# THE CHANGING DEMAND FOR SKILLS IN THE UK

Andy Dickerson and Damon Morris

Department of Economics and CVER
University of Sheffield

November 2017

**Abstract**

We present estimates of changes in skills utilisation and in the returns to skills in the UK using new measures of skills derived from a systematic and detailed matching between the US O*NET system and UK SOC. There is strongly increasing utilisation of both analytical skills and interpersonal skills, and declining use of physical skills over the period 2002-2016. A decomposition analysis reveals that most of these changes in skills utilisation are within occupations rather than between occupations, suggesting that the changes are pervasive throughout employment. The wage returns to skills are estimated using a standard Mincerian earnings function. We find positive and significantly increasing returns to analytical skills throughout the period. While the returns to interpersonal skills are lower than to analytical skills, they are also increasing over time, and are significant especially post-2010. Finally, the returns to physical skills are significantly negative over the whole period. Our findings are robust to changes in the definitions and measurement of the skills variables, and to the empirical specification of the earnings function. The results suggest that the UK labour market is strongly increasing its demand for analytical and interpersonal skills.

**Keywords:** Skills; Occupations; Earnings; O*NET

**JEL codes:** J20; J24; J31

**Acknowledgements:** The Centre for Vocational Education Research (CVER: cver.lse.ac.uk) is an independent research centre funded by the UK Department for Education (DfE). CVER brings together four partners: the LSE Centre for Economic Performance; University of Sheffield; National Institute of Economic and Social Research, and London Economics. Any views expressed are those of the authors, and do not represent the views of DfE. Part of the research for this paper was undertaken while Dickerson was Visiting Research Fellow in the Department of Economics at the University of Melbourne, and he would like to thank them for their kind hospitality. Useful comments received from participants at the 2017 CVER Annual Conference are also gratefully acknowledged.

# THE CHANGING DEMAND FOR SKILLS IN THE UK

## 1. Introduction

The literature has produced two dominant canonical explanations for the observed changes in employment and wages over the last 30 years. First, proponents of skill-based technical change (SBTC) argued that technology has monotonic effects throughout the skills distribution, and can therefore explain the observed increased returns to education for example. Second, those favouring a rather more nuanced interpretation of the impact of technology which distinguishes tasks and skills have argued that routine tasks in the middle of the skills distribution are increasingly becoming automated as compared to jobs at either ends of the skills spectrum, and this has led to job 'polarisation'. More recently, Beaudry et al (2016) present evidence for a 'great reversal' in the US, with stagnating or decreasing returns to cognitive skills since 2000 for young workers 25-35, and higher-skilled workers displacing lower-educated workers in less-skilled jobs. Finally, Deming (forthcoming) argues that there is a growing importance of 'social skills' in the US labour market, with an increasing share of US jobs requiring high levels of social interaction. He provides evidence for this hypothesis in the form of increasing returns to social skills post-2000. Similar findings are reported for Swedish prime-aged males by Edin et al (2017). One possible explanation is that this may be the flip-side of the increased automation and routinisation of jobs.

Most of the tasks vs skills literature is US-focussed, and utilises DOT and/or O*NET measures of tasks and skills (eg Autor et al, 2003; Abraham & Spletzer, 2009) or bespoke surveys (eg Autor & Handel, 2013). For the UK, while 'skills' are a major policy priority, we only have very imperfect measures of the skills available and in use in employment today. Currently in the UK, skills are typically proxied using qualifications held or by occupational classification. While these are both reasonably simple to record in surveys and censuses, they are both poor proxies for skills. Qualifications are usually obtained while still in education i.e. prior to labour market entry, and any knowledge or abilities acquired while studying may have long since become obsolete and/or forgotten, or may be irrelevant to the current employment. More fundamentally, qualifications are not, de facto, skills. Moreover, employers increasingly focus on aspects other than workers' qualifications when recruiting, including generic, key or core skills. These are undoubtedly more difficult to measure than qualifications or occupation (although some progress has been made in surveys that focus on the tasks that individuals perform in their jobs eg Felstead et al, 2007). The standard occupational classification (SOC) is also extremely imperfect as a measure of workers' skills. SOC is hierarchical, uni-dimensional, and static (it is revised only every decade), and captures neither the range nor the changing nature of skills used in different jobs over time. Our paper addresses these fundamental weaknesses in the measurement of skills utilisation in employment in the UK.

In contrast to the paucity of measures of skills for the UK, the US Occupational Information Network (O*NET) system provides almost 250 measures of skills, abilities, work activities, training, work context and job characteristics for each of around 1,000 different US occupations. O*NET is the main source of occupational competency information in the US. It has been almost 20 years in development and is constantly being revised. Information is gathered from self-reported assessments by job incumbents based on standardised questionnaire surveys as well as from professional assessments by job evaluation analysts. Ideally, we would want an O*NET-type system for the UK. But in the absence of such a system, we adopt the US O*NET to provide the same level of detail in terms of the occupations that can be separately identified and described, and the range of skills descriptors that are available. Thus we develop new, comprehensive and detailed multi-dimensional occupational skills profiles for the UK which describe the utilisation of skills used in the workplace. These occupational skills profiles have many potential uses. For example, they can enable a much richer and deeper understanding of the changing patterns of the demand for skills to be developed. They can be used to assess the changing value/returns to skills in employment. Finally, they can help inform individuals, and those who advise them, on the skills that are useful in employment today, and in the future.

More specifically, we construct a systematic, detailed and comprehensive match between the O*NETSOC and the UKSOC. We can then use the information in O*NET to produce a set of descriptors of the skills used in occupations the UK. In essence, we are assuming that, on average, the skills of eg a plumber in the UK are similar to the skills of a plumber in the US. Full details of the matching methodology are provided in the accompanying technical annex (Dickerson and Morris, 2017).

We then utilise our occupational skills profiles to assess the changing demand for skills in the UK. We construct three indices of skills: analytical/cognitive skills; interpersonal skills; and physical/manual skills. We combine these with data on employment and wages from the Annual Surveys of Hours and Earnings (ASHE) and the Labour Force Survey (LFS) to produce a 4-digit occupational-level panel for 2002-2016. We use this dataset to examine the changing utilisation of skills in employment over the period, and to estimate the wage returns to these skills. We argue that these two measures together provide good indicators of changing skills demand.

Our results indicate strongly increasing use of both analytical skills and interpersonal skills, and declining use of physical skills over the period 2002-2016. A decomposition analysis reveals that most of the change in skills utilisation for all three measures is within occupations, rather than between occupations. This indicates that the changes in skills utilisation are pervasive throughout employment. The wage returns to skills are estimated from a Mincerian-type earnings function. The returns to analytical skills are positive and increasing over time, suggesting that the demand for such skills is increasing even more strongly than the growth in their utilisation. While the returns to interpersonal skills are lower than to analytical skills, they are also increasing over time, and are significantly positive post-2010. Finally, the returns to physical skills are significantly negative over the whole period, although are stable despite the strong secular decline in their utilisation in employment.

These findings are robust to changes in the definitions and measurement of the skills variables, and to the empirical specification of the earnings function. The results suggest that the UK labour market is strongly increasing its demand for analytical and interpersonal skills.

