4	35.4
13.99	Manufacture other textiles n.e.c.	17.1	31.6
14.11	Manufacture of leather clothes	0	78.1
14.12	Manufacture of workwear	1.1	37.5
14.13	Manufacture of other outerwear	10.8	62.6
14.14	Manufacture of underwear	23.9	31.7
14.19	Manu other wearing apprl & acces	3.7	63.1
14.20	Manufacture of articles of fur	0	87.5
14.31	Manu knitted & crocheted hosiery	0	87.8
14.39	Man other knitted & crocheted appl	12.9	57.7
15.11	Tanning, dressing, dye leathrfur	0	47.6
15.12	Man lug, hndbgs, sddlry & harness	23.8	31
15.20	Manufacture of footwear	8.9	27.2
16.10	Sawmilling and planing of wood	0	53.5
16.21	Man ven sheets & wood-based panels	0	20.8
16.23	Manu of other builders	3.9	67.5
16.24	Manufacture of wooden containers	0	62.2
16.29	Man oth prod wood & plaiting mat	8.2	55
17.11	Manufacture of pulp	13	20.2
17.12	Manuf of paper and paperboard	5.4	37
17.21	Man & cont corrgatd pper & pperbrd	7.7	50.5
17.22	Manu of hhold & sanittoilet goods	1.3	41.4
17.23	Manufacture of paper stationery	9.1	43.4
17.24	Manufacture of wallpaper	2.6	76.7
17.29	Man oth art of ppr & pprbd n.e.c.	5.7	37
18.11	Printing of newspapers	24.5	52.9
18.12	Other printing	11.8	52.8
18.13	Pre-press and pre-media services	27	40
18.14	Binding and related services	11	69.8
18.20	Reproduction of recorded media	52.8	6.4
19.10	Manufacture of coke oven products	0	0
19.20	Manu of refined petroleum prod	17.2	29.1
20.11	Manufacture of industrial gases	10.7	28.9

20.12	Manufacture of dyes and pigments	2.9	35
20.13	Manu other inorganic basic chem	10.8	26.9
20.14	Manuf of other organic basic chem	0	17
20.15	Man fertilisers & nitro compounds	0	19.1
20.16	Manuf of plastics in primary forms	1.1	43.7
20.20	Manu of pest & other agrochem prod	19.4	39.6
20.30	Manu of paints & related products	7.6	34.4
20.41	Man soap & detgts clean & pol prep	10.5	27.4
20.42	Man perfumes & toilet preparations	16.1	24.4
20.51	Manufacture of explosives	0	81.2
20.52	Manufacture of glues	0	47.8
20.53	Manufacture of essential oils	47.6	33.8
20.59	Manu of other chemical prod n.e.c.	4.4	25.5
20.60	Manufacture of man-made fibres	8.3	25
21.10	Manuf of basic pharmaceutical prod	20	25.7
21.20	Man of pharmaceutical preparations	20.4	19.4
22.11	Manu, retread of rub tyres & tubes	2.6	51.6
22.19	Manuf of other rubber products	9.2	53.1
22.21	Man plastic plates, sheets, tubes	4.1	59.6
22.22	Manuf of plastic packing goods	9.5	40.8
22.23	Manuf of builders¿ ware of plastic	3.6	60.9
22.29	Manuf of other plastic products	6.6	51.7
23.11	Manufacture of flat glass	25.8	42
23.12	Shaping and procesng of flat glass	17.2	40.5
23.13	Manufacture of hollow glass	18.6	43.4
23.14	Manufacture of glass fibres	6.2	70.9
23.19	Man & proc oth glas, inc tech glas	24.6	41.5
23.20	Manufacture of refractory products	5.6	47.6
23.31	Manuf of ceramic tiles and flags	4.8	40.8
23.32	Man bricks, tiles & constr prod	11.2	46.9
23.41	Man ceramic hhold & ornm artcls	40	23
23.42	Manuf of ceramic sanitary fixtures	0	77
23.43	Manu of ceramic inslts & inslg fit	10.7	51.3
23.44	Man othr technical ceramic prod	17.2	13.6
23.49	Manuf of other ceramic products	100	0
23.51	Manufacture of cement	0	7.1
23.52	Manufacture of lime and plaster	0	55
23.61	Man conc prod for constrcn purp	8	50.1
23.62	Man plaster prod for constrcn purp	0	69.7
23.63	Manufof ready-mixed concrete	0	33

