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The Math-Verbal Divide: Unequal Returns to Cognitive Skills in Education and Work

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Abstract

We use population-level administrative data covering secondary school students in England to study how mathematical and verbal skills shape education and labour market outcomes. Following cohorts completing national exams at age 16 through higher education and into employment until age 34, we show that mathematics and verbal skills operate through fundamentally different pathways. Verbal skills strongly predict educational attainment—including college enrolment, graduation, and postgraduate study—while mathematics skills generate substantially larger earnings returns. At ages 30–34, moving from the 25th to the 75th percentile of the mathematics skill distribution is associated with 29% higher earnings, compared with 14% for verbal. This divergence operates partly through field-of-study choice: individuals with stronger verbal skills disproportionately select into fields with higher graduation rates but lower earnings returns, while those with stronger mathematics skills enter STEM and other high-paying majors. Gender differences in skills explain the female advantage in college attendance and part of the STEM gap but have little effect on the gender earnings gap due to offsetting effects across these pathways: women's verbal advantage facilitates educational access but also steers them toward lower-return fields.

JEL classification

I26, I24, I21

Keywords

math skills, verbal skills, college, field of study, STEM

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1. Introduction

It is well established that cognitive skills are important determinants of educational attainment and labour market employment and earnings. However, it is not obvious which types of cognitive skills matter most for these outcomes and whether some skills matter more in education while others have a higher payoff in the labour market. The literature has emphasised two types of cognitive skills – mathematical skills and verbal skills – that capture different skill dimensions and are complementary to different types of college majors and occupations. In this paper, we use UK administrative data to study how mathematics and verbal skills affect educational outcomes and how they are rewarded in the labour market.

We show the effects of mathematics and verbal skills on various educational outcomes including completing A-levels, starting college, college major choice, performance at undergraduate level, and graduate study choices. We also examine labour market outcomes (employment and earnings) for the same cohorts from age 21 up to age 34, capturing important dynamics that may be missed by studies that just look at a single point in time. We then use our findings to evaluate whether gender differences in mathematics and verbal skills play a role in gender gaps in earnings.

Our data allow us to follow individuals who remain in schooling until age 16 from 2002 onwards. We use GCSE test scores in mathematics and English at age 16, along with Key Stage 2 test scores obtained five years earlier at age 11. Because skills are likely to be measured with error, we adopt an instrumental variables strategy in which test scores at age 11 are used as instruments for those at age 16. Having measures of English[1] and mathematics skills prior to labour market entry is important for addressing concerns about reverse causality. For example, non-employment may lead to skill depreciation, while among the employed, the type of job held may influence the development of skills.

[1] We use the terms "verbal skills" and "English skills" interchangeably in the paper.

Our work brings together several strands of the literature. A large body of research has examined the effects of cognitive skills but has not evaluated the separate effects of mathematical and verbal skills (Murnane et al., 1995; Tyler, 2004; Castex and Dechter, 2014). Other studies analyse the relationship between earnings and numeracy and literacy using cross-national cross-sectional datasets such as PIAAC (Hanushek et al., 2015).[2] A limitation of this approach is that skills are measured contemporaneously with earnings and may therefore be influenced by labour market experiences, in addition to the usual concerns about measurement error. In contrast, our measures of skills are observed prior to labour market entry, allowing us to mitigate concerns about reverse causality while also addressing measurement error.

There is also a literature examining the effects of pre–labour market skill measures on earnings, most of which relies on survey data. Some studies use samples consisting only of college graduates (Büchner, Smits, and van der Velden, 2012; Busso et al., 2025; Kinsler and Pavan, 2015; Seki, 2013; Arcidiacono, 2004). This may be problematic because mathematical and verbal skills have been shown to influence educational choices (Aucejo and James, 2021).

Other studies analyse samples that include both graduates and non-graduates. Using several US survey datasets, Sanders (2015) finds that, conditional on mathematics scores, a one standard deviation increase in reading scores is associated with a 2–5% *decrease* in wages. He suggests that this negative relationship may arise because individuals with stronger reading skills may have weaker interpersonal skills. Using the British Cohort Study, which follows individuals born in the UK in 1970, Vignoles et al. (2011) find that a one standard deviation increase in literacy is associated with 14% higher earnings at age 34, while the corresponding estimate for mathematics skills is 11%. In contrast, Crawford and Cribb (2013), using the same dataset, find a larger effect of mathematics skills than of verbal skills. Overall, the evidence is

[2] When Hanushek at al. (2015) use PIACC survey data for OECD countries conducted in 2011-12 and control for both numeracy and literacy skills, they find larger earnings effects for numeracy and substantial heterogeneity across countries.

mixed, although most studies conclude that mathematics skills have a stronger association with earnings than verbal skills.