The remainder of this paper is structured as follows. The next section briefly reviews some previous studies which have used O*NET (and its predecessors) and similar systems to measure and assess skills. Section 3 briefly outlines the methodology we have developed to construct our occupational skills profiles (see also Dickerson and Morris, 2017). Section 4 describes the trends in these skills utilisation indices over time and presents a decomposition of the change in each skill index over the whole period into its between-occupation and within-occupation changes. Estimates of the returns to skills are then presented together with the changing patterns in these returns. Section 5 concludes with a discussion of some potential implications for education and skills policy in the UK.

## 2. Measuring skills

The importance of skills in modern economies is widely acknowledged. Skills are important at both micro level eg for the distribution of earnings, and at the macro level eg for explanations of productivity and growth. Despite the fundamental importance of skills in economic policy discourse, procedures for measuring skills are comparatively under-developed in almost all countries. Skills are multi-dimensional, intangible and often unobservable. Each of the different conceptualisations of skills and their proxies that are commonly employed in research and policy analysis can be argued to have a number of serious weaknesses (Green, 2006; Dickerson et al, 2012).

The most commonly employed proxy for the skills of an individual is their qualifications or educational attainment. This measure has the advantage of being objective, and long-term trends can be assessed. However, qualifications only have a loose link with job skills and thereby individual and economy-wide economic performance. Not all educationally-derived skills will be utilised in the labour market (due to mismatch/overqualification), and the acquisition and depreciation of skills continues after education is completed. Moreover, education may be a signal of ability rather than as a source of skills supply. Learning at work important for acquisition of new skills and for updating existing skills. Hence the relationship between education and skills, and thereby economic performance, is complex. Certainly measuring skills by education qualifications alone will be insufficient. International comparisons of skills using educational qualification attainment are also difficult because qualifications are not comparable across countries. Length of time in education is no solution since there is variable quality of education provision.

A second commonly employed proxy for skills is occupation. While this measure is easily obtained from surveys and censuses, the hierarchy of hierarchy of occupations in the SOC is contestable, uncertain and changing. Moreover, over time, skills change within and between occupations and these changes are not reflected in the SOC which is static, and only periodically updated (around every 10 years in the UK).

Formal tests of skills can be made, and international comparisons are possible. However, formal assessments of skills through tests can only ever measure a limited range of skills (literacy and numeracy are typical). They are comparatively rare and typically have small sample sizes because of the costs of administering such testing. There has also been criticism of the international comparability of universal testing even when it has been treated very carefully by researchers. An alternative is self-assessment of skills. While this is subjective, and so used very rarely, the 5th sweep of NCDS records such measures. The major problem using self-assessment to measure skills is that skill self-assessment is associated with self-esteem.

Finally, there is the job requirements approach. These are surveys which ask individuals about the generic tasks and skills they use in their jobs and use those to infer the skills that they have. Of course, mismatch and underutilisation are still a problem, but they have permitted a much richer description of individuals' skills, including soft/generic skills simply not captured by the other measures. They also permit a wide range of skills to be assessed. Obviously, job skills could differ from person skills (because of mismatch), and skills are only measured for those in employment. But this method can make use of commercial job analysis data (which is arguably objective), as well as bespoke (subjective) surveys of individuals. Examples include: O*NET (Occupational Information Network) in the US; German BIBB/IAB and BIBB/BAuA Surveys on Qualifications and Working Conditions in Germany; and the UK Skills Surveys (Felstead et al, 2007).

Table 1 summarises a number of the papers which have utilised measures of skills derived from data collected using the job requirements approach. These papers use the DOT, or O*NET, or other job-task surveys with similar structures and/or characteristics to the O*NET. It is common to select a subset of 'relevant' O*NET items corresponding to some pre-defined taxonomy of skills, although this selection can sometimes seem somewhat arbitrary. As can be seen, a three-way classification of skills/attributes has proven popular, following the development of Fine's Functional Job Analysis (FJA) theory in the 1950s and formally implemented in the DOT occupational codes as 'Data-People-Things' (although the language now used is Analytic/Cognitive, Interpersonal and Physical or some variant thereof).There is little standardisation of the measures that are chosen even when the language/description of the skills taxonomy is very similar. However, a focus on cognitive and non-cognitive routine and non-routine tasks (and the substitution of – especially – computing technology for routine tasks as emphasised by David Autor and co-authors) is also popular. Amalgamation/aggregation methods include averaging a very small number of descriptors from the O*NET system, through to factor analysis across a very broad range of (possibly heterogeneous) indicators.

## 3. Data and Methodology

### 3.1 Data

We combine 4 different sources of data to construct a SOC2010-consistent 4-digit occupational panel dataset for 2002-2016 comprising detailed occupational measures of wages, employment composition, qualifications and skills. The data sources are:

1. UK LFS data 2002-2016;
2. UK ASHE/NES data 2002-2016;
3. US O*NET 2002-2016;
4. US Occupational Employment Statistics (OES) 2002-2016;

UK LFS microdata and ASHE/NES occupation-level public release tables are used to provide 4-digit SOC2000 data for 2002-2010, and SOC2010 data for 2011-2016, on the structure and composition of earnings and employment. We use ASHE for occupational wages because of the larger sample sizes available for the detailed 4-digit occupations that we are using (and also the lack of proxy responses as compared to the LFS). Table 2 compares the average coefficient of variation for mean hourly wages calculated from ASHE with mean hourly wages and mean log hourly wages from the LFS. Clearly, 4-digit occupation-level averages are calculated with much greater precession in the ASHE data due to the larger sample size, with the ASHE coefficient of variation around one tenth of the magnitude of the comparable LFS statistic.

In order to produce data on a consistent occupational classification, we use the ONS-supplied correspondence tables to convert SOC2000 data for 2002-2010 to SOC2010. The ONS weights are derived from dual-coded individual level datasets where occupation is recorded according to both SOC2000 and SOC2010. These dual-coded datasets are then used to estimate the employment composition of SOC2010 codes in terms of SOC2000 occupations. There are three dual-coded datasets: LFS January-March 2007; 2001 Census; and LFS December 1996-February 1997. The weights differ according to the dataset used and in some cases (where occupational employment is low), there is no figure available. Each dual-coded dataset is used in turn to produce SOC2010-consistent occupational level data for the 2002-2010 period. Our main results reported below are for the average weights calculated across the three dual-coded datasets, although we investigate the sensitivity to that decision in our robustness tests.

The Occupational Information Network, O*NET, system provides measures of skills, abilities, work activities, training, and job characteristics for almost 1,000 different US occupations. It is the main source of occupational competency information in the US. Information is gathered from self-reported assessments by job incumbents based on standardised questionnaire surveys together with professional assessments by job evaluation analysts. For the four area of (a) knowledge, (b) skills, (c) abilities and (d) work activities, both the 'Importance' and 'Level' of each skill or characteristic being measured is recorded. Most descriptors are comparable between occupations (although tasks are occupation-specific).

O*NET information is gathered from postal and online questionnaires administered by the US Bureau of Labor Statistics (BLS). Respondents are only asked to complete a random selection of the questionnaires in order to avoid survey fatigue, and also to provide some background demographics (not released). They also indicate from a wide range of occupation-specific tasks those that apply to their particular job. O*NET publishes occupation averages, rather than the individual micro-data. However, these averages are based on large samples - an average of 31,000 responses for each of the 250 descriptors gathered from around 125,000 returned questionnaires. Information is published at the 'O*NET-SOC' occupation level, which is a modification (i.e. slightly more detailed) of the US SOC. There are currently 1,110 occupations in O*NET SOC2010 (cf 840 in US SOC2010), although data are only collected on 974 of these occupations (these are termed the 'data level occupations').

