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LLAKES Research Paper 50

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LLAKES is an ESRC-funded Research Centre - grant reference ES/J019135/1.

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Francis Green and Golo Henseke

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Abstract

We develop a statistically-derived indicator, conceptually based on the skill requirements of jobs, for identifying graduate jobs from their unit group occupational code. We use representative survey data on skills utilisation and clustering methods for the classification. The method is transparent, replicable, and could be flexibly applied in a variety of settings. The indicator performs better than existing indicators in validation tests.

To demonstrate the indicator's utility, we then analyse the development of the British graduate labour market between two averaged periods, 1997/2001 and 2006/2012. Key findings include:

- *Over this interval, the share of graduate jobs in the British labour market rose from 32% to 40%.*
- *Employment growth and the upskilling of jobs contributed roughly 60:40 to the growth of graduate employment, though the picture varied among socio-economic groups.*
- *While there has also been a very large growth by more than 10 percentage points in the share of graduates in the labour force, the overall prevalence of overeducation among graduates has been stable at around 30%.*
- *As in the literature, overeducated graduates receive on average lower wages compared with matched graduates, but higher wages than workers with an adequate level of education.*
- *For men the wage premium for matched graduates relative to matched non-graduates has increased over time from 89% to 104%, while for women it has remained stable at 110%.*
- *The wage gap between matched and mismatched graduate workers has increased over time from 47% to 67%, thus providing further evidence covering up to 2012 that there is an increasing dispersion in the returns to graduate education.*

1. Introduction[1]

There frequently arises the need to classify jobs according to whether or not they are "graduate jobs". Existing classifications are used by careers advisers, human resource services companies, policy-makers (Milburn 2009) and journalists. In research, graduate job indicators can be used in analyses of the market for high-skilled labour: an especially salient application is to the graduate labour market of recent decades, which have seen a rapid expansion in the supply of college-educated labour in many countries, alongside rising demand for skilled labour. Studies suggest that, overall, the returns to graduate-level education in Britain have not fallen, implying that the rising demand has kept pace with the supply (e.g. Machin and McNally 2007). Nevertheless, there is also evidence of growing differentiation in the returns, with some decline in the returns for those at the lower end of the spectrum (Green and Zhu 2010). Apart from differentiation among places of higher education and between subject areas, also under scrutiny is the potentially growing polarisation of demand in the labour market, and the dispersion of the returns appears to be linked to rising graduate 'overeducation', whereby graduates are employed in non-graduate jobs (Green and Zhu 2010; Felstead et al. 2013). An adequate method of classifying unit groups provides a potential route to analysing the expansion of high-level skills demand.

In this paper we propose and deploy a new method for classifying graduate jobs. We argue that the resulting indicator is conceptually valid, based as it is on direct evidence of skill use in jobs; it is therefore also responsive to changes in job skills within jobs. We present several empirical tests for its construct validity. The method is relatively straightforward to apply and the indicator can be used in a wide variety of settings and for multiple purposes.

The chief advantage of a graduate job classifier for unit groups – if it is flexible enough to incorporate changes in the classification when skill requirements change over time, while retaining its construct validity – is that it can be applied in analyses of high-skilled labour markets in any data sets, wherever occupation is coded to unit group level. Such analyses can

[1] We would like to thank Claire Callender for her excellent comments on an earlier draft of this paper.

illuminate the interplay of supply and demand over time, as higher education evolves, going beyond and behind the study of changing returns.

First, a word of caution is necessary. However good the classifier, there will remain an inevitable fuzziness in any simple two-way classification of jobs as graduate or otherwise. Even within unit-group (4-digit) occupations there is variation in the level and types of skills deployed; moreover, skill requirements are multiply graded, and neither absolute nor precise, so that substitution among variously-skilled co-workers is usually possible. Any two-way classification must assume, therefore, that fuzziness at the threshold, and the heterogeneity among graduate jobs, are not so extensive as to generate unacceptable measurement error, or outweigh the value of having a simple indicator for analysing high-skill labour markets.

Yet most existing indicators of graduate jobs are inadequate for the purpose of such analyses, not so much because of fuzzy thresholds but because they are inflexible, loosely connected to high skills utilisation, or inappropriately defined from the supply side (with attendant risks of pointless tautology: "graduate jobs are the jobs that graduates do"). Moreover, as Gottschalk and Hansen (2003) illustrate in the case of the United States, the chosen classification method materially affects conclusions that analysts draw about trends in the graduate labour market. In the next section, we review these existing classifications of graduate jobs in the literature, and consider desirable properties for any new indicator. Section 3 describes our data and how key variables are derived as the basis for the indicator. Classification methods are then described in Section 4, followed by construct validation in Section 5. Section 6 then utilises our chosen indicator to describe the changing supply and demand in Britain for graduate labour from the late 1990s till the near-present.

2. A review of existing occupational indicators of graduate jobs.

Here and throughout the paper, we refer to "skills" in a broad sense, to embrace knowledge and attitudes as well as technical capabilities (Green 2013: Ch. 2). We conceive a graduate job to be one where at least a substantial portion of the skills used are normally acquired in the course of higher education, its accoutrements and its aftermath; moreover, It is assumed that graduates are normally in possession of these high-level skills.

This conception does not mean that the skills acquired in college and those used in jobs are identical. In this context three points are important to note:

a) Some of the skills learned in college are an investment for life generally. Not only the skills gained through tuition and formal learning, also the higher education experience, including leaving home – a learning process in itself – and encountering those with alternative viewpoints. Among these outcomes some will also be beneficial in work life; included here is the matching process as people learn and make choices about alternative biographies they would not have encountered if they had gone straight from high school into work.

b) Equally, while in many accounts it is presumed uncritically that all graduates' high-level skills must have been acquired in higher education, the skills could have been acquired at other sites, such as family or work, independently of higher education. It is hard to be sure exactly when and where skills are acquired. In one piece of evidence from the REFLEX study of European graduates, many graduates report having acquired relevant skills during work experiences either before or during their HE courses, though the proportions that do so are rather lower in the UK than elsewhere in Europe (Little et al., 2008: 35). A small proportion manages to acquire higher skills without attending HE. Some skills may also predate work and HE entry, and be correlated with selection for HE entry – this is the foundation of the theory that education is a signal, not a cause, of higher productivity. While the evidence for education being just a signal is slim (Chevalier et al., 2004), a classification indicator will be improved if it can use available information to reclassify jobs as non-graduate where a higher education qualification is needed merely to get the job but not to do it competently.

c) Third, the skills acquired in higher education are a mix of subject-specific skills and more generic skills. In the above-mentioned REFLEX study, UK graduates in 2005 reported the following five main competencies acquired through their higher education five years earlier: analytical thinking (34% of respondents), performance under pressure (28%), ability to work productively with others (26%), mastery of own field or discipline (26%), and ability to acquire new knowledge (24%) (Little et al., 2008: 32). This last-mentioned skill is what adds significance to the aftermath of higher education, when many new work skills are acquired by graduates.

Most of all a graduate job indicator should reflect this concept as closely as possible. Our indicator is, like others, attached to unit-group (4-digit) occupations.[2] A method for classifying jobs as graduate jobs should also be transparent, replicable and flexible enough to be applied in a variety of settings. How do existing indicators fare in these respects?

Most existing studies use indicators for the concept of a graduate job that draw (at best) only indirectly upon skills requirements. Some writers utilise indicators that are essentially driven by the proportion of graduates in the occupation (e.g. Mason et al. 2009, Wilton 2012). This approach follows the tradition that measures unit group skill requirements by the mode or median educational level of the individuals doing them, in order to contribute to an indicator for overeducation (Verdugo and Verdugo 1989). Perhaps the most sophisticated approach of this kind was that of Elias and Purcell (2004a and 2004b), whose classification distinguished between different kinds of graduate jobs. Distinction was made between "traditional", "modern", and "new" graduate jobs, according to age cohorts and the differences between them. Use was also made of source materials on job titles to identify "niche" graduate jobs. A similar approach has been applied elsewhere (Figueiredo et al. 2011). This method was a step forward because it helped to highlight the breadth of the types of skilled work that graduates were doing, moving away from the traditional definition that was starting to look outdated. Nevertheless, the reliance on supply to indicate demand became increasingly questionable following the massification of higher education, and consequent greatly expanded numbers of graduates appearing on the labour market (Elias and Purcell 2013).

An alternative indirect route to identifying graduate jobs is via the assumption that graduate jobs are those where there is a high return to college education. It has been argued that this method is preferable because it identifies graduate skill requirements "objectively" via the market signal of wages. Using this method, Gottschalk and Hansen (2003) classified jobs as college or non-college, and found that the proportion of college-educated workers in non-college jobs declined during the 1980s and early 1990s, attributing this to skill-biased technological change. Unfortunately this method also has its problems. Within occupation estimates of the returns to education are biased downwards because of selection by

[2] Thus the term "job" is in this paper described by the unit group (rather than the individual contracts that employers and employees enter into). The alternative would be to treat each individual employment contract as a job. Using individual-level data, some studies classify individual jobs according to whether graduates perceive their skills are being utilised (Smetherham, 2006); such indices are inherently not transferable to other data sets.

unobserved factors into occupations that may be correlated with pay or education; if there is differential bias between occupations this will affect the classification. Biases in the estimation of returns to education (such as omitted ability bias), and the possibility that signalling may partially break the link between college education and human capital acquisition, also add questions to the desirability of measuring skill requirements through wage returns. Moreover, if a classification is to be *defined* by wage effects it cannot then be used in models to explain wages or related outcomes, ruling out many potential uses for a graduate skills indicator.

Although no indicator can be expected to be a perfect reflection of the concept of a graduate job, indicators derived directly from measures of skills use are closest to the concept and therefore preferable. Some studies in this mould have stuck with a broad occupational classification. The traditional association linking graduates with major occupation group 2 (professional occupations) is now normally extended to embrace, as well, major group 1, covering all the unit groups involved in management. Thus, major groups 1 and 2 (i.e. managers and professionals) are regarded as the "high-status" occupations (Macmillian and Vignoles 2013). But, given the possibility that many other jobs outside these two groups are now utilising graduates' skills, for a classification of graduate jobs it is necessary to go beyond the traditional notion of high-status. Our preference for a direct skills-based indicator is consonant with the development in several countries of task-based analyses of labour markets (Autor et al. 2003, Gathmann and Schönberg 2010, Green 2012). One approach has been to draw on US-based job classifications based on expert-derived information about skills requirements. Thus, Chevalier and Lindley (2009) use the 1991 Dictionary of Occupational Titles (DOT) definition of graduate jobs which augments the definition beyond managers and professionals to include nurses, midwives and IT associate professionals. Since the DOT and its successor the O'NET classifications tend not to be updated except at very long intervals, inevitably this method of classifying graduate jobs is not ideal for identifying where jobs are upskilled and become graduate jobs, or indeed where new jobs come into being that do not fit into old classifications.

