Oxford Economic Papers, 2024, 1–22
https://doi.org/10.1093/oep/gpae020
Article

OXFORD

Degrees of demand: a task-based analysis of the British graduate labour market

Golo Henseke[1,*], Alan Felstead[2], Duncan Gallie[3], Francis Green[4]

[1]Department of Education, Practice and Society, University College London, London, WC1H 0NS, United Kingdom
[2]School of Social Sciences, Cardiff University, Cardiff, CF24 4HQ, United Kingdom
[3]Nuffield College, Oxford University, Oxford, OX1 1NF, United Kingdom
[4]Department of Education, Practice and Society, University College London, London, WC1H 0NS, United Kingdom

*Corresponding author. Department of Education, Practice and Society, University College London, 20 Bedford Way, London, WC1H 0NS, United Kingdom. E-mail: g.henseke@ucl.ac.uk

Abstract
This study investigates the evolving demand for graduate skills in the British workforce, leveraging a task-based approach with data from the Skills and Employment Survey Series. Focused on the changing importance of job tasks related to graduate skills, the research explores the mapping of these tasks to educational attainment, discerns the price employers pay for tasks requiring graduate skills, and addresses regional variation in graduate supply and demand. Despite a slowing growth of graduate skills requirements post-2006, we find a stable assignment of graduate education with job tasks and an overall flat task price related to graduate skills requirements. We present regional evidence showing education expansion rather than exogenous factors drove high-skills demand, balancing the development of supply and demand in the British graduate labour market over 1997–2017.

Keywords: graduate skills; task-based approach; education expansion; task price; regional variation
JEL classifications: J24, J23, J31

1. Introduction
The British workforce has never been better qualified. According to UK Labour Force Survey estimates, university graduates accounted for 33 per cent of the working-age population aged 20–64 by 2022, up from 11 per cent in 1995. However, amidst this surge in educational attainment, questions surrounding the value-for-money proposition of university degrees have become ever more prevalent (Brown et al. 2020). Against this backdrop, leveraging data from the British Skills and Employment Survey Series since 1997, this study employs a task-based approach to examine the evolving demand for graduate skills amidst rapid education expansion. The objective is to scrutinize the changing importance of job tasks related to graduate skills requirements, map them to graduate education, discern the price employers pay for the performance of those tasks, and connect these shifts in employment and prices with the education expansion over this period. Through this investigation, we contribute insights into the connection of job tasks with the skills graduates bring to the

labour market and how changes in job task content have contributed to graduate skills demand, affecting employment and wages.

A better understanding of the mechanisms behind graduate outcomes matters. Policy circles often interpret differences in graduate outcomes as measures of *degree quality* (Hinds 2019; Johnson 2020; Department for Education 2023a; Department for Education 2023b). However, for higher education to deliver 'value for money', employers need to demand these distinctly graduate skills (Tholen et al. 2016). In other words, for graduate skills to be rewarded, jobs need to make productive use of them. A poor match between individual skills and the skills required by their job means a relative loss of productivity and earnings (Van Der Velden and Bijlsma 2019; Leighton and Speer 2023).

Current evidence based on graduate earnings and employment delivers a mixed picture of the state of the British graduate labour market. On the one hand, a stable graduate pay premium over the education expansion of the last 30 years suggests a balanced growth of demand and supply (Blundell et al. 2022). On the other, evidence for occupation downgrading (Montresor 2019) and growing heterogeneity in graduate outcomes related to a rising prevalence of overqualification (Green and Zhu 2010; O'Leary and Sloane 2016) have been interpreted as indicators of a potentially weakening demand for graduate skills. Our proposed assessment of the job tasks related to graduate skills requirements, how much they have changed over time, and how much employers are willing to pay for the activities that require skills typically acquired during higher education will add a job-level understanding of the drivers of changing graduate labour market outcomes.

Changing labour market outcomes related to educational attainment are usually contextualized against task-biased technological change, transforming the content and organization of what workers do (e.g. Autor et al. 1998; Green 2012; Autor et al. 2020). A *job task* is defined as a unit of work activity producing outputs, whereas skills describe workers' proficiency in performing tasks. Workers are paid wages according to their skill-based productivity, where employers pay a price for the outputs resulting from the performance of job tasks (Acemoglu and Autor 2011). New technologies are thought to have complemented workers in carrying out hard-to-automate (nonroutine) tasks. At the same time, machines and algorithms have increasingly taken over automatable (routine) job tasks (Acemoglu and Autor 2011). University graduates are believed to command the skills to perform hard-to-automate abstract 'problem-solving and complex communication activities' (Autor et al. 2003). With the shift in job task profiles towards nonroutine abstract tasks, the productivity of university-educated, 'knowledge' workers has risen with positive consequences for their employment and pay (Cavaglia and Etheridge 2020).

However, within this framework, not all graduates will have benefited equally from task-biased technological change. Specifically, task-biased technological change might have affected male and female graduates differently due to gendered patterns of skills specializations (Lindley 2012). Concurrently, regional variations in population density, industry structure, or long-term innovation patterns may have intersected with technological changes, leading to further spatial concentration of high-skills demand (Overman and Xu 2022).

Moreover, in the absence of task-biased technological change and the shift towards abstract tasks, the growth of graduate skills demand may slow (Mason 2002). As a result, university-educated workers might slide down the job skills ladder, with adverse downstream effects on non-graduates' labour market position (Beaudry et al. 2016). While the applicability of the task-biased technological change hypothesis is subject to ongoing debate (e.g. Fernández-Macías and Hurley 2016; Blundell et al. 2022), tracking movements in job task profiles and task prices has yielded valuable insights into patterns of graduate employment and wages during periods of education expansion in various industrialized countries (Alda et al. 2020; Cavaglia and Etheridge 2020; Carneiro et al. 2023). The present study leverages the task-approach to assess job content relates to graduate employment and the price employers pay for task-based graduate skills requirements.

Measurement has been a substantial challenge in testing the implications of the task-approach (Autor 2013). Most research in the field deploys broad, time-constant occupation groups as proxies for job tasks (e.g. Montresor 2019; Cavaglia and Etheridge 2020; Cortes et al. 2020; Dabla-Norris et al. 2023). However, there is considerable heterogeneity in workers' job content at any given point, even within narrowly defined occupations (Autor and Handel 2013; De La Rica et al. 2020). Moreover, changes within occupation dominate the dynamics of what workers do over time (Freeman et al. 2020), particularly pertinent when education expansion and technological change potentially interrupt traditional occupation-education linkages (Baker 2011). Furthermore, the performance of granular job tasks predicts current and future wages within individuals (Stinebrickner et al. 2019), highlighting the need for a job-level approach to tasks.

Using unique worker-reported data on their job in 1997, 2001, 2006, 2012 and 2017 and drawing on the insights of the task-based approach, the current study makes several contributions to the understanding of graduate labour market dynamics:

1) First, we derive and validate a job-level, task-based index of graduate skills requirements by amalgamating the workers' assessments of cognitive and interpersonal task importance, self-planning and computer use with their judgment on whether a degree is required to get their job (referred to as *degree requirement* in the following). Workers are best placed to assess their job content (e.g. Storm 2023). Our derived index retains the variation in worker-assessed degree requirements related to their reported job tasks. We interpret this index as a lower bound of the requisite level of graduate skills for effective job performance. We show that the index construct is approximately time consistent, and its value closely aligned with occupation skill levels and hourly wages, a typical proxy for workers' productivity.
2) Secondly, we explore the long-term evolution of graduate skills requirements. Our data suggest a substantial increase between 1997 and 2017 but signs of decelerating growth post-2006. Comparing across genders, degree requirements rose faster and the slowdown in graduate skills requirements post-2006 was somewhat less pronounced in the female than in the male workforce.
3) Thirdly, we evaluate how the mapping of educational attainment to graduate skills requirements has evolved during the expansion of higher education. Overall, we find no evidence of a significant change in the association of graduate education with job skills requirements.
4) Fourthly, we examine movements in the price employers pay for the outputs arising from job tasks that require graduate skills. Drawing on Autor and Handel (2013), we leverage the heterogeneity in job task profiles and earnings within narrow occupation groups to net out the price related to graduate skills requirements from workers' wages. The estimates reveal a substantial premium related to graduate skills requirements. About 40 per cent of the graduate pay advantage might be due to differences in the job task profiles typically performed by graduates and non-graduates, strongly supporting the notion that job tasks govern effective skills use. Despite a temporary drop in the price of graduate skills requirements between 2006 and 2012, we find an overall flat price related to graduate skills requirements.
5) Finally, we synthesize these findings to assess how the expansion of higher education influenced the trajectory of graduate skills requirements and, consequently, the graduate wage premium and associated task prices across British regions within a demand-supply framework. While limited by small numbers of observations, results indicate that the expansion of higher education boosted regional graduate skills requirements and wages, counterbalancing an underlying exogenous slowdown in graduate skills demand.