### 3.2 Methodology

A full description of the matching methodology used to construct our skills indices is provided in Dickerson and Morris (2017). A brief description is provided in this subsection. Our skills measures are constructed as follows. We compute a vector of skills, $S_{jt}^{(x)}$, where the measure of each skill *x*, $S^{(x)}$, for each UK 4-digit occupation $j = 1, \dots J$ at time $t$ is defined as:

$$S_{jt}^{(x)} = \sum_{\substack{k=1 \\ k \in \{S_j\}}}^{K_j} O_{kt}^{(x)} \frac{n_{kt}}{\sum_k n_{kt}} \qquad (1)$$

where $O_{kt}^{(x)}$ is the measure of skill *x* for O*NET occupation *k*, $n_{kt}$ is employment in occupation *k* as derived from OES, and $\sum_k n_{kt}$ is total employment across all occupations *k*. The summation is over the set $k \in \{S_j\}$ of the $K_j$ O*NET occupations that are matched to the particular UKSOC 4-digit occupation *j*. Essentially, this is the OES employment-weighted average of the O*NET measure of skill for the set of O*NET occupations that matches to each 4-digit UK occupation *j*, using the CASCOT-plus-expert-derived match between O*NET and UK SOC as described in Dickerson and Morris (2017). We calculate this for each of the $x = 1, \dots, 35$ measures of skills in O*NET.

We then aggregate the resulting 35 skills measures into three indices closely informed by the 'data-people-things' taxonomy originally utilised in DOT. We here use the terms analytical, interpersonal, and physical respectively. As detailed by Dickerson and Morris (2017), the taxonomy is defined as:

Analytical skills (21 items):
*Reading Comprehension, Writing, Mathematics, Science, Critical Thinking, Active Learning, Learning Strategies, Monitoring, Coordination, Negotiation, Complex Problem Solving, Operations Analysis, Technology, Design, Programming, Troubleshooting, Judgment and Decision Making, Systems Analysis, Systems*

*Evaluation, Time Management, Management of Financial Resources, Management of Material Resources*

Interpersonal skills (7 items):
*Active Listening, Speaking, Social Perceptiveness, Persuasion, Instructing, Service Orientation, Management of Personnel Resources*

Physical skills (7 items):
*Equipment Selection, Installation, Operation Monitoring, Operation and Control, Equipment Maintenance, Repairing, Quality Control Analysis*

There are a number of ways in which these items can be aggregated to provide a single index of skills – simply averaging, PCA, etc. - and with additional choices regarding the inclusion of the Levels as well as Importance measures of each skill. In our main results, we simply take the average of the importance measures of skills only, although we examine the sensitivity of our findings to this choice in the extensive robustness analysis.

In order to produce a SOC2010-consistent 4-digit panel for 2002-2016, we have to resolve the change in the occupational classification that have taken place in the US as well as in the UK over our sample period. 'Crosswalks' for the US are available to convert between the different SOC classifications in US SOC, and also between the various O*NET SOCs. We use these as described in Dickerson and Morris (2017) to produce a UK SOC2010-consistent 4-digit panel for 2002-2016 with information on employment composition and structure, wages, together with measures of skills and abilities derived from O*NET.

One further issue is that the O*NET measures of skills in the early part of our sample period (2002-2009) were partially provided by job incumbents rather than job analysts. From O*NET v.15.0 (2010) onwards, the skills measures were exclusively provided by job analysts for all occupations. This changing mix of incumbents and analysis has been previously analysed by O*NET (REFERENCE) and their conclusion is that the different measures are equally valid. However, this issue does have implications for the measures of skills over time as shown in Dickerson and Morris (2017). Our solution is to use the changing mix of incumbents and analysts between occupations to impute the 'incumbent-effect' by occupation, which we then subtract from the skills measure to produce a job-analyst consistent measure of skills for the whole period. We also investigate the robustness of our findings to the adjustment method we have chosen.

## 4. Results

### 4.1 Skill trends and decomposition

The overall changes in the 3 skills indices are reported in the first column of Table 3. Over the whole period, our (employment-weighted[1]) aggregate index of analytical skills suggests

[1] i.e. the 4-digit indices are weighted by their employment shares in total employment for each year.

that utilisation of this skill set grew by 10% over the period. The increase in people skills was more than double this (+23%), while utilisation of physical skills fell by 14%. These trends accord with our general understanding of the changing occupational structure of employment and the large literatures on skill-biased technical change, routinisation of jobs, the growth of services and the decline of manufacturing etc.

At the aggregate level, these trends are a consequence of a combination of both changing skills within (broader) occupations, and changes in the occupational structure of employment. Some evidence on where the changes are situated can be obtained from undertaking a decomposition of the overall change in skills utilisation between 2002 and 2016 in each of our skills. Specifically, we examine the extent to which the aggregate changes in each index of skills is a consequence of within-occupation or between-occupation changes. The change in average skill utilisation over time, $\Delta S$, can be decomposed as follows:

$$\Delta S = \sum_{j=1}^{J} \Delta e_j \bar{S}_j + \sum_{j=1}^{J} \Delta S_j \bar{e}_j \quad (2)$$

where *j* indexes occupations, $j = 1, \ldots, J$, an overscore denotes an average over time, $e_j = \frac{E_j}{E}$ is the share of total employment in occupation *j*, and $S_j$ is the level of skill utilisation in occupation *j*. The first term on the right hand side of equation (2) is the between-occupation change in skill utilisation, while the second term is the within-occupation change.

Table 3 reports the decomposition of the overall change in analytical skills, people skills and physical skills over the period 2002 to 2016 using 1-digit, 2-digit, 3-digit and 4-digit occupational classifications. As can be seen, the within-occupation changes in skills dominate the between-occupations changes for all 3 indices whatever level of occupational disaggregation classification is employed. Around 20-25% of the increase in analytical skills utilisation is between occupations, while the remaining 75-80% is within occupations. The within-occupation changes for people skills and things skills are even greater at almost 90%. This suggests the overall changes in skill utilisation are pervasive and affecting all occupations, rather than being concentrated in certain occupational groups.

### 4.2 Returns to skills

We next turn to examine the returns to skills. We use a simple Mincerian log earnings function specification to estimate the conditional (wage) returns to skills and to compute the changing returns over time. This is similar in spirit to Ingram and Neumann (2006) for example, although here the unit of observation is the 4-digit occupation. Table 4 presents the basic log hourly wage regression results. Column (1) shows that wages are positively correlated with analytical skills, and negatively correlated with interpersonal and physical skills. These correlations are highly significant statistically. Column (2) reports the basic earnings function estimates. This demonstrates that higher qualifications are associated with higher earnings in general; wages increase with age at a decreasing rate, and that the age-earnings profile is inverse-U-shaped; occupations with higher proportions of women and public sector workers pay less on average; and that larger firms tend to pay significantly more. These are all standard findings in the earnings function literature. Column (3) augments our earnings equation with the 3 indices of skills. This suggests that skills and education are correlated and at least some of the returns to education are, in fact, returns to skills (and vice versa). Year dummies are included in column (4) since there are macro and other temporal changes which have impacted on earnings in this period. These do not change the qualitative findings.