Best by far among skill-based classifications of graduate jobs in Britain is a relatively new index – termed "SOC(HE) 2010_EP"[3] – derived by Peter Elias and Kate Purcell, replacing

[3] We have added the suffix "EP" in order to distinguish this classifier from the one we develop below.

their 2004 classification with one based on the indicators of skills use found in the most frequently-cited job titles in each unit group (Elias and Purcell 2013). Using as their base the Quarterly Labour Force Surveys in 2011(Q1)-2012(Q3) they scored each unit groups by making a qualitative assessment about the use of three types of skills deemed graduate skills – what they term “specialist expertise”, “orchestration expertise” and “communications expertise” – in the most frequently occurring job titles within each group. Where the scores exceeded a threshold in any of these three categories, the unit groups were classified to be graduate jobs. In effect, this is an ‘expert’-based classification method where, in order to gain an economy-wide classification, the industry expert is replaced by an expert interpreter of the job titles that are used as the raw material for occupational coding. A similar method is used in other countries to allocate "most appropriate" educational requirement levels to occupational codes (Baert et al. 2013), though how such judgements are made and how far they are embedded in labour regulations lack transparency. This method has the key advantage that it is based on the skills used in jobs, and not on the qualifications, gender, age or any other characteristics of the job-holders. For now, also, the new Elias-Purcell classification is also very up-to-date.

As validation of the SOC(HE) 2010_EP indicator, Elias and Purcell (2013) show that graduates are more likely than non-graduates to be employed in SOC(HE) 2010_EP occupations, and that when they are they make better use of their skills and are paid more than graduates in non-graduate jobs. While these findings are welcome, they are not very surprising: comparisons with all non-graduate occupations are weaker tests than comparisons with just those occupations in major groups containing the unit groups that are potentially becoming graduate occupations – especially, major group 3 (Associate Professionals and Technicians). In addition to these validation tests being somewhat weak, it would have been encouraging to have seen evidence that scoring had been repeated with two or more independent markers; moreover, no direct evidence is obtained as to the type of qualification that may be required to do jobs competently. Nevertheless, these are quibbles: the new index is undoubtedly an advance over previous ones.

Yet, no doubt due to the considerable time cost involved in extensive forensic examination of unit groups, it is a concern that we do not have equivalent, commensurate classifications available for earlier occupational codes before SOC2010 (which would be needed for trend analyses). Moreover, the method is not easily applied to international comparisons without, again, considerable cost from devoting resources to equivalently classifying ISCO-coded unit groups. There is also a potential concern that the information contained in (sometimes brief) job titles does not fully capture the main generic functions of a job involving high skills use.

In the new method we propose below, we follow the same principle of Elias and Purcell in using only skills-based information. The difference is that, in place of expert assessment of job titles, we are able to systematically access a range of information about job requirements, using data drawn directly from representative samples of job-holders. The principle underlying this choice is the same as that underpinning many task-oriented surveys around the world, and now utilised in the OECD's Survey of Adult Skills (OECD 2013): job-holders are likely to be the most precise informants about their jobs, even if their perspectives may sometimes be open to self-esteem bias. Our method avoids the use of hard-to-replicate expert judgements, and deploys an observer-neutral classification procedure, based on relatively simple statistical classification methods that are easily replicable. Our method is also updatable and applicable across countries.

3. Data and skills use indicators

The Skills and Employment Survey Series

The primary requirement for classification is a set of data on skills use in all types of jobs, alongside occupational classification at the 4-digit level. An efficient and reliable way to collect such information is via a representative survey of the employed labour force. The Skills and Employment Survey 2012 (SES2012) is the latest in a series of nationally representative sample surveys of individuals in employment in Britain aged 20-60 years old (although the 2006 and 2012 surveys additionally sampled those aged 61-65). For the purposes of this paper we use the surveys in 1997, 2001, 2006 and 2012, all of which collected information about broad skills requirements – such as the length of prior training and the qualification requirements to get and do jobs, the generic tasks carried out in each respondent's job, indicators of skills mismatch, and a wealth of contextual information about job quality and the job-holder's personal characteristics. All these surveys collected responses from working adults in England, Scotland and Wales, interviewed in their own homes. Samples of households were drawn using random probability principles subject to stratification based on a number of socio-economic indicators. One eligible respondent per address was then randomly selected for interview. For each survey, weights were computed to take into account the differential probabilities of sample selection, the over-sampling of certain areas and some small response rate variations between groups (defined by sex, age and occupation).[4] By design, the Skills and Employment survey is thus representative of filled jobs but not open vacancies.

Skills Indicators

Statistical sources in Britain usually structure jobs according to the Standard Occupational Classification. The current revision is from 2010 (ONS 2010). Like its predecessors, SOC2010 groups jobs according to the typical skills level requirements and skills specialisation (i.e., field of knowledge and type of work). The classification distinguishes between four hierarchical levels with an increasing degree of differentiation. 369 unit groups form the lowest, most detailed level of the hierarchy. The top level of the hierarchy consists of nine broad occupational major groups which bring together jobs with similar skill levels. The skill levels range from compulsory education (1) to skill intensive 'professional' occupations (4) (Elias and McKnight 2001). Within skill levels, the skills specialisation criterion is used to further differentiate between occupations. As a result, the classification distinguishes between increasingly homogenous occupations in terms of type of work and field of knowledge with each level of differentiation. To increase the number of observations we use a cross-walk from SOC 2000 to SOC 2010 to recode observations in unit groups which can be safely assigned to a corresponding unit group in the revised classification.

While the SOC is built on theoretical sound principles, a certain level of heterogeneity at the unit group level is unavoidable. The problem is amplified by ambiguity in the mapping of job titles to occupational groups, misreported job titles by survey respondents and potentially misallocated job titles within the classification framework. There is only little research on the extent of misclassification error in occupational classifications in survey data. The few existing studies, mainly based on US data sets, conclude that the error in occupational coding can be substantial (Mathiowetz 1992) and vary across occupations (Sullivan 2009). For our classification of graduate jobs we deal with this issue by carefully exploring the distribution of skills requirements within major groups. We only classify unit groups with five or more

[4] Full details of these surveys can be found at Ashton and Felstead. (1998), Felstead et al. (2002, 2007), Felstead and Green (2008) and for the 2012 survey in Felstead et al. (2014) at http://www.cardiff.ac.uk/socsi/ses2012/ [accessed 1.8.2014]

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valid observation in the data. Variable values of unit groups with less than 5 observations are imputed with averages from the next level of the occupational hierarchy (i.e., 3 digit level).

Indicator selection is guided by the principles outlined in Section 2. We include five measures which together capture knowledge requirements, the importance of using high-level generic skills, and the amount of prior training:

i. Workers are asked which qualifications would be required by a current job applicant to get the job they are doing, and in a follow-up question whether they judge that qualification to be essential or fairly necessary to perform their job competently. The information is coded as a binary variable with the value 1 if a worker reports that a qualification at degree level (or equivalent level 4) or above is required and zero otherwise. A special situation arises if workers state that a post-graduate level is required to get the job, but not necessary to perform it. It is plausible to assume that a qualification at first degree level or similar will be nonetheless essential to carry out the job tasks. We therefore replace the value of the binary variable with the value 1 in such situations.

   In an earlier study this item has been shown to be reasonably reliable (Green and James 2003); moreover, similar indicators are now used in the OECD's Survey of Adult Skills. Nevertheless, single items are rarely ideal, and in this case occupational norms and occupational status might influence workers' perception of educational requirements. Therefore, we supplement reported qualification requirements by direct measures of job skills as well as the averaged degree requirements of similar occupations.

ii. The Standard Occupational Classifications groups similar jobs in terms of required skill level, field of knowledge and type of work together into occupational groups. We exploit this construction principle to calculate a measure of the degree requirement in jobs similar to the workers current position. Similar jobs are defined by all observations within the same minor group (3 digit occupational group). Formally,

$$DN_i = \frac{\sum_{k=1}^{K} D_{k(i)}}{K(i)},$$

where k(i) describes the set of jobs that form the neighbourhood of job i, $D_{k(i)}$ represents whether a degree is required to perform job k in worker i's neighbourhood and DN_i is the average extent of degree requirements in similar jobs.

iii. A college education enables the holder to efficiently carry out a number of high-level generic job tasks. The SES series has collected systematic and consistent data on the importance in jobs of a large range of tasks since 1997; these tasks have been grouped (following factor analyses) into a smaller set of ten generic tasks (Green 2012). We deploy a subset of these and some related variables to derive, as follows, a skills intensity index that comprises a mix of generic skills thought to be needed in graduate jobs: high levels of literacy skills (e.g. writing long reports), high levels of professional communication skills (e.g. making speeches or presentations), supervisor responsibilities, high self-planning skills, high importance of specialist knowledge and a high need to learn new things. Each component is defined as a binary variable which is one if the corresponding high level generic skill is required and zero otherwise. The generic skills index is given by the arithmetic mean over all the components and ranges from 0 to 1. Because the 1997 data does not include information on the need to learn new things, the index is formed of the remaining 5 items

$$SI_i = \text{mean}(generic\ skill_i)$$

iv. There is a vast literature on the close link between the use of computer technology at work and the upskilling of jobs (e.g. Haskel and Heden 1999; Green et al. 2003); ICT is held to complement and facilitate the application of other generic skills, and to improve the productivity of high skilled workers in the production of skills intensive tasks. Computerisation is often seen as the main driver in the increasing demand for graduates in the labour market. But it is not so much the importance of computers in jobs that counts, as the level at which they are used. Respondents were asked to say how they used computers at work, responding against a scale with anchored examples. With their responses we include, as a separate complementary measure to the generic skills intensity index, a dummy variable indicating that computers are important and used at a high level – either "complex" (e.g., for computer-aided design or statistical analysis packages) or "advanced" (e.g. using computer syntax).

v. Finally, another broad indicator of graduate skill levels is whether the job requires job-holders to have had a long-lasting formal training for the type of work they do. We thus include a binary measure of the prior training received for the type of work on a worker's current job. The dummy variable is one if a worker reports having received over 2 years of training.

