VERTICAL AND HORIZONTAL MISMATCH IN THE UK: ARE GRADUATES' SKILLS A GOOD FIT FOR THEIR JOBS?

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Vertical and Horizontal Mismatch in the UK: Are Graduates' Skills a Good Fit for Their Jobs?

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Abstract

We examine graduates' vertical and horizontal mismatch in the UK focusing on graduates' heterogeneous skills. We introduce a new, objective measure of horizontal mismatch (fit index) and account for skills beyond education. Despite the complementarity between technology and skills, approximately 30% of graduates in the UK are employed in non-graduate jobs. Our new measure for horizontal mismatch shows that nearly 33% of graduates work in fields unrelated to their degree subjects. The wage penalty for horizontal mismatch is lower than for vertical mismatch as graduates working in fields unrelated to their degree may still be employed in graduate jobs. However, both measures of mismatch indicate a misallocation of resources that can contribute to the UK productivity slowdown and the often-cited lack of necessary skills to face the fourth industrial revolution.

Classification: I21, I26, J24, J31

Keywords: vertical/horizontal mismatch, graduates' heterogeneity, wage penalty

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Introduction

The Information and Communication Technology (ICT) revolution led to important organizational changes, accompanied by an increased demand for skilled workers (O'Mahony et al. 2008, Silva and Lima 2017, Falck et al. 2020). Moving into the fourth industrial revolution, a wider variety of skills is in high demand, including technical (STEM) and soft skills (Black et al. 2021, Deming 2017). Within this context, the rise in the number of graduates in the UK, whose supply has steadily increased since the 1990s (O'Leary and Sloane 2005, Green and Zhu 2010, Savic et al. 2019), should be considered an important step towards ensuring positive labour market outcomes during a period of fast-changing employment opportunities. Graduates generally develop a variety of 'soft' skills (for example social and communication skills), next to acquiring knowledge related to the specific subject of choice. In addition, the increasing number of graduates is believed to help address the issue of skill deficiencies, considered one of the contributing factors to the UK productivity slowdown (Mason et al. 2018, Augar et al. 2019).

However, despite the complementarity between graduates' skills and technology, a high proportion of graduates are overqualified, or overeducated, as they possess higher qualifications than required for the job. This type of skill mismatch, often defined as vertical mismatch, has been widely discussed in the literature and the evidence consistently shows that overqualified graduates suffer a wage penalty, that is they earn less than graduates who find employment in a graduate job. [1] There is also evidence showing that the skill mismatch may negatively affect innovation (Igna and Venturini 2019), exacerbating concerns about its contribution to the productivity slowdown (Augar 2019).

While empirical evidence of this mismatch is important, focussing purely on the quantity of education does not account for workers whose level of education is appropriate for the job but the field of education is not. Achieving a better understanding of the skill mismatch and its relation to wages requires a more in-depth analysis of different graduates' skills. In contrast to vertical mismatch, horizontal mismatch describes the situation where a graduate finds employment in an occupation that requires skills different to those associated with their degree field. Together, these two dimensions of mismatch provide a more nuanced and complete picture, offering greater understanding of skill mismatch.

The overarching aim of this paper is to present new evidence on the skill mismatch among graduates in the UK and its effect on graduates' wages, examining both vertical and horizontal

[1] See, for example, Hartog 2000, Savic et al. 2019, Verdugo and Verdugo 1989, Alba-Ramirez 1993, Dolton and Vignoles 2000 Hartog 2000, Bauer 2002, Leuven and Oosterbeek 2011, among others.

mismatch. While the evidence for the former is extensive, fewer studies have focused on the match between degree field and skills used on the job (Robst 2007a, 2007b, 2008, McGuinness et al. 2018), hence our analysis contributes to a less explored aspect of skill mismatch. Investigating horizontal mismatch can also give important insights into which skills learnt as part of a degree are rewarded in other occupations (Robst 2008). In addition, accounting for both vertical and horizontal mismatch is important since, given the same degree, overqualified workers whose skills are related to the job are expected to earn more than overqualified workers whose skills are underutilized (Pecoraro 2014, Robst 2007a, 2007b).

Both vertical and horizontal mismatch rely on certified skills acquired as part of a graduates' education, which might not necessarily reflect their skill endowment (Pecoraro 2016). Although graduates may have the same quantity of education and a degree in the same field, they are likely to possess a wide range of unobservable skills, such as cognitive abilities and motivation. In fact, differences in skills are believed to explain a substantial part of overqualification and a graduate may appear overqualified, while their skills are appropriate for the job (Sloane 2002, Green and McIntosh 2007). As discussed in Robst (2007a) "One should not examine the wage effects of mismatch without considering the role of ability" (page 406).

Recent papers have proposed measures of overqualification that address this skill heterogeneity issue by relying on self-reported measures of workers' job match (Chevalier 2003, Chevalier and Lindley 2009, and Green and Zhu 2010, Meroni and Vera-Toscano 2017). Chevalier (2003) and Chevalier and Lindley (2009) distinguish between the *apparently* overeducated (those who are satisfied with their job match) and *genuinely* overeducated (those who are not satisfied with their job match)[2]. Although they are all overeducated, the characteristics of the two groups differ along different dimensions such as reasons for accepting the current job and earnings. Meroni and Vera-Toscano (2017) adopt a similar classification of genuinely and apparently overeducated but instead of relying on information on job satisfaction, they use graduate's own evaluation of the job match. Green and Zhu (2010) distinguish between 'real' and 'formal' overqualification, according to whether it is accompanied by underutilization of skills or not. Although these are important developments, they all rely on workers' self-evaluation and this can lead to a biased assessment of their skill level and skill match. Biases can arise from, for example, a lower response rates among overeducated workers, leading to an underestimation of its incidence; or workers may exaggerate either their occupational status or the qualification required to do a certain job, as there is general reticence

[2] One shortcoming of using job satisfaction to evaluate a job match is that satisfaction may be driven by many such as working conditions and promotion opportunities (Robst 2008).

to admit overeducation (McGuinness 2006). There is also no uniform approach to the implementation of the overeducation question within datasets, which makes comparison across studies/countries particularly challenging (Leuven and Oosterbeek 2011). A second objective of our analysis is to provide a new approach to account for skill heterogeneity, both in the vertical and horizontal dimension, using a new measure.

Accounting for skills beyond education is important particularly when evaluating the effect of the skills mismatch on wages. Given that several skills are unobservable, excluding them from a wage regression analysis generates an omitted variable bias. In fact, endogeneity issues are endemic in this type of study. Some contributions have accounted for non-observable skills either by using panel data techniques, under the assumption that individuals' unobserved heterogeneity is fixed over time (Bauer 2002, Frenette 2004, Tsai 2010); by using instrumental variables (Dolton and Silles 2008, Korpi and Tåhlin 2009) or by including information on numeracy and literacy scores (Levels et al. 2014, Green and Henseke 2016a). In most cases, correction for unobserved skills results in a lower wage penalty for overqualified graduates. However, the weakness of instruments is often an issue and it can generate unreliable estimates; in addition, when instruments are used together with a fixed effect estimator, results are not significantly different from Ordinary Least Squares (OLS), indicating that either the endogeneity issue has not been fully addressed or that different types of bias may offset each other (Dolton and Silles 2008).

Our analysis addresses the issues highlighted above using the 2017 UK Annual Population Survey (APS). We begin by constructing measures of vertical and horizontal mismatch, accounting for university education only. While the vertical measure is based on a well-known methodology, which compares a graduate worker with the average level of education within an occupation, we introduce a new objective measure of horizontal mismatch which captures the intensity of the use of each degree field within occupations - field intensity (*fit) index*. According to this measure, workers are mismatched when their degree field is not intensively used within their occupation. We then extend both measures to account for skills beyond education, using the ONS classification of occupations into high and low skills (ONS 2010). Our underlying assumption is that the skill content of graduates' occupation reveals their own ability levels. Hence, we can discriminate between low-skilled and high-skilled overqualified graduates depending on whether they work in a high-skilled or low-skilled occupation. Accounting for unobservable skills in both vertical and horizontal mismatch in this way, we can distinguish between 6 types of graduates and we expect that these are characterized by different labour market outcomes, particularly in terms of wages.