A related literature examines the effects of mathematical and verbal skills on educational outcomes. Using Irish data, McCoy and Byrne (2017) find that school mathematics grades are more important than English grades in predicting dropout after the first year of college. Similarly, Delaney and Devereux (2020) find that mathematics grades are more important than English grades in determining the likelihood of obtaining the highest degree classification upon graduation. Using US data, Arcidiacono (2004) finds that students with stronger mathematics ability are more likely to choose more lucrative college majors. Song et al. (2008) show that students in fields of study with higher average quantitative GRE scores are less likely to pursue postgraduate degrees, while those in fields with higher average verbal GRE scores are more likely to do so.

Our paper builds on the important study by Aucejo and James (2021). Using UK data similar to ours, they find that verbal skills have a much larger effect on college attendance and graduation probabilities than mathematics skills. They argue that, because verbal skills play a stronger role in educational attainment, estimates of the earnings returns to skills that control for education may understate the effect of verbal skills relative to mathematics skills.

The authors therefore suggest that policy should focus on improving verbal skills in addition to mathematics skills. However, their data do not allow them to examine graduate study or labour market outcomes such as earnings for the same cohorts that they use to study educational attainment. Our contribution is to examine both labour market and educational outcomes for the same cohorts, allowing us to clearly assess how the effects of different types of skills vary across outcomes. We further contribute by analysing how the returns to verbal and mathematics skills evolve with age, by examining whether these skills influence the choice of high-return college fields, and by studying their effects on the likelihood of pursuing graduate degrees. In addition, we investigate the extent to which educational pathways explain the relationship between skills and earnings, and assess whether gender differences in the mix of mathematical and verbal skills help explain gender gaps in earnings.

We find a systematic divergence in the roles played by verbal and mathematics skills across the education and earnings lifecycle. Consistent with Aucejo and James (2021), English skills are substantially more important than mathematics skills for most measures of educational attainment, including college enrolment, graduation, graduation conditional on enrolment, and postgraduate participation. However, compared to verbal skills, math skills are a much stronger predictor of labour market earnings from age 21 up to age 34 and, so, mathematics skills play a central role in shaping economic returns. We show that these findings are related: Stronger mathematics skills robustly predict selection into higher-return fields of study at both undergraduate and postgraduate levels, whereas stronger verbal skills predict entry into lower-return majors. As a result, the earnings gains associated with the higher educational participation of individuals with strong verbal skills are largely offset by their field choices, while mathematics skills remain a much stronger predictor of labour market earnings.

This pattern also helps explain gender differences. Females tend to exhibit relatively stronger verbal skills, and accounting for this difference closes the gender gap in college attendance and explains roughly one-third of the gender gap in STEM participation. However, because of the offsetting effects of verbal skills on educational attainment and the economic return of courses chosen, math and verbal skills have little effect on the gender earnings gap. Finally, while Aucejo and James (2021) show that conditioning on educational attainment reduces the relative importance of verbal skills for earnings, we demonstrate that further conditioning on field of study substantially attenuates the earnings advantage of mathematics. This highlights the pivotal role of subject choice as a key mechanism linking skills to labour market outcomes.

The remainder of the paper proceeds as follows. Section 2 describes the data, institutional setting, and the construction of our measures of English and mathematics skills. Section 3 outlines the empirical methodology. Section 4 presents the effects of skills on educational attainment and examines how mathematics and verbal skills shape subject and programme choices at the undergraduate and postgraduate levels. Section 5 studies labour market outcomes, documenting how skill returns evolve over the life cycle, examining gender differences, and analysing the role of skills in explaining gender gaps in education, field choice, and earnings. Section 6 investigates the extent to which the relationship between skills and earnings is mediated through educational attainment and field of study. Section 7 concludes.

2. Data

We use the UK Longitudinal Education Outcomes (LEO) dataset. This dataset includes all individuals who completed their GCSEs (national examinations taken at around age 16) between 2002 and 2020. The educational information includes Key Stage exam performance, school identifiers, GCSE and A-level subjects and grades, university field of study, university degree class, and whether the student undertook postgraduate study. The labour market variables include earnings from all UK employments during this period. However, the data do not include individuals who emigrated or those who did not sit their GCSEs in an English school.