We make no claim that this list exhausts the range of skill types, or possible skill measures, that could be required in graduate jobs; nor is it asserted that each of the above is always required in a graduate job. Nevertheless, when combined into a summary measure the variables do yield a measure of the extent to which high-level skills are being required, making the job appropriate for a graduate to do it. Table 1 summarises the distribution of these indicators for the pooled sample 1997-2012.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Degree essential (*D*)	17539	0.234	0.424	0	1
Degree essential (similar jobs) (*DN*)	17539	0.234	0.256	0	1
Graduate Generic Skills Intensity Index (*GS*)	17915	0.300	0.267	0	1
• High level literacy skills	17915	0.273	0.446	0	1
• High level professional communication skills	17915	0.087	0.281	0	1
• High level self-planning skills	17915	0.384	0.486	0	1
• Supervisor responsibilities	17889	0.252	0.434	0	1
• Specialist knowledge	17915	0.487	0.500	0	1
• Need to develop new skills and knowledge	15442	0.330	0.470	0	1
High or Advanced Computer Use (*CS*)	17643	0.194	0.395	0	1
Long Prior Training (*LT*)	17737	0.268	0.443	0	1

Source: SES 1997-2012.

The pooled data since 1997 contains almost 18,000 observations. The number of observations varies between 15,442 for the measure of the need to learn new skills and knowledge (not observed in 1997) and 17,915. According to the summary statistics (Table 1), 23% of respondents report that their job requires a degree to be carried out competently, 19% uses computers at an advanced or complex level at the job and slightly more than a quarter reported over 2 years of prior training. The graduate generic skills index is slightly right skewed; the mean is 0.300 whilst the median value is 0.267. Overall, about half of the jobs in the data require no or only a few high level skills.

The five variables capture distinct dimensions of high-skilled jobs, whose relations are reflected in the positive linear correlations between the variables – see Table 2. All pairwise correlation coefficients are positive and statistically significantly different from zero. Quantitatively, they vary from a negligible 0.08 (high or advanced computer use vs. training level requirements of 2 years or more) to a strong 0.59 (degree required to do the job vs. degree requirements in similar jobs). The index of generic skills intensity is clearly associated with both measures of degree requirements.

Missing values in survey data is an issue. Generally, item non-response is low in the SES data set, which speaks to its overall quality. Degree essential to do the job and degree needed in similar jobs suffer from highest non-response rates, but the prevalence never exceeds 2.1%. In order to make maximal use of the information in the data, we calculate the graduate generic skills intensity index, even if single values of the included items are missing. This is not possible for measures based on single items. In this case, we assume random item non-response and discard the observation in the classification procedure. This leaves us with 17,105 observations.

Table 2: Pairwise Pearson Correlation Coefficients

	Degree essential	Degree essential (similar jobs)	Generic Skills Intensity Index	High Computer Skills	Long Prior Training
Degree essential	1.000				
Degree essential (similar jobs)	0.593	1.000			
Graduate Generic Skills Intensity Index	0.403	0.480	1.000		
High or Advanced Computer Use	0.237	0.241	0.229	1.000	
Long Prior Training	0.247	0.283	0.295	0.082	1.000

Source: SES 1997-2012

4. Classification Methods

To obtain a classification of 'graduate occupations', we construct a classifier which combines the measures of high-level skill requirements. In Section 5 we shall compare their properties with those of SOC(HE) 2010_EP and other existing classifiers. All statistical analyses are conducted with Stata SE 13.1.

The classifier involves a multi-step procedure. On the first step, the individual job data are aggregated into a uni-dimensional measure of skills requirements. This is done by means of a linear probability model. Next, we average the univariate index across unit groups and remove potential outliers. The final step consists of the classification of occupations into broad groups of graduate and non-graduate occupations by k-medians clustering.

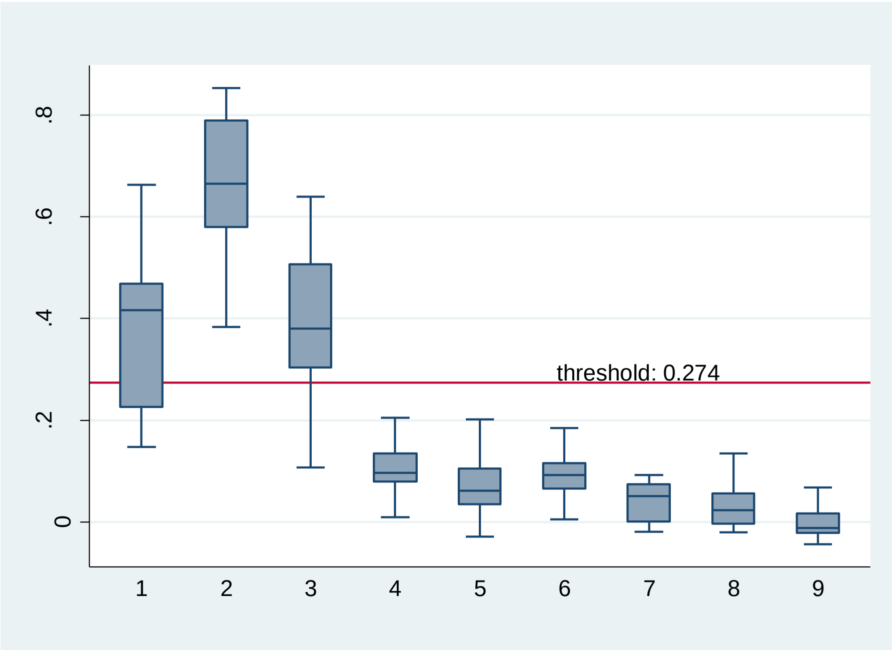
In step one, we run a linear probability model of whether a degree is required to do the jobs on the graduate generic skills intensity index, computer skills, required training and the degree requirements in similar jobs. The model recovers the variation in the dependent variable that is due to differences in objective skills and knowledge measures. This approach is conceptually similar to methods applied in health economic research to purge self-reported health from reporting error (Jürges 2007).

$$P(D_i = 1|X_i) = \beta_0 + \beta_1 GS_i + \beta_2 CS_i + \beta_3 LT_i + \beta_4 DN_i + e_i,$$

where GS_i denotes the generic skills intensity for the job of worker i, CS_i a dummy variable for use of high-level computer skills, and LT_i a dummy for training requirements of over 2 years. From the estimation results, we compute an overall index of graduate skills requirements as a weighted linear combination of the independent variables, the weights being the estimated coefficients of the linear probability model. Our indicator is interpreted in this model as the probability of a degree-level qualification being required, as predicted by the separate high-skills requirements indicators.

Next, we average the skill requirement scores across unit groups. The distributions of the average scores follow intuitively sensible patterns. The scores are highest in major group 1, 2 and 3, and lowest in major groups at the bottom of the classification (Figure 1). The linear probability model appears to discriminate sharply between occupations. To protect against outliers and to take the heterogeneity of jobs at the unit group level into account we impute the derived scores of unit groups with less than five observations with average values from the 3 digit level of the occupational classification. The procedure helps to minimise noise due to reporting errors and misclassification. The remaining outliers in the boxplots of Figure 1 are believed to represent true heterogeneity.

Figure 1: Box Plot of the Graduate Skills Requirements Index by Major Groups



Note: The 25% and 75% Quartile of the distribution determine a box's edges. The median is represented by a line in the box. The length of the box gives the Interquartile Range (IQR). The whiskers cover all values within 1.5 IQR above the 75% or below the 25% quartile. Values outside this range are sometimes considered outliers. They are suppressed from the figures.

In the third and final step, we partition the unit groups into a group of graduate and non-graduate occupations. Simple clustering techniques are among the most widely adopted methods to approach the classification problem. They can be broadly grouped into hierarchical and partition cluster-analysis methods. Since the goal is to derive two distinct non-overlapping groups of occupations, namely graduate and non-graduate jobs, we apply k-medians clustering. K-medians clustering is a variant of the well-established k-means clustering method. The algorithm uses the median instead of the mean as centre of the derived clusters and is therefore better in dealing with outliers in the data. The main idea of k-means/ k-medians is to find a cluster solution which minimizes the distance between observations and their cluster centroids. The allocation of observations to clusters follows an iterative EM-procedure. During the E-step the observations are assigned to the closest cluster. In the M-step the medians are re-calculated to minimise the within cluster variance. The algorithms stops once the cluster solutions remains stable over the iteration steps. The process generates two occupational groups with distinct levels of skills requirements. All occupations which score above the calculated cut-points are labelled “graduate job”, whereas all occupations with skills and knowledge requirements below the threshold are summarised as “non-graduate” jobs. We assume that the derived threshold is time invariant. In other words, the skills and knowledge level from which point on a degree is essential to carry out the job competently does not change over time. Therefore, we will keep this cut-point fixed throughout our study.

We term the classification that results from these steps as SOC(HE) 2010_GH. The mean values and cut-points between graduate and non-graduate jobs are summarised in Table 3. The threshold for the high skills requirements score is .274. In general, there is no sharp distinction between graduate and non-graduate jobs at the margin; occupations appear to be distributed across the whole range of the skills scores. The full list of graduate and non-graduate occupations in the first four major groups is given in the Appendix, Table A2, including their skills scores.

Table 3: Skills and Knowledge Requirements Scores across Clusters by Classification

	SOC(HE) 2010_GH	
	Non-graduate	Graduate
# Unit Groups	217	136
min	-0.044	0.279
mean	0.073	0.525
max	0.274	0.854

5. Construct Validation

In this section, we examine the validity of this new indicator. Our method is to compare its predictive power in terms of expected outcomes in comparison with the performances of existing indicators. We examine three outcomes. First, graduates in graduate jobs are expected to receive a wage premium over graduates who are mismatched in non-graduate jobs. Second, graduates are expected to have better opportunities to utilise their skills, when employed in graduate jobs. Third, even though matching processes are imperfect we would expect that graduates are more likely to be employed in graduate jobs. Against each of these three outcomes, validation requires that each classification helps to explain the outcome (i.e. does better than a random allocation classification); moreover, the more accurate is the classification, the better we will be able to explain variation in wages, skills utilisation and matching. We are interested in whether there is a benefit over "naïve" classifiers of graduate jobs, and in whether our statistical classification approach fares at least as well as SOC(HE) 2010_EP, the classification proposed by Elias and Purcell (2013). Since the latter is available only for SOC2010 we use the Skills and Employment Survey 2012 and, where the data allow, the four waves of the Quarterly Labour Force Survey in 2013 which are also coded in this way. We test predictions, not just within the whole sample (where validity should be easily established), but also just within what we term the "risk zone" of jobs in major occupational groups which are not all in one category, i.e. 1, 3 and 4, where there is therefore a greater risk of misclassification.

We begin with a descriptive picture in Table 4 of how graduate jobs are distributed among the major occupational groups in 2006/2012 across SOC2010 major groups.[5] We include two "naïve" classifiers in the first two columns. The first is based on the use of graduates in each unit group, and applies the same kmedians clustering technique to divide unit groups between graduate and non-graduate jobs. The second is a "traditional graduate jobs" classifier, defined as belonging to the first two major occupational groups. The third column shows the SOC(HE) 2010_EP classifier and the last column shows our new statistically derived classifier. Do the distributions appear plausible?