Overall, the results point towards a balanced growth of graduate supply and demand, expressed in stable levels of job skills requirements within graduates and the continued willingness of employers to pay a premium for the tasks related to graduate skills requirements. This stable growth was driven by an education-led transformation of Britain towards a knowledge economy rather than exogenous forces such as task-biased technological change. While specific to Britain, we might expect similar patterns for other technology followers, where graduates are plentiful, productivity growth slow and occupation-education linkages sufficiently malleable (Di Stasio et al. 2016).

Our article is close to other studies illuminating graduate outcomes following the mass expansion of higher education in Britain since the mid-1990s. Blundell et al. (2022) examined long-term trends in the graduate pay premium. They focused on endogenous organizational change enabled by higher education expansion as a mechanism boosting graduate skill demand. The current study is agnostic about the drivers that lifted graduate productivity to establish more broadly what happened to graduate skills demand. Green and Henseke (2016) derived a task-based classification of occupations into graduate and non-graduate jobs, an approach the current paper takes further by going beyond a binary classification of occupations. Most previous research in this strand is concerned with rising graduate heterogeneity along supply-side characteristics, including degree level (Lindley and Machin 2016), degree class (Naylor et al. 2016), major (Lindley and McIntosh 2015), or programme selectivity (Britton et al. 2022). By contrast, our contribution is primarily to untangle how well the task-based demand for graduate skills has kept pace with the graduate supply.

Our paper also contributes to the broader 'task-based' literature, as discussed, for example, in Autor (2013). Of relevance are Beaudry et al. (2016), who rely on occupation-based cognitive task proxies to assess demand trends for college-educated workers and the knock-on effects for the rest of the workforce. Using longitudinal panel data, Cavaglia and Etheridge (2020) estimate task prices from movers between broad occupation groups. Neither considers changes in job content. By contrast, Kawaguchi and Toriyabe (2022) use worker-reported job task data to derive skill use indices from the OECD's Survey of Adult Skills. They show that differences in task endowment explain wage gaps by gender and between native and immigrant workers. We draw on their insights to derive a task-based measure of graduate skills requirements. Using the same data source, De La Rica et al. (2020) illuminate heterogeneity in job task content in occupations within and between countries. They exploit this heterogeneity to estimate prices related to different task domains following an approach developed by Autor and Handel (2013). The current study shares their approach to estimate the task price of graduate skills requirements. Like us, Green (2012) uses the British Skills and Employment Survey to track changes in the importance of detailed job tasks over time. We build on his insight that job content relates to job qualification requirements. None of the papers has directly examined changes in job tasks related to graduate skills requirements, their mapping to graduate education and the price related to these task-based graduate skills requirements.

The remainder of the paper is organized as follows. Section two introduces the data and variables. Section three derives and validates a task-based index of graduate skills requirements. Findings are presented and discussed in section four. The closing section concludes.

2. Data and variables

2.1 Data

The following analyses use unique British Skills and Employment Survey Series (SES) data. SES is a collection of nationally representative sample surveys of working adults aged 20–60 (since 2006: 65 years) fielded roughly every five years. Since 1997, SES has measured the importance of more than 30 job tasks alongside information on job qualification requirements, work organization and tools using the job requirements approach. All surveys in the series are independent random probability surveys of households in Britain. Interviews were conducted face-to-face in people's homes (Felstead et al. 2019).

This study uses the combined SES surveys of 1997, 2001, 2006, 2012 and 2017. Job content analyses were restricted to the employed workforce aged 20 to 60-year-olds in Great Britain, for whom we have consistent data for all survey years. All estimates are weighted using survey weights to adjust for non-response and oversampling. Standard errors were clustered by three-digit occupation to account for intra-cluster correlation in outcomes (MacKinnon et al. 2023).

2.2 Variables

2.2.1 Dependent variables

2.2.1.1 Degree requirements

To derive an index of graduate skills requirements, we rely on workers' assessment of what qualifications are necessary to get the type of job they have. SES participants were asked, 'If they were applying today, what qualifications, if any, would someone need to *get* the type of job you have now?' Participants pick up to three qualifications from a list of UK educational certificates. We define degree requirements if the respondent states that a 'Masters or PhD Degree' or 'University or CNAA Degree' is required to get the job.[1]

2.2.1.2 Hourly pay

SES asks employees to report the usual gross earnings they receive. Self-employed workers report their income after expenses before tax. The values are converted into an hourly pay rate using the information on regular work hours, including any usual overtime. Following Blundell et al. (2022), we deflate wages by the total implicit GDP price deflator (OECD 2022).

2.2.2 Job tasks

Since 1997, SES participants have reported on the importance of more than 30 job tasks, computer use, expert knowledge, task discretion, and task variety. Job task data were collected through self-completion to limit social desirability bias. Respondents report how important each task was for their job, ranging from 'essential' to 'not at all important'. This study focuses on cognitive, interpersonal, and self-planning tasks for which graduates might hold a comparative advantage.

Incumbents are likely to be the most precise source of information about their job tasks and duties. Indeed, for most tasks, there is good agreement between workers and their supervisors' (Green and James 2003) or experts' rating (Storm 2023). On this basis, we use information from workers to describe job content. The assumptions behind this approach also underlie a range of large-scale surveys, including the OECD's Survey of Adult Skills (OECD 2019) and O*NET's Work Activities Questionnaire (O*NET 2021).

Tasks map to three broad domains: cognitive, interpersonal, and self-planning (Table 1). Work tools and work organization may change how these tasks intersect and are carried out; therefore, we add information on task discretion, task variety, and computer use (Fernández-Macías and Hurley 2016). Table 1 summarizes job task items and the associated task domains. We use the individual task items and the whole response spectrum to predict jobs' graduate skills requirements.

[1] The Council for National Academic Awards (CNAA) was the central degree-awarding authority for polytechnics and other non-university higher education institutions before they gained degree-awarding powers in 1992.

Table 1. Job task domains.

Task domains	Individual tasks
Literacy (cognitive)	Reading or writing long documents
Numeracy (cognitive)	Importance of advanced mathematics
Problem-solving (cognitive)	Analysing complex problems in-depth
Specialist knowledge (cognitive)	Importance of specialist knowledge
Learning requirements (cognitive)	Amount of learning required to do the job well.
Professional communication (interpersonal)	Persuading others, giving presentations and speeches, planning, managing, and supervising others
Self-planning	Thinking ahead
Task discretion (work organization)	Personal influence over the work process, task order, quality, and task effort
Task variety (work organization)	Task repetition, variety, and multi-tasking
Computer use (work tools)	Complexity of computer use

Source: Authors.

2.2.3 Occupation classification

Occupation grouping follows the UK Standard Occupational Classification 2000 (SOC 2000). At the top tier, SOC 2000 distinguishes between nine broad major groups broken down into 353 four-digit unit groups at the lowest level of disaggregation. Jobs are classified based on their skill level and skill specialization. Skill levels approximate the length of education and training necessary to become proficient in the performance of tasks required for the job, informing the top-tier classification of jobs. Skill specialization describes the required area of expertise for efficient job performance, informing occupation classification below the major group level (Office for National Statistics 2000).

2.2.4 Further variables

Further variables include indicators of human capital, including educational attainment (lower secondary, upper secondary, higher education, first degree, higher degree), years of potential experience (=age-25), and demographic information such as sex, region of residence, birth cohort, ethnicity (white, black, Asian, mixed, other), and survey year. Workplace controls include a dummy variable distinguishing public from private sector organizations and a variable measuring the number of employees at the workplace.

3 Deriving and validating an index of graduate skills requirements

Consistent with the multifaceted nature of work graduates might carry out, we conceptualize a job's required skill level as a formative latent construct shaped by the tasks it encompasses (Bollen and Diamantopoulos 2017). Thus, we formulate a measurement model that links job tasks, $a_{\cdot jt}$, to the required level of graduate skills, S^*_{jt}, in job j at time t given by Equation (1).

$$S^*_{jt} = \alpha_1 + \sum\nolimits_k \beta_k \cdot a_{kjt} + \nu_{jt} \tag{1}$$

The latent level of graduate skills requirements is determined by the importance of the $k = 1, \ldots, K$ tasks, a_{kjt}, in job j as reported by the incumbent worker. The intercept α_1 measures systematic degree requirements unrelated to job tasks, while the variable ν_{jt} represents a continuously distributed error term, independent of the job tasks, symmetrically distributed about zero. The intercept in Equation (1) will be zero if the K tasks are a sufficiently complete representation of the work graduates are expected to do. Nonetheless, it remains conceivable that unobserved tasks contribute to skills requirements. The index is thus best understood as a lower-bound estimate of graduate skills requirements.

If graduate skills requirements exceed a certain threshold, $S^*_{jt} > 0$, the job will necessitate a degree on access ($D_{jt} = 1$). We focus on the index $\sum_k^k \beta_k \cdot t_{kjt}$ mapping abstract job tasks to latent job skills requirements.

Through probit estimation of Equation (1), we derive a *graduate skills requirements* index, $\hat{S}_{jt}$, as the predicted probability that a university degree is required for the job based on the job task profile. This procedure removes variation unrelated to the job tasks from the reported degree requirements. We refrain from making assumptions about the relationship between job tasks and individual skills at this stage.