23.64	Manufacture of mortars	0	0
23.65	Manufacture of fibre cement	18.3	74.1
23.69	Man othr art of conc, plstr & cmnt	0	100
23.70	Cutting, shaping & finishing stone	5	61.7
23.91	Production of abrasive products	6.3	19.4
23.99	Man othr non-met min prod n.e.c.	15.4	46.9
24.10	Man basic iron, steel & ferro-ally	6.7	48.1
24.20	Man holow prof & rltd fit of steel	9.6	46.2
24.31	Cold drawing of bars	0	100
24.32	Cold rolling of narrow strip	0	43.3
24.33	Cold forming or folding	18.3	19.1
24.34	Cold drawing of wire	0	25
24.41	Precious metals production	0	69.3
24.42	Aluminium production	3.2	46.4
24.43	Lead, zinc and tin production	0	25.2
24.44	Copper production	1.8	70.7
24.45	Other non-ferrous metal production	0	50.2
24.46	Processing of nuclear fuel	0	31.2
24.51	Casting of iron	2.9	62.6
24.52	Casting of steel	8.5	35.4
24.53	Casting of light metals	0	79.8
24.54	Casting of othr non-ferrous metals	4.1	44.3
25.11	Man met structs & parts of structs	6.8	51.1
25.12	Manu doors and windows of metal	2.7	58
25.21	Manu cent heating radiators & boil	19.6	37.3
25.29	Man oth tnks, resvrs & cont of met	10.6	54.5
25.30	Manu of steam gen, exc CH boilers	10.5	32.6
25.40	Manuf of weapons and ammunition	11.5	38.3
25.40	Forg, press, stamp & roll-form met	12.3	60.9
25.61	Treatment and coating of metals	3	58
25.62	Machining	5.8	41.3
25.71	Manufacture of cutlery	5.7	31.2
25.72	Manufacture of locks and hinges	0.9	30.2
25.73	Manufacture of tools	9.1	38.6
25.91	Man steel drums & sim containers	0	82.8
25.92	Manuf of light metal packaging	7.3	32
25.93	Man of wire prods, chain & springs	2	40.6
25.94	Man of fasteners & screw mchn prod	0	65.1
25.99	Man other fabr metal prod n.e.c.	11.5	44.8
26.11	Manuf of electronic components	20.3	41.8

26.12	Manuf of loaded electronic boards	11.1	62.3
26.20	Manuf computers & peripheral eqmt	40.6	22.3
26.30	Manuf of communication equipment	25.6	28.3
26.40	Manuf of consumer electronics	23.9	18.8
26.51	Man instr for meas, testing & nav	19.1	21.6
26.52	Manufacture of watches and clocks	0	5.5
26.60	Man irradiation & electromed eqmt	23.6	13.9
26.70	Man opt instruments & photo eqmt	36.2	21.2
26.80	Manu magnetic and optical media	24.2	26.9
26.80	Manu of elect motors, gen & transf	14.8	45.1
27.12	Man elctrcty dist & cont apparatus	15.8	27.2
27.20	Manu batteries and accumulators	17.3	38.9
27.31	Manufacture of fibre optic cables	5.4	3.8
27.32	Man oth elctrnc & elec wirescable	8.9	36.2
27.33	Manufacture of wiring devices	22.8	59.4
27.40	Manu electric lighting equipment	18.4	44.8
27.51	Manu electric domestic appliances	8.9	45.4
27.52	Manu of non-electric domestic appl	14.5	52.9
27.90	Manu of other electrical eqmt	18.6	41.5
28.11	Man eng & turb, ex airvehcyc eng	9.5	32.7
28.12	Manuf of fluid power equipment	4.8	46.4
28.13	Man other pumps and compressors	12.3	32.1
28.14	Manuf of other taps and valves	16.3	28.5
28.15	Man bear, gear, grng & drvng elmnt	2.6	44.9
28.21	Man ovens, furnaces & furnace burn	11.6	27.5
28.22	Manu lifting & handling equipment	6.1	25.4
28.23	Man off mchn & eqmt exc PC & acc	12.7	33.7
28.24	Manuf of power-driven hand tools	46.6	32.3
28.25	Man non-dom cooling & ventiln eqmt	14.8	42.7
28.29	Man other gen-purp machinry n.e.c.	9	29
28.30	Man agricultural & forestry mchnry	13	36.2
28.41	Manuf of metal forming machinery	2.8	58
28.49	Manufacture of other machine tools	9.1	38.6
28.91	Manuf of machinery for metallurgy	28.4	29.7
28.92	Man mchnry for mng, quarr & constr	13.8	29.8
28.93	Man mcnry for food, bev & tob proc	1.9	36.7
28.94	Man mchn for txt, app & lethr prod	8	44.7
28.95	Man mchnry for pper & pperbrd prod	3.1	42.7
28.96	Man plastics and rubber machinery	7.9	66
28.99	Man othr spec-purp mchnry n.e.c.	12	44.3