[5] For this purposes 2006 wave cases were re-coded to SOC2010 where using the supplied cross-walk.

The distributions of graduate occupations across major occupational groups between classifications share similar features, but also reveal differences. First, graduate jobs cluster as expected within occupational major groups 1, 2 and 3 across all classifications. Second, not all occupations in major group 1 but some in major group 3 require skills at a degree level. Classifying whole major groups as graduate occupations (as Column 2) ignores the heterogeneity of the encompassed unit groups. Third, classifying occupations based on what jobs graduates do in the labour market (as Column 1) appears to inflate the number of graduate jobs, especially outside the first three major occupation groups. By ignoring that a substantial number of graduates are potentially mismatched, this naïve method will lead to over-optimistic conclusions about the state of the graduate labour market. Fourth, there are differences between the SOC(HE) 2010_EP and SOC(HE) 2010_GH classification. They both imply that the proportion in Major Groups 1 and 3 that are graduate jobs is positive though less than 100%; yet SOC(HE) 2010_GH classifies a greater proportion of Major Group 3 jobs as graduate jobs.

Table 4: Proportion of Unit Groups Classified as Graduate Jobs within Major Occupational Groups (%)

Major Group	Freq. of Graduates	Major Groups 1&2	SOC(HE) 2010_ EP	SOC(HE) 2010_ GH
Managers, directors and senior	72.2	100.0	69.4	69.4
Professional occupations	98.6	100.0	100.0	100.0
Associate professional and technical	83.3	0.0	40.0	86.4
Administrative and secretarial	24.0	0.0	8.0	0.0
Skilled trades occupations	1.8	0.0	0.0	0.0
Caring, leisure and other service	19.2	0.0	3.8	0.0
Sales and customer service	11.1	0.0	0.0	0.0
Process, plant and machine	2.4	0.0	0.0	0.0
Elementary occupations	0.0	0.0	0.0	0.0
Total	44.9	28.9	33.9	41.4

Source: SES 2006/2012

In addition to the plausibility of the occupational distributions, the following validation will help to discriminate between the approaches.

We first ask, how well do the classifications reflect the expectation that graduates should receive higher wages in graduate jobs than in non-graduate jobs? The top panel of Table 5 reports wage regression results based on SES 2012 and QLFS 2013. The reference population differs across datasets. SES contains information on hourly earnings for employed and self-employed members of the labour force, whereas QLFS collects this information for employees only.

Table 5: Wage Premium of Matched compared with Mismatched Graduates, by Classification Method

	Freq. of Graduates	Major Groups 1&2	SOC(HE) 2010_EP	SOC(HE) 2010_GH
Employees and Self-Employed – SES 2012				
Graduate Job	0.44	0.39	0.45	0.48
	(0.04)	(0.04)	(0.04)	(0.04)
R^2 (N=1,034)	22.6	21.8	25.0	25.8
RMSE (N=1,034)	0.50	0.50	0.49	0.49
Employees – QLFS 2013				
Graduate Job	0.50	0.41	0.47	0.53
	(0.01)	(0.01)	(0.01)	(0.01)
R^2 (N=17,377)	30.4	27.8	30.8	33.1
RMSE (N=17,377)	0.47	0.48	0.47	0.46
Employees and Self-Employed in Major Groups 1, 3, and 4 – SES 2012				
Graduate Job	0.23	0.25	0.33	0.34
	(0.06)	(0.10)	(0.07)	(0.06)
R^2 (N=414)	14.1	14.6	18.6	18.5
RMSE (N=414)	0.56	0.55	0.54	0.54
Employees in Major Groups 1, 3, and 4 – QLFS 2013				
Graduate Job	0.29	0.28	0.30	0.34
	(0.01)	(0.02)	(0.01)	(0.01)
R^2 (N=6,735)	19.8	19.9	21.7	22.4
RMSE (N=6,735)	0.51	0.51	0.50	0.50

OLS Regression using calibrated survey weights with age, age squared and a gender dummy as control variables. Additional dummy for proxy interviews included in the QLFS based regressions. Asymptotically robust standard errors in parentheses. All estimated wage premiums are statistically significant at least at the five per cent level.
Source: SES 2012, QLFS Q(1)2013-Q(4)2013

The results confirm that working in a graduate job is associated with a statistically and quantitatively highly significant wage premium for graduates across all classifications. However, the point estimates and the accuracy of the estimations vary. The proportion of explained variance is lowest and Root Mean Squared Error (RMSE) is largest for the naïve classifications. SOC(HE) 2010_EP does a better job – the explained variance is clearly higher, but our statistical approach fares better. The improvement is particularly marked in the LFS data, where the proportion of explained variance is 33.1% for SOC(HE) 2010_GH, compared with 30.8% for SOC(HE) 2010_EP.

The ‘risk zone’ consists of major groups 1, 3 and 4, where some but not all occupations require skills and knowledge at a graduate level. As expected, restricting the estimation to graduates employed in this set of occupations lowers the model fit across all specifications. But even in this narrower field, the wage premium of matched compared with mismatched graduates is substantive and significant. The results confirm the previous ranking across the classification. Both naïve approaches fare worse, and SOC(HE) 2010_EP is a clear improvement over these; but our approach explains the same or a higher fraction of inter-individual wage differences.

Next we investigate differences in skills usage. Our classification is based on the assumption, that graduate jobs require high levels of skills use. Therefore, investigating the differences in the opportunities to use skills provides a direct test of the classifications’ construct validity. For this purpose, we estimate the average skills utilisation penalty for mismatched graduates. Who is matched/ mismatched is defined by the classifications of graduate jobs. A larger penalty suggests a better discriminatory power.

The Skills and Employment survey contains two measures of skills utilisation. Measure one summarises a worker’s opportunity to utilise his or her knowledge and skills on the job. The second measure refers to how much of “past experiences/ skills/ abilities” can be used on the current job. We estimate skill usage penalties, i.e. how much less likely mismatched graduates are to report high levels of skills utilisation. There is no comparable information in the QLFS.

The estimation results confirm the findings from the wage regressions. On the average, mismatched graduates report lower skills utilisation according to both these measures of utilisation. Overall, the penalties estimated by SOC(HE) 2010_GH exceed those based on both the naïve classifications and SOC(HE) 2010_EP, particularly with regard to the usage of previously accumulated experiences, skills or ability. Again, SOC(HE) 2010_GH performs best.

Table 6: Skills-Usage Penalty for Mismatched Graduates, by Classification.

	Freq. of Graduates	Major Groups 1&2	SOC(HE) 2010_EP	SOC(HE) 2010_GH1
Total Sample	Opportunity to use knowledge and skills (disagree, strongly disagree)			
Coef.	0.10	0.10	0.10	0.11
S.E.	(0.03)	(0.02)	(0.02)	(0.03)
R^2 (N=1,283)	2.6	2.8	2.8	3.0
Risk Zone				
Coef.	-0.02	0.01	0.01	0.02
S.E.	(0.04)	(0.04)	(0.04)	(0.04)
R^2 (N=538)	0.1	0.0	0.0	0.1
Total Sample	How much of past experiences/skills/ability can be used (Very little, a little)			
Coef.	0.18	0.13	0.11	0.19
S.E.	(0.03)	(0.03)	(0.03)	(0.03)
R^2 (N=1,283)	8.9	7.1	6.0	9.9
Risk Zone				
Coef.	0.16	0.05	-0.02	0.18
S.E.	(0.06)	(0.05)	(0.04)	(0.05)
R^2 (N=538)	5.7	3.0	2.7	7.0

Estimated coefficient from linear probability models using calibrated survey weights with age, age squared and a gender dummy as control variables. Asymptotically robust standard errors in parentheses.
Source: SES 2012

Finally, we explore across classifications the outcome of the matching process. We calculate the percentage of matched graduates and non-graduate workers in the employed labour force. If there is a matching process between job demands and workers' human capital, we expect that a large fraction of workers is employed in an occupation which matches his or her skills and knowledge level. By construction, there will be a trade-off between the derived matching successes of graduates and non-graduates. For instance, if we were to classify all occupations as graduate jobs, all degree holders would be "properly" matched, but the whole non-graduate workforce would be classified as undereducated and vice versa. Classification success is therefore represented, here, by the extent of matching in the whole sample.

Table 7 presents the matching extent for all workers and for graduates and non-graduates separately, according to each of the classification methods. (The naïve classification based on the frequency of graduates is not considered in this comparison since its construction is based on this information). SOC(HE) 2010_GH shows a larger fraction of skill matches in the labour force than SOC(HE) 2010_EP, particular among graduates. Thus, the SOC(HE) 2010_EP classifier implies that 39% (=100%-61%) of graduate workers were mismatched in 2012, and 37% in 2013. By contrast SOC(HE) 2010_GH shows somewhat lower proportions at 32% and 31% respectively. In Appendix A2 we list the top examples of where overeducated graduates work: half are clustered in just 23 occupations, with the largest share working as sales and retail assistants.

The figures also show (as in the literature) that it is easier to define non-graduate jobs. That is, with all classifiers over-education among graduates is a lot more common than under-education among non-degree holders.

Table 7: Skills Matching by Classification Method (% of workers)

	Major Groups 1&2	SOC(HE) 2010_EP	SOC(HE) 2010_GH
SES 2012			
Non-Graduates	87.3	83.4	82.6
Graduates	53.3	61.4	67.9
ALL	72.6	73.9	76.2
QLFS 2013			
Non-Graduates	85.9	82.1	80.7
Graduates	54.0	63.4	69.0
ALL	72.6	74.1	75.7

Source: SES 2012, QLFS Q(1)2013-Q(4)2013

In a nutshell, our classification method meets multiple validation criteria well, either better than or the same as SOC(HE) 2010_EP, whether for the whole sample or confined to what we have called the "risk zone". Although our classification method starts from the same concept and principles as SOC(HE) 2010_EP, it is distinguished by using job-holders reports incorporating task-based measures of skills utilisation and by deploying formal statistical classification methods, which support the purely binary partitioning of jobs into a group of graduate and non-graduate jobs.

One final point worth noting is that with our data the cluster analysis did not give rise to a solution with multiple types of graduate jobs as in SOC(HE) 2010_EP. One can sensibly reduce the types of high-level skills used by graduates into a small set, including high-level communication skills, analytical expertise and managerial expertise, which are similar to the skill-types discussed by Elias and Purcell (2013). Nevertheless, we found that graduate jobs used these skills in varied mixes, but that it was not possible to statistically cluster graduate jobs into ones that predominantly used only one of these.

How sensitive is the classifier to our choice of statistical procedure for the classification? We describe and operationalise two alternative procedures in the Appendix using the same data. We find that in each case the above conclusion remains valid. Overall, SOC(HE) 2010_GH appears to capture well the graduate/non-graduate differences in skills utilisation and wages.