Supplementary Appendix Table A.1 summarizes the bivariate polychoric correlation coefficients between degree requirements and job tasks (Kolenikov and Angeles 2004). Additionally, Table A.2 reports the Equation (1) coefficients from a probit and linear estimations. In bivariate comparison, tasks such as giving speeches, the complexity of computer use on the job and the importance of long-writing exhibited the strongest association with jobs' degree requirements. The multivariate model sustains the relevance of computer use, public speaking, and long-writing tasks. Multitasking positively predicted degree requirements, while coefficients for job autonomy shifted slightly negatively, approaching zero. Jobs, where neither of the tasks were relevant, had a probability of near zero to require a degree, suggesting the index was overall complete.

3.1 Measurement equivalence

To facilitate a meaningful comparison of job skills requirements based on the index, $\hat{S}_{it}$, the index should consistently measure the underlying latent construct, S^*_{it}. This necessitates the coefficients, particularly the intercept in Equation (1), to remain uniform over time. In essence, the same survey response should map to the same latent skills requirement score, irrespective of context, calling for *measurement equivalence* or *invariance* (Leitgöb et al. 2023).

The significance of measurement equivalence in group comparisons of latent variables, especially for formative constructs like graduate skills requirements, has been a subject of ongoing debate (Greiff and Scherer 2018; Welzel et al. 2023). Unlike reflective measures that treat observed indicators as expressions of an underlying latent construct, formative constructs are thought to be shaped by the observed indicators (Meuleman et al. 2022). The central concern lies in discerning how potential interactions between the measurement model and group membership confound 'true' differences in the latent construct (Robitzsch and Lüdtke 2023).

Measurement equivalence is typically assumed in the task-based literature, whether in comparisons over time (Koomen and Backes-Gellner 2022), across countries (De La Rica et al. 2020), or among sub-groups of workers (Kawaguchi and Toriyabe 2022). However, violations can occur due to inconsistencies in survey design, variations in tasks' skill content, the emergence of new job tasks, evolving connotations of survey questions and response options over time, or other subjective influences introducing measurement error.

Following a strictly consistent data collection approach, the SES survey series has employed a largely unchanged set of job task questions in a computer-based self-completion module as part of a longer in-person interview. Consistent survey design minimizes bias, yet even the most rigorous design cannot guarantee longitudinal comparability.

To assess measurement equivalence, Equation (1) is estimated without constraints on coefficients across survey waves. We are interested in *intercept equivalence* and *slope equivalence*. Under intercept equivalence, changes in graduate skills requirements over time are due to shifts in job task profiles. It might fail if new job tasks not considered in the measurement model become increasingly relevant predictors of degree requirements. Intercept equivalence is required for meaningful comparison of levels over time. Under slope equivalence, a change in reported job tasks relates to the same shift in job skill requirements irrespective of the survey wave. It might fail due to, for example, changing relative graduate quality or shifts in tasks' skills content. Varying task coefficients do not necessarily render comparisons meaningless. Instead, they can illuminate the evolving mapping of graduate qualifications to job tasks in the economy. Supplementary Appendix Table A.3 summarizes the wave-specific probit coefficients of Equation (1).

According to the estimates, intercept equivalence holds (chi2(4) = 4.1, $P = .40$), but slope equivalence is rejected (chi2(56) = 725.8, $P \approx .000$). The application of advanced maths and job task variety, including multitasking requirements, have become stronger predictors of degree requirements. In contrast, the association of task discretion or the complexity of computer with degree requirements weakened. Despite variations in task coefficients, predictions of graduate skills requirements based on pooled and wave-specific coefficients were highly similar, with correlation coefficients ranging from 0.98 to above 0.99 (Supplementary Appendix Table A.4), indicating approximate measurement equivalence for longitudinal comparison.

Assessments of measurement equivalence by gender reveal intercept equivalence (chi2(1) = 1.40, $P = .237$) but a violation of slope equivalence (chi2(14) = 78.27, $P = .000$). In the female workforce, degree requirements were less strongly related to the importance of advanced maths tasks and more strongly related to the importance of specialist knowledge, learning requirements and job task variety than in the male workforce. Comparing within gender over time, we find the same pattern of intercept equivalence with time-varying task coefficients in the male workforce, but violation of intercept (chi2(1) = 4.98, $P = .026$) and, possibly, slope equivalence (chi2(14) = 22.33, $P = .072$) in the female workforce. Supplementary Appendix Table A.5 provides details.

Throughout all comparisons, the predicted graduate skills requirements score was indistinguishable from zero when the K tasks were not important at all, confirming job content as main predictor for reported degree requirements. Subsequent analyses will focus on the total workforce with gender-specific results delegated to Supplementary Appendix. Where meaningful, analyses will include measurement models with time-varying parameters or sensitivity checks with alternative task coefficients.

3.2 Validation

This section valuates the validity of the derived skills requirement index, by assessing its relationship with job skill levels approximated by occupation major groups and workers' productivity approximated by hourly wages.

First, between 2012 and 2017, professions in science, research, engineering, and technology, followed by teaching and educational professionals, exhibited the highest occupation-mean graduate skills requirement scores. In contrast, elementary occupations recorded the lowest values on average. Although high-skill occupations generally displayed higher graduate skills requirements, there was notable heterogeneity within all occupations (Fig. 1). Nonetheless, occupation major groups accounted for 41 per cent of the variation in graduate skills requirements, indicating a clear relationship between occupation-based skill levels and the derived job-task-based skills requirement index.

Secondly, by pooling the five SES waves, restricting the comparison to the age group 20–60 years, and aggregating worker-level data to the three-digit occupation level, we observed a strong relationship between graduate skills requirements and wages ($r = 0.92$) at the occupation level. This close correlation held in the earlier waves up to 2006 (r = 0 .91) and the more recent waves 2012 and 2017 (r = 0 .90).

Figure 2 underscores the close alignment of jobs' skills requirements with wages in the British labour market and highlights distinct patterns: Transport Associate Professionals (e.g. Air traffic controllers, Aircraft pilots, Train drivers) and Health Professionals (e.g. Medical or Dental practitioners, Psychologists, Veterinarians) had

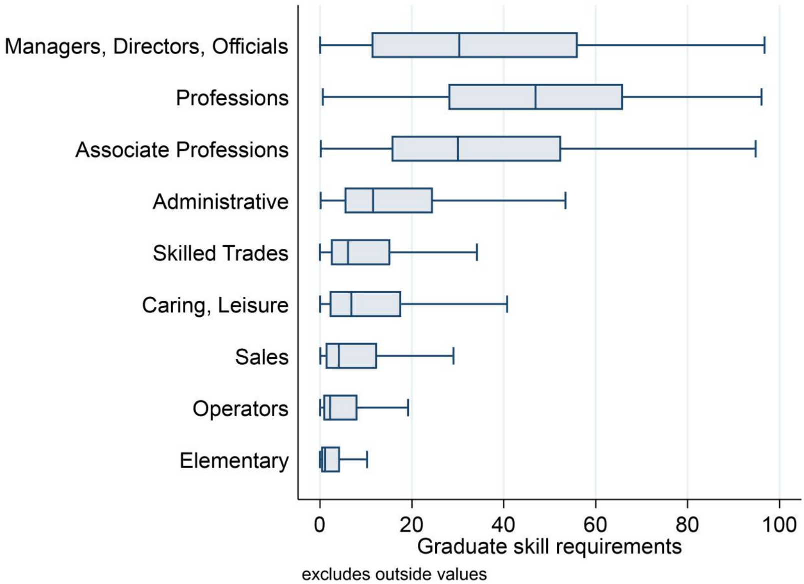

Figure 1. Graduate skills requirements within and across major occupation groups.

Note: Sample of 5,947 workers aged 20–60 in 2012 and 2017.

Source: Author's calculations.

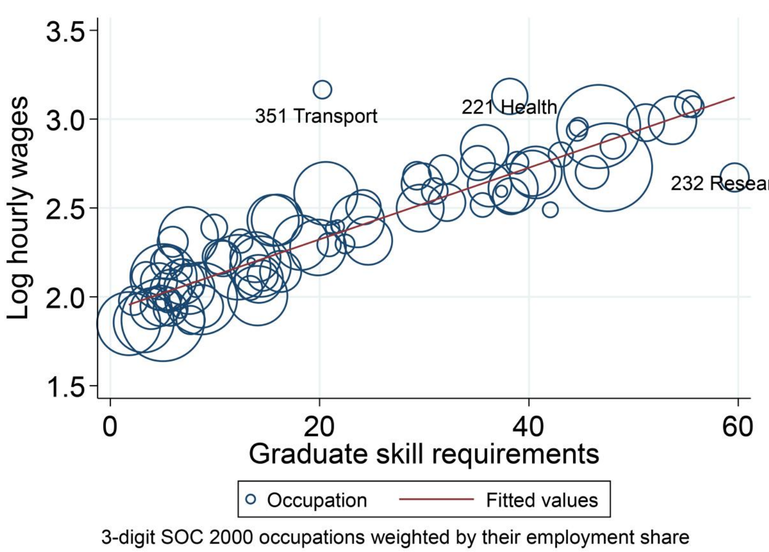

Figure 2. Occupation-median hourly wages and graduate skills requirements.