Over the period of our sample, there have been considerable changes in the UK labour market at both micro and macro levels. Both the composition of the labour force and of employment have changed significantly over the period, as evidenced by both the changing utilisation of skills reported in subsection 4.1 above. In order to allow for this, we estimate a fully interacted variant of Table 4, column (4) in which the regression coefficients are allowed to differ by year. This is equivalent to estimating a series of cross-section regressions. The returns to our three measures of skills are illustrated in Figure 1, where we we have standardised (mean 0, variance 1) the measures of skills in order that comparisons can more easily be made.

The dashed lines connect the year-by-year point estimates of the wage returns to analytic, interpersonal and physical skills. As can be clearly seen, the returns to analytic skills are strongly trended upwards over time. An alternative specification which interacts a linear time trend with analytical skills is superimposed (together with its 95% confidence interval). Clearly, over the sample period, the returns to analytic skills have been positive and significant, and have been increasing strongly. It is important to note that this increase in returns has occurred even while the utilisation of analytical skills has been increasing strongly.

The returns to interpersonal skills were close to zero in the early part of the sample period, but have also been increasing over time. A linear time trend has a statistically significant slope coefficient, and the returns are significantly positive at 5% post-2010. Again, this increasing return has occurred at the same time as the utilisation of interpersonal skills has been increasing sharply.

Finally, the returns to physical skills are negative throughout the period, but are fairly over time (the slope of the time trend is insignificantly different from zero). Recall that the utilisation of these skills has been falling sharply over the period.

### 4.3 Robustness Checks

In order to investigate the robustness of our findings to the various decisions made in constructing the dataset, as well choices regarding our specification and econometric approach, we undertake a number of checks of our main results.

### 4.3.1 Data Transformations and Sources

In Table 5A we present the robustness of our findings to the particular method we use to aggregate the 35 skills into our DPT measures.

Panel A reports results which are based on aggregations using the importance of skills only. In the first three columns of Panel A the results are based on average of the importance measures of the relevant skills in column (1), standardised measures in column (2) to zero mean and unit variance within years which allows for any aggregate rescaling shift between years due to incumbent-analyst changes, and the percentile rank within year of the skills measures in column (3) (which will again be robust to rescaling of the indices). Columns (4), (5) and (6) repeats this except that Principal Components Analysis (PCA) is used to aggregate the skills measures into each category rather than the mean, and the scores produced by the first principal component are used as the skill measures. 54% of the variance in analytic skills is explained by the first principal component. For interpersonal and physical skills the respective figures are 76% and 71%. Standardised and rank based transformations are again also investigated.

In Panel B we incorporate the levels information as well as importance measure of skills. We again compute a mean based measure and a PCA based measure. Rather than a simple mean, however, we follow the approach of Blinder (2007) and calculate a weighted average, using Cobb-Douglas weights of 2/3 and 1/3 respectively for the importance and levels measures.

The results presented in Table 5A provide evidence that the way in which we aggregate the skills information from 35 measures of skill in the raw data to our 3 summary indices does not have an impact on our findings. In each of the 12 estimates, the coefficients for analytical skills and physical skills are consistently statistically significant at the 1% level. Notably, incorporating levels information produces some significant estimates for interpersonal skills. The magnitudes of the raw skill measures are not directly comparable as different aggregation methods produce variables on different scales with coefficients differing in their interpretation. The coefficients on the standardized and percentile rank transformations do, however, indicate that the size of the effects of skills is similar across the four aggregation methods.

Returning to our chosen method of aggregation for our main variables of interest (simple means of the importance measures of skills only), we also report a range of other robustness checks in Table 5B to assess the sensitivity of our results to transformations we have made to the data or assumptions we have made in constructing it. In particular, we check the robustness of the results to using the LFS rather than the ASHE as our source of data on wages, using the occupational mean of log wages rather than the log of occupational mean wages, to using the raw skill measures in O*NET (i.e. without any adjustment of incumbent-provided skill information), and finally the choice of weights we use to convert information at the SOC2000 level to SOC2010.

Column (1) In Table 5B reports our baseline results. Comparing these results to those of column (2), it is clear that estimates of the return to skill are not sensitive to whether or not we attempt to correct for the mix of job incumbents and analysts providing skills information in the raw O*NET data.

Our preferred measure of wages is derived from ASHE for the reasons stated above. As an alternative, we can use log mean wages from LFS. We could also use mean log wages for LFS data where we have individual earnings, since the aggregation of individual log earnings functions yields this as the 'correct' dependent variable (although cell-mean regressions of this kind (eg Blanchflower et al (1996) and Dearden et al (2006)) frequently use log mean wages rather than mean log wages). Our results are not substantially affected by how wages are aggregated to the occupation level, or the dataset we source the wage information from. Column (3) is directly comparable to column (1) as both of these use log mean wages, and we find no significant difference between the two, indicating the choice between LFS and ASHE wages has no bearing on our results. Comparing columns (3) and (4), using mean log wages rather than log mean wages does attenuate the magnitude of the returns to analytical skills and things skills slightly, although the main conclusions are unaffected.

The baseline results use the average across the three SOC2000-SOC2010 weighting matrices provided by the ONS to construct the correspondence between SOC2000 and SOC2010. In columns (5) to (7) we use each of the three weighting matrices separately in turn to convert the 2002-2011 data to SOC2010 consistency. The three matrices each produce a very similar magnitude of results for the three skill measures, and there are no statistically significant differences from the baseline.

The changes to data source and construction we have investigated in Table 5B do not substantially alter any of our main findings or conclusions. Our estimates of the returns to skill remain the same in terms of sign and significance at the 5% level and the magnitudes are robust to thee choices of aggregation methods.

#### 4.3.2 Specification and Estimation of the Earnings Function

Table 5C presents a final set of robustness checks for our main result, in this case focussing on the robustness of results to our chosen specification and estimation technique.

Our main results are based on variables derived from gender-specific variables combined using an employment share weight. In columns (2) and (3) of Table 5C, we compare the results when our variables are based on, respectively, males only and females only. We find that both male and female occupational average wages are influenced by analytical, people, and things skills in the same way – positive effect of analytical skills, negative effect of things skills, and no significant effect of people skills. The magnitudes, in both cases, are larger than the baseline results. The difference in results will in part reflect the fact that when splitting by gender we lose occupations with very small or no employment. This is particularly the case for females, where we lose around one fifth of our sample observations. In column (4) we restrict the individual observations used to construct our occupation level variables to those where the individual is employed full time. Relative to our baseline results in column (1), we find larger effects of skills on earnings.

In column (5) we report estimates of our standard specification with the addition of 1-digit SOC dummies. As we would expect, this decreases the magnitudes of the estimated returns to skills but the general conclusions remain unchanged. We also experimented with 2-digit and 3-digit occupation dummies and still found positive and significant coefficients for analytical skills and negative and significant coefficients for things skills. Even when comparing 4-digit occupations within the same detailed 3-digit grouping of occupations, differing skill levels across the occupations still account for some of the differences in wages.

Given the multiple changes in SOC classifications in the UK and the US (both O*NET and SOC) prior to 2010, together with the changing incumbent-analyst ratio in reporting the measures of skills (Annex B), we re-estimated the returns to skills for the period 2011-2016 since this period is unaffected by any of the changes in SOC or in the reporting of skills. The results of this exercise are shown in column (6). The average returns to analytical skills for this subperiod are rather higher than the average for the period 2002-2016, but the substantive results are the same. This suggests that the additional manipulations and adjustments required in order to construct the SOC2010 consistent database for 2002-2010 are not unduly responsible for the results obtained, though one caveat to this is that we find much stronger positive and now significant returns to people skills when focussing on the later period only.