6. The growth of graduate jobs in Britain

Among the advantages of our statistical classifiers is its easy application to different time periods given available data on skills requirements. To analyse longitudinal trends in the British graduate labour market, we use our methodology to identify the changing pattern of graduate occupations. The Skills and Employment Survey waves 1997, 2001, 2006 and 2012 provide the necessary data to identify graduate jobs and to explore trends in employment and pay in the employed labour force. Jobs are grouped into occupations using the older Standard Occupational Classification from 2000. To classify graduate jobs, we pool waves 1997 and 2001 to make one period, and 2006 and 2012 for another period.

Underpinning this analysis is an implicit dynamic model of supply and demand in the graduate and non-graduate labour markets, with persistent imperfect matching. This model provides the framework for the description of the market, but we are not offering explanations for the observed trends. Any such explanations, which would typically be couched in terms of skill-biased technical change and other social forces leading to increased demand and the changing incentives to acquire a degree, are beyond the scope of this paper.

The exploration of labour market trends follows this pattern. First, we derive classifications of graduate jobs as discussed in section 4. A comparison between the two time periods allows us to identify ‘new’ graduate occupations: occupations which were classified as graduate in the later but not in the earlier period. We test whether this change is associated with upskilling on the job as reported by incumbent workers. Next, we apply our classifier to explore the changes in the demand and supply of graduate labour between 1997/2001 and 2006/2012 in Britain. A decomposition of the growing employment in graduate jobs sheds light on the drivers of change, whether it is mainly the occupational upskilling or the employment expansion in existing graduate jobs which contribute to the expansion of graduate jobs. Finally, we describe the changing wage differentials between matched and mismatched graduates and non-graduates differentiated by demographic groups over time.

Validating the Classification of Graduate Jobs over time

The number of graduates and jobs' skills intensity have increased in the British labour market (Felstead et al. 2013). The development is often correlated with Britain's transition into a knowledge-based economy. Our classification can track the rising skills requirement by identifying 'new graduate jobs'. These are jobs whose educational requirements have increased according to our classifiers. Examples of new graduate jobs are quality assurance managers and farm managers. Table A4 in the Appendix lists the unit groups classified as new graduate jobs.

The change in the educational requirements should be associated with an intensified skills usage. This hypothesis opens another possibility to validate our classification. Workers in the SES are asked whether the level of skill use has increased over time on their current job.[6] We regress this information on a set of dummies for non-graduate, graduate jobs with new graduate jobs as reference category and age, age squared and a gender dummy as control variables for the years 2006. The regression is run for observations in the risk zone, that is major groups 1, 3 and 4, only. Furthermore, if there is non-random matching between job-specific educational demands and education level of workers in the labour market, we expect to see a larger proportion of graduates in new graduate jobs than in non-graduates jobs. Again, we use a simple regression model to estimate the differences in the proportion of graduate workers by occupational categories and test of their statistical significance.

Table 8 displays the result. Workers in non-graduate jobs are less likely to report skills intensification compared with respondent in graduate and new graduate jobs (column 2). There is no significant difference in the reported skills intensification between the latter two. In other words, skills dynamics in both categories of graduate occupations within the risk zone were both similar to each other and clearly distinct from non-graduate jobs. Similarly, we observe a significantly lower proportion of graduate workers in the employed workforce of non-graduate jobs than new graduate jobs (by 19 percentage points).

[6] This item is only asked of those who had been in employment 3 or more years ago, and we restrict the analysis to those who remained in the same job.

Table 8: Skills Intensification and educational matches across Occupational Groups in the Risk Zone

	(1) Skills Intensification	(2) Fraction graduates
Non-Graduate Jobs	-0.140**	-0.189***
	(0.052)	(0.036)
Existing Graduate Jobs	-0.035	0.110**
	(0.051)	(0.036)
New Graduate Jobs	Ref.	Ref.
Constant	1.540***	0.526***
	(0.289)	(0.033)
Age, Age2, gender	X	
Observations	1465	4003
R^2	5.0	8.2

Estimated coefficient from linear probability models using calibrated survey weights. Model (1) included age, age squared and a female dummy as control variables. Standard errors in parentheses. Source: SES 2006/2012. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Employment Trends in the British Graduate Labour Market

Based on our classification of graduate jobs, how has the British graduate labour market developed between 1997/2001 and 2006/2012? Since we are interested in the labour market outcomes of graduates, we confine the analysis to the age range 25 – 60 years. The upper age limit of 60 years is determined by the SES data; it also helps to minimise any bias due to education-specific transition patterns into retirement.

We found that the number of graduate occupations has increased only slightly over time from about 37% to roughly 40% of all SOC2000 unit groups between1997/2001 and 2006/12. However, as shown in Table 9, the UK has witnessed a marked expansion of graduate employment across all demographic groups since the end of the 1990s. In 2006/2012 40% of the employed labour force was active in graduate jobs up from 32% in the period 1997/2001. The growth in the share of graduate jobs was particularly pronounced in the group of workers aged between 25 to 39 years and in the female labour force.

Not only employment in graduate jobs, but also the fraction of degree holders in the labour force has risen (columns 4 and 5 in Table 9). Overall, the proportion has increased by more than 10 percentage points since 1997/2001, from 31% to 42%. The changes were again most pronounced among employed women and in the age-group 25-39 years. By 2006/2012 almost half (47%) of the employed younger labour force had a degree or an equivalent level of educational attainment.

Despite the rapid diffusion of graduates through the labour force, the proportion of mismatched graduates in the labour market has remained stable at about 30% over time. The small difference between both periods is statistically insignificant. This finding is somewhat at odds with earlier results which had reported overeducation among British graduates to have increased steadily between 1986 and 2006 (Green, 2013). Nevertheless (Felstead et al. 2013) reported that graduate overeducation became less prevalent between 2006 and 2012, partly cancelling out the earlier increases. The difference is also partly due to different age spans and to different definitions of over-education. The earlier finding, as with much of the over-education literature, relies on a single measure of workers' judgement on the educational requirements of the current job. We included this information in the construction of SOC(HE) 2010_GH, but additionally incorporated several measures of high skills intensity.

Not only has over-education remained stable in the employed workforce as a whole, but it also has not changed significantly within demographic subgroups. However, our figures suggest that the over-education figures appear to converge between age-groups. In the end of the 1990s/ beginning of 2000 over-education was more common in the age bracket 25-29 years than among older workers. This difference has vanished by 2006/2012. Gender differences in the prevalence of over-education are not statistically significant in either period.

Table 9: Trends in the Graduate Labour Market between 1997/2001 and 2006/2012 by Gender and Age (in %)

	employed in graduate jobs		**graduates in employed labour force**		**graduates in non-graduate jobs**	
	97/01	06/12	97/01	06/12	97/01	06/12
Men	34.4	40.5	32.0%	40.5%	31.5%	31.9%
	(0.903)	(0.922)	0.893	0.934	1.610	1.458
Women	28.9	39.7	29.0%	42.0%	27.6%	28.9%
	(0.908)	(0.927)	0.920	0.934	1.779	1.345
Age 25-39	30.9	41.0	31.5%	47.3%	33.0%	31.8%
	(0.920)	(1.064)	0.952	1.082	1.818	1.510
Age 40-60	32.8	39.5	29.9%	36.7%	26.8%	29.3%
	(0.898)	(0.824)	0.869	0.818	1.545	1.320
Total	31.9	40.1	30.6%	41.2%	29.8%	30.5%
	(0.644)	(0.655)	0.642	0.663	1.195	0.999

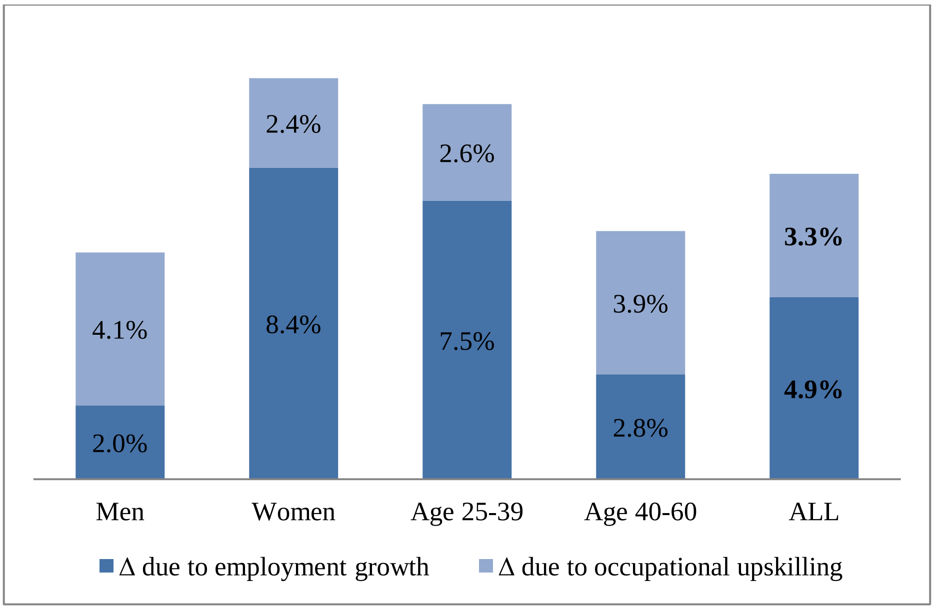
Population averages. Standard errors in parentheses.
Source: SES 1997 – 2012

Decomposition of the Growth in Graduate Employment

The growth in graduate employment between the two periods is potentially fuelled by two sources. First, there is the employment expansion in core graduate jobs – those occupations that were and have remained graduate level occupations. Second, graduate employment has grown as the result of occupational upskilling – an increasing number of occupations require graduate skills. The first component is derived by projecting the old classification of graduate jobs from 1997/2001 onto employment data in the period 2006/2012. This standardisation captures the counterfactual rise in graduate employment if the distribution of graduate occupations had remained stable over both periods. The contribution of changes in graduate occupations is derived by calculating the net percentage of the employed labour force in new graduate occupations in 2006/2012. The net percentage totals the increase in graduate employment from up-skilling minus the loss in graduate employment due to occupational down-skilling.

The outcome of this exact decomposition is shown in Figure 2. Growth in total employment in graduate occupations can be attributed to 60% (=100*4.9/8.2) to expanding employment in the core graduate jobs and to 40% to the increasing number of graduate occupations over time (Figure 2). However, the picture differs for demographic groups. Growing employment in graduate jobs for women is driven foremost by employment expansion in core graduate jobs, whereas men benefit more strongly from up-skilling. Similarly by age-group, the growing employment in graduate jobs amongst 25 to 39 year olds can be largely attributed to gains in existing graduate occupations, whereas up-skilling is the main driver of the observed employment growth at ages 40 and above. The finding suggests that 'new' graduate jobs are neither specifically female nor young. Up-skilling has taken place within established occupations with a predominantly male workforce.