Note: The figure shows the correlation between the median-occupation log hourly wages and mean graduate skill requirements. The size of each circle indicates the employment rate of each occupation in the pooled SES survey sample of 20–60-year-olds in 1997, 2001, 2006, 2012, and 2017. Fitted values were obtained by weighted least squares, with the occupation-specific employment rates as weights.

Source: Author's calculations.

higher-than-expected pay given the overall relationship between graduate skills requirement scores and earnings. In contrast, Research Professionals (e.g. Scientific researchers or social science researchers) had lower earnings than expected based on their position in the graduate skills requirements distribution. Overall, graduate skills requirements were closely associated with worker's wages, a standard proxy of productivity in the literature.

4 Analysis and finding

4.1 Trends in degree and graduate skills requirements

4.1.1 Changes over time

Our substantive interest is in changes in jobs' graduate skills requirements.

Figure 3 compares the development of the derived index with the evolution of worker-reported degree requirements. Both time series displayed an upward trend, but after 2006, degree requirements increased more rapidly than graduate skill use. Overall, worker-reported degree requirements nearly doubled, rising from 15 per cent of all jobs in the age bracket 20–60 in 1997 to 29 per cent in 2017. During the period, the graduate skills requirement index rose from 17 to 25. Although wider confidence intervals (CI) limit inference, the diverging trend post-2006 is noticeable.

To gauge how changing graduate skills requirements explained trends in degree requirements, we estimate the following linear probability model:

$$D_{jt} = \tau_{0t} + \gamma \hat{S}_j(t) + \varepsilon_{0jt} \tag{2}$$

Here, D_{jt} represents worker-reported degree requirements, $\hat{S}_j(t)$ is the derived graduate skills requirements score for job j in survey wave t, τ_t captures period effects, and ε_{0it} is the error term. To assess the contribution of rising job skills requirements to the growth in D_{jt}, we combine Equation (2) with an equation tracking the time trend of $\hat{S}_{jt}$ over survey waves:

$$\hat{S}_{jt} = \tau_{1t} + \varepsilon_{1jt}$$

This creates a linear structural equation model. Table 2 summarizes the results of the decomposition.

Column 1 presents the total change in the percentage of jobs requiring a degree upon entry. As mentioned, their employment share rose by fourteen points between 1997 and 2017.

According to column (2), changes in job skill requirements explained just over half (55% = 100*7.7/13.9) of this rise in degree requirements from 1997 to 2017. But whereas changes in job task profiles fully accounted (5.5-point change with 95% CI: 3.7–7.3) for the 5.0-point change in the first decade (1997–2006), they contributed only about 2.2 (95% CI: 0.7–3.7) to the nine-point increase (95% CI: 5.5–12.5) in degree requirements in the second decade. The roughly 3.2-point decline in the task-based contribution between 2017/2006 and 2006/1997 was statistically significant at $P < .05$, indicative of a potential slowdown in the demand for graduate skills.

This deceleration in the expansion of graduate skills requirements withstands variations in the task coefficients that underpin the estimated skill levels, as detailed in Supplementary Appendix Table B.1. When scrutinized through the lens of gender, the overall increase in degree and skills requirements was swifter in the female workforce compared to their male counterparts. Despite a less pronounced deceleration in skills requirements post-2006 within the female sample, the surge in potentially task-unwarranted degree requirements exhibited similarity across gender, as outlined in Supplementary Appendix Table B.2.

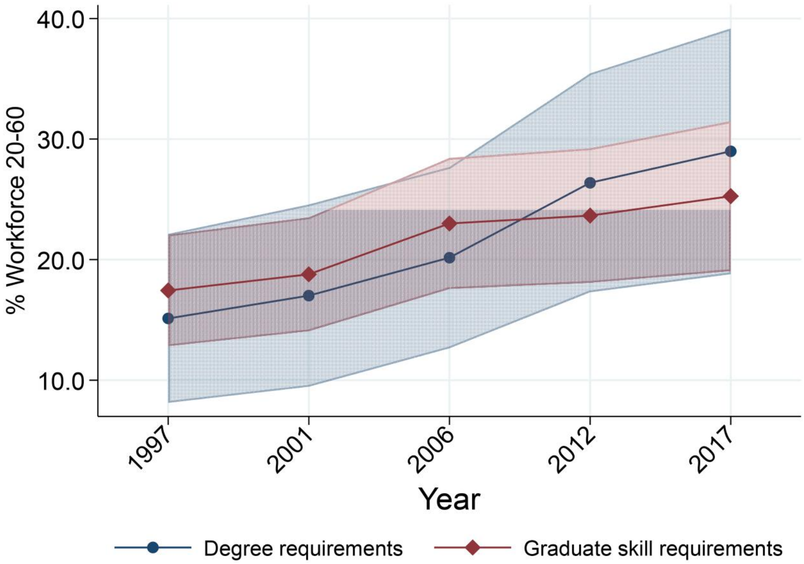

Figure 3. Trends in degree requirements and graduate skills requirements.

Note: N = 18,791 workers 20–60, 1997, 2001, 2006, 2012, 2017. 95% CI computed from robust standard errors clustered by three-digit occupations.

Source: Author's calculations.

4.2 Matching of educational attainment to job skills requirements

With the deceleration of graduate skills requirements, it is conceivable that graduates have started to descend the job skills ladder, taking on jobs with lower skill requirements. This section aims to scrutinize two facets: 1) the initial match of graduates to jobs requiring high levels of graduate skills, and 2) potential changes in the relationship of university attainment with jobs' level of graduate skills requirements.

The Ordinary Least Squares (OLS) regression model is specified as follows:

$$S^*_{jt} = \alpha_3 + \tau_{3t} + \delta_{1t}E_{it} + \delta_2 X_{it} + \delta_3 Z_{jt} + \varphi_{ijt} \tag{3}$$

Here, S^*_{jt} represents graduate skills requirements approximated by $\hat{S}_{jt}$. τ_{3t} captures a period-specific intercepts. E_{it} is a factor variable measuring workers' level of educational attainment, and X_{it} is a vector of control variables, including a quadratic polynomial of experience interacted with gender, birth cohort dummies, an ethnic minority indicator, and region of residence in Great Britain. Z_{jt} factors in public sector employment and number of employees at the workplace. The error term is given by φ_{ijt}.

The focus is on the coefficient vector δ_{1t}, gauging the potentially time-varying gap in job skills requirements between graduates and non-graduates. In a scenario where graduate supply surpassed demand, graduates might have navigated towards roles with lower requirements, leading to a reduction in δ_{1t} relative to non-graduates over time. The term 'non-graduate' refers to individuals who achieved at least five good GCSE passes but abstained from obtaining degree qualifications by the age of 25 (Blundell et al. 2022). This group had the option to pursue higher education but did not.[2]

[2] In addition to GCSEs, access to UK universities usually requires upper-secondary qualifications (e.g., 2+ A-levels). In 2010–20, slightly more than half of those aged 25–34 who had achieved at least five good GCSE passes or equivalent also completed upper-secondary qualifications. However, only about a quarter of those did not hold a degree qualification, making it a very selective comparison group.

Table 2. Decomposition of changing degree requirements into a task-based and residual period effect, 1997, 2001, 2006, 2012, 2017 (N = 18,791).

	(1) Total	(2) Task-based	(3) Residual
1997	(ref)	(ref)	(ref)
2001	1.8	1.3	0.4
	(1.36)	(1.02)	(0.80)
2006	4.9***	5.4***	−0.6
	(1.30)	(1.23)	(1.00)
2012	11.2***	6.1***	5.1***
	(2.07)	(1.30)	(1.48)
2017	13.8***	7.6***	6.2***
	(2.40)	(1.59)	(1.41)
$\Delta(2017 - 2006)$ - $\Delta(2006 - 1997)$	4.1*	−3.2*	7.3***
	(1.99)	(1.32)	(2.01)

Note: Estimated period effects (reference 1997) from a linear structural equation model of degree and graduate skill requirements in a pooled sample of workers aged 20–60 years in Great Britain. Clustered-robust standard errors in parentheses.
* $P < .05$, ** $P < .01$, *** $P < .001$.
Source: Author's calculations.

The sample is confined to workers aged 25–60, presumed to have completed their initial education and yet to retire from the labour market. As an extension, to assess the sensitivity of the estimates to rising rates of female participation and variation in graduate skills requirements, Equation (3) is re-estimated separately by gender.

Figure 4 illustrates the relationship between education attainment and jobs' graduate skills requirements. Graduate skills requirements rose with educational attainment, demonstrating a close match between individual skills and job task profiles. However, there were apparent inequalities within each education level, with graduates active across the entire job skills requirement distribution. In all, the five education levels explained 32 per cent of the variation in graduate skills requirements.