29.10	Manufacture of motor vehicles	10.2	35.4
29.20	Man bodies for motor veh & trailer	3.6	41.9
29.31	Man of electric eqmt for motor veh	22.2	38.9
29.32	Man othr parts & acc for motor veh	5.2	59.2
30.11	Buildng of ships & floating struct	15.9	23
30.12	Buildng pleasure & sportng boats	7.7	37.3
30.20	Manu railway loco & rolling stock	10.7	34.6
30.30	Manu air & spacecraft & rel mchnry	16	25.1
30.40	Manuf military fighting vehicles	10	2
30.91	Manufacture of motorcycles	15.9	17.9
30.92	Manu bicycles & invalid carriages	22.4	33.6
30.99	Manu other transport eqmt n.e.c.	0	24.3
31.01	Manuf of office and shop furniture	9.1	43.6
31.02	Manufacture of kitchen furniture	9.4	52.4
31.03	Manufacture of mattresses	0	58
31.09	Manufacture of other furniture	6.2	61
32.11	Striking of coins	11.4	81.6
32.13	Man imitation jewellery & rltd art	23.6	59.5
32.20	Manufacture of musical instruments	1.9	33.2
32.30	Manufacture of sports goods	2.3	32.8
32.40	Manufacture of games and toys	16	31.4
32.50	Man med & dental instruments & sup	6.7	27.4
32.91	Manufacture of brooms and brushes	36.2	6.7
32.99	Other manufacturing n.e.c.	10.7	41.4
33.11	Repair of fabricated metal prodts	1.2	46.7
33.12	Repair of machinery	7.2	21.3
33.13	Repair of electrnc & optical eqmt	8.2	19.9
33.14	Repair of electrical equipment	5.5	29.2
33.15	Repair & maintenance ships & boats	5.4	13.4
33.16	Repair & main aircraft & spacecrft	14.9	15.7
33.17	Repair & main trnsport eqmt n.e.c.	4.9	28.5
33.19	Repair of other equipment	4.9	37
33.20	Installation ind mchnry & equipmnt	14.8	29.6
35.11	Production of electricity	20.2	17.6
35.12	Transmission of electricity	13	10.6
35.13	Distribution of electricity	13.3	33.7
35.14	Trade of electricity	11.4	46.4
35.21	Manufacture of gas	8.1	31.7
35.22	Dist of gaseous fuels thrgh mains	6.9	32.3
35.23	Trade of gas through mains	0	36.9

35.30	Steam and air conditioning supply	10.4	18.7
36.00	Water collction, treatmnt & supply	17.1	31.1
37.00	Sewerage	6.9	12.3
38.11	Collection of non-hazardous waste	2	11.8
38.12	Collection of hazardous waste	49.3	9.9
38.21	Treatmnt & disp of non-hazrd waste	2	22.4
38.22	Treatmnt & disp of hazrdous waste	15.8	22.3
38.31	Dismantling of wrecks	0	63.6
38.32	Recovery of sorted materials	2.5	29.7
39.00	Remdiatn actv & oth wste mgmt serv	10.9	22
41.10	Development of building projects	9.7	23.4
41.20	Constr of res and non-res buildngs	6.5	41.7
42.11	Construction of roads and motrways	11.6	56.1
42.12	Constr railwys & undgrnd railwys	17.7	30.7
42.13	Constructn of bridges and tunnels	1.9	18.5
42.21	Constr of utility proj for fluids	8.6	37.5
42.22	Constr util proj for elec & telcom	19.6	22.6
42.91	Construction of water projects	26.4	43
42.99	Constr other civil eng proj n.e.c.	22.8	25.7
43.11	Demolition	0	52.9
43.12	Site preparation	3.8	60
43.13	Test drilling and boring	21.8	57.1
43.21	Electrical installation	8.4	16.1
43.22	Plumbng, heat & air-con installatn	3.9	12.3
43.29	Other construction installation	4.8	37.8
43.31	Plastering	2	80.6
43.32	Joinery installation	1.1	69
43.33	Floor and wall covering	0.8	86.7
43.34	Painting and glazing	0.9	80.1
43.39	Othr buildng completn & finishing	0.6	53
43.91	Roofing activities	0.7	70.6
43.99	Othr specsd constr actv n.e.c.	2.5	57.5
45.11	Sale of cars & light motor vehles	3.8	45.7
45.19	Sale of other motor vehicles	7.5	33.3
45.20	Maintenance & repair motor vehles	1.1	14.5
45.31	Wsale trade motor veh parts & acc	1.7	19.4
45.32	Ret trade of motor veh parts & acc	0.3	41.7
45.40	Sale, main, rep mtrcycle & rel prt	5.5	27
46.11	Agents inv in sale of agri raw mat	33.8	66.3
46.12	Agents inv sale fuelmetind chem	7.4	25.1

46.13	Agents inv in sale timb & bldng mat	6.6	9.6
46.14	Agents inv sale ind eqmtshipsairc	28.8	3.3
46.15	Agents inv sale hhold gdsironmngry	10.8	60.6
46.16	Agents inv sale text & lether goods	9.3	48.6
46.17	Agents inv in sale food, bev & tob	0	56.2
46.18	Agents specsd sale othr part prod	12.3	29.7
46.19	Agents inv in sale variety goods	5.7	0
46.21	Wsale grainuman tobseedsanml fd	5.4	37.2
46.22	Wholesale of flowers and plants	0	12.9
46.23	Wholesale of live animals	0	53.9
46.31	Wholesale of fruit and vegetables	1.4	24.8
46.32	Whlesale of meat and meat products	0	47
46.33	Wsale dairy prod, edible oilsfats	4.4	21.3
46.34	Wholesale of beverages	3.1	18.9
46.35	Wholesale of tobacco products	14.3	37.6
46.36	Wsale of sugar & choc & sugar conf	3.8	33.5
46.37	Wsale coffee, tea, cocoa & spices	0	27.8
46.38	Wsale of oth food, inc seafood	2.3	25.2
46.39	Non-spec wsale of food, bev & tob	0.9	35.4
46.41	Wholesale of textiles	7.5	28.1
46.42	Wholesale of clothing and footwear	7.5	28.4
46.43	Wsale of electrical household appl	8.5	23.6
46.44	Wsale china & glasswre & clean mat	0	15.2
46.45	Wholesale of perfume and cosmetics	15.4	17.5
46.46	Wholesale of pharmaceutical goods	10.5	22.8
46.47	Wsale furn, carpts & lightng eqmt	4.6	29.9
46.48	Wholesale of watches and jewellery	16.2	17.5
46.49	Wholesale of other household goods	8	27.9
46.51	Wsale comp, comp perp eqmt & sftwr	17.7	19.4
46.52	Wsale elctrnc & telecom eqmt & prt	16.1	30.7
46.61	Wsale of agric mchnry, eqmt & supp	7.8	35.5
46.62	Wholesale of machine tools	3.6	59.6
46.63	Wsale mining, cons & civ eng mcnry	13.4	26.9
46.64	Wsale of mchnry for textile ind	0	0
46.65	Wholesale of office furniture	22	19.6
46.66	Wsale of other off machinry & eqmt	10.1	4.8
46.69	Wsale of other machinery & eqmt	9.6	26.7
46.71	Wsale solliqgas fuel & rltd prod	7.5	20.6
46.72	Wholesale of metals and metal ores	5.7	33.7
46.73	Wsale wood, constr mat & san eqmt	4.4	30.3