Figure 2: Decomposing the Growing Share of Graduate Jobs



Note: This is an exact decomposition into a component due to the expansion of existing graduate occupations and a component arising from up-skilling within occupations (Source: SES 1997 – 2012)

The Changing Wage Differentials of Matched and Mismatched Workers

Inequality in wages has seen a rapid increase in the UK and other OECD countries over the last decades (van Reenen 2011). To explore the dynamics in labour income over educational attainment and job match quality, we run Mincer type wage regression of log hourly pay on categories of educational mismatch by workers' educational attainment and a set of common control variables (age, gender). We distinguish between four types of labour; matched and mismatched non-graduates and graduate workers, respectively. Changes within demographic groups over time are captured by interaction terms between the types of labour and dummy variables for women and the age-group 25-39 years. The reference labour category is matched non-graduate workers. Table 10 summarises the estimated mean differences in pay by type of labour within demographic groups over time.

Compared with matched non-graduates, matched graduates have received a substantial wage premium on the average, which for men has risen over time from 0.638 to 0.711 log points (from 89% to 104%). The wage premium of overeducated graduates is significantly bigger than zero but below the figure of properly matched graduates. Undereducated non-graduates receive higher wages on the average than matched workers with the same level of education, but lower wages than matched graduate workers.

The prevalence of over-education might not have changed by much, but the wage differences between mismatched and matched graduates have become more marked. Compared with 1997/2011, matched graduates have enjoyed an increase in average wages relative to matched non-graduates (from 0.384 to 0.513 log points, or 47% to 67%), whereas mismatched graduates have experienced declining wages relative to matched non-graduates. The pattern is consistent across all investigated demographic groups of the employed labour force. Returns to college education, once a degree holder secures a graduate job, have improved relative to the other types of labour – even in comparison to under-educated workers in graduate jobs. There is no trend of growing wage differentials between matched and mismatched non-graduates.

There is a trend of converging wage differentials across gender over time, but due to different dynamics. The differences in the averages wages by type of labour across gender have vanished between 1997/2001 and 2006/2012. But unlike for men, the income position of matched female graduates has not improved compared with matched female non-graduate workers. It was high and remained high. Instead, the initially relatively high pay premium of mismatched female graduates over matched non-graduates has dropped in the second period. By contrast, the growing wage dispersion among male graduate workers is more driven by an improvement in the relative pay of matched graduates. Overall, the wage dispersion among college educated women has been higher than for men. Though still significant, the gender pay gap has declined. In contrast to the wage distribution over degree holders, the differentials in pay between matched and mismatched non-graduates have remained stable (male workforce) or have become more compressed (female workforce).

Wages of graduates in the age bracket 25-39 years were more compressed, but have become increasingly unequal. Over time, the average wage difference between employed graduates under 40 has been getting closer to the levels computed for the older fraction of the work force. Similar to the trends discussed for women, the growing dispersion among younger graduate workers is mostly the result of a drop in the average wage premium of mismatched over matched workers and not due to a relative improvement of matched graduates. In the top half of the age distribution there is both an improvement at the top of the wage distribution but also a relative decline of the average pay of mismatched graduate workers. Among non-graduate workers the estimates suggest a slight trend of wage compression over time for other age-groups.

Table 10: The Returns to Education across Demographic Groups by Matching Status

		97/01		06/12	
	Type of Labour	Marginal Effects	SE	Marginal Effects	SE
Men	Matched Graduates	0.638	(0.026)	0.711	(0.031)
	Mismatched Graduates (Over-educated)	0.270	(0.037)	0.211	(0.039)
	Mismatched Non-Graduates (Under-educated)	0.457	(0.032)	0.428	(0.038)
	Matched Non-Graduates	Ref.		Ref.	
Women	Matched Graduates	0.741	(0.021)	0.741	(0.019)
	Mismatched Graduates (Over-educated)	0.338	(0.035)	0.216	(0.025)
	Mismatched Non-Graduates (Under-educated)	0.569	(0.042)	0.480	(0.033)
	Matched Non-Graduates	Ref.		Ref.	
Age 25-39	Matched Graduates	0.663	(0.023)	0.691	(0.027)
	Mismatched Graduates (Over-educated)	0.331	(0.033)	0.215	(0.031)
	Mismatched Non-Graduates (Under-educated)	0.443	(0.036)	0.433	(0.042)
	Matched Non-Graduates	Ref.		Ref.	
Age 40-60	Matched Graduates	0.705	(0.025)	0.754	(0.025)
	Mismatched Graduates (Over-educated)	0.262	(0.043)	0.206	(0.038)
	Mismatched Non-Graduates (Under-educated)	0.554	(0.035)	0.460	(0.032)
	Matched Non-Graduates	Ref.		Ref.	
ALL	Matched Graduates	0.685	(0.017)	0.726	(0.018)
	Mismatched Graduates (Over-educated)	0.301	(0.026)	0.213	(0.024)
	Mismatched Non-Graduates (Under-educated)	0.501	(0.026)	0.450	(0.026)
	Matched Non-Graduates	Ref.		Ref.	

Results from Mincer type wage regression of log hourly earnings on age, age squared, female dummy, mismatch categories by educational attainment and interaction terms between mismatch categories and demographic characteristics. OLS using calibrated survey weights. Standard errors in parentheses. Table displays marginal effects only.

7. Conclusions.

In this paper we have developed a new indicator for identifying graduate jobs, using representative survey data on skills utilisation, and applying statistical methods for the classification. We argue that, like SOC(HE) 2010_EP, SOC(HE) 2010_GH is conceptually valid because it is derived from skills use indicators. We present validation tests suggesting that the statistically-derived indicator derived from this information is better than SOC(HE)

2010_EP, and much better than naive classifiers, for explaining three expected outcomes, namely wages, the opportunity for graduates to use their skills in their jobs, and the matching of graduates and non-graduates to appropriate jobs.

We also maintain that it has advantages over SOC(HE) 2010_EP, in that it is transparent and replicable, requires no expert judgements, and is flexible enough to allow for occupations to switch categories over time as they are upskilled (or downskilled). The method can also be applied and adapted to other data sets where skills requirement information is available, and in further work we intend to develop a suitable cross-national indicator. The main requirement for deriving an indicator using such statistical methods is a sufficiently large data set with information on skills utilisation. The SES series, after pooling waves, provides sufficient sample size for most purposes; nevertheless, special provision had to be made here for sparsely populated unit groups. In coming years, to continually track the progress of graduate jobs, the SES series will need to be updated with sufficient sample, or else a special module could be inserted in a large existing survey such as the Quarterly Labour Force Survey.

Using our new indicator we then analysed the way the British graduate labour market has developed between 1997/2001 and 2006/2012, utilising only those workers aged over 25. Almost all of these would have entered the labour market before the economic recession of 2008. There are several findings, of which these are the headlines:

i. There has been a very substantial growth, from 32% to 40%, in the share of graduate jobs. Overall, employment growth in existing graduate occupations and upskilling contribute roughly 60:40 to graduate employment growth, but the drivers differ by socio-economic group. Among women and in the age-group 25-39 years, employment growth is more important than upskilling. By contrast, upskilling is the main driver for the male labour force.

ii. While there has also been a growth in the supply of graduates, from 31% to 42% of the labour force, the overall prevalence of overeducated graduates has been stable at around 30%. In particular the massive influx of graduates into the labour force in the age bracket 25 – 39 years has been absorbed, with no increase in overeducation.

iii. As in the literature, overeducated graduates receive on average lower wages compared with matched graduates, but higher wages than workers with an adequate level of education. Further, undereducated non-graduates receive higher pay than matched non-graduates, but less than matched graduates.

iv. For men the wage premium for matched graduates relative to matched non-graduates has increased over time, from 89% to 104%, while for women it has remained stable at 110%. Given the increase in the supplies of graduates, this finding is consistent with the view that the demand for high-level skills has risen.

v. The wage gap between matched and mismatched graduates is increasing over time from 47% to 67%, thus providing further evidence covering up to 2012 that there is an increasing dispersion in the returns to graduate education. In contrast, the wage gap between matched and mismatched non-graduates has remained stable or even declined in some groups of workers.

These findings are informative in themselves. They also provide a further demonstration of the potential utility of a statistically-based indicator of graduate jobs for future analyses of the graduate labour market in the period of recovery from economic crisis.

References

Ashton, D. and Felstead, A. (1998) *Organisational Characteristics and Skill Formation in Britain: Is There A Link*?, Working Paper 22, Centre for Labour Market Studies, Leicester University

Autor, D. H. and Handel, M.J. (2013) 'Putting Tasks to the Test: Human Capital, Job Tasks, and Wages', *Journal of Labor Economics* , 31(2): S59-S96

Autor, D. H., Levy, F.and Murnane, R.J. (2003) 'The skill content of recent technological change: An empirical exploration' *Quarterly Journal of Economics*, 118(4): 1279-1333

Baert, S., Cockx, B. and Verhaest, D. (2013) 'Overeducation at the start of the career: Stepping stone or trap?', *Labour Economics* ,25: 123-140

Chevalier, A., Harmon, C. Walker, I. and Zhu, Y. (2004) 'Does education raise productivity, or just reflect it?' *Economic Journal* 114(499): F499-F517

Chevalier, A. and Lindley, J. (2009) 'Overeducation and the skills of UK graduates', *Journal of the Royal Statistical Societ: Series a - Statistics in Society*, 172: 307-337

Elias, P. and McKnight, A. (2001) 'Skill measurement in official statistics: recent developments in the UK and the rest of Europe', *Oxford Economic Papers*, 53(3): 508-540

Elias, P. and Purcell, K. (2004a) 'Is mass higher education working? Evidence from the labour market experiences of recent graduates', *National Institute Economic Review* (190): 60-74

Elias, P. and Purcell, K. (2004b) 'SOC (HE): a classification of occupations for studying the graduate labour market.' Employment Studies Research Unit and Warwick Institute of Employment Research, *Research Graduate Careers Seven Years On, Research Paper* (6)

Elias, P. and Purcell, K (2013) 'Classifying graduate occupations for the knowledge society' *Futuretrack. Working Paper (5)*, 1-37

Everitt, B. S., Landau, S. and Leese, M. (2001) *Cluster Analysis*. London, UK: Arnold

Felstead, A., Gallie, D. and Green, F. (2002) *Work Skills In Britain 1986-2001*. Nottingham: DfES Publications

Felstead, A., Gallie, D., Green, F. and Inanc, H. (2013) *Skills at Work in Britain: First Findings from the Skills and Employment Survey 2012*. London: LLAKES Centre