Our main measures of interest are math and English test scores. We measure these using GCSE grades in each subject and use the terms *ability* and *achievement* interchangeably throughout the analysis. GCSE grades take the values A*, A, B, C, D, E, F, G, and U. We convert letter grades into a numeric scale from 0 (U) to 8 (A*), then compute percentile ranks within each exam cohort.[3] Because English has two exams—literature and language—we take the average of the two grades to construct the English score.[4] We then calculate the percentile rank of the student's score within each GCSE exam year and use this rank measure in our analysis.[5] To address measurement error in GCSE subject grades, we instrument them using lagged test scores from the Key Stage 2 (KS2) mathematics and English assessments. These standardized tests are taken at age 11 and scores range from 0 to 100. For each KS2 exam year, we compute the percentile rank of the subject test score in the national distribution and use this rank to instrument for the corresponding GCSE subject rank.

As a marker for poverty, we create an indicator of eligibility for free school meals using the annual school census. We set this variable to 1 if at any point over the sample period we observe that the student was eligible for a free school meal. We calculate 5 ethnicity indicators denoting Mixed Race, Chinese, Black, Asian, and White. We also create quintiles of the IDACI area deprivation score as an additional marker for disadvantage. We limit our sample to those who did their GCSEs between 2002 and 2004 so that we can look at the effects of earnings from ages 21 to 34.

Our main college variables (degree class and undergraduate (UG) field) relate to the student's first bachelor's degree that they entered between the ages of 17 and 20. This allows us to incorporate students taking gap years after finishing school but excludes mature students who are defined as entering college after age 20. Our postgraduate degree (PG) outcome is measured as having entered a PG degree within 3 years of graduating from their first bachelor's

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[3] The linear mapping of GCSE grades (A*–G, U) to numeric scores (8–0) is a standard approach that preserves the grade hierarchy and has precedent in government analyses (e.g. Hodge et al. 2021). This mapping is also conceptually consistent with the subsequent 9–1 grading reform introduced in 2017, which formalised a numeric scale for GCSE outcomes.
[4] For example, if a student received an A in literature and a C in language, we allocate a score of 7 for literature and 5 for language. Then, taking the average, the student has a score of 6 for English.
[5] Appendix Figure A1 shows that the distribution of GCSE grades in math and English approximate a normal distribution.

degree. This means that, if a student enters PG after a second UG degree or more than 3 years after completing UG, they are assigned as not doing one.

We define a student as having graduated college if they have a degree classification in the dataset. The degree classifications range from first class, upper second, lower second, third, pass, and unclassified. We calculate "good degree" as those who scored at least an upper-second degree class and we assign "great degree" as those who obtained a first-class honours degree. Many fields such as medicine and other courses assign a "pass" or "unclassified" degree classification and so we omit them from our good and great degree measures as the quality of the grade is unclear.

We examine two broad fields of study. These are STEM and Humanities, Arts, and Social Sciences (HASS). We calculate earnings returns to more detailed UG field of study using 30 different UG subjects.[6] We do this by regressing log pay (at the maximum age at which we observe earnings, provided the person is aged at least 30) on indicator variables for graduating from each of the subjects with history being the reference category. We also calculate the returns to each of our 30 fields of study relative to not going to college at all. In this set up we regress log pay on indicators for graduating from each of the 30 subjects with non-college goers being the reference category.[7]

We calculate real earnings by indexing earnings to 2020 prices. We then set to missing those who earn less than £5,000 or greater than £1,000,000 in 2020 pounds. The LEO dataset

[6] The 30 subjects include agriculture, architecture, biosciences, business, chemistry, commerce, computing, creative arts, economics, education, engineering, English, geography, history, languages, law, maths, medicine, nursing, pharmacology, philosophy, physics, physical sciences, politics, psychology, social care, sociology, sports sciences, technology, and veterinary sciences.