46.74	Wholesale of DIY eqmt & supp	2.4	33
46.75	Wholesale of chemical products	20.4	22.1
46.76	Wsale of other intermediate prod	6.4	27.9
46.77	Wholesale of waste and scrap	4.7	31.1
46.90	Non-specialised wholesale trade	4.8	25.3
47.11	Ret sale non-spec str foodbevtob	1.1	63.7
47.19	Oth ret sale in non-spec stores	2.2	59.9
47.21	Ret sale fruit & veg in spec store	0.7	63.8
47.22	Ret sale meat & rel prod spec strs	0	71.1
47.23	Ret sale of seafood in spec stores	0	51.2
47.24	Ret sale of bakery prod spec stres	0.5	69.1
47.25	Ret sale of bev in spec stores	4	48.9
47.26	Ret sale of tob prod in spec stres	0	30.2
47.29	Othr ret sale of food in spec strs	0.6	60.2
47.30	Ret sale of auto fuel in spec strs	1	74.6
47.41	Ret sale PC eqmt & acc spec strs	18.4	25.6
47.42	Ret sale of telcom eqp spec store	4.4	66.8
47.43	Ret sale aud & video eqmt spec strs	1.9	38.8
47.51	Ret sale of text in specsd stores	5.3	61.8
47.52	Ret sale hardware eqmt spec strs	2.1	54.5
47.53	Ret sale of d¿r eqmt spec stores	2.6	52.4
47.54	Ret sale of white goods spec stres	3.3	51.2
47.59	Ret sale of fixfit in spec strs	8.2	47.4
47.61	Ret sale of books in specsd stores	3.9	59.2
47.62	Ret sale newsp & stat in spec strs	5	50.4
47.63	Ret sale mus & video rec spec strs	0	34.4
47.64	Ret sale of sprt eqmt in spec strs	6.5	60.6
47.65	Ret sale of games & toys spec stre	0.7	79.3
47.71	Ret sale of clothing in spec stres	3.1	64.4
47.72	Ret sale ftwr & lthr gds spec strs	2.4	58.7
47.73	Disp chemist in specsd stores	0.8	63.8
47.74	Ret sale of med eqmt in spec stres	12.1	23.9
47.75	Ret sale cos & toltries spec strs	5.9	53.6
47.76	Ret sale flwrs & pets in spec strs	2.7	47.2
47.77	Ret sale jewlry items in spec strs	5.7	46
47.78	Oth ret sale new gds in spec strs	5.5	47.7
47.79	Ret sale of secnd-hnd goods in str	5.3	34.4
47.81	Ret sale; stlls & mrkt fd,bev,tobc	4.5	70.8
47.82	Ret sale; stlls & mrkt clthg, ftwr	0	100
47.89	Ret sale via stalls & mrkt oth gds	0.7	71.2