Felstead, A., Gallie, D., Green, F. and Zhou, Y. (2007). *Skills At Work, 1986 to 2006*. Oxford: University of Oxford, SKOPE

Felstead, A. and Green, F. (2008) *Skills at Work in Scotland, 1997 to 2006*. Glasgow: Scottish Enterprise

Felstead, A. and Green, F. (2013) *Underutilization, Overqualification and Skills Mismatch*. Glasgow: Skills in Focus, Skills Development Scotland

Figueiredo, H., Teixeira, P. and Rubery, J. (2011) *Is Mass Higher Education Working? An Update and a Reflection on the Sustainability of Higher Education Expansion in Portugal.* ALMALAUEA Working Papers, 14

Gathmann, C. and Schönberg, U. (2010) 'How General Is Human Capital? A Task-Based Approach', *Journal of Labor Economics*, 28(1): 1-49

Gottschalk, P. and Hansen, M. (2003) 'Is the proportion of college workers in noncollege jobs increasing?', *Journal of Labor Economics*, 21(2): 449-471

Green, F. (2012) 'Employee Involvement, Technology and Evolution in Job Skills: A Task-Based Analysis', *Industrial & Labor Relations Review*, 65(1): 35-66

Green, F., Felstead, A. and Gallie, D. (2003) 'Computers and the changing skill-intensity of jobs', *Applied Economics*, 35(14): 1561-1576

Green, F. and James, D. (2003) 'Assessing skills and autonomy: the job holder versus the line manager', *Human Resource Management Journal*, 13(1): 63-77

Green, F. and Zhu, Y. (2010) 'Overqualification, Job Dissatisfaction, and Increasing Dispersion in the Returns to Graduate Education', *Oxford Economic Papers*, 62(2): 740-763

Haskel, J. and Heden, Y. (1999) 'Computers and the Demand for Skilled Labour: Industry- and Establishment-level Panel Evidence for the UK' *Economic Journal*, 109 (March): C68-C79

Jürges, H. (2007) 'True health vs response styles: exploring cross-country differences in self-reported health', *Health Economics*, 16(2): 163-178

Little, B., Braun, E. and Tang, W. (2008) *Competences possessed and required by European graduates*. London: Centre for Higher Education Research and Information, The Open University

Machin, S. and McNally, S., (2007) 'Tertiary education systems and labour markets', *Tertiary Review*, 1-57

Macmillian, L. and Vignoles, A. (2013) *Mapping the occupational destinations of new graduates.* Centre for Analysis of Youth Transitions

Makles, A. (2012) 'Stata tip 110: How to get the optimal k-means cluster solution', *Stata Journal*, 12(2), 347-351

Mason, G., Williams, G. and Cranmer, S. (2009) 'Employability skills initiatives in higher education: what effects do they have on graduate labour market outcomes?', *Education Economics*, 17(1): 1-30

Mathiowetz, N. A. (1992) 'Errors in Reports of Occupation', *Public Opinion Quarterly*, 56(3): 352-355

Milburn, A. (2009) *Unleashing Aspiration: The Final Report of the Panel on Fair Access to the Professions*. London, UK: Cabinet Office

OECD (2013) *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills.* OECD Publishing

ONS (2010) *SOC2010: Volume 1 Structure and Descriptions of Unit Groups*.

Smetherham, C. (2006) 'Firsts among equals? Evidence on the contemporary relationship between educational credentials and the occupational structure', *Journal of Education and Work* 19(1): 29-45

Sullivan, P. (2009) 'Estimation of an Occupational Choice Model when Occupations are Misclassified', *Journal of Human Resources*, 44(2): 495-535

Van Reenen, J. (2011) 'Wage inequality, technology and trade: 21st century evidence', *Labour Economics*, 18(6): 730-741

Verdugo, R. R. and Verdugo, N.T. (1989) 'The Impact of Surplus Schooling on Earnings - Some Additional Findings', *Journal of Human Resources*, 24(4): 629-643

Wilton, N. (2012) 'The impact of work placements on skills development and career outcomes for business and management graduates', *Studies in Higher Education*, 37(5): 603-620

Appendix

Alternative classifiers

The main text presented our method for deriving a graduate job classifier starting from individual-level data on skills utilisation. Alternative ways for classifying are, however, available. Here we present two which we have tested extensively alongside SOC(HE) 2010_GH.

1. Principal component analysis is quite commonly used, and has been used in the economic literature to aggregate job characteristics into indices of task demands (Autor and Handel 2013). We computed the first principal component of several high skills requirements indicators to generate a single index of high skills requirements. More formerly,

$$PC_1 = \alpha_{11}D_i + \alpha_{12}DN_i + \alpha_{13}HS_i + \alpha_{14}CS_i + \alpha_{15}LT_i,$$

where α_{1n} $(n = 1\ to\ 5)$ represents the unknown weight of each variablein the 1st principal component. The first component explains 46% of the variation in the SES data. The remaining classification steps follow the outlined procedure in the main text. We term this classification SOC(HE)_GH2.

2. Alternatively, we reverse the first two steps and conduct cluster analyses. We first compute unit-group averages for each of the ten skills indicators (breaking up the skills intensity score into its single components). This approach lets us explore the potential for different types of graduate jobs. We use agglomerative hierarchical clustering (median linkage, weighted average linkage) and k-medians to partition jobs into groups of similar occupations. All methods point to a two cluster solution (non-graduate versus graduate jobs) based on Calinski-Harabasz pseudo F and the visual inspection of the change in the within cluster sum of squares (Everitt, Landau et al. 2001, Makles 2012). Given the two cluster solution, k-medians clustering gives the lowest within -cluster sum of squares. The resulting classification is termed SOC(HE)_GH3.

SOC(HE)_GH2 and SOC(HE)_GH3 each generate similar distributions of graduate jobs across major groups to that of SOC(HE)_GH (Table 11). In terms of the validation outcomes, these alternative classification fare only slightly worse than our selected classifier SOC(HE)_GH.

Table 11: Distribution of graduate jobs in Major Groups 1 to 4, using alternative statistical classifiers.

Major Group	SOC(HE) 2010_ GH	SOC(HE) 2010_ GH2	SOC(HE) 2010_ GH3
Managers, directors and senior officials	69.4	69.4	66.7
Professional occupations	100.0	100.0	98.6
Associate professional and technical occupations	86.4	83.3	71.2
Administrative and secretarial occupations	0.0	4.0	4.0
All other occupations	0.0	0.0	0.0
Total	41.4	41.1	38.4

Source: SES 2006/2012

List of Graduate, Non-graduate and New Graduate Jobs

Table 12: List of Graduate and Non-Graduate SOC2010 Unit Groups in Major Groups 1 to 4

Unit Group	Occupational Title	High Skills Requirement Score	SOC2010(HE)_GH
1115	Chief executives and senior officials	0.682	Graduate
1116	Elected officers and representatives	0.682	Graduate
1121	Production managers and directors in manufacturing	0.395	Graduate
1122	Production managers and directors in construction	0.404	Graduate
1123	Production managers and directors in mining and energy	0.400	Graduate
1131	Financial managers and directors	0.632	Graduate
1132	Marketing and sales directors	0.612	Graduate
1133	Purchasing managers and directors	0.609	Graduate
1134	Advertising and public relations directors	0.627	Graduate
1135	Human resource managers and directors	0.617	Graduate
1136	Information technology and telecommunications directors	0.695	Graduate
1139	Functional managers and directors n.e.c.	0.638	Graduate
1150	Financial institution managers and directors	0.500	Graduate
1161	Managers and directors in transport and distribution	0.252 *	Non-Graduate
1162	Managers and directors in storage and warehousing	0.265 *	Non-Graduate
1171	Officers in armed forces	0.478	Graduate
1172	Senior police officers	0.477	Graduate
1173	Senior officers in fire, ambulance, prison and related services	0.472	Graduate
1181	Health services and public health managers and directors	0.793	Graduate
1184	Social services managers and directors	0.793	Graduate
1190	Managers and directors in retail and wholesale	0.120	Non-

			Graduate
1211	Managers and proprietors in agriculture and horticulture	0.434	Graduate
1213	Managers and proprietors in forestry, fishing and related services	0.375	Graduate
1221	Hotel and accommodation managers and proprietors	0.137	Non-Graduate
1223	Restaurant and catering establishment managers and proprietors	0.158	Non-Graduate
1224	Publicans and managers of licensed premises	0.106	Non-Graduate
1225	Leisure and sports managers	0.150	Non-Graduate
1226	Travel agency managers and	0.140	Non-Graduate
1241	Health care practice managers	0.578	Graduate
1242	Residential, day and domiciliary care managers and proprietors	0.571	Graduate
1251	Property, housing and estate managers	0.280 *	Graduate
1252	Garage managers and proprietors	0.315 *	Graduate
1253	Hairdressing and beauty salon managers and proprietors	0.263 *	Non-Graduate
1254	Shopkeepers and proprietors – wholesale and retail	0.247 *	Non-Graduate
1255	Waste disposal and environmental services managers	0.272 *	Non-Graduate
1259	Managers and proprietors in other services n.e.c.	0.309 *	Graduate
2111	Chemical scientists	0.859	Graduate
2112	Biological scientists and biochemists	0.865	Graduate
2113	Physical scientists	0.859	Graduate
2114	Social and humanities scientists	0.799	Graduate
2119	Natural and social science professionals n.e.c.	0.890	Graduate
2121	Civil engineers	0.653	Graduate
2122	Mechanical engineers	0.681	Graduate
2123	Electrical engineers	0.674	Graduate
2124	Electronics engineers	0.670	Graduate
2126	Design and development engineers	0.677	Graduate
2127	Production and process engineers	0.670	Graduate
2129	Engineering professionals n.e.c.	0.670	Graduate
2133	IT specialist managers	0.532	Graduate
2134	IT project and programme managers	0.515	Graduate
2135	IT business analysts, architects and systems designers	0.547	Graduate
2136	Programmers and software development professionals	0.536	Graduate
2137	Web design and development professionals	0.534	Graduate
2139	Information technology and telecommunications professionals n.e.c.	0.540	Graduate
2141	Conservation professionals	0.904	Graduate
2142	Environment professionals	0.904	Graduate
2150	Research and development managers	0.825	Graduate
2211	Medical practitioners	0.839	Graduate
2212	Psychologists	0.815	Graduate
2213	Pharmacists	0.797	Graduate
2214	Ophthalmic opticians	0.745	Graduate
2215	Dental practitioners	0.812	Graduate
2216	Veterinarians	0.802	Graduate