The final specification issue is the use of OLS, when it can be argued we should use weighting since we are using group mean regressions. There is some debate in the literature about the necessity of weighting (REFS), but it is important to investigate if it makes a difference to the estimated returns. We follow the approach of Dickens (1990) in weighting our regressions. In group mean regressions we cannot simply weight by the square root of the cell size. This is because individuals within groups (in this case occupations) are likely to share unobserved characteristics, in which case the regression error term will consist of an individual error component and a shared group component. The variance of the group-mean regression residuals is, in this case, given by equation (3):

$$Var(\bar{e}_j) = \sigma_\gamma^2 + \sigma_u^2 / N_j \quad (3)$$

The error variance for group *j* is given by the shared group component, $\sigma_\gamma^2$, plus the individual component, $\sigma_u^2 / N_j$. If the two variances are equal, and the group sizes are large then there will be little variation in the overall variances and heteroscedasticity will be minimal. In this case, weighting by the square root of group size will introduce substantial heteroscedasticity if there are large differences in group size. If, however, $\sigma_\gamma^2$ is zero or small relative to $\sigma_u^2$, then large variation in the $N_j$ will result in considerable heteroscedasticity. In this case, the regressions should be weighted.

First we estimate our standard specification by WLS, weighting by the square root of group size (in this case, employment in the occupation) and test for heteroscedasticity by regressing the squared residuals on employment in the occupation. The coefficient on employment in this regression is significant, suggesting the presence of a group component in the error term. We then estimate the following regression, where the group-specific residual is regressed on a constant and the inverse of employment in the occupation.

$$\hat{\varepsilon}_j^2 = \alpha + \delta \, {}^{1}\!/_{N_j} \tag{4}$$

The parameters are estimates of the error variance components in equation (3). These estimates, $\hat{\sigma}_\gamma^2$ and $\hat{\sigma}_u^2$, are used to construct the weight $1/(\sigma_\gamma^2 + \sigma_u^2/N_j)$. The earnings function is then re-estimated using this weight, from which the new error component variances can be constructed to again re-estimate the earnings function. This iterative process continues until both coefficients in the residuals regressions are identical to 5 decimal places between two iterations. This convergence occurs at the 4$^{th}$ iteration, and it is these results presented in column (7) of Table 5C.

The full results of this weighting procedure are presented in Table 6, and show that the coefficient estimates (to 3 decimal places) in the earnings function converged immediately at the first iteration. The coefficient estimates in column (7) of Table 5C do not differ significantly from our main results reported in column (1). Our results are therefore not sensitive to whether or not we weight the earnings regressions.

Taken as a whole, our comprehensive set of robustness checks show that our main estimates presented in section 4.2 are highly robust and stable. Despite uncertainties around how (or if) to deal with the issue of job incumbent/job analyst valuations of O*NET skills, the best source of data for wages, how to aggregate raw skills, and how to convert between SOC2000 to SOC2010, we find that our results are not sensitive to these choices in the construction of the dataset.

## 5. Summary and Conclusions

We derived new measures for measuring skills at the 4-digit level for 2002-2016 and examined the evolution of the utilisation of three indices of skills over time as the occupational composition and skills content of jobs changed. Strong secular growth in analytical/cognitive and people/interpersonal skills and declining usage of physical/manual skills is consistent with other literatures which have documented the skill content of jobs. We then estimated earnings functions which controlled for education, gender, firm size and other established determinants of differences in earnings, in order to investigate the conditional returns to these skills. High and statistically significant and increasing returns over time to analytical skills was contrasted with lower, but still increasing returns to interpersonal skills, especially in the last 5 years or so. Finally, the returns to physical skills is significantly below zero for the whole of the period.

Our findings demonstrate the importance of work-related skills for individual earnings over and above their educational qualifications, and in particular, the demand for higher levels of analytical skills (mirrored by the findings on cognitive abilities) and interpersonal skills in the workforce.

Our interpretation of the increased utilisation coupled with increasing returns to analytic and interpersonal skills is that the UK is experiencing significantly increased demand for these skills in the labour market.

## References


Abraham, K G and J R Spletzer (2009), “New evidence on the returns to job skills”, *American Economic Review Papers and Proceedings*, 99(2), 52-57.

Autor, David H, Frank Levy and Richard J Murnane (2003), “The Skill Content of Recent Technological Change: An Empirical Investigation”, *Quarterly Journal of Economics*, 118(4), 1279-1333.

Autor, David H and Michael J Handel (2013), “Putting Tasks to the Test: Human Capital, Job Tasks, and Wages”, *Journal of Labor Economics*, 31(2), S59-S97.

Beaudry et al (2016, AER)

Black, Sandra E and Alexandra Spitz-Oener (2010), “Explaining Women’s Success: Technological Change and the Skill Content of Women’s Work”, *Review of Economics and Statistics*, 92(1), 187-194.

Blanchflower, D. Oswald, A. and Sanfey, P (1996), “Wages, profits, and rent-sharing” *The Quarterly Journal of Economics,* 111, 227-251

Blinder, A (2007), “How many U.S. jobs might be offshorable?”, Princeton University Center for Economic Policy Studies Working Paper no. 142, Princeton University

BLS (Bureau of Labor Statistics) (2015) Occupational Employment Statistics (OES) Survey http:/stat.bls.gov/oes/home.htm last accessed 11 November 2015.

CASCOT (no date) (Computer Assisted Structured Coding Tool) http://www2.warwick.ac.uk/fac/soc/ier/software/cascot/ last accessed 12 January 2016.

Dearden, L. Reed, H. and Van Reenen, J (2006), “The impact of training on productivity and wages: Evidence from British panel data” *Oxford Bulletin of Economics and Statistics,* 68(4), pp.397-421

Deming (forthcoming QJE)

Dickens, W (1990). “Error components in grouped data: is it ever worth weighting?” *The Review of Economics and Statistics,* 72(2), 328-333

Dickerson, Andy and Damon Morris (2017), “Creating a Database of Occupational Skills: Technical Report”, CVER mimeo, September 2017.

Dickerson, Andy, Rob Wilson, Genna Kik and Debra Dhillon (2012), *Developing Occupational Skills Profiles for the UK: A Feasibility Study*, Evidence Report 44 February 2012, UK Commission for Employment and Skills.

Dustmann, Christian, Johannes Ludsteck and Uta Schoenberg (2009), “Revisiting the German wage structure”, *Quarterly Journal of Economics* 114(May), 843–882.

Edin et al (2017, IZA)

Felstead, Alan, Duncan Gallie , Francis Green and Ying Zhou (2007), *Skills at Work 1986-2006*, ESRC Centre on Skills, Knowledge and Organisational Performance, SKOPE, Universities of Oxford and Cardiff.

Goos, Maarten, Alan Manning and Anna Salomons (2009), “Job polarization in Europe”, *American Economic Review Papers and Proceedings*, 99 (2), 58-63.

Goos, Maarten, Alan Manning and Anna Salomons (2014), "[Explaining Job Polarization: Routine-Biased Technological Change and Offshoring](#)", [American Economic Review](#) 104(8), 2509-2526.

Green, Francis (2006), *Demanding Work: The Paradox of Job Quality in the Affluent Society*, Princeton. Princeton University Press.