The assessment of wage differentials across different types of graduates is carried out by means of a wage equation that includes measures of mismatch, next to a wide range of control variables. These are typically included in the specification of wage regressions - gender, experience, tenure, marital status, number of children, ethnicity, industry and regional dummies. In addition to these usual 'suspects', we include information on graduates' university background to capture the quality of the institution awarding the degree; the type of degree classification, to further account for unobserved abilities; and the nationality of the university awarding the degree, i.e. whether the degree is from a UK or a foreign institution. As discussed in Vecchi et al. (2021), studying in a foreign university affects both the size of the mismatch and the effect on wages, while also being an additional proxy for other unmeasured skills that may prevent a successful job match (for example, language skills). While a causal interpretation of our estimates might still be problematic, the way we control for unobserved abilities both in the construction of our mismatch indicator and in the inclusion of additional controls in the estimation of the wage equation, may provide a valuable attempt at dealing with endogeneity issues.

The final step in our analysis is to investigate possible factors that may be correlated with the different type of mismatch, to understand the reasons behind this phenomenon. Specifically, we are concerned with the factors that are associated with the probability of being employed in a job that requires a degree field different from the university qualification and with the reasons why a graduate might be prepared to work in a non-graduate job.

Our results show that the extent of the vertical skill mismatch among graduates has remained quite constant over time, even compared with measures based on different methodological approaches and over different time periods. Our initial estimate shows that 31% of graduates are mismatched**, but this proportion falls to** 24% when we consider graduates in low-skilled occupation. As discussed in Green and McIntosh (2007) and Pecoraro (2016) these workers may be overqualified for their job but not overskilled, as their skills may be right for their job. As for the horizontal mismatch, our results show that approximately 34% of graduates in the UK work in fields that are not related to their degree subject. As horizontal mismatch indicates an underutilization of skills, the loss in terms of human capital accumulation may be substantial. Both types of mismatch indicate the presence of inefficient allocations of human capital, which may be a contributing factor to the UK productivity slowdown.

Vertical and horizontal mismatch, together with unmeasured skill heterogeneity, also matter in wage determination. The wage penalty for overqualification is significantly larger for low-skilled overqualified graduates compared to those with higher skill levels. For horizontally mismatched graduates the penalty is lower, particularly for those employed in higher skilled occupations. However, the wage penalty increases when graduates are both vertically and horizontally mismatched and are endowed with low levels of unobserved skills.

A final investigation of the reasons behind the different types of mismatches shows that low-level skills, nationality and family circumstances are positively associated with the probability of working in jobs unrelated to the quantity and quality of education. This suggests a role for social class in determining job opportunities beyond the scope of this paper.

Our paper contributes to the debate of the skill mismatch in the UK by providing new evidence on different types of mismatches, while accounting for skills beyond education. Our main contribution is to enhance our understanding of the measurement of skill mismatch, introducing new indicators that account for horizontal mismatch and for skills beyond education, using data widely available in labour force surveys. As well as providing much needed evidence for the UK, our indicators offer the potential to facilitate the analysis of the mismatch worldwide allowing for cross-country comparisons to become particularly meaningful since they will be based on more comparable measures. Our results are also important for education policy informing the discussion of possible reforms of the UK university system (Augar et al. 2019).

In the next section we discuss methodological issues related to the construction of mismatch indicators and introduce a new *fit index* to measure horizontal mismatch. In section 3 we extend our mismatch measures to account for unobservable skills. This is followed by a descriptive analysis of the data (section 4). In section 5 we present results for the estimation of the relationship between skill mismatch and wages, while in section 6 we investigate what factors are correlated to the probability of a bad job match, both in terms of quantity and quality of education. Section 7 concludes the paper with an overall discussion of our results, implications for policy and possible avenues for future research.

Vertical and horizontal skill mismatch

2.1 Methodology

The first concept of skill mismatch used in this study is based on a well-known methodology which computes the difference between the level of education required for an occupation – the benchmark - and the education attained by the worker. We define this as vertical mismatch. There are different ways of constructing a benchmark, each with its own advantages and disadvantages; appendix table A.1 presents a summary of the three most used measures. Using the 2017 Annual Population Survey (APS), this study follows the ONS methodology in using the realised matches method by matching the educational qualification achieved by the worker with the average educational qualification required in the job (Savic et al. 2019). To allow for flexibility in the construction of the benchmark, we compute a 1-standard deviation interval around the mean, hence identifying a range of qualification as the benchmark. Each individual is then assigned a status based on whether their own level of education falls within or outside this range for their occupation. Occupations are defined following the 3-digit Standard Occupational Classification (SOC) 2010, while the level of education is identified using 8 educational groups, listed in appendix table A.2. Vertical mismatch can be interpreted as the proportion of graduates not employed in a graduate job, where 'job' identifies an occupation rather than a specific task. Our analysis of graduate overqualification will focus on workers with Degree or Equivalent, for a total of approximately 20,000 observations. Post-graduate qualifications are excluded from the study.

One of the issues related to the use of the statistical method is that, by construction, the average educational requirement increases across all occupations if participation in education and the average level of educational attainment in the population increases. The effect on the degree of matching across the whole economy is therefore dependent on the age composition of each occupational group and the distribution of older and younger workers across occupations. To mitigate a potential age composition bias, we construct estimates of required education for two age groups (1) 16 to 35 years and (2) 36 to 64 years.

We next construct an indicator to evaluate the gap between graduates' field of study and the field of study required in an occupation. This measure captures the horizontal mismatch - a type of mismatch that has not been as widely analysed and the evidence is quite scant (McGuinness et al. 2018). The extant literature has predominantly used workers' own assessment of the quality of match (Robst, 2007a, 2008). While an important and useful measure, it has the disadvantage of not being easily replicable because of differences in survey questions, making cross- study and cross-country comparison particularly challenging.

In contrast, our method relies on the use of data on graduates' degree field and occupation; variables that are easily available in labour force surveys in most countries. To construct our indicator, we adapt the methodology commonly used to analyse countries' international specialisation (Balassa 1965) to the analysis of skill mismatch[3]. The starting point is the computation of the intensity of use of each degree field within each occupation. To this end, we construct a field intensity index (*fit index*) by dividing the proportion of workers who graduated

[3] We wish to thank an anonymous referee for suggesting the construction of this indicator.

in a particular field within an occupation, by the overall proportion of graduates with the same specialization:

$$fit\ index_{ij} = \frac{f_{ij}/\sum f_{ij}}{f_i/\sum f_i} = \frac{Share\ of\ degree\ i\ among\ all\ degree\ fields\ in\ a\ given\ occupation}{Share\ of\ degree\ i\ among\ all\ degrees},$$

where f_{ij} is the number of workers with degree '*i*' in occupation '*j*' and $\sum f_{ij}$ is the sum of all degree subjects within the same occupation; f_i is the total number of workers with degree '*i*', and $\sum f_i$ is the sum of all graduates with any degree in the UK. A value of the *fit index* > 1 indicates that a particular degree is intensively used in a specified occupation. The larger the value of the index, the more intense the demand for a particular field of study. For example, we may think of a graduate with a degree in medicine being in high demand among health professionals. In this occupation, the *fit index* for graduates in medicine will likely be >1 as this occupation will use medics more intensively than any other occupation. The *fit index* defines a benchmark for the computation of the skill mismatch. Specifically, a graduate (*k*) is horizontally mismatched if the *fit index* is less than 1:

Horizontal $Mismatch_{k,i,j}$: $fit\_Index_{ij} < 1$

To compute the *fit index*, we use 10-degree subjects across 9 occupational groups, defined following the 1-digit SOC. While a more granular occupational and degree classification would be desirable, it is not possible due to data constraints. The chosen classification ensures that there are at least 10 observations for each field-occupation cell.