Table 3 summarizes the estimates from Equation (3).

First, in the combined sample (Column 1), there was a 31.4-point graduate skills requirement score difference between graduate workers and workers with at most GCSE or equivalent. This difference was highly statistically significant and about 1.4 times the skill requirements index's grand mean.

Secondly, despite negative interaction term coefficients, there was no firm statistical evidence for systematic differences in how higher educational attainment matched graduate skills requirements. A Wald test of time-varying higher education effects failed to reject the null hypothesis ($P = .50$). Allowing for time-varying task coefficients in estimating graduate skills requirements does not alter the headline finding (column 2), nor do findings by gender indicate distinct dynamics (Supplementary Appendix Table B.3).

Across samples, the model explained about 35%–38% of the variation in graduate skills requirements.

The results suggest that higher education was a crucial predictor of job requirements for graduate-level skills, indicative of the close match between individual skills and job requirements. We find no evidence for systematic changes in the association of graduate attainment with jobs' typical requirements for graduate-level skills. On the one hand, this result does not support a marked slowdown in the demand for graduate skills over the observation period despite the expansion of education and decelerating growth of graduate skills requirements. On the other hand, there has been no movement towards higher skill

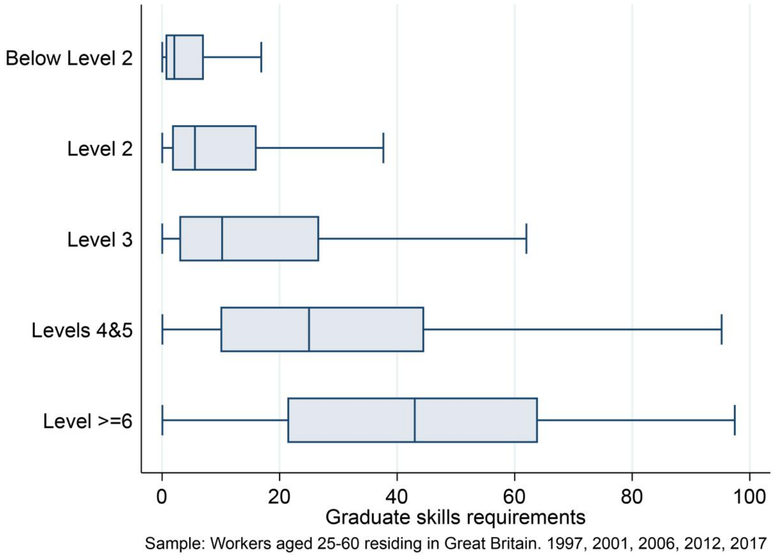

Figure 4. Distribution of graduate skills requirements by educational attainment, 1997–2017.

Note: Below Level 2 "Less than secondary education", Level 2 "Secondary education", Level 3 "Upper-secondary education", Levels 4 & 5 "Post-secondary education and short-cycle tertiary education", Level >=6 "First degree or above".

Source: Author's calculations.

requirements among graduates, in contrast to what one might expect from task-biased technological change.

4.3 Estimating the price related to graduate skill requirements

Alongside the movement in employment, changes in the demand for graduate-level skills should show in price movements. This section therefore examines changes in the price related to graduate skills requirements over time.

While conceptually distinct, empirically disentangling job tasks from individual skills and, thus, task prices from wages is not trivial. There are two primary concerns. First, in pursuit of comparative advantage, workers who are more proficient or have greater self-efficacy in carrying out a particular set of tasks tend to select jobs where those tasks have greater importance. Secondly, workers can have discretion to change task inputs to apply their skill set to meet job requirements (Autor and Handel 2013; Stinebrickner et al. 2019). As a result, workers' reported job tasks are likely endogenous.

Drawing on the exposition in Autor and Handel (2013), we start with a simple log-linear model of individual hourly wages as a function of jobs' required level of graduate skills determined by the execution of abstract tasks and workers' skill endowment:

$$\ln(w_{ijt}) = \mu_i + p_j\left[S^*_{jt}\cdot\theta_i\right] + \tau_t + \psi_{ijt} \tag{4}$$

Job j requires a specific level of graduate skills, S^*_{jt}, determined by a job's task profile at time t. The total units of tasks related to graduate skills requirements performed by workers i in job j at time t in a given interval (e.g. an hour) is a product of the worker's own endowment with graduate-level skills, θ_i, and the job skill requirements, $S^*_{jt}\cdot\theta_i$. The productivity of each efficiency unit of graduate-level tasks is given by p_{jt}. The terms μ_i captures general ability differences between workers. Macro-level productivity shocks are

Table 3. Differences in graduate skills requirements between degree-holders and workers with at most GCSE or equivalent qualifications, N = 17,193.

	(1) Pooled Task coefficient	(2) Wave-specific Task coefficients
Degree attainment	31.42***	30.09***
	(2.79)	(2.757)
# 1997	Ref.	Ref.
# 2001	−2.15	−1.34
	(2.68)	(2.67)
# 2006	−1.32	−2.09
	(2.46)	(2.46)
# 2012	−1.98	0.11
	(2.89)	(2.88)
# 2017	−3.92	0.08
	(2.89)	(3.03)
Mean Outcome	22.8	22.8
R-sq	0.354	0.375
H0: $\delta_{1t} = \delta_1$(p-val)	0.499	0.652

Note: Results from a linear regression of Equation (3). The dependent variable was the predicted graduate skills requirements score, with pooled (column 1) or wave-specific task coefficients (column 2). Independent variables included a second-order polynomial of experience interacted with gender, cohort dummies (<=1945, 1946–55, 1956–65, 1965–70, 1971–5, 1976–80, >1980), ethnic minority dummy, region of residence, public/private sector, workplace size. Standard errors clustered by three-digit occupations in parentheses.
$^{*}P < .05$, $^{**}P < .01$, $^{***}P < .001$.
Source: Author's calculations.

represented by τ_t, and ψ_{ijt} are idiosyncratic productivity shocks. Workers are assumed to being paid their marginal products.

The challenge in estimating Equation (4) is twofold. First, endogenous job choice and the potential relationship of general ability, μ_i, with individual skill endowment, θ_i, and job skills requirements S^*_{jt}, renders the term $S^*_{jt} \cdot \theta_i$ endogenous. Secondly, in practical terms, using the estimate of graduate skills requirements $\hat{S}_i$ as a generated regressor instead of the latent variable S^*_{jt} leads to wrong standard errors and potentially biased estimates.

First, to net out the price related to graduate skills requirements from individual skill heterogeneity, we draw on De La Rica et al. (2020) and control in the empirical application of Equation (4) for human capital (educational attainment, experience, occupation), demographic characteristics (gender, ethnicity, birth cohort, region of residence), and job characteristics (firm size, public or private sector organization). By controlling for occupation, the model exploits the close relationship of workers' skills with occupation's skill levels and skill specialization. Identification is achieved through within-occupation variation in job skill requirements and wages conditional on the covariates.

Secondly, to obtain the correct standard errors, we combine the measurement model given by equation (1) in the first stage with the wage equation in the second stage within a structural equation model:

The resulting model is given by:

$$S^*_{jt} = \alpha_1 + \sum\nolimits_k \beta_k \cdot a_{kjt} + \nu_{jt} \tag{1}$$

$$\ln(w_{ijt}) = \alpha + \lambda S^*_{jt} + \pi_1 X_{it} + \pi_2 Z_{jt} + \sigma_j + \tau_t + \psi_{ijt} \tag{5}$$

As before, the measurement equation (1) connects worker-reported degree requirements with the importance of K tasks, a_{kjt} in their job to estimate the level of graduate skills requirements.

Equation (5) is the empirical specification for the wage setting process described by Equation (4). Here, $\ln(w_{ijt})$ denotes log hourly earnings and S^*_{jt} represents jobs' graduate skills requirements. Vectors X_{it} and Z_{jt} comprise worker and job characteristics, respectively. Occupation fixed effect σ_j control for differences in workers' skill level and specialization beyond education and experience. A set of year dummies represents the period effects τ_t, measuring macro-level shocks. The coefficient $\lambda = E(p_j E(\theta_i))$ measures the average return to graduate skill use. The model given by Equations (1) and (5) will be estimated simultaneously using linear structural equation model estimation in Stata 17 with standard errors clustered by three-digit occupations. Error terms ν_{jt} and ψ_{ijt} are allowed to covary. The estimator will compute a linear approximation of the graduate skills requirements score S^*_{jt} and take care of the standard errors in the wage Equation (5).

Estimates of λ in Equation (5) will be biased upwards if the estimation model does not account for relevant differences in individual skills. Convincing instruments that exogenously alter job tasks for a given skill set are rare. In the absence of more detailed information on individual skills, we first compute the robustness value, which describes how strong unobserved confounders would need to be, in terms of their partial R-square, to drive the task price down to exactly zero in the wage model (Cinelli et al. 2020; Cinelli and Hazlett 2020). Secondly, in Supplementary Appendix C, we replicate our analysis with data from the British PIAAC sample 2011/2012, adding their measures of adult numeracy and literacy skills to the estimation model to gauge the sensitivity of the estimated task price and compare skills' partial R-square contribution to the wage model with the computed robustness value.