2217	Medical radiographers	0.815	Graduate
2218	Podiatrists	0.781	Graduate
2219	Health professionals n.e.c.	0.817	Graduate
2221	Physiotherapists	0.652	Graduate
2222	Occupational therapists	0.634	Graduate
2223	Speech and language therapists	0.662	Graduate
2229	Therapy professionals n.e.c.	0.647	Graduate
2231	Nurses	0.654	Graduate
2232	Midwives	0.672	Graduate
2311	Higher education teaching professionals	0.831	Graduate
2312	Further education teaching professionals	0.798	Graduate
2314	Secondary education teaching professionals	0.796	Graduate
2315	Primary and nursery education teaching professionals	0.793	Graduate
2316	Special needs education teaching professionals	0.779	Graduate
2317	Senior professionals of educational establishments	0.805	Graduate
2318	Education advisers and school inspectors	0.785	Graduate
2319	Teaching and other educational professionals n.e.c.	0.755	Graduate
2412	Barristers and judges	0.681	Graduate
2413	Solicitors	0.668	Graduate
2419	Legal professionals n.e.c.	0.701	Graduate
2421	Chartered and certified accountants	0.744	Graduate
2423	Management consultants and business analysts	0.742	Graduate
2424	Business and financial project management professionals	0.792	Graduate
2425	Actuaries, economists and statisticians	0.799	Graduate
2426	Business and related research professionals	0.757	Graduate
2429	Business, research and administrative professionals n.e.c.	0.746	Graduate
2431	Architects	0.652	Graduate
2432	Town planning officers	0.640	Graduate
2433	Quantity surveyors	0.547	Graduate
2434	Chartered surveyors	0.615	Graduate
2435	Chartered architectural technologists	0.617	Graduate
2436	Construction project managers and related professionals	0.617	Graduate
2442	Social workers	0.752	Graduate
2443	Probation officers	0.742	Graduate
2444	Clergy	0.739	Graduate
2449	Welfare professionals n.e.c.	0.742	Graduate
2451	Librarians	0.383	Graduate
2452	Archivists and curators	0.384	Graduate
2461	Quality control and planning engineers	0.736	Graduate
2462	Quality assurance and regulatory professionals	0.736	Graduate
2463	Environmental health professionals	0.736	Graduate
2471	Journalists, newspaper and periodical editors	0.467	Graduate
2472	Public relations professionals	0.463	Graduate
2473	Advertising accounts managers and creative directors	0.459	Graduate
3111	Laboratory technicians	0.406	Graduate
3112	Electrical and electronics technicians	0.405	Graduate
3113	Engineering technicians	0.428	Graduate
3114	Building and civil engineering technicians	0.425	Graduate
3115	Quality assurance technicians	0.414	Graduate
3116	Planning, process and production technicians	0.405	Graduate

3119	Science, engineering and production technicians n.e.c.	0.357	Graduate
3121	Architectural and town planning technicians	0.682	Graduate
3122	Draughtspersons	0.685	Graduate
3131	IT operations technicians	0.343	Graduate
3132	IT user support technicians	0.305 *	Graduate
3213	Paramedics	0.327	Graduate
3216	Dispensing opticians	0.323 *	Graduate
3217	Pharmaceutical technicians	0.323 *	Graduate
3218	Medical and dental technicians	0.325	Graduate
3219	Health associate professionals n.e.c.	0.323 *	Graduate
3231	Youth and community workers	0.325	Graduate
3233	Child and early years officers	0.294 *	Graduate
3234	Housing officers	0.298 *	Graduate
3235	Counsellors	0.294 *	Graduate
3239	Welfare and housing associate professionals n.e.c.	0.285 *	Graduate
3311	NCOs and other ranks	0.186	Non-Graduate
3312	Police officers (sergeant and below)	0.211	Non-Graduate
3313	Fire service officers (watch manager and below)	0.172	Non-Graduate
3314	Prison service officers (below principal officer)	0.141	Non-Graduate
3315	Police community support officers	0.179	Non-Graduate
3319	Protective service associate professionals n.e.c.	0.185	Non-Graduate
3411	Artists	0.297 *	Graduate
3412	Authors, writers and translators	0.313 *	Graduate
3413	Actors, entertainers and	0.267 *	Non-Graduate
3414	Dancers and choreographers	0.305 *	Graduate
3415	Musicians	0.293 *	Graduate
3416	Arts officers, producers and directors	0.311 *	Graduate
3417	Photographers, audio-visual and broadcasting equipment operators	0.327	Graduate
3421	Graphic designers	0.363	Graduate
3422	Product, clothing and related designers	0.348	Graduate
3441	Sports players	0.285 *	Graduate
3442	Sports coaches, instructors and officials	0.292 *	Graduate
3443	Fitness instructors	0.273 *	Non-Graduate
3511	Air traffic controllers	0.301 *	Graduate
3512	Aircraft pilots and flight engineers	0.347	Graduate
3513	Ship and hovercraft officers	0.244 *	Non-Graduate
3520	Legal associate professionals	0.539	Graduate
3531	Estimators, valuers and assessors	0.455	Graduate
3532	Brokers	0.494	Graduate
3533	Insurance underwriters	0.453	Graduate
3534	Finance and investment analysts and advisers	0.495	Graduate
3535	Taxation experts	0.554	Graduate
3536	Importers and exporters	0.495	Graduate
3537	Financial and accounting technicians	0.551	Graduate

3538	Financial accounts managers	0.500	Graduate
3539	Business and related associate professionals n.e.c.	0.495	Graduate
3541	Buyers and procurement officers	0.295 *	Graduate
3542	Business sales executives	0.325	Graduate
3543	Marketing associate professionals	0.325	Graduate
3544	Estate agents and auctioneers	0.277 *	Graduate
3545	Sales accounts and business development managers	0.334	Graduate
3546	Conference and exhibition managers and organisers	0.286 *	Graduate
3550	Conservation and environmental associate professionals	0.405	Graduate
3561	Public services associate professionals	0.372	Graduate
3562	Human resources and industrial relations officers	0.380	Graduate
3563	Vocational and industrial trainers and instructors	0.416	Graduate
3564	Careers advisers and vocational guidance specialists	0.363	Graduate
3565	Inspectors of standards and regulations	0.388	Graduate
3567	Health and safety officers	0.424	Graduate
4112	National government administrative occupations	0.169	Non-Graduate
4113	Local government administrative occupations	0.185	Non-Graduate
4114	Officers of non-governmental organisations	0.208	Non-Graduate
4121	Credit controllers	0.173	Non-Graduate
4122	Book-keepers, payroll managers and wages clerks	0.190	Non-Graduate
4123	Bank and post office clerks	0.176	Non-Graduate
4124	Finance officers	0.184	Non-Graduate
4129	Financial administrative occupations n.e.c.	0.171	Non-Graduate
4131	Records clerks and assistants	0.108	Non-Graduate
4132	Pensions and insurance clerks and assistants	0.130	Non-Graduate
4133	Stock control clerks and assistants	0.129	Non-Graduate
4134	Transport and distribution clerks and assistants	0.114	Non-Graduate
4135	Library clerks and assistants	0.092	Non-Graduate
4138	Human resources administrative occupations	0.078	Non-Graduate
4151	Sales administrators	0.169	Non-Graduate
4159	Other administrative occupations n.e.c.	0.126	Non-Graduate
4161	Office managers	0.164	Non-Graduate
4162	Office supervisors	0.159	Non-Graduate
4211	Medical secretaries	0.110	Non-Graduate
4212	Legal secretaries	0.069	Non-Graduate
4213	School secretaries	0.111	Non-

			Graduate
4214	Company secretaries	0.105	Non-Graduate
4215	Personal assistants and other secretaries	0.092	Non-Graduate
4216	Receptionists	0.085	Non-Graduate
4217	Typists and related keyboard occupations	0.094	Non-Graduate

Note:)* ±0.05 around threshold of 0.274

Table 13: Where do mismatched graduates work? The Top Half of the Distribution of Graduates across Non-Graduate jobs in 2013 (in %)

Unit Group	Occupational Title	Fraction of mismatched graduates in total number of mismatched graduates	Cumulative Percentage	High Level Skills Requirement
7111	Sales and retail assistants	4.93	4.93	-0.006
4159	Other administrative occupations n.e.c.	4.67	9.60	0.126
4122	Book-keepers, payroll managers and wages clerks	4.40	14.00	0.190
6145	Care workers and home carers	3.88	17.88	0.079
6125	Teaching assistants	3.37	21.25	0.148
1190	Managers and directors in retail and wholesale	2.89	24.14	0.120
6141	Nursing auxiliaries and assistants	2.76	26.90	0.076
4112	National government administrative occupations	2.03	28.93	0.169
4215	Personal assistants and other secretaries	1.91	30.84	0.092
7219	Customer service occupations n.e.c.	1.79	32.63	0.043
3312	Police officers (sergeant and below)	1.71	34.34	0.211
4161	Office managers	1.67	36.01	0.164
6121	Nursery nurses and assistants	1.63	37.64	0.149
6126	Educational support assistants	1.63	39.27	0.142
4129	Financial administrative occupations n.e.c.	1.49	40.76	0.171
9233	Cleaners and domestics	1.4	42.16	-0.025
4113	Local government administrative occupations	1.36	43.52	0.185
7130	Sales supervisor	1.32	44.84	0.059
9274	Bar staff	1.26	46.1	-0.026
9272	Kitchen and catering assistants	1.25	47.35	-0.020
9273	Waiters and waitresses	1.23	48.58	-0.023
5241	Electricians and electrical fitters	1.22	49.8	0.153
4216	Receptionists	1.2	51	0.085

Source: QLFS Q(1)2013-Q(4)2013

Table 14: New Graduate Jobs in 2006/2012 based on SOC2000

	High Skills Requirement Score	
Unit Group (SOC2000)	**1997/2001**	**2006/2012**
1141 Quality assurance managers	0.218	0.304
1211 Farm managers	0.266	0.472
1212 Natural environment and conservation managers	0.266	0.428
1219 Managers in animal husbandry, forestry and fishing n.e.c.	0.266	0.408
1231 Property, housing and land managers	0.191	0.311
1232 Garage managers and proprietors	0.201	0.285
1235 Recycling and refuse disposal managers	0.188	0.310
1239 Managers and proprietors in other services n.e.c.	0.179	0.333
3231 Youth and community workers	0.256	0.293
3412 Authors, writers	0.271	0.340
3511 Air traffic controllers	0.225	0.274
3512 Aircraft pilots and flight engineers	0.225	0.331
4114 Officers of non-governmental organisations	0.064	0.277

Table 15: Down-skilled Jobs in 2006/2012 based on SOC2000

	High Skills Requirement Score	
Unit Group (SOC2000)	**1997/2001**	**2006/2012**
3449 Sports and fitness occupations n.e.c.	0.33	0.24
6131 Veterinary nurses and assistants	0.30	0.17
6139 Animal care occupations n.e.c.	0.30	0.14

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