Table 1 presents the *fit index* for each field-occupation cell. As expected, there is large variation across occupations, even within the standard STEM/non-STEM taxonomy. STEM qualifications are generally considered to be more specialised and therefore more difficult to fit within different occupations. As discussed in Robst (2008), working in an occupation unrelated to an individual's degree field implies doing a job which differs from the initial choice, i.e. some degree of occupational mobility. Switching across occupations is expected to be more difficult when graduates acquire more specific, rather than more general, human capital (Dolton and Kidd 1998). Results in Table 1 show that medicine/medical related studies and maths/computer science have a *fit index* >1 only among professional occupations. Although professional occupations include several types of jobs (for example information technology and telecommunication professionals, health professionals, including nursing and midwifery, ONS 2010), our figures imply that these two types of degrees are more specialised than the other STEM subjects (biological sciences, engineering, technology and architecture), characterised by a *fit index* larger than 1 in several occupations. Results also reveal that a degree in engineering has the highest values of the *fit index*, respectively in skilled trades occupations (3.14) and process, plant and machine operatives (2.57), indicating that these occupations intensively employ graduates with this specialisation. Non-STEM subjects tend to be more generic as we observe a *fit index*>1 in several occupations.

Table 1: Field Intensity (FIT) index

Major occupation group (main job)	Medicine & Medical related studies	Biological Sciences	Agric./Physical & Environmental subjects	Maths & Computer Science	Engineering	Technology & Architecture	Social Sciences	Business, Finance & Law	Media & Languages	Humanities, Arts & Education
Managers and Senior Officials	0.28	0.78	1.32	0.89	1.48	1.37	1.18	1.37	0.91	0.80
Professional Occupations	2.02	0.79	0.93	1.37	1.13	1.08	0.76	0.63	0.75	0.90
Associate Professional & Technical	0.33	1.26	0.90	0.85	0.79	0.95	1.13	1.21	1.28	1.08
Administrative & Secretarial	0.23	1.03	0.77	0.60	0.26	0.36	1.21	1.75	1.46	1.00
Skilled Trades Occupation	0.16	0.86	1.85	0.95	3.14	1.54	0.51	0.63	0.59	1.29
Personal Service Occupation	0.74	1.53	1.00	0.43	0.18	0.40	1.78	0.72	1.02	1.38
Sales & Customer Service Occupation	0.29	1.53	0.76	0.61	0.37	0.79	1.02	1.19	1.36	1.34
Process, Plant & Machine Operatives	0.35	1.13	1.59	0.73	2.57	1.54	0.91	0.89	0.81	0.87
Elementary Occupation	0.23	1.37	1.24	0.55	0.36	1.10	0.99	0.99	1.28	1.50

Source: Annual Population Survey 2017, ONS

2.2 UK evidence

Table 2 presents evidence on the skill mismatch in the UK, using the definitions of vertical and horizontal mismatch. In 2017, 31.21% of graduates were employed in non-graduate jobs in the UK (vertical mismatch). These estimates are consistent with an earlier study by Dolton and Vignoles (2000), and Battu et al. (2000).[4] These results predate the significant expansion of student numbers in the early 1990s, which suggests that alongside the increase in the number of graduates, there has also been an increase in the number of graduate jobs. Technical change has been one of the main contributing factors to the expansion in the number of jobs requiring a degree (Green and Henseke 2016b). Evidence for the US, discussed in Hersbein and Kahn (2018) show that there has been a general upskilling of occupations over time, which has intensified after the 2007 recession.[5] It is likely that a similar upskilling trend has taken place in the UK.

For horizontal mismatch, overall estimates are slightly above those for vertical mismatch at 32.73%. However, the two measures imply different situations for graduates as a horizontally mismatched graduate could still be holding a graduate job although the skills required for the job are different from those learnt as part of their university degree. Although similar, the two indicators are only weakly correlated (-4.4%) and only 29.67% of those who are horizontally mismatched are employed in a non-graduate job. The two definitions undoubtedly capture different phenomena. This can be seen when analysing variations of the mismatch according to some relevant features of our sample of graduates. Both indicators estimate a higher proportion of mismatched graduates among females compared to males workers, consistent with related studies (McGuinness and Bennett 2007), while there is a substantial difference when distinguishing between STEM and non-STEM degrees. Vertical mismatch is approximately 16% lower for STEM graduates compared to non-STEM, while the horizontal mismatch is nearly 8% larger. This suggests that STEM graduates will more easily find a graduate job but not necessarily matched with their field of study. As discussed above, this is consistent with the

[4] The use of realised matches to compute the educational mismatch has been criticised in the literature in favour of measures that make more effort to directly compute the skill requirement of a job, for example by relying on workers' assessment (Green and Henseke 2016a, 2016b). However, our estimates are consistent with similar to existing ones. For example, Green and Henseke (2016a) estimate the incidence of graduate overeducation in the UK at 34.1% and in Green and Henseke (2016b) the proportion is 29.1% in the 1997-2001 period, and 30.5% between 2006 and 2012.

[5] Three main factors can contribute to the upskilling phenomenon during recessions: firms may become pickier when labour, and especially skilled labour, becomes more plentiful; elevated skill requirements might reflect opportunistic behavior on the part of firms that cannot ordinarily attract more skilled workers in a tight labour market; firms take advantage of recessions to re-structure production and adopt routine-biased technologies, which are complementary with high skills (Hersbein and Khan 2018).

higher specificity of STEM specialization. Both vertical and horizontal mismatches are higher among recent graduates (those who graduated in the past 5 years) but while the vertical mismatch reduces substantially with more labour market experience, the horizontal mismatch hardly changes. This suggests that while experience can help graduates to find a graduate job, it does not help to find a better match in terms of degree-specialization, possibly due to obsolescence of skills learnt while at university – some of the skills acquired in initial education may be lost over time if they are not continuously used while new skills, acquired through on-the-job training and labour market experience, will become more relevant (Quintini 2011).

Table 2: Vertical and horizontal mismatch, UK 2017

	Vertical Mismatch	Horizontal Mismatch
Overall	31.22	32.73
Male	29.37	31.20
Female	33.01	34.20
STEM	21.45	37.79
Non-STEM	35.69	30.42
Graduated in the past 5 years (recent graduates)	39.68	34.86
Graduates with 10 years' work experience	33.56	32.77
Graduates with 20 years' work experience	26.02	33.10

Data source: Annual Population Survey 2017, ONS.

Extending the overqualification measures: correcting for unobserved skills

Over time, increasing access to higher education in the UK has generated greater skill heterogeneity in graduates entering the job market. Relying on measures of overqualification based on formal education may overestimate the size of the skill mismatch, as graduates may appear overqualified, but their skills might be suitable for the job. Skills can be of cognitive and non-cognitive nature both of which contribute to labour market outcomes (Heckman et al. 2006, Deming 2017). Cognitive skills are generally associated with the quantity and quality of schooling (Hanushek and Woessman 2008), while non-cognitive skills include a range of individual characteristics such as personality traits (conscientiousness, agreeableness, emotional ability, extroversion and openness to experience) [6] and motivation (Risse et al. 2018), which can be important in finding a suitable job match. Assessing skills beyond education is

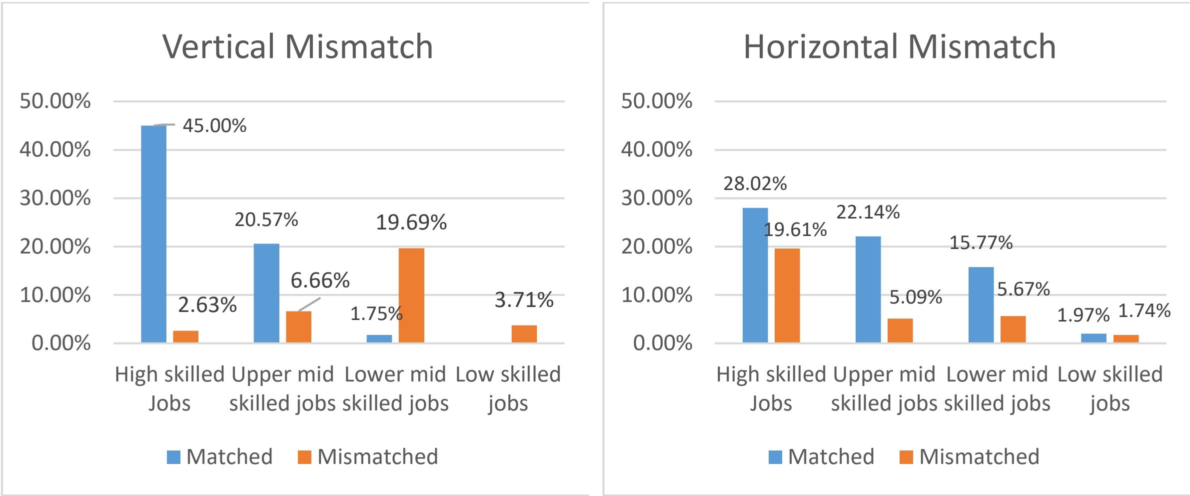
[6] These are also called the Big Five traits. Agreeableness is the tendency to act in a way that is cooperative, tolerant, forgiving, trusting, altruistic; conscientiousness is the tendency to be , responsible, hard-working, and efficient; emotional stability is the degree to which an individual's emotional reactions are consistent and predictable; extraversion is the orientation of an individual's interests towards the outer world of people and things, characterized by being active, sociable, and talkative; and openness to experience describes the tendency to be open to new intellectual, cultural, aesthetic experiences (Costa and McCrae1985, 1992).