Table 4 summarizes the estimation results. As a benchmark, column (1) reports the raw relationship of reported degree requirements with wages without task adjustment. Hourly wages were about 80 per cent (=exp(0.597)) higher in jobs reported to require a degree on entry than those that did not. Shifting to graduate skills requirement (i.e. task-based degree requirements) in column (2) increased the log wage difference to 1.49. Conditioning on worker and job characteristics reduces the estimate to 1.17 (column 3) and adding occupation-fixed effects to the model in column (4) yields a price estimate of 0.74. The estimated task price is sizeable. Given the mean difference in typical graduate skills requirements between graduates and non-graduates, the estimated task price can explain approximately 40 per cent of the mean log wage differential between both groups.[3]

As discussed, a potential concern is that the included covariates do not fully account for all relevant skill differences between workers required to net out prices related to task-based skills requirements from wages.

Table 4 shows task price estimates vary with the included proxies of individual skills: the estimate approximately halves from about 1.5 in column (2) to 0.7 in column (4), while R-squared rose by 18 points with the additional controls. More detailed skills measures will likely reduce the estimate further. Ignoring measurement error and clustered standard errors, we compute a robustness value for our preferred point estimate in column (4) of 18 per cent using the *sensemakr* package in Stata (Cinelli et al. 2020). The figure implies that unobserved confounders (orthogonal to the covariates) which explain more than 18 per cent of the residual variance of the task assignment and log hourly wages are strong enough to bring the price estimate to a range where it is no longer statistically significant at the 5 per cent level.

In practice, the remaining skills bias might be small. Re-estimating Equations (1) and (5) using the UK PIAAC sample, the inclusion of direct measures of adults' numeracy and literacy skills on top of our list of covariates reduced the estimated price related to graduate

[3] The estimated log wage differential between graduates and school leavers was 0.51 in the pooled SES sample of 25–60-year-olds workers conditional on the same vectors of control variables X_{it}, Z_{jt} and τ_t as Equation 5.2. The adjusted mean difference in graduate skill requirements was 0.29 between both groups. Together with the task price estimate in Table 4 column (4), this yields a predicted graduate log wage premium of 0.21, approximately 42 per cent of 0.51.

Table 4. The task price of graduate skill requirements.

	(1) Degree req	(2) Skill req 1	(3) Skill req 2	(4) Skill req 3
Log hourly wages				
Graduate skills requirements	0.597***	1.486***	1.167***	0.736***
	(0.052)	(0.159)	(0.131)	(0.088)
Period effects	X	X	X	X
Worker and job characteristics			X	X
Occupation				X
Observations	14,763	14,763	14,763	14,763
R-squared (wage equation)	20.8	19.7	25.5	37.7

Note: Results of a structural education model with a measurement equation estimating graduate skills requirements from abstract job tasks and a structural wage equation relating log hourly wages to graduate skills requirement, worker (educational attainment, second-order polynomial of age interacted with gender, ethnic minority, broad birth cohort, region of residence) and job characteristics (public sector, workplace size), three-digit occupation dummies, and survey wave dummies. Error terms of the measurement and log wage equation were permitted to covary. Clustered standard errors in parentheses.
$^{*}P < .05$, $^{**}P < .01$, $^{***}P < .001$.
Source: Author's calculations.

skills requirements from 0.678 to 0.634, with a partial R-square of 4.9 per cent, below the computed robustness value. The estimates are summarized in Supplementary Appendix Table C.2. Since the derived index is likely to be a lower bound of graduate skills requirement, bias working in the opposite direction is also conceivable. Overall, the task price estimate appears sufficiently robust for longitudinal comparison.

To ascertain movements in the price related to graduate skills requirements over time, we re-estimate the model described by Equations (1) and (5) by survey wave. Because of sample size constraints, we switch from three-digit to two-digit occupation group fixed effects. This change pushes the pooled price estimate up to 0.78 log points. Figure 5 illustrates the resulting task price coefficients by survey wave.

Figure 5 shows a largely stable price related to graduate skills requirements in 1997, 2001, and 2006, varying between 0.74 and 0.88, followed by a drop to 0.67 in 2012 with a recovery back to 0.82 by 2017, close to the long-term average price. Relatively wide CI make firm conclusions difficult, but the sharp drop in the estimated price between 2006 and 2012 was statistically significant ($P = .015$), whereas overall time-invariance was not rejected ($P = .119$). Allowing time-varying task weights in the graduate skills requirement score does not alter the conclusions (for detailed estimates, see Supplementary Appendix Table B.4).

Gender differences in the price related to a unit increase in graduate skills requirements were marginal in the time-pooled sample (0.77 in the male vs 0.73 in the female workforce). However, the drop in the price between the surveys before and after 2012 was sharper in the female (from 0.83 to 0.61, $P = .01$) than in the male workforce (from 0.85 to 0.71, $P = .32$). Given the more significant uncertainties around measurement equivalence of job skill requirements in the female workforce, the former difference should be interpreted cautiously. Estimation results by survey wave and gender are reported in Supplementary Appendix Table B.5.

The results document a sizeable price related to graduate skills requirements. Our headline estimate can explain 40 per cent of the average graduate pay premium through difference in what graduates and non-graduates typically do on their jobs. The bias from omitted skills in our preferred specification might be small. There is evidence for a temporary decline in the price related to graduate skills requirements around the time of the

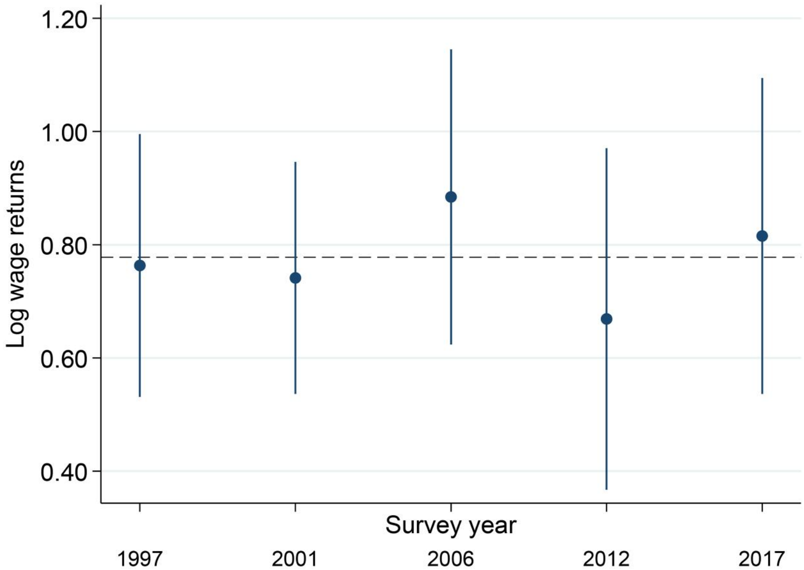

Figure 5. Price related to graduate skill requirements over time.

Note: Displayed coefficients are the estimated task price related to graduate skills requirements from an estimation of the structural equation model given by (1) and (5). For control variables in the wage equation see Table 4's footnote. The estimation sample comprises 25–60-year-old workers in 1997 (N = 1,943), 2001 (N = 3,660), 2006 (N = 4,937), 2012 (N = 2,035), and 2017 (N = 2,186). All estimates are weighted using survey weights. Bounds represent 95% CI from standard error clustered by three-digit occupations. The dashed line represents the estimated task price in the pooled sample.

Source: Author's calculations.

Great Recession, with recovery to the long-term average after that. The price drop was less apparent in the male workforce.

To sum up, task prices related to graduate skills requirements remained roughly constant over the two decades between 1997–2017, suggesting an overall balance between graduate supply and demand in the British graduate labour market during the period of education expansion. The drop between 2006 and 2012 was temporary.

4.4 Regional graduate labour markets

The stable alignment of graduate education with job skills requirements and the constant price related to graduate skills requirements signal a balanced growth in the supply and demand for graduate labour. This section investigates how education expansion across Britain's regions reshaped job task profiles and graduate pay.

Examining British regions holds significance for two main reasons. First, these historically distinct regional labour markets underwent varying rates of educational expansion and high-skill demand. Secondly, the UK stands out as one of the most spatially unequal industrialized economies (McCann 2020). Disparities in graduate labour supply and the efficient utilization of graduate skills likely contribute to productivity and earnings differentials (Stansbury et al. 2023). The interplay between regional skills supply and demand is bidirectional and potentially self-reinforcing: Employers will be more likely to seek graduate skills where they are abundant, and graduates will gravitate towards regions where employers value their skills.

We combined regional estimates of graduate skills requirements and task prices from the SES surveys (1997, 2001, 2006, 2012, and 2017) with data on the region-median hourly graduate wages and graduate employment share from the UK LFS spanning 1996–8,

Table 5. The relationship of education expansion, graduate skills requirements, and graduate earnings (N = 55).