[7] In both regressions, we include controls for gender, ethnicity, quintiles of the IDACI area deprivation score, a free school meal indicator, KS2 math and English scores, KS4 math and English scores, and KS4 school cohort fixed effects. We also restrict the sample to those aged at least 30 (we measure earnings at the highest age possible for each individual) and having real earnings of at least £5,000 in 2020 pounds, working at least 183 days and having at least 5 GCSE grades from A* to C and having at least 1 KS5 (A-level) record and define college attendance as entering college before age 21 (the mature student cutoff). Our approach is very similar to Belfield et al. (2018) whose goal is to take a selection-on-observables approach to estimate the returns to various college fields of study.

does not include self-employment income prior to 2014. As our primary analyses focus on earnings at age 30 and above, we include self-employed individuals in our main analysis. For the 2002–2004 GCSE cohorts we study, earnings observed at age 30 or older occur from 2014 onwards, ensuring consistent coverage of both PAYE and self-employment income. However, when analysing the relationship between skills and earnings over the life cycle, we restrict the sample to PAYE employment income only. This ensures that earnings are measured consistently across ages and avoids compositional changes arising from the introduction of self-employment income in later years.[8] To measure labour market attachment, we define an individual as working if they are employed for at least 183 days in the tax year and earn at least £5,000 (in 2020 prices). Information on days worked is not available for the self-employed. For these individuals, we therefore define labour market attachment as having self-employment income of at least £5,000 (in 2020 prices). Earnings are observed from tax years 2003/04 to 2020/21.[9] To assess the robustness of our results to potential COVID-related effects, we also report estimates that exclude the 2020/21 tax year.

Table 1 shows descriptive statistics for the main variables used in the analysis. We see that for the full sample we have information on almost 1.3 million individuals. As expected, females and those who do not qualify for a free school meal are disproportionately more likely to go to college. Interestingly, whites are less likely to go to college. We also see that test scores, earnings, and the probability of employment are higher on average for college entrants.

[8] In our sample approximately 9 percent of individuals who are aged at least 30 have some form of self-employment income.
[9] The tax year runs from April to April so the last earnings information we have relates to annual earnings from the beginning of April 2020 to the beginning of April 2021.

Table 1: Descriptive Statistics

	All mean/(std dev)	**High School Only** mean/(std dev)	**College Entrants** mean/(std dev)
Female	0.49	0.45	0.55
	(0.50)	(0.50)	(0.50)
Free School Meal	0.14	0.18	0.08
	(0.35)	(0.38)	(0.27)
White	0.90	0.94	0.84
	(0.30)	(0.24)	(0.37)
Mixed race	0.01	0.01	0.01
	(0.10)	(0.09)	(0.11)
Chinese	0.00	0.00	0.01
	(0.06)	(0.03)	(0.09)
Black	0.03	0.02	0.03
	(0.16)	(0.14)	(0.18)
Asian	0.06	0.03	0.10
	(0.23)	(0.17)	(0.30)
Other Ethnicity	0.00	0.00	0.01
	(0.05)	(0.04)	(0.07)
IDACI Q1	0.18	0.22	0.12
	(0.39)	(0.41)	(0.32)
IDACI Q2	0.19	0.22	0.15
	(0.40)	(0.42)	(0.35)
IDACI Q3	0.20	0.21	0.19
	(0.40)	(0.41)	(0.40)
IDACI Q4	0.21	0.19	0.24
	(0.41)	(0.39)	(0.43)
IDACI Q5	0.21	0.16	0.30
	(0.41)	(0.37)	(0.46)
Year of Birth	1986.74	1986.75	1986.73
	(0.94)	(0.94)	(0.95)
GCSE Exam Year	2003.07	2003.08	2003.06
	(0.81)	(0.81)	(0.83)
GCSE Math Rank	0.42	0.29	0.65
	(0.28)	(0.22)	(0.22)
GCSE English Rank	0.45	0.31	0.68
	(0.28)	(0.22)	(0.21)
Key Stage 2 Math Rank	0.49	0.40	0.66
	(0.29)	(0.26)	(0.25)
Key Stage 2 English Rank	0.49	0.39	0.67
	(0.29)	(0.26)	(0.24)
A- Levels	0.54	0.29	0.97
	(0.50)	(0.45)	(0.18)
College Age 17 -20	0.32	0.00	1.00
	(0.47)	(0.00)	(0.00)
Log Pay (at maximum age)	10.05	9.90	10.29
	(0.66)	(0.62)	(0.66)
Employed	0.80	0.77	0.87
	(0.40)	(0.42)	(0.33)
Potential Experience (at maximum age)	14.03	16.34	10.68
	(3.29)	(1.24)	(2.32)
Returns to UG Field vs No College (log points)	0.06		0.15