47.91	Ret sale mail order houses, intrnt	12.2	34.2
47.99	Othr ret sale exc stores etc	2	57.9
49.10	Passngr rail transport, interurban	5.2	18.6
49.20	Freight rail transport	14.2	23.4
49.31	Urban & sub passngr land transport	3.8	13.4
49.32	Taxi operation	0.2	6.4
49.39	Other passngr land transprt n.e.c.	2.1	8.6
49.41	Freight transport by road	1.2	12.6
49.42	Removal services	0	22.5
49.50	Transport via pipeline	22.5	25.8
50.10	Sea & coastal pass water transport	5.8	33.2
50.20	Sea & coastal freight watr trnsprt	5.3	29.7
50.30	Inland passenger water transport	0	26.7
50.40	Inland freight water transport	4.4	26.3
51.10	Passenger air transport	3	6.6
51.21	Freight air transport	0	33.1
51.22	Space transport	2.8	0
52.10	Warehousing and storage	0.9	11.1
52.21	Serv actv incidental to land trans	2.5	38.6
52.22	Serv actv incidental to wter trans	10.3	24.9
52.23	Serv actv incidental to air trans	3	32.3
52.24	Cargo handling	1.1	23.1
52.29	Other transportation supp acts	4.3	35.5
53.10	Post activities under univesl serv oblig	0.9	75
53.20	Other postal and courier acts	2.1	33.6
55.10	Hotels and similar accommodation	1.4	51.9
55.20	Holiday and other short stay accom	3.4	26.4
55.30	Cmpg grnd, rec veh prk & trail prk	2.2	15.3
55.90	Other accommodation	5.8	18.4
56.10	Restnt & mobile food servc activities	1	60.6
56.21	Event catering activities	2.3	52.7
56.29	Other food service activities	0	66.8
56.30	Beverage serving activities	0.4	67.5
61.10	Wired telecomtions activities	28.5	26.2
61.20	Wireless telecomtions activities	31.9	24.2
61.30	Satellite telecoms activities	39.4	12.6
61.90	Other telecomtions activities	28	28.2
62.03	Computer facilities mangmnt activities	39	29
62.09	Other IT & computer service activities	50.9	17.2
63.11	Data proc, hosting & related activities	31.1	38

63.12	Web portals	0	0
63.91	News agency activities	15.2	64.5
63.99	Other info service acts n.e.c.	66	10.6
64.11	Central banking	13.5	40.9
64.19	Other monetary intermediation	8.6	47.4
64.20	Activities of holding companies	9.9	29.6
64.30	Trusts, funds & sim financial ents	18.7	21.1
64.91	Financial leasing	0	40.6
64.92	Other credit granting	9.4	39.7
64.99	Oth fin ser,exc ins & pen fund,nec	9.3	26.8
65.11	Life insurance	12.8	46.1
65.12	Non-life insurance	11.1	47.3
65.20	Reinsurance	14.8	36.4
65.30	Pension funding	4.6	55.5
66.11	Administration of financial markts	13.1	33.1
66.12	Sec & commodity contrcts brokerage	8.4	31.9
66.19	Oth act ax fin ser,ex in & pen fnd	5.4	27.4
66.21	Risk and damage evaluation	2.1	58.6
66.22	Actv of insurance agents & brokers	8.2	32.6
66.29	Othr actv aux to ins & pensn fndng	24.9	40.1
66.30	Fund management activities	10	31
68.10	Buying and selling own real estate	6.4	29
68.20	Renting & op ownleasd real estate	2.6	23.7
68.31	Real estate agencies	5.5	21.1
68.32	Mgmt real estate on feecont basis	2.1	22.5
69.10	Legal activities	2.8	24.3
69.20	Accntng & auditng actv;tax consult	3.4	77.4
70.10	Activities of head offices	12.4	29.7
70.22	Bus & other mangmnt constny actv	20.9	14.9
71.12	Eng actv & related tech consltncy	30.1	14.6
71.20	Technical testing and analysis	16.8	25
72.11	Res & experimental dev on biotech	58.9	14
72.19	Othr R&D on natural sciences & eng	50.9	10.9
72.20	R&D on social sci and humanities	28.1	13.9
73.20	Market resch & pub opinion polling	40.2	30.7
74.90	Otr prof,scntfc & tech actv n.e.c.	40.9	21.8
75.00	Veterinary activities	2.4	20.1
77.11	Rent & lease cars & light motr veh	8.1	35.6
77.12	Renting and leasing of trucks	3	23.8
77.21	Rentng & leasing rec & sport goods	13.7	35.1

77.22	Renting of video tapes and disks	20.9	59.9
77.29	Rent & lease othr per & hhold good	10.5	45.3
77.31	Rentng & leasng agr mchnry & eqmt	12.4	20
77.32	Rentleas constr & eng mchn & eqmt	2.2	24.9
77.33	Rentlease off mchn & eqmt inc PC	6.5	24.2
77.34	Rentng & leasng watr trnprt eqmt	0	13.9
77.39	Rentleas mchn,eqmt & tang gds nec	4.1	27.2
77.40	Lease intel prop, exc cpyrghtd wrk	12.3	50.1
78.10	Actv of emplymnt placment agncies	7.5	16.1
78.20	Temp employment agency activities	7.4	30
78.30	Other human resources provision	12.7	17.4
79.11	Travel agency activities	9.4	19.4
79.12	Tour operator activities	6	14.4
79.90	Othr reservtn serv & related activities	11.9	29.3
80.10	Private security activities	2.2	80.7
80.20	Security systems service activities	7.1	24.6
80.30	Investigation activities	9.6	36.1
81.10	Combined facils support activities	7.6	28.1
81.21	General cleaning of buildings	0.5	13.5
81.22	Other building & ind cleaning activities	0.4	13.6
81.29	Other cleaning activities	1.7	30.5
81.30	Landscape service activities	2.3	11.4
82.11	Combined office admin service activities	1	49.8
82.19	Copyng,doc prep & othr off sup activities	23.4	53.8
82.20	Activities of call centres	3.9	75.9
82.30	Convntn and trade show organisers	15.5	20.2
82.91	Actv coll agncies & credit bureaus	11.9	59.7
82.92	Packaging activities	4.2	33.6
82.99	Other bus supp service actv n.e.c.	15.4	41.2
84.11	General public admin activities	10.8	32.3
84.12	Reg of actv providing social serv	9	24.8
84.13	Reg & contr to mre eff op of busin	14.8	24.9
84.21	Foreign affairs	24.4	30.8
84.22	Defence activities	11.6	20.9
84.23	Justice and judicial activities	3.1	22.4
84.24	Public order and safety activities	3.8	20.8
84.25	Fire service activities	2.7	10
84.30	Complsry social security activities	2	26.1
85.10	Pre-primary education	11.8	7.4
85.20	Primary education	36.8	13.2