Handel, Michael J (2007), A new survey of Workplace Skills, Technology, and Management Practices (STAMP): Background and descriptive statistics. Paper presented at Workshop on Research Evidence Related to Future Skill Demands, National Academies, Washington, DC.

Handel, Michael J (2008), What do people do at work? A profile of U.S. jobs from the Survey of Workplace Skills, Technology, and Management Practices (STAMP). Paper presented at the Labor Seminar, Wharton School of Management, University of Pennsylvania.

Handel, Michael J (2010), "The O*NET content model: strengths and limitations", mimeo, June 2010.

Howell, D R and E N Wolff (1991), "Trends in the Growth and Distribution of Skills in the US Workplace, 1965-1985", *Industrial and Labour Relations Review*, 44(3), 486-502.

Howell, D R and E N Wolff (1992), "Technical Change and the Demand for Skills for US Industries", *Cambridge Journal of Economics*, 16, 127-146.

Ingram, Beth and George R Neumann (2006), "The returns to skill", *Labour Economics*, 13, pp.35-59.

LMI for All (2013), *Developing a Careers LMI Database: Phase 2A Report,* Career Database Project Team, Warwick Institute for Employment Research, UK Commission for Employment and Skills, July 2013.

LMI for All (2015), *Developing a Careers LMI Database: Final Report*, Career Database Project Team, Warwick Institute for Employment Research, UK Commission for Employment and Skills, July 2015.

LMI for All (2016), http://www.lmiforall.org.uk/ last accessed 12 January 2016.

ONS (2012), *Relationship between: Standard Occupational Classification 2010 (SOC2010) and Standard Occupational Classification 2000 (SOC2000)*, Classification and Harmonisation Unit, User Guide 2010: 22 available at: https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2010, last accessed: XX XXX 20XX.

Peterson, Norman G, Michael D Mumford, Walter C Borman, P. Richard Jeanneret and Edwin A Fleishman (1999), *An occupational information system for the 21st century: The development of O*NET*, Washington, DC: American Psychological Association.

SOC2010 (2010), *Volume 1: Structure and Descriptions of Unit Groups*, Basingstoke: Palgrave MacMillan.

Spitz-Oener, Alexandra (2006), "Technical change, job tasks and rising educational demands: Looking outside the wage structure", *Journal of Labor Economics* 24(2), 235–70.

Taylor, Paul J, Wen-Dong Li, Kan Shi, and Walter C Borman (2008) "The transportability of job information across countries". *Personnel Psychology*, 61(1), 69-111.

Tippins, Nancy and Margaret L Hilton (eds.) (2010), *A Database for a Changing Economy: Review of the Occupational Information Network (O*NET)*, National Research Council, National Academies Press, Washington DC.

US Department of Labor (1991), *Dictionary of occupational titles: Revised fourth edition*, Washington, DC: Employment and Training Administration.

**Table 1: Summarising Skills, Tasks and Work Activities: Examples from the Literature**

| Reference | Taxonomy | Data | Measures/Methods | Notes/Findings |
|---|---|---|---|---|
| Autor, Levy and Murnane (QJE 2003) | Non-routine analytic tasks<br>Non-routine interactive tasks<br>Routine cognitive tasks<br>Routine manual tasks<br>Non-routine manual tasks (omitted from most analysis) | DOT (US Dictionary of Occupational Titles) 1977 and 1991 | (i) Single DOT variable for each task measure<br>(ii) Principal components for 4 selected DOT variables for each task measure | Computers have substituted routine tasks and complemented non-routine tasks.<br>This shift in job tasks can help explain the increased returns to college education.<br>Within-occupation change is a significant component of the change in task demand. |
| Howell and Wolff (ILRR 1991 and CJE 1992) | Cognitive skills<br>Interactive/People skills<br>Motor skills | DOT 1977 | Cognitive skills: factor analysis over 46 DOT variables<br>Interactive skills: single DOT variable<br>Motor skills: factor analysis over 3 DOT variables | Suggests education is a poor measure of workforce skills.<br>Technical change helps to explain increasing cognitive skill requirements and changing occupational distribution of employment. |
| Autor and Handel (2013) | Cognitive tasks<br>Interpersonal tasks<br>Physical job tasks<br>(aka data- people-things as used in DOT) | Princeton Data Improvement Initiative (PDII)<br>O*NET v.14<br>40 items from a number of domains (work activities, skills, knowledge, work context) | Additive multi-item scales - O*NET items collated into 10 measures (minimum 2 items, maximum 8 items) | Job tasks vary within occupations (by race, gender and English language proficiency) as well as between occupations.<br>Tasks at both individual and occupational level are important predictors of hourly wages. |

| Reference | Taxonomy | Data | Measures/Methods | Notes/Findings |
|---|---|---|---|---|
| Abraham and Spletzer<br>(AER 2009) | Analytic activities<br>Interpersonal activities<br>Physical activities | O*NET v. 13 (June 2008)<br>41 work activities | Analytic: average of 2 O*NET activities<br>Interpersonal: average of 2 O*NET activities<br>Physical: 1 O*NET activity | Jobs that require more analytical activity pay significantly higher wages, while those that require more interpersonal and physical activity pay lower wages. |
| Black and Spitz-Oener (REStats 2010), Spitz-Oener (JLE 2006) | Non-routine analytic tasks<br>Non-routine interactive tasks<br>Routine cognitive tasks<br>Routine manual tasks<br>Non-routine manual tasks<br>(i.e. based on ALM 2003) | West Germany Qualification and Career Survey 1979-99 | Task measure is the proportion of job activities in each task group | Substantial relative decline in routine task input for women driven by technological change has significantly contributed toward the narrowing of the gender pay gap. |
| Goos, Manning and Salomons<br>(AER 2009 and AER 2014) | Abstract tasks (intense in non-routine cognitive skills)<br>Routine tasks (intense in cognitive and non-cognitive routine skills)<br>Service tasks (intense in non-routine, non-cognitive skills) | O*NET v. 11 (2006)<br>96 items selected from a range of domains | (i) Abstract=first principal component of 72 O*NET items; Routine=first principal component of 16 O*NET items; Service=first principal component of 8 O*NET items<br>(ii) Principal components of all items together – identifies 2 components corresponding to the 'Routine', and the 'Abstract and Service' dimensions | Evidence of job polarization across Europe.<br>Technologies are becoming more intensive in non-routine tasks at the expense of routine tasks.<br>Evidence for off-shoring and inequality driving polarisation is much weaker. |

**Table 2: Coefficients of variation for SOC2010 mean hourly wages**

| | (1)<br>2011 | (2)<br>2012 | (3)<br>2013 | (4)<br>2014 | (5)<br>2015 | (6)<br>2016 |
|---|---|---|---|---|---|---|
| ASHE (Level) | 3.96 | 3.89 | 3.84 | 3.79 | 3.69 | 3.92 |
| LFS (Log) | 15.02 | 15.13 | 15.04 | 15.34 | 15.25 | 15.20 |
| LFS (Level) | 34.92 | 34.83 | 34.47 | 35.74 | 35.51 | 35.47 |
| N | 367 | 367 | 366 | 365 | 365 | 364 |

**Table 3: Decomposition of changing skill utilisation 2002 to 2016**

| | Aggregate change in skills 2002-16 | Decomposition of changing skills utilisation | | |
|---|---|---|---|---|
| | | Between occupations | Within occupations | Total Change |
| 1-digit SOC2010 *(9 categories)* | | % | % | |
| Analytic skills | +10% | 24 | 76 | 100% |
| Interpersonal skills | +23% | 11 | 89 | 100% |
| Physical skills | −14% | 10 | 90 | 100% |
| 2-digit SOC2010 *(25 categories)* | | % | % | |
| Analytic skills | +10% | 25 | 75 | 100% |
| Interpersonal skills | +23% | 12 | 88 | 100% |
| Physical skills | −14% | 14 | 86 | 100% |
| 3-digit SOC2010 *(90 categories)* | | % | % | |
| Analytic skills | +10% | 26 | 74 | 100% |
| Interpersonal skills | +23% | 15 | 85 | 100% |
| Physical skills | −14% | 17 | 83 | 100% |
| 4-digit SOC2010 *(369 categories)* | | % | % | |
| Analytic skills | +10% | 18 | 82 | 100% |
| Interpersonal skills | +23% | 11 | 89 | 100% |
| Physical skills | −14% | 24 | 76 | 100% |

Note:
1. Decomposition of the overall change in skill utilisation between 2002 and 2016 into between-occupation and within-occupation changes. See text, equation (2), for details.