	(1) Log graduate share	(2) Log graduate skills requirements	(3) Log median graduate wages	(4) Log task prices
Log graduate share		0.990***	0.639***	0.404*
		(0.287)	(0.122)	(0.205)
Log graduate skills requirements			0.175*	0.185
			(0.087)	(0.139)
Bartik instrument	6.938***			
	(0.714)			
Time trend	0.006	−0.019#	−0.026***	−0.023**
	(0.005)	(0.011)	(0.005)	(0.008)
Region FE	X	X	X	X

Note: Regional estimates combining aggregate SES with UK LFS figures for 1997, 2001, 2006, 2012, 2017 into a panel of eleven regions over five periods (N = 55). Results from a structural equation model combining a first stage equation of regional graduate labour supply on the Bartik instrument (column 1) with structural equations linking educational attainment to graduate skills requirements (column 2) and both to graduate earnings (column 3). Error term variances for the endogenous variables were e.graduate_share = 0.003, e.skill_requirements = 0.007, e.wages = 0.002, e.taskprice = 0.01, error covariance terms include cov(e.wages, e.graduate_share) = −0.002, cov(e.skill_requirements, e.graduate_share) = −0.002, and cov(e.taskprice, e.graduate_share). Standard errors in parentheses, clustered at region level.
# $P < .1$, * $P < .05$, ** $P < .01$, *** $P < .001$.
Source: Author's calculations.

2000–2, 2005–7, 2011–3, 2016–8, forming a small panel of eleven regions over 5 years. Region-fixed effects models were employed to account for time-constant regional disparities in graduate supply and demand, incorporating a linear time trend to capture national trends. To address concerns about the endogeneity of graduate labour supply, we adopted a Bartik-style graduate supply shifter from Blundell et al. (2022). The instrument measures the regional cohort composition in 1993–5 interacted with the national growth in graduate education, assuming regions with a higher share of individuals directly affected by educational expansion would experience a faster increase in graduate supply. The equations describing the regional graduate employment share, graduate skills requirements, graduate pay, and regional task prices were estimated jointly.

Table 5 presents the results of the combined fixed effect estimations. Column (1) validates the shift-share instrument as a predictor of regional graduate labour supply. Column (2) suggests that this population structure fuelled expansion of the graduate labour supply has shifted job content towards abstract tasks increasing graduate skills requirements. Column (3) indicates that both the expansion of skills and skills requirements positively contributed to the regional level of graduate pay. Finally, column (4) suggests that task prices related to graduate skills requirements and graduate pay might share the same determinants. The estimated time trend in columns (2), (3), and (4) was negative and, at about −2 per cent, of similar magnitude across outcomes, suggesting a secular, average annual decline in graduate skill requirements, graduate wages, and task price. Excluding London from the sample or treating the regional share of graduates as exogenous did not alter the core findings.

While confined to a specific period and limited by sample size, the findings imply that education expansion, rather than exogenous skill-biased technological change approximated by the national time trend, drove the observed shift in the job task profile towards greater graduate skills requirements and growing high-skills wages. The negative association of task prices related to graduate skills requirement with technological change reproduces in a cross-country sample of European and Asian technology followers in comparison with the

USA as technology leader in Supplementary Appendix C (Supplementary Appendix Table C.3 and Fig. C.1).

Conclusion

In conclusion, this study contributes relevant insights into the dynamics of the British graduate labour market. By developing and validating a novel task-based index, we shed light on the changing landscape of graduate skills demand since the end of the 1990s. Our findings of a rapid but slowing shift towards job tasks requiring graduate skills, stable matching of graduates to job skills requirement, and an overall flat task price related to graduate skills requirements suggest a balanced graduate labour market throughout education expansion. This aligns with the work of Salvatori (2018) or Blundell et al. (2022) and underscores the pivotal role of higher education in driving the knowledge economy.

These results have important implications for policymakers and practitioners. The stability of the price of graduate skills requirements, coupled with the consistent assignment of graduates to high-skills tasks, emphasizes the critical link between skills demand and their productive application to tasks (see also Supplementary Appendix D). As we navigate potential challenges, such as the observed secular decline in high-skills demand (Beaudry et al. 2016; Autor et al. 2020), understanding these dynamics becomes paramount for ensuring the continued effective deployment of graduates.

Looking ahead, future research could delve deeper into the interplay between education policies, technological change, high-level skills development, and dynamics in job content. By addressing these complexities, we can further refine our understanding of the evolving demand for university-educated labour and inform strategies to enhance the long-term value proposition of higher education. In doing so, we contribute not only to the academic discourse but also to the broader conversation on equipping graduates for success in a rapidly changing labour market.

Supplementary material

Supplementary material is available at the Oxford Economic Papers Journal online. These are the data and replication files and the Supplementary Appendix. The data used in this paper are publicly available from the UK Data Service (https://ukdataservice.ac.uk/) and the website of the OECD Skills Survey (https://www.oecd.org/skills/piaac/data/). Please see the README file in the online supplementary file for further details.

Funding

This work was supported by the Economic and Social Research Council [ES/M010082/2, ES/P005292/1].

Conflict of interest

All authors declare that they have no conflicts of interest.

Acknowledgements

We would like to extend our gratitude to two anonymous reviewers of the journal, whose expertise, insight, and patience helped strengthen the article significantly. The paper also benefited from participants' comments at the 5th Assisi Workshop in Economics 'The Future of Education, Skills, and Productivity', especially those offered by Hugh Lauder, Sandra McNally, and Kate O'Mahony. Finally, we thank Matt Dickson, Franz Buscha, and the participants of the 'Higher Education in a Cold Climate' workshop for their invaluable feedback.

References

Acemoglu, D., and Autor, D. (2011) 'Skills, Tasks and Technologies: Implications for Employment and Earnings'. In: Card, D. and Ashenfelter, O. (eds) *Handbook of Labor Economics*. Amsterdam and Boston: Elsevier.

Alda, H., Friedrich, A., and Rohrbach-Schmidt, D. (2020) 'Educational Expansion and Educational Wage Premiums of Young Male Employees: A Long-Term Analysis for West Germany 1976–2010', *Social Science Research*, **85**: 102351.

Autor, D., Goldin, C., and Katz, L.F. (2020) 'Extending the Race Between Education and Technology', *AEA Papers and Proceedings*, **110**: 347–51.

Autor, D.H. (2013) 'The "Task Approach" to Labor Markets: An Overview', *Journal for Labour Market Research*, **46**: 185–99.

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

Autor, D.H., Katz, L.F., and Krueger, A.B. (1998) 'Computing Inequality: Have Computers Changed The Labor Market?' *The Quarterly Journal of Economics*, **113**: 1169–213.

Autor, D.H., Levy, F., and Murnane, R.J. (2003) 'The Skill Content of Recent Technological Change: An Empirical Exploration', *The Quarterly Journal of Economics*, **118**: 1279–333.

Baker, D.P. (2011) 'Forward and Backward, Horizontal and Vertical: Transformation of Occupational Credentialing in the Schooled Society', *Research in Social Stratification and Mobility*, **29**: 5–29.

Beaudry, P., Green, D.A., and Sand, B.M. (2016) 'The Great Reversal in the Demand for Skill and Cognitive Tasks', *Journal of Labor Economics*, **34**: S199–S247.

Blundell, R., Green, D.A., and Jin, W. (2022) 'The U.K. as a Technological Follower: Higher Education Expansion and the College Wage Premium', *The Review of Economic Studies*, **89**: 142–80.

Bollen, K.A., and Diamantopoulos, A. (2017) 'In Defense of Causal-Formative Indicators: A Minority Report', *Psychological Methods*, **22**: 581–96.

Britton, J., Van Der Erve, L., Belfield, C., Vignoles, A., Dickson, M., Zhu, Y., Walker, I., Dearden, L., Sibieta, L., and Buscha, F. (2022) 'How Much Does Degree Choice Matter?' *Labour Economics*, **79**: 102268.

Brown, P., Lauder, H., and Cheung, S.Y. (2020) *The Death of Human Capital?: Its Failed Promise and How to Renew It in an Age of Disruption*, New York, Oxford University Press.

Carneiro, P., Liu, K., and Salvanes, K.G. (2023) 'The Supply of Skill and Endogenous Technical Change: Evidence from a College Expansion Reform', *Journal of the European Economic Association*, **21**: 48–92.

Cavaglia, C., and Etheridge, B. (2020) 'Job Polarization and the Declining Quality of Knowledge Workers: Evidence from the UK and Germany', *Labour Economics*, **66**: 101884.

Cinelli, C., Ferwerda, J., and Hazlett, C. (2020) *Sensemakr: Sensitivity Analysis Tools for OLS in R and Stata*, Los Angeles, University of California.

Cinelli, C., and Hazlett, C. (2020) 'Making Sense of Sensitivity: Extending Omitted Variable Bias', *Journal of the Royal Statistical Society Series B: Statistical Methodology*, **82**: 39–67.