	(0.10)		(0.12)
		Conditional on Entering College	
Graduate from first UG degree			0.72
			(0.45)
Good Degree			0.63
			(0.48)
Great Degree			0.12
			(0.33)
UG Field STEM			0.33
			(0.47)
UG Field HASS			0.26
			(0.44)
Returns to UG Field in Log Points (relative to studying History)			0.03
			(0.12)
		Conditional on Graduating	
PG Degree within 3 Years			0.22
			(0.42)
		Conditioning on Entering PG Degree	
PG Field STEM			0.24
			(0.43)
PG Field HASS			0.19
			(0.39)
N	1,252,835	741,785	405,110

Note: Authors calculation using Longitudinal Educational Outcomes (LEO) dataset and GCSE exam cohorts from 2002 to 2004. College column is defined as those who enter their first bachelor's degree between the ages of 17 and 20. The sample is restricted to individuals observed between ages 30 and 34, using the maximum observed age within this range. Good Degree refers to an upper second-class degree or better while Great Degree refers to attaining first-class honours. PG refers to graduate level study.

3. Empirical Methodology

We regress educational and labour market outcomes on English and mathematics grades (percentile ranks within each exam cohort). Our main specification has the form:

$$y = \beta_0 + \beta_1 Math + \beta_2 Verbal + \delta' X + u \qquad (1)$$

where y denotes the outcome of interest and Math and Verbal represent GCSE scores in mathematics and English respectively. The vector X includes gender, year-of-birth fixed effects, quintiles of the IDACI area deprivation score, an indicator for ever being eligible for free school meals, ethnicity indicators, and secondary school fixed effects. The analysis focuses on cohorts who completed GCSE examinations between 2002 and 2004.

We examine three broad sets of outcomes. First, we analyse educational attainment, including A-level attainment, university enrolment, university performance (including degree completion and degree classification), and whether postgraduate study was pursued. Second, we study field choices at undergraduate and postgraduate level and the implied returns to undergraduate programmes. Finally, we analyse labour market employment and earnings, which we observe annually from ages 21 to 34. We report heteroskedasticity robust standard errors in all estimation.

To address potential measurement error and endogeneity in GCSE performance, we instrument mathematics and English GCSE grades using Key Stage 2 (KS2) test scores. The relevance condition is satisfied by the strong correlation between KS2 and GCSE achievement, which we verify through large first-stage F-statistics. Conditional on controls, KS2 scores primarily capture underlying cognitive skills measured several years prior to GCSE examinations and prior to subject specialization in secondary school. They therefore provide a plausible source of predetermined variation in subject-specific achievement.

4. Results for Education

Educational Attainment

Table 2 reports the effects of math and verbal skills on a range of educational outcomes. Several of these outcomes -- college enrolment, college graduation, and graduation conditional on enrolment -- are also examined by Aucejo and James (2021). Reassuringly, our findings for these outcomes are similar to theirs: once we take account of measurement error using instrumental variables, the effect of verbal skills on these outcomes is about 3-times larger than the effects of math skills.[10] The difference in the magnitudes are large – an increase in rank in

[10] Aucejo and James (2021) develop a complicated latent factor model of skills using a multiplicity of tests from UK key stage data at various ages and specifying selection corrections to account for the fact that many of these tests were not taken by all students. This enables them to create measures of math and English skills that are less-susceptible to test-retest measurement error. Our IV approach of instrumenting Key Stage 4 math and English

verbal skills of 0.1 (such as from the median to the 60^{th} percentile) is associated with an increase in college attendance of 7 percentage points; the equivalent for maths is 3 percentage points.

We extend Aucejo and James (2021) by examining several additional measures of educational attainment. Column (1) shows that even before the decision to attend college, verbal skills have a substantially larger effect than math skills on whether students take A-level examinations, which are required for university admission in England. When examining performance in college, verbal skills are much more predictive than math skills of obtaining at least an upper second-class degree, whereas both skills are similarly associated with achieving first-class honours. Finally, we examine whether individuals who complete an undergraduate degree continue to postgraduate study. Consistent with the other measures of educational attainment, the IV estimates suggest that verbal skills play a substantially larger role than math skills.

Correcting for measurement error using instrumental variables materially affects the estimates. In most cases, the gap between the verbal and math coefficients widens: the verbal coefficients increase while the math coefficients decline.[11] The only exception is graduation conditional on college enrolment, where the verbal coefficient decreases slightly, although the estimated effect remains larger than that of math. Aucejo and James (2021) show that measurement error can have complex effects when two positively correlated explanatory variables are both measured with error. Our findings -- that measurement error tends to understate the relative importance of verbal skills compared with math skills for educational attainment -- are consistent with their results for college enrolment. For the rest of the paper, we will focus on the instrumental variables estimates.

ranks with those from Key Stage 2 is a simpler and more direct approach to account for measurement error in the test scores.