particularly difficult because of the lack of data. Related studies have often used subjective information on workers' own evaluation of their job match (Chevalier 2003, Chevalier and Lindley 2009, Green and Zhu 2010, Meroni and Vera-Toscano 2017). Following Vecchi et al. (2021), we account for unobservable skills using information on the skill content of occupations, provided by the ONS (2010). Our underlying assumption is that the skill content of the occupation reveals the skill of graduates, in both in graduate and non-graduate jobs.

The ONS have an established classification that allocates all occupations to one of four skill groups, identified by qualification and length of time deemed necessary for a person to become fully competent in performing the tasks associated with a job. The first skill level equates with the competence associated with a general education, usually acquired by the time a person completes their compulsory education. Examples include postal workers, hotel porters, cleaners and catering assistants. The second skill level covers a group of occupations which require the knowledge provided via a good general education, but which typically have a longer period of work-related training or work experience (machine operation, driving, caring occupations, retailing, and clerical and secretarial occupations). The third skill level applies to occupations that normally require a body of knowledge associated with a period of post compulsory education but not always to degree level. Several technical occupations fall into this category, as do a variety of trades occupations and proprietors of small businesses. The fourth skill level relates to what are termed 'professional' occupations and high-level managerial positions in corporate enterprises or national/local government. Occupations at this level require either a degree or an equivalent period of relevant work experience.

Using this classification, we can map all graduates in our sample to the different skill groups, as shown in figure 1. We find substantial differences between vertical and horizontal mismatch. For vertical mismatch, we find the highest incidence of matches in the fourth skill level (45%) as this primarily includes graduate jobs. We also find some overqualified graduates in this group although the incidence is very small (2.63%). At the opposite end of the distribution, there are no graduate jobs in the first skill group and therefore no matches.

Figure 1: Mapping graduates over the skill classification



Source: Annual Population Survey 2017, ONS.

When analysing the horizontal mismatch, the distribution of mismatched graduates is substantially different. Figure 1 shows that the highest proportion of horizontal mismatch is observed among the highly skilled (19.61%) followed by lower intermediate (5.67%) and upper intermediate skills (5.09%). The proportion of mismatched graduates in low skilled occupations is 1.74%, approximately 2% lower than the vertical mismatch for the same skill group. By definition, these graduates are both horizontally and vertically mismatched as there are no graduate jobs among low skilled occupations.

For our empirical analysis, we aggregate the four groups into two as there are few observations for the lowest skill group for both definitions of mismatch. Thus, we distinguish between high-skilled and low-skilled overqualified graduates. Of all graduates in non-graduate jobs, 23.4% are employed in low skilled occupation. Our assumption is that these graduates are endowed with low levels of unobservable skills, hence they may be overqualified but not overskilled. The remaining 9.28% of overqualified graduates are employed in high-skilled occupations, and we assumed that these have a higher level of unobserved skill. For the horizontal mismatch, we find that 7.4% of graduates are in low skilled occupations while 24.7% are in high skilled occupations. The proportion of mismatched graduates is therefore larger when considering the gap between fields learnt while studying and field required on the job, compared to the vertical mismatch.

Using information on different types of mismatch and skills, we can further differentiate between six types of graduates as shown in table 3.

Table 3: Vertical – horizontal mismatch and graduates' skills

	Graduate type	*Description*	*Proportion of all graduates*
Skill 1	*Vertical match, same field of study*	Graduates in a graduate job related to their degree field	44.33%
Skill 2	*Vertical match, different field of study*	Graduates in a graduate job unrelated to their degree field	22.86%
Skill 3	*Vertical mismatch, high skills, same field of study*	Graduates in a high-skilled non-graduate job, related to their field	7.45%
Skill 4	*Vertical mismatch, high skills, different field of study*	Graduates in a high-skilled non-graduate job, unrelated to their field	1.98%
Skill 5	*Vertical mismatch, low skills, same field of study*	Graduates in a low-skilled but non-graduate job, related to their field	16.33%
Skill 6	*Vertical mismatch, low skills, different field of study*	Graduates in a low-skilled non-graduate job, unrelated to their field	7.05%

Data source: Annual Population Survey 2017, ONS.

Each of the 6 groups can be considered as capturing the gap between graduates' skills and skills required on the job. This gap is non-existent for those graduates at the top of the ranking (matched same field), and it gradually increases as we move down the ranking. As hypothesised in the next session, there will be different returns in terms of wages for each of type of graduate. The bottom group (skill 6) include those workers who are mismatched under both definitions of skills mismatch and work in low skilled occupations. There are likely to make very little use of the skills acquired during their university degree and they are therefore the ones who we expect to lose out the most from their mismatched status, or to put it another way, likely to experience least benefit from their university degree.

Empirical model and hypothesis development

The estimation of the relationship between overqualification and wages follows the Verdugo and Verdugo (1989) model. This specifies the logarithmic transformation of hourly wages, *ln(w)*, as a function of the vertical skills mismatch, typically captured by a dummy for the overqualification (D^O), a dummy for the underqualification status (D^U), the total number of years of education (E^T) and a vector of controls (**x**):

$$(1) \quad ln(w_k) = \beta_1 D_k^O + \gamma_2 D_k^U + \gamma_3 \mathrm{E}_k^T + \boldsymbol{x_k \delta} + \epsilon_k$$

When analysing graduates, the number of years of education (attained) is assumed to be the same and, by definition, there are no underqualified workers.[7] Therefore, the model simplifies to:

$$(2) \quad ln(w_k) = \beta_1 D_k^O + \boldsymbol{x_k \delta} + \epsilon_k$$

We generalize equation (2) to account for the two different types of mismatch (vertical and horizontal) which are initially treated separately. Hence, we can rewrite equation (2) as follows:

$$(3) \qquad ln(w_k) = \beta_1 mismatch_{k,q} + \boldsymbol{x_k \delta} + \epsilon_k$$

Where q = 1,2, represents the two types of vertical/horizontal mismatch.

A negative sign for the coefficient β_1 implies that a mismatch graduate, either in terms of quantity or type of education, earns less than a graduate whose job matches their level of education (the benchmark) and provides a measure of the overqualification penalty. For vertical mismatch, the benchmark is a graduate employed in a graduate job, while for horizontal mismatch the benchmark is a graduate working in a job that matches their degree field (Battu et al. 1999, Dolton and Vignoles 2000, Green and Zhu 2010, McGuinnes and Sloane 2011, Robst 2008).[8]

A graduate who is horizontally mismatched might still hold a graduate-type job. As graduate jobs attract higher earnings, the wage penalty for horizontal mismatch is expected to be below the penalty for vertical mismatch:

H1: The size of the wage penalty for horizontal mismatch is lower than the size of the penalty for vertical mismatch.

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[7] McGuinnes and Bennett (2007) estimate a similar relationship which includes the total number of years of achieved education, with the idea of assessing the impact of ability as in the standard Mincer equation. However, in a graduate sub-sample, this variable would capture differences in the type of degree, or it would indicate low level of ability, in cases where students take longer to achieve the same degree. In fact, in McGuinness and Bennett (2007) the coefficient on acquired education is either negative or non-statistically significant.