Cortes, G.M., Jaimovich, N., Nekarda, C.J., and Siu, H.E. (2020) 'The Dynamics of Disappearing Routine Jobs: A Flows Approach', *Labour Economics*, **65**: 101823.

Dabla-norris, E., Pizzinelli, C., and Rappaport, J. (2023) 'Job Polarization and the Declining Wages of Young Female Workers in the United Kingdom', *Oxford Bulletin of Economics and Statistics*, **85**: 1185–210.

De La Rica, S., Gortazar, L., and Lewandowski, P. (2020) 'Job Tasks and Wages in Developed Countries: Evidence from PIAAC', *Labour Economics*, **65**: 101845.

Department for Education. (2023a) *Crackdown on rip-off university degrees* [Online], https://www.gov.uk/government/news/crackdown-on-rip-off-university-degrees, accessed 31 Oct. 2023].

Department for Education. (2023b) *How we're improving the quality of degrees* [Online]. the Education Hub, https://educationhub.blog.gov.uk/2023/07/17/how-were-improving-the-quality-of-degrees/, accessed 31 Oct. 2023].

DI Stasio, V., Bol, T., and Van De Werfhorst, H.G. (2016) 'What Makes Education Positional? Institutions, Overeducation, and the Competition for Jobs', *Research in Social Stratification and Mobility*, **43**: 53–63.

Felstead, A., Gallie, D., Green, F., and Henseke, G. (2019) Skills and Employment Surveys Series Dataset, 1986, 1992, 1997, 2001, 2006, 2012 and 2017. UK Data Service.

Fernández-Macías, E., and Hurley, J. (2016) 'Routine-Biased Technical Change and Job Polarization in Europe', *Socio-Economic Review*, **15**: mww016.

Freeman, R.B., Ganguli, I., and Handel, M.J. (2020) 'Within-Occupation Changes Dominate Changes in What Workers Do: A Shift-Share Decomposition, 2005–2015', *AEA Papers and Proceedings*, **110**: 394–9.

Green, F. (2012) 'Employee Involvement, Technology, and Evolution in Job Skills: A Task-Based Analysis', *ILR Review*, **65**: 36–67.

Green, F., and Henseke, G. (2016) 'The Changing Graduate Labour Market: Analysis Using a New Indicator of Graduate Jobs', *IZA Journal of Labor Policy*, **5**: 1–25.

Green, F., and James, D. (2003) 'Assessing Skills and Autonomy: The Job Holder Versus the Line Manager', *Human Resource Management Journal*, **13**: 63–77.

Green, F., and Zhu, Y. (2010) 'Overqualification, Job Dissatisfaction, and Increasing Dispersion in the Returns to Graduate Education', *Oxford Economic Papers*, **62**: 740–63.

Greiff, S., and Scherer, R. (2018) 'Still Comparing Apples with Oranges?', *European Journal of Psychological Assessment*, **34**: 141–4.

Hinds, D. (2019) *Education Secretary calls for an end to low value degrees* [Online]. Department for Education, https://www.gov.uk/government/news/education-secretary-calls-for-an-end-to-low-value-degrees, accessed 31 October 2023.

Johnson, P. (2020) *Too many students take courses that don't benefit them or the economy [Comment]* [Online]. The IFS, https://ifs.org.uk/articles/too-many-students-take-courses-dont-benefit-them-or-economy, accessed 31 Oct. 2023.

Kawaguchi, D., and Toriyabe, T. (2022) 'Measurements of Skill and Skill-Use Using PIAAC', *Labour Economics*, **78**: 102197.

Kolenikov, S., and Angeles, G. (2004) *The Use of Discrete Data in PCA: theory, Simulations, and Applications to Socioeconomic Indices*. Chapel Hill, NC: University of North Carolina.

Koomen, M., and Backes-Gellner, U. (2022) 'Occupational Tasks and Wage Inequality in West Germany: A Decomposition Analysis', *Labour Economics*, **79**: 102284.

Leighton, M., and Speer, J.D. (2023) 'Major-Occupation Match Quality: An Empirical Measure Based on Relative Productivity', *The B.E. Journal of Economic Analysis & Policy*, **23**: 285–92.

Leitgöb, H., Seddig, D., Asparouhov, T., Behr, D., Davidov, E., De Roover, K., Jak, S., Meitinger, K., Menold, N., Muthén, B., Rudnev, M., Schmidt, P., and Van De Schoot, R. (2023) 'Measurement Invariance in the Social Sciences: Historical Development, Methodological Challenges, State of the Art, and Future Perspectives', *Social Science Research*, **110**: 102805.

Lindley, J. (2012) 'The Gender Dimension of Technical Change and the Role of Task Inputs', *Labour Economics*, **19**: 516–26.

Lindley, J., and Machin, S. (2016) 'The Rising Postgraduate Wage Premium', *Economica*, **83**: 281–306.

Lindley, J., and Mcintosh, S. (2015) 'Growth in Within-Graduate Wage Inequality: The Role of Subjects, Cognitive Skill Dispersion, and Occupational Concentration', *Labour Economics*, **37**: 101–11.

Mackinnon, J.G., Nielsen, M.Ø., and Webb, M.D. (2023) 'Cluster-Robust Inference: A Guide to Empirical Practice', *Journal of Econometrics*, **232**: 272–99.

Mason, G. (2002) 'High Skills Utilisation Under Mass Higher Education: Graduate Employment in Service Industries in Britain', *Journal of Education and Work*, **15**: 427–56.

Mccann, P. (2020) 'Perceptions of Regional Inequality and the Geography of Discontent: Insights from the UK', *Regional Studies*, **54**: 256–67.

Meuleman, B., Żółtak, T., Pokropek, A., Davidov, E., Muthén, B., Oberski, D.L., Billiet, J., and Schmidt, P. (2022) 'Why Measurement Invariance Is Important in Comparative Research: A Response to Welzel et al. (2021)', *Sociological Methods & Research*, **52**: 1401–19.

Montresor, G. (2019) 'Job Polarization and Labour Supply Changes in the UK', *Labour Economics*, **58**: 187–203.

Naylor, R., Smith, J., and Telhaj, S. (2016) 'Graduate Returns, Degree Class Premia, and Higher Education Expansion in the UK', *Oxford Economic Papers*, **68**: 525–45.

OECD 2019. *Technical Report of the Survey of Adult Skills (PIAAC)* (3rd Edition). Paris: OECD.

OECD 2022. *Main Economic Indicators - Complete Database*. In: **OECD** (ed.). Paris.
Office for National Statistics 2000. *Standard Occupational Classification 2000: Volume 1 Structure and Descriptions of Unit Groups* London, UK: Office for National Statistics.
O'leary, N., and Sloane, P. (2016) 'Too Many Graduates? An Application of the Gottschalk–Hansen Model to Young British Graduates Between 2001–2010', *Oxford Economic Papers*, **68**: 945–67.
O*NET. (2021) *Generalised Work Activities Questionnaire* [Online], https://www.onetcenter.org/dl_files/MS_Word/Generalized_Work_Activities.pdf, accessed 2023.
Overman, H., and Xu, X. (2022) 'Spatial Disparities Across Labour Markets', *IFS Deaton Review of Inequalities*. London, UK: The IFS.
Robitzsch, A., and Lüdtke, O. (2023) 'Why Full, Partial, or Approximate Measurement Invariance Are Not a Prerequisite for Meaningful and Valid Group Comparisons', *Structural Equation Modeling: A Multidisciplinary Journal*, **30**: 859–70.
Salvatori, A. (2018) 'The Anatomy of Job Polarisation in the UK', *Journal for Labour Market Research*, **52**: 8–15.
Stansbury, A., Turner, D., and Balls, E. (2023) Tackling the UK's regional economic inequality: binding constraints and avenues for policy intervention. *Contemporary Social Science*, 18: 318–356.
Stinebrickner, R., Stinebrickner, T., and Sullivan, P. (2019) 'Job Tasks, Time Allocation, and Wages', *Journal of Labor Economics*, **37**: 399–433.
Storm, E. (2023) 'On the Measurement of Tasks: Does Expert Data Get It Right?' *Journal for Labour Market Research*, **57**: 1–24.
Tholen, G., Relly, S.J., Warhurst, C., and Commander, J. (2016) 'Higher Education, Graduate Skills, and the Skills of Graduates: The Case of Graduates as Residential Sales Estate Agents', *British Educational Research Journal*, **42**: 508–23.
Van Der Velden, R., and Bijlsma, I. (2019) 'Effective Skill: A New Theoretical Perspective on the Relation Between Skills, Skill Use, Mismatches, and Wages', *Oxford Economic Papers*, **71**: 145–65.
Welzel, C., Brunkert, L., Kruse, S., and Inglehart, R.F. (2023) 'Non-Invariance? An Overstated Problem with Misconceived Causes', *Sociological Methods & Research*, **52**: 1368–400.

Oxford Economic Papers, 2024, 00, 1–22
https://doi.org/10.1093/oep/gpae020
Article