[11] Table A1 in the appendix shows that the first stage is very strong.

Table 2: Effect of Math and Verbal Skills on Educational Attainment and Performance

VARIABLES	(1) A-Levels	(2) College Attendance	(3) College Graduation	(4) College Graduation (conditional)	(5) Good Degree	(6) Great Degree	(7) Postgraduate Degree within 3 Years
Math	0.539***	0.447***	0.368***	0.204***	0.282***	0.211***	0.130***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)	(0.004)
Verbal	0.719***	0.584***	0.439***	0.202***	0.504***	0.162***	0.203***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.005)
R-squared	0.477	0.401	0.303	0.065	0.123	0.061	0.037
				Instrumental Variables Estimation			
Math	0.374***	0.276***	0.220***	0.104***	0.124***	0.189***	0.067***
	(0.005)	(0.005)	(0.005)	(0.009)	(0.011)	(0.007)	(0.009)
Verbal	0.827***	0.700***	0.521***	0.166***	0.691***	0.173***	0.243***
	(0.005)	(0.005)	(0.005)	(0.011)	(0.013)	(0.009)	(0.012)
Observations	1,252,455	1,252,455	1,252,455	404,870	291,020	291,020	292,245

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. In the lower panel, these scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. Good Degree refers to an upper second-class degree or better while Great Degree refers to attaining first-class honours. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$.

Subject Choices

Aucejo and James (2021) show that math skills strongly predict choosing a STEM programme in college, while verbal skills negatively predict this choice. Table 3 replicates this finding and extends it in several ways.

Column (1) confirms that math skills strongly increase the probability of choosing a STEM degree, while verbal skills strongly reduce it. Column (2) shows the opposite pattern for Humanities and Social Sciences (HASS): Verbal skills strongly predict entry into HASS fields, while math skills reduce the likelihood of doing so. These symmetric patterns suggest that students sort into fields that match their comparative advantage in skills.[12]

[12] We find similar patterns for A-Level subject choices but, for brevity, do not report them.

Next, we examine the earnings implications of undergraduate field choices. In column (3), we regress the average earnings return associated with each undergraduate field on math and verbal skills. Greater math skills predict choosing fields with higher earnings returns (0.22), while conditional on math skills, greater verbal skills predict choosing fields with lower-return fields (–0.11). These results indicate that skill-based sorting across fields directly affects earnings prospects, motivating our later analysis of the relationship between skills and earnings. They also suggest that the earnings effects of verbal and math skills may differ from their effects on educational attainment. Column (4) extends the analysis to include non-college-goers by constructing a measure of field-specific returns relative to not attending college. While the coefficients on both skills remain positive, the math coefficient is more than twice as large as that for verbal. Overall, higher math skills predict more lucrative undergraduate choices, whereas the larger effect of verbal skills on the likelihood of attending college (shown in Table 2) is partially offset by the stronger association between math skills and entry into high-return degree programmes.

Graduation rates differ substantially across courses. Column (5) reports estimates for graduation conditional on college entry when course fixed effects are included.[13] In this specification, only math skills significantly predict graduation (0.10), while the coefficient on verbal skills becomes small and statistically insignificant (0.02). This contrasts with the positive effects of verbal skills on graduation in Column (4) of Table 2. This pattern likely reflects the fact that individuals with stronger verbal skills disproportionately enter programmes with higher completion rates. In other words, students with stronger verbal skills tend to select into courses where graduating is easier; this must be taken into account when interpreting the relationship between skills and graduation outcomes.

[13] These course fixed effects are both institution- and field-specific. For example, English Literature at a specific university. There are on average 6,400 courses per year with approximately 70 students on average in each course.

Finally, columns (6) and (7) extend the analysis to postgraduate choices. Conditional on enrolling in a graduate programme, math skills strongly predict choosing STEM fields (0.55), while verbal skills negatively predict postgraduate STEM (–0.57). Column (7) shows the reverse pattern for postgraduate HASS: Verbal skills strongly predict this choice (0.75), while math skills negatively predict it (–0.43). These results closely mirror the undergraduate findings and indicate that comparative advantage in skills continues to shape field choices at the postgraduate level.