[8] Another approach used for the analysis of overqualification is based on the distinction between years of required education, years of overeducation and years of undereducation. Except for Savic et al. (2019) this specification has not often been used in the analysis of overeducated graduates, which has instead relied on discriminating between graduate and non-graduate jobs, as in equation (2) above. The main shortcoming of using this measure is that years of education is not directly available in APS and needs to be imputed, a process that might raise measurement issues.

Equation (3) is then extended to account for skills beyond education, using the methodology described in the previous section. We therefore distinguish between graduates in high-skilled ($mismatch^{HS}$) and low-skilled ($mismatch^{LS}$) occupations:

$$(4) \qquad ln(w_k) = \beta_1 mismatch_{k,q}^{HS} + \beta_2 mismatch_{k,q}^{LS} + \boldsymbol{x_k \delta} + \epsilon_k$$

Under the assumption that the skill content of the occupation reveals the worker's skill level, graduates in low skilled occupation may be overqualified but not overskilled. On the other hand, graduates in high-skilled occupations can be defined as both overqualified and overskilled as they have higher skills than required for their job. It is natural to assume that higher skills are associated with higher earnings, thus we expect the high-skilled overqualified group of graduates to suffer a lower wage penalty than the low-skilled overqualified:

H2: The mismatch penalty is related to graduates' skills. Low-skilled mismatched graduates will suffer a higher wage penalty compared to high-skilled mismatched graduates.

In our final specification, we account for the interaction between vertical and horizontal mismatch, using the categories listed in table 3, section 2.2. Using *Skill 1* (matched graduate in a job that requires the same degree field) as the benchmark, we rewrite equation (4) as follows:

$$(5) \qquad ln(w_k) = \sum_{s=1}^{5} \theta_s mismatch_k + \boldsymbol{x_k \delta} + \epsilon_k$$

Each type of mismatched graduate represents a gap, or distance, between the skills supplied and skills demanded. The larger the distance, the larger we expect the wage penalty to be:

H3: the size of the penalty for overqualification increases with the increasing gap between graduates' skills and the skills required for a job.

Descriptive analysis

Equations (3) - (5) account for a large set of controls, including individual characteristics (gender, experience, tenure, ethnicity, nationality), job characteristics (full time status, firm size, permanent contract), and dummy variables to account for region and industry. Among the individual characteristics we include controls for workers' abilities by using information on the degree-awarding institution quality and degree classification. More specifically, we distinguish between the Russell group and non-Russell group universities[9], as the former usually have stricter selection criteria. In addition, information on Russell group degrees could capture other

[9] The Russell Group is an association of 24 public research universities in the UK, established in 1994. They are generally perceived to be of higher quality compared to non-Russell group institutions.

unobservable factors such as family background and connections, which can be important in determining labour market outcomes. Achieving a first-class degree is challenging in any institution and may requires both cognitive and non-cognitive skills. Hence, we construct an additional dummy to capture this effect.

Table 4 presents proportions of mismatched graduates by match status and quality of degree. Figures show that among students from Russell-group universities, 18.7% are in non-graduate jobs, compared to over 30% of students from non-Russell group institutions. Table 4 also shows that there is a lower incidence of overeducation among top graduates (first class outcomes) (21.15%) compared to those with lower degree classification (32.26%). As for horizontal mismatches, the picture is quite different. We observe a higher proportion of mismatched graduates among Russell-group students and among those with a first-class degree; 44.39% and 29.84%, respectively. As discussed above, a horizontally mismatched graduate may be holding a graduate job, but in a field which differs from their university choice.

Table 4: Mismatch and university background (%)

	Vertical	Horizontal
Overeducated Russell	18.70	44.39
Overeducated non-Russell	34.33	29.84
Overeducated First-class degree	21.60	40.21
Overeducated other degree classifications	32.26	31.92

Data source: Annual Population Survey 2017, ONS.

Summary statistics for the other control variables are presented in Table 5. UK born and those holding a UK degree make up for the largest proportion of vertically matched graduates, at 83.24% and 74.87%, respectively. Graduates with foreign degrees account overall for 18% of all vertically matched graduates and a much larger proportion of mismatched graduates (32.34%). As discussed in Vecchi et al. (2021) graduates with foreign degrees account for a significant proportion of the skill mismatch in the UK. On the other hand, horizontally mismatched graduates are mainly UK born and from UK universities, while the horizontal mismatch for foreign degrees is negligible (0.52%). This suggests that foreign degrees are (or are perceived to be) more specialized than degrees from UK institutions. In fact, it is reasonable to assume that employers are likely to be more familiar with the UK education system and better able to evaluate general vs specific skills within each degree field. We also observe a higher proportion of married workers among those who are mismatched compared to those who are matched, both for vertical (43%) and horizontal mismatch (41.52%). This is consistent with existing evidence showing that for certain groups, particularly married women, labour markets tend to be more geographically restricted, and this may affect their mismatch status (Savic et al. 2018).

In terms of job characteristics, average years of experience are slightly lower for horizontally, compared to vertically, mismatched workers and we observe a lower proportion of horizontally mismatched graduated in the private sector (66.41% compared to 78.56% for vertically mismatched). Differences across regions are quite pronounced. In London and the South-East, we find the highest proportion of graduates with a graduate job (21.8% and 14.17% respectively) and also the larger proportion of vertically mismatched graduates (19.25% and 14.17% respectively), while horizontally mismatched graduates are more evenly distributed across the regions, except for the South-East (15.64%), Merseyside (1.90%) and Northern Ireland (2.18%). Among different industries, both vertical and horizontal mismatch are highest in the Hotel and recreation sectors, Finance and the public sector. However, in the Hotel and Recreation sectors, the proportion of graduates without a graduate job is nearly 13% larger than graduates whose are horizontally mismatched. We observe the opposite in the finance and public sector. In the latter the proportion of horizontally mismatched graduates is over 10% above the proportion of vertically mismatched.

Table 5: Summary statistics of all controls included in the regression analysis

% of the following groups unless otherwise specified:	Vertical matched graduates	Vertical mismatched graduates	Horizontal matched graduates	Horizontal mismatch graduates
Number of observations	18,365	9,340	11,991	6,099
Individuals' characteristics				
UK-born	83.24	70.73	73.56	90.98
UK born, UK degree	74.87	60.15	60.39	90.58
Foreign born, UK degree	7.14	7.51	6.50	8.89
UK born, foreign degree	8.37	10.58	13.17	0.40
Foreign born, foreign degree	9.62	21.76	19.95	0.12
AGE (average)	39.62	39.73	39.91	39.11
N. Children (average)	0.79	0.70	0.77	0.74
Married	37.00	43.00	37.79	41.52
White ethnic background	76.14	71.37	72.85	78.21
Declared disability	8.85	11.37	9.62	9.83
Mortgage	58.52	43.02	51.47	57.54
Property owner	18.41	22.47	19.35	20.60
Job's characteristics				
Experience (average)	15.77	17.31	16.48	15.82
Tenure (average)	7.93	6.84	7.63	7.48
Private sector	69.40	78.56	75.24	66.41
Full-time job	85.65	72.02	78.81	77.57
Permanent contract	81.63	77.42	79.83	81.12

Small company	22.07	32.50	25.69	25.13
UK Regions				
North-East	3.00	3.30	2.94	3.44
North-West	7.67	8.39	7.67	8.41
Merseyside	1.80	1.70	1.70	1.90
Yorkshire	6.89	6.95	6.59	7.60
East Midlands	6.93	6.43	6.18	5.89
West Midlands	7.11	8.15	7.41	7.55
Est	8.51	8.34	7.41	7.55
London	21.08	19.25	8.55	8.23
South-East	15.61	14.17	14.9	15.64
South-West	8.08	9.06	8.4	8.41
West	3.84	4.33	3.90	8.41
Scotland	8.20	7.59	7.81	8.41
Norther Ireland	2.29	2.35	2.37	2.18
Industry				
Agriculture, Energy, Construction	3.81	5.48	5.00	3.01
Manufacturing	6.66	7.44	7.41	2.55
Hotels and recreation	5.88	23.30	12.12	10.53
Transport	10.97	8.36	10.27	9.77
Finance	26.60	16.50	24.03	21.68
Public Sector	39.27	30.19	33.71	41.77
Other services	5.31	7.34	6.04	5.85

Data source: Annual Population Survey 2017, ONS.