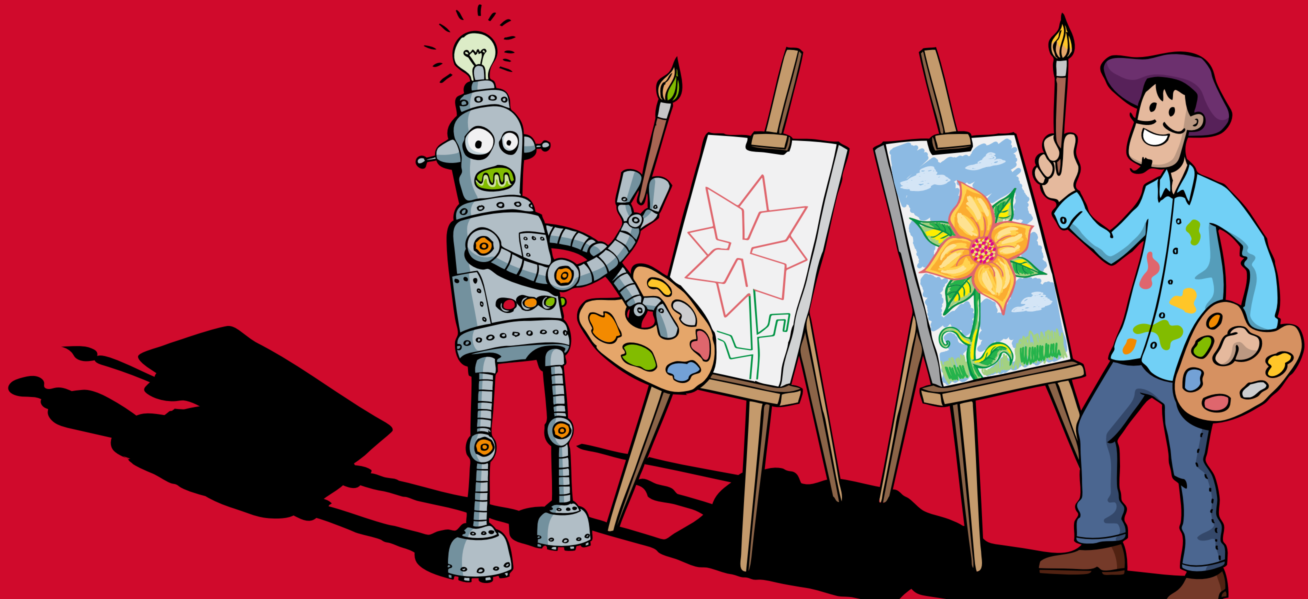
85.31	General secondary education	50.3	9.6
85.32	Techl & vocational secondary educ	21.6	13.7
85.41	Post-secndry non-tertiary educatn	12	14.6
85.42	Tertiary education	43.3	14
85.51	Sports and recreation education	6.3	4.3
85.53	Driving school activities	1.9	7.5
85.59	Other education n.e.c.	21.3	10.5
85.60	Educational support activities	12	12.1
86.10	Hospital activities	3.3	13.9
86.21	General medical practice activities	0.6	41
86.22	Specialist medical practice activities	2	22.7
86.23	Dental practice activities	0.5	15.9
86.90	Other human health activities	2.3	10.3
87.10	Residential nursing care activities	0.5	11.3
87.20	Res care activs for mental health	0.7	7.2
87.30	Res care actv for the eldly & disb	0.8	10.9
87.90	Other residential care activities	2	12.3
88.10	Soc wrk act wo accm fr eld & disb	0.5	5.5
88.91	Child day-care activities	1.1	3.8
88.99	Other soc work actv wo accom nec	6.3	17.7
91.03	Op of hist sites & sim vis atrctns	28	33.6
91.04	Bot & zoolgicl grdns & nat res activities	18.1	18.6
92.00	Gambling and betting activities	5.3	51.9
93.11	Operation of sports facilities	3.5	28.3
93.12	Activities of sport clubs	2.8	35.4
93.13	Fitness facilities	2.3	13.8
93.19	Other sports activities	9	12.1
93.21	Act of amusement park & theme park	0	43.9
93.29	Other amusement and rec activities	27.6	27
94.11	Act of busness & employrs memb org	23	18
94.12	Activities of prof mem org	18.8	42.1
94.20	Activities of trade unions	1	58.2
94.91	Activs of religious organisations	3.5	15
94.92	Activs of political organisations	13.3	21.3
94.99	Activities of other mem org n.e.c.	21.1	23.7
95.11	Repair of comps & peripheral eqmt	28.8	19.2
95.12	Repair of communication equipment	2.9	41.3
95.21	Repair of consumer electronics	9.5	24
95.22	Rep hhold apps & home & grden eqmt	0.5	19.1
95.23	Repair of footwr and leather goods	0	16.2