Table 3: Effect of Math and Verbal Skills on Field of Study and Graduation

VARIABLES	(1) UG STEM	(2) UG HASS	(3) Returns to UG Field	(4) Returns to UG Field (relative to no college)	(5) Graduation (with course fixed effects)	(6) PG STEM	(7) PG HASS
Math	0.495***	-0.336***	0.149***	0.124***	0.205***	0.406***	-0.295***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.004)	(0.010)	(0.010)
Verbal	-0.382***	0.526***	-0.038***	0.063***	0.113***	-0.296***	0.431***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.005)	(0.011)	(0.010)
R-squared	0.073	0.049	0.119	0.221	0.016	0.062	0.033
				Instrumental Variables Estimation			
Math	0.686***	-0.549***	0.216***	0.124***	0.100***	0.547***	-0.432***
	(0.009)	(0.008)	(0.002)	(0.001)	(0.010)	(0.021)	(0.020)
Verbal	-0.646***	0.905***	-0.109***	0.058***	0.016	-0.570***	0.751***
	(0.011)	(0.010)	(0.003)	(0.001)	(0.013)	(0.027)	(0.025)
Observations	404,870	404,870	404,870	1,252,455	403,995	64,975	64,975

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. In the lower panel, these scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. PG refers to graduate level study. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** p < 0.01

5. Results for Labour Market Outcomes

Table 4 presents the effects of skills on log earnings for individuals aged 30 and above. All specifications use the same demographic and school controls as in previous tables. As before, we focus on instrumental variables estimates that address measurement error in test scores. The results reveal a striking reversal relative to the educational attainment results: Mathematics skills now generate earnings returns roughly twice as large as those associated with verbal skills.

Column (1) reports results for the full sample. The IV coefficient for mathematics skills is 0.58 compared with 0.29 for verbal skills, implying that the earnings return to mathematics is approximately twice as large. In terms of magnitudes, moving from the 50th to the 60th percentile of the mathematics distribution is associated with approximately 6% higher earnings, while an equivalent increase in verbal skills raises earnings by about 3%. This contrasts sharply with the educational attainment results in Table 2, where verbal skills had substantially larger effects than mathematics skills. Together, these results suggest that verbal skills generate economic returns partly through increased educational attainment, while mathematics skills generate returns through field choice and other channels more directly linked to earnings (as most individuals do not go to college).

Columns (2) and (3) show results separately for males and females. For males, the mathematics coefficient (0.55) is nearly three times the verbal coefficient (0.19), indicating that earnings returns are heavily driven by mathematics skills. For females, mathematics skills remain more strongly associated with earnings (0.63 vs. 0.40), although the gap between the two skills is smaller. These patterns suggest that verbal skills play a relatively larger role in determining earnings among women than among men.[14]

Columns (4) to (6) examine employment probability rather than earnings conditional on employment. Mathematics skills significantly increase employment probability in the full

[14] We have verified the robustness of the estimated effects of math and verbal skills on earnings and employment outcomes when excluding the tax year that was affected by COVID-19 (the 2020–2021 tax year) from the sample. The results excluding that year are in Appendix Table A2.

sample (0.16), while verbal skills have a smaller effect (0.09). The gender pattern mirrors the earnings results: mathematics skills have substantially larger effects than verbal skills for males (0.13 vs. 0.04), while the gap is a little smaller for females (0.20 vs. 0.13). The smaller magnitudes relative to the earnings results suggest that these skills primarily influence the type of job individuals obtain rather than whether they work at all.

The reversal between educational attainment (where verbal dominates) and earnings (where mathematics dominates) may result from several mechanisms. First, as suggested by Table 3, individuals whose college attendance is driven primarily by strong verbal skills may disproportionately enter lower-return degree programmes or institutions, limiting their earnings gains. Second, quantitative skills may generate larger productivity gains in many high-paying occupations, including finance, technology, and data-intensive roles. Third, mathematics ability may serve as a stronger signal of general cognitive ability to employers. In Section 6, we examine the extent to which the earnings results can be explained by the relationship between verbal and math skills with educational attainment and college field choice.