**Table 4: Returns to Skills 2002-2016**

| Dependent Variable:<br>Log Average Hourly Real Wages | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Analytic skills | 0.839*** | | 0.191*** | 0.172*** |
| | (0.013) | | (0.013) | (0.014) |
| Interpersonal skills | -0.225*** | | -0.032*** | 0.004 |
| | (0.011) | | (0.009) | (0.010) |
| Physical skills | -0.150*** | | -0.057*** | -0.058*** |
| | (0.007) | | (0.007) | (0.007) |
| Highest Qual NQF 4+ | | 1.130*** | 0.869*** | 0.899*** |
| | | (0.025) | (0.029) | (0.029) |
| Highest Qual NQF 3 | | 0.643*** | 0.462*** | 0.489*** |
| | | (0.032) | (0.034) | (0.033) |
| Highest Qual NQF 2 | | 0.584*** | 0.422*** | 0.438*** |
| | | (0.043) | (0.044) | (0.044) |
| Highest Qual below NQF 2 | | 0.236*** | 0.195*** | 0.206*** |
| | | (0.051) | (0.050) | (0.049) |
| Highest Qual Apprenticeship | | 0.542*** | 0.584*** | 0.599*** |
| | | (0.049) | (0.049) | (0.048) |
| Female | | -0.312*** | -0.289*** | -0.298*** |
| | | (0.011) | (0.012) | (0.012) |
| Age | | 0.133*** | 0.121*** | 0.117*** |
| | | (0.004) | (0.004) | (0.004) |
| Age Squared | | -0.001*** | -0.001*** | -0.001*** |
| | | (0.000) | (0.000) | (0.000) |
| Firm Size 25-49 | | 0.016 | 0.041 | 0.034 |
| | | (0.038) | (0.037) | (0.037) |
| Firm Size 50-499 | | 0.066*** | 0.082*** | 0.093*** |
| | | (0.018) | (0.018) | (0.018) |
| Firm Size 500+ | | 0.340*** | 0.341*** | 0.357*** |
| | | (0.021) | (0.021) | (0.021) |
| Public Sector | | -0.154*** | -0.130*** | -0.160*** |
| | | (0.011) | (0.012) | (0.012) |
| Constant | 1.435*** | -1.222*** | -1.071*** | -1.310*** |
| | (0.028) | (0.116) | (0.117) | (0.116) |
| Region dummies (11) | | YES | YES | YES |
| Year dummies (14) | | | | YES |
| N | 5156 | 5172 | 4944 | 4944 |

Notes:

1. The dependent variable is log mean real hourly wages.
2. Standard errors in parentheses: * p<0.10; ** p<0.05; *** p<0.01.
3. Base category for highest qualification is other qualifications or no qualifications. Base category for firm size is less than 25 employees.

**Table 5A: Robustness Checks 1 – Aggregation Method**

| | **Panel A: Importance Measures Only** | | | | | |
|---|---|---|---|---|---|---|
| | Means | | | PCA | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Raw | Std. | Pctile | Raw | Std. | Pctile |
| Analytic skills | 0.172*** | 0.077*** | 0.001*** | 0.027*** | 0.095*** | 0.003*** |
| | (0.014) | (0.006) | (0.000) | (0.002) | (0.006) | (0.000) |
| Interpersonal skills | 0.004 | 0.007 | 0.000 | -0.004 | -0.008 | -0.000 |
| | (0.010) | (0.005) | (0.000) | (0.003) | (0.006) | (0.000) |
| Physical skills | -0.058*** | -0.037*** | -0.000*** | -0.014*** | -0.034*** | -0.001*** |
| | (0.007) | (0.004) | (0.000) | (0.002) | (0.004) | (0.000) |
| N | 4944 | 4944 | 4944 | 4944 | 4944 | 4944 |

| | **Panel B: Importance and Levels Measures** | | | | | |
|---|---|---|---|---|---|---|
| | Cobb-Douglas Weighted Mean | | | PCA | | |
| | (7) | (8) | (9) | (10) | (11) | (12) |
| | Raw | Std. | Pctile | Raw | Std. | Pctile |
| Analytic skills | 0.007*** | 0.072*** | 0.002*** | 0.017*** | 0.086*** | 0.003*** |
| | (0.001) | (0.007) | (0.000) | (0.001) | (0.007) | (0.000) |
| Interpersonal skills | 0.002* | 0.020*** | 0.001*** | 0.002 | 0.008 | 0.001** |
| | (0.001) | (0.006) | (0.000) | (0.002) | (0.007) | (0.000) |
| Physical skills | -0.008*** | -0.043*** | -0.002*** | -0.010*** | -0.033*** | -0.001*** |
| | (0.001) | (0.004) | (0.000) | (0.001) | (0.004) | (0.000) |
| N | 4934 | 4934 | 4934 | 4944 | 4944 | 4944 |

Notes:
1. The dependent variable is log average real hourly wages.
2. Standard errors in parentheses: * p<0.10; ** p<0.05; *** p<0.01.
3. All regressions in this table are estimated using the same specification as column (4) in Table 2.
4. Panel A reports results for skill aggregations which only use the importance measure of the 35 source skills in the aggregation. In Panel B the aggregations are based on both importance and levels information.

**Table 5B: Robustness Checks 2 – Alternative Transformations**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Baseline | Raw Skills | LFS Log Mean | LFS Mean Log | LFS 96-97 | Census 01 | LFS JM 07 |
| Analytic skills | 0.172*** | 0.173*** | 0.170*** | 0.153*** | 0.167*** | 0.165*** | 0.175*** |
| | (0.014) | (0.014) | (0.013) | (0.012) | (0.014) | (0.014) | (0.014) |
| Interpersonal | 0.004 | -0.013 | -0.015 | -0.016* | 0.003 | 0.008 | 0.002 |
| | (0.010) | (0.009) | (0.010) | (0.009) | (0.010) | (0.010) | (0.010) |
| Physical skills | -0.058*** | -0.065*** | -0.065*** | -0.051*** | -0.056*** | -0.056*** | -0.056*** |
| | (0.007) | (0.006) | (0.006) | (0.006) | (0.007) | (0.007) | (0.007) |
| N | 4944 | 4944 | 5060 | 5060 | 4887 | 4920 | 4930 |

Notes:

1. The dependent variable is log average real hourly wages.
2. Standard errors in parentheses: * p<0.10; ** p<0.05; *** p<0.01.
3. The column (1) regression coefficients repeat the specification reported in column (4) of Table 2. Column (2) uses raw skills data, not corrected for incumbent/analyst valuation. Column (3) uses the log of occupational mean wages as an alternative dependent variable and column (4) uses the occupational mean of log wages, using LFS data in both cases. Columns (5) to (7) re-estimates with data which is converted from SOC2000 to SOC2010 with weights using each of the 3 dual-coded datasets separately. See text for details.