Results: The relationship between wages and skill mismatch.

A widely documented consequence of the skill mismatch is the difference in pay between matched and mismatched workers, with the former earning significantly more than the latter. This result is evident in the UK and in other countries (Hartog 2000, de Oliveira et al. 2000, Bauer 2002, Chevalier 2003, McGuinnes and Bennett 2007, Green and Henseke 2016). In our case, we account for different types of workers with different skills and we expect wages to vary accordingly.

Table 6 presents results from the estimation of equations (3) and (4), using Ordinary Least Squares (OLS). Coefficient estimates for the total overqualification measure (equation 3) are presented in columns (1) and (2) for the vertical and horizontal mismatch, respectively. Results from the estimation of equation (4), which distinguishes between low-skilled and skilled overqualified graduates, are reported in columns (3) and (4). In all cases, coefficient estimates for the mismatch variable provide an estimate of the wage penalty, i.e. the wage difference between a graduate whose skills match those required in the job and a skill-mismatched graduate.

Results in table 6 column (1), show that there is a 35.5% wage penalty for vertical mismatch. This result is consistent with related studies, such as McGuinness and Sloane (2011), whose estimates range between 37% and 40% depending on the estimation method used. In Chevalier (2003) the overall wage penalty is lower (14%), while it reaches 27% for the genuinely overeducated, i.e. those graduates who are unsatisfied with their job match.

In contrast to the vertical mismatch, the wage penalty for a horizontally mismatched worker is much lower (column 2), thus providing support for H1. Our results show that a graduate employed in a field that does not match their degree subject earns on average 1.5% less compared to a matched graduate and the effect is significant at the 10% significance level.

In columns (3) and (4) we distinguish between graduates employed in high skilled and low skilled occupations. Differences in skills also reveal differences in the wage penalty. Consistent with H2, coefficient estimates in column (3) show that for graduates in high-skilled occupations the size of the penalty (19.6%) is significantly lower than the wage penalty for graduates in low skilled occupations (38.7%). Results in column (4) show a similar pattern, that is the wage penalty is larger for graduates in low skilled occupations. However, the size of the penalty for horizontal mismatch (6.4% for the high-skilled and 28.3% for the low skilled) is lower compared to vertically mismatched graduates, which is consistent with our findings in (1) and (2).

Variables capturing the effect of university background (Russell, degree1) are all positive and statistically significant, indicating that more able graduates earn higher wages, on average, and the premium is high. For example, results in column (1) show that graduates from Russell Group universities are associated with a 12.3% higher wage compared to those who graduate from a non-Russell group institution. Independent of university selectivity, average hourly wage for a graduate with a first-class degree is 6% higher than a graduate with lower grade classification. Results are similar in column (2), although the coefficient estimates are slightly larger, respectively 14.7% and 8.1%.

Our results also show that recent graduates earn, on average less than those who graduated more than 5 years ago, as expected given their relative lack of work experience. We find a wage premium for STEM degrees, but only when considering the horizontal mismatch (columns 2 and 4). Coefficient estimates also indicate the presence of a fairly large penalty for foreign degrees, ranging from 9.6% (column 3) to 16.3% (column 4). Hence a degree from a UK institution is associated with higher wages, *ceteris paribus*. Our results also confirm the presence of a gender pay gap between 5.7% and 8.1%, Coefficient estimates for the remaining control variables are generally consistent with expectations. For example, we find that age, tenure, being married, being white, owning your own property, having a mortgage, working in the private sector, being in a full-time job and being in a permanent position, are all positively associated with average earnings. Factors that tend decrease wages are the presence of disabilities and working for a small company (< 25 employees).

Table 6. Vertical and horizontal mismatch and wages. Dependent variable: ln(hourly wage)

	Vertical	Horizontal	Vertical	Horizontal
Mismatch	-0.355***	-0.015*		
	(0.009)	(0.009)		
Over. High skilled			-0.196***	0.064***
			(0.016)	(0.010)
Over. Low skilled			-0.387***	-0.283***
			(0.009)	(0.013)
Russell group	0.123***	0.147***	0.121***	0.136***
	(0.011)	(0.011)	(0.011)	(0.011)
First class degree	0.057***	0.081***	0.054***	0.068***
	(0.014)	(0.014)	(0.013)	(0.014)
STEM subject	0.012	0.041***	0.007	0.051***
	(0.009)	(0.009)	(0.009)	(0.009)
UK born, Foreign degree	-0.008	-0.018	-0.011	-0.015
	(0.015)	(0.016)	(0.014)	(0.016)
FR born, UK degree	-0.019	-0.034**	-0.018	-0.024
	(0.016)	(0.017)	(0.016)	(0.017)
FR born, Foreign degree	-0.101***	-0.161***	-0.096***	-0.163***
	(0.014)	(0.016)	(0.014)	(0.016)
Recent graduates	-0.077***	-0.074***	-0.063***	-0.061***
	(0.015)	(0.015)	(0.015)	(0.015)
Age	0.035***	0.044***	0.039***	0.044***
	(0.004)	(0.004)	(0.004)	(0.004)
Female	-0.102***	-0.099***	-0.089***	-0.099***
	(0.008)	(0.009)	(0.008)	(0.009)
Dependent children	0.007	0.005	0.006	0.005
	(0.005)	(0.005)	(0.005)	(0.005)
Married	-0.062***	-0.079***	-0.060***	-0.071***
	(0.010)	(0.010)	(0.010)	(0.010)
White	0.074***	0.085***	0.069***	0.079***
	(0.013)	(0.014)	(0.013)	(0.014)
Disability	-0.063***	-0.072***	-0.060***	-0.064***
	(0.012)	(0.013)	(0.012)	(0.013)
Mortgage	0.110***	0.130***	0.107***	0.124***
	(0.010)	(0.010)	(0.010)	(0.010)
Property-owned	0.045***	0.054***	0.046***	0.059***
	(0.013)	(0.014)	(0.013)	(0.014)
Tenure	0.012***	0.013***	0.011***	0.012***
	(0.001)	(0.002)	(0.001)	(0.001)
Private sector	0.030***	0.014	0.033***	0.020*
	(0.011)	(0.011)	(0.011)	(0.011)
Full time job	0.091***	0.145***	0.079***	0.117***
	(0.011)	(0.011)	(0.011)	(0.011)
Permanent job	0.047**	0.054**	0.042**	0.048**
	(0.020)	(0.021)	(0.020)	(0.021)

Small company	-0.157***	-0.174***	-0.158***	-0.172***
	(0.010)	(0.010)	(0.010)	(0.010)
Constant	1.184***	1.029***	1.360***	1.486***
	(0.104)	(0.119)	(0.120)	(0.102)
Industry dummies	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Observations	18,016	18,016	18,016	18,016
R-squared	0.417	0.348	0.424	0.370

*Notes: robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1 Data: Annual Population Survey 2017, ONS.*

In table 7 we follow Robst (2008) in assuming that the effect of the mismatch on wages increases the greater the distance between qualification/skills of graduates and those required on the job. The distance is represented by the 6 categories of graduates listed in table 3, where the first group (matched graduates, *Skill 1*) is used as the benchmark.

Table 7: Distance between graduates' skills and skills required on the job.