95.24	Rep of furnitre & home furnishngs	2.5	46.4
95.25	Rep of watches, clocks & jewellery	0	36.6
95.29	Rep of other personl & hhold goods	0	66.6
96.01	Wash & (dry)cleang text & fur prod	1.4	63.4
96.02	Hairdressng & othr beauty treatmnt	0.8	5
96.03	Funeral and related activities	0	21.2
96.04	Physical well-being activities	1	14.9
96.09	Other personal service actv n.e.c.	5.8	12.7
97.00	Act hhold as emplyers of dom pers	0	20.7
98.10	Undif good-prod act of priv hholds	0	23.7
98.20	Undif serv-prod act of priv hholds	0	19.1
99.00	Act extraterritorial org & bodies	13.1	27.9

ENDNOTES

1. Riedl, M. (2014), 'The Lovelace 2.0 Test of Artificial Creativity and Intelligence', School of Interactive Computing, Georgia Institute of Technology, mimeo. http://arxiv.org/abs/1410.6142
2. As pointed out by Autor (2013), relative costs matter to technology adoption. When Nissan produces cars in Japan, for example, it relies heavily on robots, while the same work is still performed by cheap labour in India. See Autor, D. (2013), "The "task approach" to labor markets: an overview," Journal for Labour Market Research,vol. 46(3), pages 185-199.
3. Braverman, H. (1974), Labour and monopoly capital: The degradation of work in the twentieth century, NYU Press.
4. Hounshell, D. (1985), From the American system to mass production, 1800-1932: The development of manufacturing technology in the United States, vol 4. JHU Press.
5. James, J. and Skinner, J. (1985), 'The resolution of the labor-scarcity paradox', The Journal of Economic History. Vol. 45(3): 513-540.
6. Goldin, C. and Katz, L. (1998), 'The origins of technology-skill complementarity', The Quarterly Journal of Economics. Vol 113(3): 693-732.
7. MacCrory, F., Westerman, G., Alhammadi, Y., and Brynjolfsson, E. (2014), 'Racing with and against the machine: Changes in occupational skill composition in an era of rapid technological advance', Thirty fifth International Conference on Information Systems, Auckland 2014.
8. Autor, D. and Dorn, D. (2013), 'The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market', American Economic Review, Vol. 103(5): 1553-1597.
9. Goos, M. and Manning, A. (2007), 'Lousy and lovely jobs: The rising polarization of work in Britain', The Review of Economics and Statistics, Vol. 89(1): 118-133.
10. Goos, M., Manning, A. and Salomons, A. (2009), 'Job polarization in Europe', The American Economic Review, Vol. 99(2): 58-63.
11. Facundo, A., Atkinson, A.B., Piketty, T., and Saez E. (2013), "The Top 1 Percent in International and Historical Perspective." Journal of Economic Perspectives, 27(3): 3-20; Piketty, T. (2014), Capital in the Twenty-First Century, The Belknap Press of Harvard University Press.
12. Brynjolfsson, E. and McAfee, A. (2011), Race Against The Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy, Digital Frontier Press; Brynjolfsson, E. and McAfee, A. (2014), The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies, W.W. Norton & Company.
13. Mokyr, J. (2013), 'Is Technological Progress a Thing of the Past?', EU-Vox essay, http://www.voxeu.org/article/technological-progress-thing-past
14. Frey, C. B. and Osborne, M. (2013), 'The Future of Employment: How Susceptible Are Jobs to Computerisation?', University of Oxford mimeo, http://www.oxfordmartin.ox.ac.uk/downloads/academic/The_Future_of_Employment.pdf
15. Autor, D. (2014), 'Polanyi's Paradox and the Shape of Employment Growth', Federal Reserve Bank of Kansas City's symposium on "Re-evaluating Labor Market Dynamics', August 21-23, 2014, in Jackson Hole, Wyoming http://economics.mit.edu/files/9835
16. McCormack, J. and d'Inverno, M. (2014), 'On the Future of Computers and Creativity', AISB14 Symposium on Computational Creativity, London, April 1-4, 2014 http://www.csse.monash.edu.au/~jonmc/research/Papers/AISB14McCormack-dInverno.pdf
17. Op. cit.
18. Gordon, R. (2014), 'The Demise of US Economic Growth: Reststament, Rebuttal, and Reflections', NBER Working Paper 19895
19. Lycett, M. (2013), ''Datafication': making sense of (big) data in a complex world', European Journal of Information Systems, 22: 381-386
20. Bakhshi, H. and Whitby, A. (2014), 'Estimating the impact of live simulcast on theatre attendance: an application to London's National Theatre', Nesta Working Paper 14/04, Nesta: London
21. Mestyan, Yasseri and Kertesz (2013), 'Early prediction of movie box office success based on Wikipedia activity big data', PLoS ONE 8(8): e71226
22. West, D.M (2012), 'Big data for education: data mining, data analytics, and web dashboards', Governance Studies at Brookings, The Brookings Institution: Washington DC
23. By computerisation, Frey and Osborne mean "job automation by means of computer-controlled equipment".
24. Op. cit.