**Table 5C: Robustness Checks 3 – Earnings Function Specification**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Baseline | Male | Female | Full Time | 1-Digit SOC | 2011-16 | WLS |
| Analytic skills | 0.172*** | 0.290*** | 0.375*** | 0.236*** | 0.119*** | 0.308*** | 0.175*** |
| | (0.014) | (0.017) | (0.016) | (0.015) | (0.014) | (0.031) | (0.014) |
| Interpersonal | 0.004 | -0.018 | -0.027** | -0.004 | 0.004 | 0.066*** | 0.003 |
| | (0.010) | (0.013) | (0.013) | (0.011) | (0.010) | (0.025) | (0.010) |
| Physical skills | -0.058*** | -0.095*** | -0.141*** | -0.072*** | -0.042*** | -0.055*** | -0.066*** |
| | (0.007) | (0.008) | (0.008) | (0.007) | (0.007) | (0.013) | (0.007) |
| N | 4944 | 4362 | 3774 | 4647 | 4944 | 1918 | 4531 |

Notes:

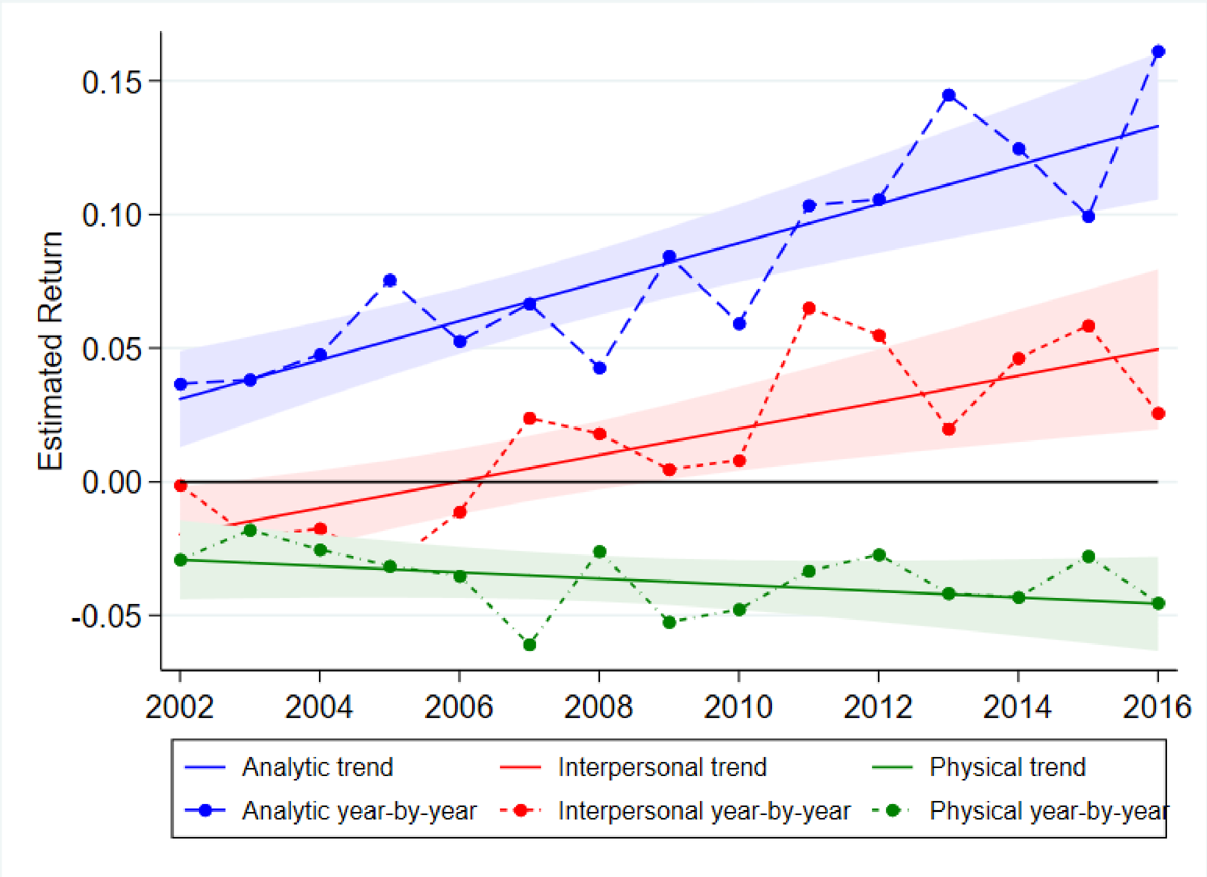
1. The dependent variable is log average real hourly wages.
2. Standard errors in parentheses: * p<0.10; ** p<0.05; *** p<0.01.
3. The column (1) regression coefficients repeat the specification reported in column (4) of Table 2. Column (2) constructs the outcome and independent variables from male observations only. Column (3) constructs the outcome and independent variables from female observations only. Column (4) constructs the outcome and independent variables from full-time workers observations only. Columns (5) includes 1-digit SOC occupation fixed effects. Column (6) estimates only for 2011 to 2016. Column (7) uses WLS rather than OLS with weights proportional to occupation-year cell sizes. See text for details.

**Table 6: WLS Estimates – Full Results**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | OLS | WLS | Dickens (1990) Iterative WLS | | | |
| | | | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
| Analytic skills | 0.172*** | 0.163*** | 0.175*** | 0.175*** | 0.175*** | 0.175*** |
| | (0.014) | (0.013) | (0.014) | (0.014) | (0.014) | (0.014) |
| Interpersonal | 0.004 | 0.011 | 0.003 | 0.003 | 0.003 | 0.003 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Physical skills | -0.058*** | -0.084*** | -0.066*** | -0.066*** | -0.066*** | -0.066*** |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| | $\varepsilon^2$ | $\varepsilon^2$ | $\varepsilon^2$ | $\varepsilon^2$ | $\varepsilon^2$ | $\varepsilon^2$ |
| 1/N | 0.020*** | 0.022*** | 0.021*** | 0.021*** | 0.021*** | 0.021*** |
| | (0.005) | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) |
| Constant | 0.025*** | 0.025*** | 0.024*** | 0.024*** | 0.024*** | 0.024*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| N | 4531 | 4531 | 4531 | 4531 | 4531 | 4531 |

Notes:
1. The dependent variable is log average real hourly wages.
2. Standard errors in parentheses: * p<0.10; ** p<0.05; *** p<0.01.
3. The lower panel regresses the squared residuals from the regression in the upper panel on a constant and the inverse of ASHE employment in the occupation. See text for details.

**Figure 1: Trends in the returns to skills 2002-2016**




Notes:

1. These are regression coefficients using the specification in Table 2, column (4), supplemented by interactions of each of the 3 skills indices with: (i) a linear time trend (solid lines) and (ii) year dummies (broken lines).
2. 95% confidence intervals for the linear trends are shaded.