Variables	Ln(hourly wage)
Vertical match, different field of study (skill 2)	-0.020*
	(0.011)
Vertical mismatch, high skills, same field of study (skill 3)	-0.225***
	(0.020)
Vertical mismatch, high skills, different field of study (skill 4)	-0.236***
	(0.032)
Vertical mismatch, low skills, same field of study (skill 5)	-0.381***
	(0.012)
Vertical mismatch, low skills, different field of study (skill 6)	-0.415***
	(0.015)
Constant	1.278***
	(0.108)
Individual controls	YES
Job characteristics	YES
Industry dummies	YES
Regional dummies	YES
R-squared	0.392
OBS	17,877

Data: Annual Population Survey 2017, ONS

As expected, we find larger wage effects from mismatch as the distance between skills supplied and skill required on the job increases, consistent with Robst (2008). Graduates in a graduate job who are horizontally mismatched suffer the smallest penalty, earning 2% less than graduates who are both vertically and horizontally matched. The penalty increases to 22% for high-skilled vertically mismatched graduates. For this group, the size of the wage penalty is independent of the match between field of study and field required on the job as coefficient estimates for skill groups 3 and 4, are not statistically different. Thus, being horizontally mismatched does not make a significant difference for the most skilled overqualified graduates. On the other hand, horizontal mismatch matters for those endowed with lower levels of (unobserved) skills. In fact, the penalty increases significantly when we move to graduates with field match (38.1%) and graduates without a field match (41.5%). As discussed above, these graduates are likely to be overqualified but not overskilled, hence the wage penalty is mainly caused by low-level skills rather than their mismatch status. Our results provide support for H3 and they are consistent with the evidence in Robst (2008), which shows that an individual who is mismatched both in terms of quantity and type of degree is likely to suffer a larger wage penalty. However, in our analysis, this is true only for the low-skilled. For the high-skilled, differences in the field of study are not relevant as the quantity of education drives the wage penalty. Coefficient estimates for the control variables are consistent with those reported in Table 6 and they are omitted for simplicity.

As discussed in the introduction, we believe that our analysis has addressed endogeneity issues related to unobservable skills. However, there can be other sources of bias. For example, we are not accounting for labour force participation decision, which may introduce a selection bias in our model. For examples, individuals with low reservation wage may prefer to be mismatched rather than unemployed, while the reverse may be true for those with higher reservation wage. This is likely to increase the size of the wage penalty. We believe this is an important development for future research

The skill mismatch can be viewed as a case of resource misallocation as skills are not utilized in the *right* job. This may be true for the high-skilled overqualified; however, low skilled overqualified graduates may be correctly allocated as their overall skill-set is likely to match the requirements of their job. But this raises the question of why some workers, who have invested in tertiary education, have not developed the adequate skills to find a good job match. While our data does not allow us to answer this question, we explore which factors are likely to drive the skill mismatch in section 6.

Factors are associated with the different types of mismatch

To get an understanding of what factors are responsible for the different types of mismatch, we use a multinomial Probit model where the probability of being in one of the 5 skill-mismatch groups, presented in table 3, is modelled as a function of the same individuals and job characteristics described in section 4. Table 8 reports the estimated marginal effects. Probabilities are estimated at the sample means of explanatory variables for all definitions of skill mismatch.

Pure horizontal mismatch (col. 1) is significantly and positively correlated to our proxies for unobserved cognitive and non-cognitive skills as graduating from a Russell group university and graduating with a First-class degree increases the probability of a horizontal mismatch by 5.2 and 2.9 percentage points (pp) respectively. This positive association may be surprising; however, these are graduates employed in graduate jobs who have perhaps they decided to change occupation at the end of their study. This choice is not very costly as the wage penalty associated with this type of mismatch is relatively low and weekly significant, as shown in table 6. This type of mismatch is also positively associated with female graduates and with graduates of white ethnic background. A degree from a foreign university significantly decreases the probability of this type of mismatch, compared to UK-born graduates who studied in the UK (our benchmark), confirming the results of our descriptive analysis. This result suggests that UK degree may provide, on average, more generals skills that fit several occupations/job requirements. As for the field of study, although the literature generally assumes that STEM degrees are more specialised and are therefore more likely to positively affects the mismatch, our results show that this is not the case, at least for graduates who find employment in graduate jobs.

Results differ substantially when we consider vertical mismatch and heterogenous skills. Starting with graduates endowed with higher level skills, estimates in column 2 reveal that they are less likely to be employed in a graduate job if they hold a degree from a Russell group university, they have graduated in the past 5 years, they are female and hold a STEM degree. Studying in a foreign university increases the probability of this type of mismatch by 5.7 pp, for UK-born graduates, and by 9.9pp for foreign born graduates. Thus, having a UK degree is associated with a lover probability of vertical mismatch among high-skilled graduates.

The role of tenure is also very different between graduates in a graduate job but in a field different from their studies (column 1) , and those high-skilled graduates in non- graduate job, with matching degree (column 2). For the former, tenure is negatively correlated to the mismatch status, indicating that this type of mismatch tends to decline over time. For the second group, the effect of tenure is positive and statistically significant, indicating that this type of mismatch may be long-term (Meroni and Vera-Toscano 2017). However, the consequences of this type of mismatch are likely to be less severe as the wage penalty is lower compared to low-skilled mismatch graduates. Coefficient estimates for tenure are not statistically significant for the remaining skill groups.

In col. 3 we consider high-skilled mismatched graduates who are also horizontally mismatched. The probability of being in this group is positively associated with a STEM degree, which somehow reconciles our results with the intuition that students endowed with more specific skills are more likely to be horizontally mismatched (Robst 2008). The probability also increases with age and with holding a full-time job by 0.2pp and 0.4pp respectively.

The last two columns present results for the lowest-skilled group, i.e. those who are most seriously affected by the mismatch status in terms of wage penalty, as discussed in the previous section. Our discussion mainly focuses on the last column, which represents the probability of the most serious type of mismatch, i.e. both vertical and horizontal. As expected, higher levels of unobservable skills decrease the probability of a bad job match, as coefficient estimates for Russel group universities and first-class degree are negative and statistically significant. Having graduated in the past 5 years has a positive association with the probability of belonging to this group, suggesting that recent graduates with low skills and with little or no work experience, are less likely to find a good job match. However, as years of experience increases the probability of this mismatch status (0.3pp), it is likely that this type of mismatch is driven by low skills alone. Gender also matters as female workers are 0.6pp more likely to belong to this group of graduates. Being married also has a positive and significant effect, increasing the probability of this type of mismatch by 1.3pp. This is expected as married individuals are more constrained in their job search. Robst (2008) also finds that significant gender differences are primarily observed among married men and women, hence family related reasons are important in determining the mismatch status. Having a STEM degree is also positively associated with being mismatched but only when the worker is horizontally mismatched; otherwise, STEM degree increases the probability of finding employment in a graduate job.

Table 8. Investigating the probability of different types of mismatch (Multinomial Probit)

	Graduates in graduate jobs	Graduates in non-graduate jobs – high skilled		Graduates in non-graduate jobs – low skilled	
	Different degree	Same degree	Different degree	Same degree	Different degree
Russell group	0.052***	-0.013**	0.000	-0.049***	-0.016***
	(0.007)	(0.006)	(0.002)	(0.009)	(0.004)
First class degree	0.029***	-0.003	0.002	-0.070***	-0.022***
	(0.009)	(0.008)	(0.002)	(0.012)	(0.005)
Recent graduates	0.003	-0.080***	-0.003	0.013	0.026***
	(0.013)	(0.009)	(0.003)	(0.012)	(0.006)
Female	0.012*	-0.061***	-0.007***	0.069***	0.006**
	(0.006)	(0.005)	(0.002)	(0.006)	(0.003)
STEM subject	-0.061***	-0.014***	0.007***	-0.162***	0.009***
	(0.006)	(0.005)	(0.002)	(0.008)	(0.003)
UK born Foreign degree	-0.479***	0.057***	-0.032***	0.111***	-0.130***
	(0.024)	(0.007)	(0.006)	(0.011)	(0.015)
Foreign born UK degree	-0.036***	0.008	0.001	0.026**	0.013**
	(0.012)	(0.009)	(0.003)	(0.013)	(0.005)
Foreign born Foreign degree	-0.600***	0.099***	-0.039***	0.268***	-0.154***
	(0.027)	(0.008)	(0.007)	(0.012)	(0.014)
age	0.016***	-0.031***	0.002***	-0.015***	0.000
	(0.003)	(0.002)	(0.001)	(0.003)	(0.001)
N. children	-0.009**	0.011***	-0.001	0.005	-0.002
	(0.003)	(0.002)	(0.001)	(0.003)	(0.002)
Married	-0.020***	0.004	0.001	0.027***	0.013***
	(0.008)	(0.006)	(0.002)	(0.008)	(0.004)
White	0.028***	0.017***	0.002	-0.034***	-0.010*
	(0.010)	(0.006)	(0.003)	(0.010)	(0.006)
Disability	-0.017*	-0.003	0.002	0.021**	0.016***
	(0.009)	(0.006)	(0.003)	(0.010)	(0.006)
Mortgage	0.017**	-0.008	0.002	-0.047***	-0.011***
	(0.008)	(0.005)	(0.002)	(0.008)	(0.004)
Property-owned	-0.002	-0.014**	0.003	-0.023***	0.004
	(0.010)	(0.006)	(0.003)	(0.009)	(0.005)
Experience	-0.004***	-0.001	-0.001	0.001	0.003***
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)
Tenure	-0.005***	0.005***	<0.001	<0.001	-0.001
	(0.002)	(0.001)	(<0.001)	(<0.001)	(0.001)
Urban	0.012	-0.029***	-0.005	-0.023	-0.016**
	(0.019)	(0.010)	(0.003)	(0.018)	(0.007)
Private sector	-0.052***	-0.006	-0.001	0.021**	-0.004
	(0.009)	(0.006)	(0.003)	(0.009)	(0.005)
Full time job	0.045***	0.007	0.004**	-0.103***	-0.054***
	(0.007)	(0.005)	(0.002)	(0.009)	(0.006)
Permanent job	-0.003	-0.038***	-0.012***	0.061***	0.004
	(0.008)	(0.006)	(0.003)	(0.007)	(0.004)
Small company	0.002	0.010**	0.004**	0.029***	0.007**
	(0.007)	(0.005)	(0.002)	(0.007)	(0.003)
Industry dummies		YES	YES	YES	YES
Regional dummies		YES	YES	YES	YES
Observations	26,865	26,865	26,865	26,865	26,865