25. Knowles-Cutler, A., Frey, C. and Osborne, M. (2014), Agiletown: the relentless march of technology and London's response, Deloitte. http://www2.deloitte.com/content/dam/Deloitte/uk/Documents/uk-futures/london-futures-agiletown.pdf
26. Op. cit.
27. http://www.oxforddictionaries.com/definition/english/creativity
28. DCMS (2015), 'Creative Industries Economic Estimates – January 2015', https://www.gov.uk/government/statistics/creative-industries-economic-estimates-january-2015
29. Florida, R. (2014), 'The Creative Class and Economic Development', Economic Development Quarterly, Vol. 28:196-205.
30. https: www.onetonline.org Unfortunately, no equivalent data are collected in the UK.
31. Op. cit.
32. DCMS (2013), 'Classifying and measuring the creative industries', https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/203295/Classifying_and_Measuring_the_Creative_Industries_Consultation_Paper_April_2013-final.docx
33. See McCormack, J. and d'Inverno, M. (2014), 'On the Future of Computers and Creativity', AISB14 Symposium on Computational Creativity, London, April 1-4, 2014 and Swann, P. and Birke, D. (2005), 'How do Creativity and Design Enhance Business Performance? A Framework for Interpreting the Evidence', DTI Economics Paper No. 15 for useful reviews.
34. Bakhshi, H., Freeman, A. and Higgs, P. (2013), 'A Dynamic Mapping of the UK's Creative Industries', Nesta Research Report, Nesta: London https://www.nesta.org.uk/publications/dynamic-mapping-uks-creative-industries
35. http://www.ons.gov.uk/ons/guide-method/classifications/current-standard-classifications/soc2010/soc2010-volume-2-the-structure-and-index/index.html
36. Op. cit.
37. Op. cit.
38. For example, for Judicial Law Clerks, selected as a non-creative occupation, the tasks include "Respond to questions from judicial officers or court staff on general legal issues", "Attend court sessions to hear oral arguments or record necessary case information" and "Verify that all files, complaints, or other papers are available and in the proper order."
39. Rasmussen, C. and Williams, C. (2006), Gaussian Processes for Machine Learning, MIT Press.
40. GPy Authors (2012-2015), GPy: A Gaussian Process Framework in Python, http://github.com/SheffieldML/GPy
41. Murphy, K. (2012), Machine Learning: A Probabilistic Perspective, MIT Press.
42. The exponentiated quadratic model was also the best performing in the analysis of Frey and Osborne (2013).
43. Op. cit.
44. Op. cit.
45. Bowles (2014), 'The computerisation of European jobs – who will win and who will lose from the impact of new technology onto old areas of employment?', Bruegel http://www.bruegel.org/nc/blog/detail/article/1394-the-computerisation-of-european-jobs/
46. Op. cit.
47. These thresholds where chosen to ensure comparability with Frey and Osborne (2013; 2014).
48. A well-known problem with the craft-related occupational classifications in the UK is that they conflate highly creative maker activities with less creative industrial activities. It is not possible to separately identify these occupations using the existing occupational codes. Crafts Council (2013), 'Defining and measuring craft: a review for the Crafts Council' by TBR Economics http://www.craftscouncil.org.uk/content/files/13-06-13-defining_and_measuring-proposals.pdf.
49. Op. cit.
50. Op. cit.
51. Autor, D., Levy, F. and Murnane, R. (2003), 'The Skill Content of Recent Technological Change: An Empirical Exploration', Quarterly Journal of Economics, 118(4): 1279-1334.
52. Op. cit.
53. Op cit.
54. Chapain, C., Cooke, P., de Propris, L., MacNeill, S. and Mateos-Garcia, J. (2010), 'Creative Clusters and Innovation: Putting creativity on the map', Nesta Research report, Nesta: London
55. Op. cit.
56. Op cit.
57. Acemoglu, D. and Autor, D. (2011), 'Skills, Tasks and Technologies: Implications for Employment and Earnings', in Ashenfelter, O. and Card, D. eds Handbook of Labour Economics Volume 4, Amsterdam: Elsevier.
58. Op. cit.
59. Sennett, R. (2009), The Craftsman, Penguin: London.
60. Boden, M. (1994), 'Creativity: a framework for research', Behavioral and Brain Sciences, 17(3):558-570.
61. Bakhshi, H. (2012), 'Measuring Cultural Value', http://www.nesta.org.uk/publicaions/measuring-cultural-value
62. Caves, R. (2002), Creative Industries: Contracts Between Art and Commerce, Harvard University Press.
63. Op. cit.
64. Op. cit.
65. Op. cit.
66. Isaacson, W. (2014), The Innovators: How a group of hackers, geniuses, and geeks created the digital revolution, Simon & Schuster.



Nesta...

Nesta

1 Plough Place
London EC4A 1DE

research@nesta.org.uk
@nesta_uk
www.facebook.com/nesta.uk

www.nesta.org.uk

April 2015