*Notes: ***significant at 1% level; **significant at 5 %; *significant at 10% level. Data source: Annual Population Survey 2017, ONS.*

Discussions and conclusion

This study has provided new evidence on the UK skill mismatch among graduates, comparing different definitions of mismatch and accounting for skill heterogeneity. While prior research focuses on the mismatch in terms of the quantity of education (vertical mismatch) this study also accounts for the mismatch based on degree fields, using a newly developed indictor for horizontal mismatch, the *fit index*. Both measures reveal the presence of skill underutilization and are therefore important in understanding the returns to human capital investments both for the individual and for society. However, the interpretation of both measures requires a common caveat: they rely on certified skills learnt in formal education, which may not be an accurate evaluation of the full graduates' skill set. To address this issue, we have extended both measures to account for skills beyond education and are able to rank graduates into 6 skills groups. At the top of the scale, we find fully matched graduates (both vertically and horizontally), while at the bottom we find low-skilled graduates in non-graduate jobs with/without a field of study match. These are the type of graduates who suffer the most in terms of earnings; however, this higher wage penalty is likely to be mostly associated with their low levels of skills rather than their mismatch status. Thus, although they are overqualified their skills may be suitable for the job.

The question is then to understand why approximately 23% of graduates in the UK have not developed the right skills despite investing in tertiary education. Part of this mismatch is due to personal circumstances; marital status, nationality and place of study are significant factors and, consistent with previous work by the authors, non-UK nationals graduating abroad are at higher risk of a mismatch (Vecchi et al. 2021). From a supply side perspective, foreign workers may have language barriers, lower reservation wages and poorer knowledge of the UK job market to allow them to secure a perfect job match. From the demand side, it is possible that employers in the UK do not have adequate knowledge of the education system in other countries. Further investigation of these issues is an important avenue for future research.

Our results also show that the overall wage penalty for purely horizontal mismatch (1.5% - 6.4%) is on average considerably lower than the penalty for vertical mismatch (19.6% - 39%); thus, provided graduates have developed high levels of observable and unobservable skills, the consequences of this mismatch for individuals are not too severe. For example, a chemistry graduate may decide to manage an hotel chain rather than working for a pharmaceutical company and the consequences in terms of wages are likely to be minor. However, for society horizontal mismatch indicates that investments in education, on behalf of graduates and government, are lost as the skills learnt as part of a degree are not used in the workplace. It also suggests that part of the often-discussed lack of skills in the UK economy might be due to a problem of skill misallocation, rather than skill mismatch. Hence, from a policy perspective, the presence of high-skilled mismatched graduates signal inefficiencies in the allocation of skills and skills underutilization, hence it requires an improved allocation of resources; for those graduates who are overqualified in low-skilled occupation, the main question is how to raise both observable and unobservable skills.[10]

Recent recommendations from the Augar review (Augar et al., 2019) include increasing the support for the provision of STEM education to boost the provision of key skills, increase productivity and reduce the problem of skills mismatch in the UK. The Government response to the review has led to budget cuts to arts and creative subjects in higher education from October 2021. Our results show that having a STEM degree is positively correlated with the probability of finding a graduate job, and in some specifications, it has a positive and significant effect on wages. STEM subjects are certainly important, but one must bear in mind that the fourth industrial revolution will most likely increase the demand for a large variety of skills, including artistic and creative skills, that are less likely to be replaced by Artificial Intelligence (AI). The World Economic Forum ranks creativity as one of three top skills workers will need, after complex problem solving and critical thinking[11]. In addition, the arts have proven to play a crucial role in improving mental health and wellbeing (Hanna 2015) as well as providing physical and mental benefits to healthy seniors and those affected by degenerative conditions such as Parkinson's (Kattenstroth et al. 2013, Rehfeld et al. 2017). With an ageing population and an ageing workforce there might be an increasing demand for arts-related jobs in the future. Improving our understanding of the relationship between technology, ageing and the skill mismatch is an important development for future research.

[10] It is also possible that a graduate chooses a job that does not require a degree because of personal choices. Unfortunately, it is not possible to make this distinction because of luck of information.
[11] The 10 skills you need to thrive in the Fourth Industrial Revolution | World Economic Forum (weforum.org), accessed on 10th January 2022.

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Appendix

Table A.1. Measures of Educational requirements for occupations

Measure	Type of mismatch	Measure	Advantages	Examples	Disadvantages
Self-assessment (subjective)	Vertical mismatch/ Horizonal mismatch	Respondents are asked to what extent their education or skills are used in their job. Examples: REFLEX, OECD Survey of Adult Skills.	Always up-to-date. Corresponds to specific requirements in individual firms.	Vertical mismatch: Chevalier (2003), Chevalier and Lindley (2009), McGuinness and Sloane (2011), Meroni and Vera-Toscano (2017). Horizontal mismatch: Allen and de Weert 2007, Robst 2007, 2008, Verhaest et al. 2017	Subjective bias: respondents may overstate job requirements, inflate their status or reproduce actual hiring standards. Usually available for small sample of workers.
Normative (objective)	Vertical mismatch	Use a pre-determined mapping between the job and the required education level.	Easily measurable Objective	O*Net (Occupational Information Network). Data base of occupational requirements and workers' attributes.	Assumes constant mappings over all jobs of a given occupation. Costly to create and update Occupational requirements can change over time.
Statistical/ Realised Matches (objective)	Vertical mismatch/Horizontal mismatch	Derived from data on occupations and workers' educational attainment, expressed in years of education or type of qualification.	Ease of calculation, easy to apply to existing datasets, facilitates cross-country comparisons (McGuinness et al 2018). Objective, always up-to-date	Range measure (1 standard deviation around the mean number of years of education observed for each occupation). Mode measure (the most common	Assumes constant mappings over all jobs in a given occupation. Sensitive to cohort effects (Chevalier 2003). It does not contain information of the actual skill requirements of the

				years/qualification in each occupation).	job (McGuinness et al. 2018).

Source: Authors' elaboration: Hartog (2000)

Table A.2: Education groups in APS

Education group – based on HIQUAL	Percent
1 Higher degree	12.39
2 Degree or equivalent	23.22
3 Certificates of education	11.39
4 GCEs, A-Levels or equivalent	22.53
5 GCSE grades A*-C or equivalent	19.9
6 Other qualifications	5.25
7 No qualifications	4.45
Don't know	0.86
Total	100

Data source: Annual Population Survey 2017, ONS