Table 4: Effect of Math and Verbal Skills on Log Pay and Employment

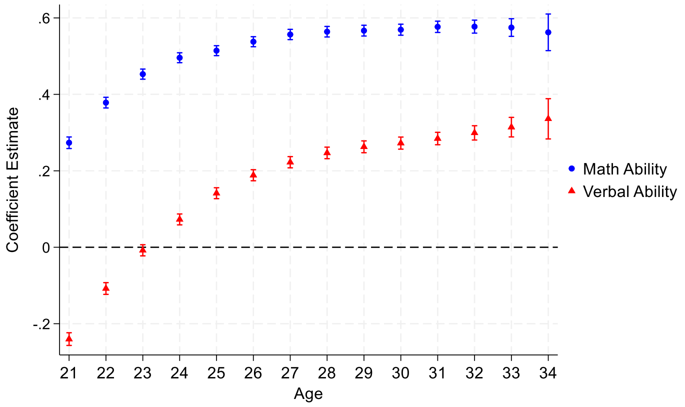
VARIABLES	(1) Log Pay Full Sample	(2) Log Pay Male	(3) Log Pay Female	(4) Employed Full Sample	(5) Employed Male	(6) Employed Female
Math	0.497***	0.458***	0.541***	0.155***	0.132***	0.182***
	(0.003)	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)
Verbal	0.350***	0.285***	0.422***	0.124***	0.084***	0.162***
	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)
R-squared	0.270	0.189	0.257	0.123	0.113	0.132
			Instrumental Variables Estimation			
Math	0.583***	0.545***	0.628***	0.163***	0.133***	0.199***
	(0.007)	(0.010)	(0.011)	(0.005)	(0.006)	(0.007)
Verbal	0.287***	0.189***	0.397***	0.085***	0.038***	0.129***
	(0.008)	(0.011)	(0.012)	(0.005)	(0.006)	(0.008)
Observations	1,107,495	576,045	531,110	1,252,455	637,805	614,250

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. In the lower panel, these scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** p < 0.01

Life-Cycle Patterns in Skill Returns

We next examine how the effects of skills on labour market outcomes evolve over the life cycle up to age 34. Studying the life cycle is important because several studies show that the returns to ability increase with labour market experience as employers learn about worker productivity (e.g., Altonji and Pierret, 2001; Lin et al., 2018). To ensure comparability across ages, we exclude self-employment income, which is only available in the data from 2014 onwards. We also restrict the sample to individuals with employee earnings of at least £5,000 and at least 183 days of work in the tax year.

Figure 1: Effect of Math and Verbal Skills on Log Pay over the Life Cycle



Note: Math and verbal ability refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004. We exclude self-employed earnings since this is only available from 2014 onwards. We also restrict the sample to having real PAYE earnings of at least £5000 and working at least 183 days per year.

Figure 1 plots the estimated effects of math and verbal skills on log earnings from ages 21 to 34. Each point represents the coefficient from a separate IV regression estimated at each age using the same control variables specified in equation (1). The results show clear differences between the two skills. Returns to verbal skills are initially negative but rise rapidly and stabilize at approximately 0.3 from around age 30 onwards. In contrast, the coefficients for mathematics skills are positive at all ages, rising to roughly 0.6 by age 30 and remaining stable thereafter. In terms of magnitudes, a 10-percentile increase in the math skill distribution is associated with roughly 6 percent higher earnings, while the equivalent increase in verbal skills raises earnings by about 3 percent. Thus, throughout most of the observed career span, the earnings returns to mathematics skills are approximately twice those of verbal skills.

The negative early-career coefficients for verbal skills reflect differences in educational trajectories by skill profile. Individuals with stronger verbal skills are substantially more likely to remain in education completing undergraduate or postgraduate degrees (Appendix Figure A2). During these years they often have low earnings, which generates a negative relationship between verbal skills and earnings at younger ages. By around age 27 most individuals have completed their education and entered the labour market, at which point the verbal coefficient stabilizes at a positive level.[15]

Gender Differences

Figure 2 presents the life-cycle evolution of skill returns separately for males and females. For both genders, mathematics skills are strongly associated with higher earnings throughout the early career, but the magnitude and trajectory of verbal returns differ substantially.

For males (top panel), mathematics returns are positive from age 21 onwards, rising from roughly 0.35 at age 21 to around 0.55 by age 27, after which they remain stable. Verbal returns, in contrast, are negative until the late twenties before turning slightly positive after age 27. This pattern is consistent with males with strong verbal skills remaining longer in education and disproportionately entering humanities and social science fields, which tend to have lower early-career earnings.

For females (bottom panel), mathematics returns follow a trajectory similar to that for males, rising from around 0.20 at age 21 to approximately 0.60 by age 27. However, the pattern for verbal skills differs markedly: Verbal returns are positive from the early twenties onward and increase steadily with age, reaching approximately 0.40 by age 27. The consistently larger verbal coefficients for women likely reflect differences in occupational sorting, with women with strong verbal skills more likely to enter communication-intensive occupations where these skills are directly rewarded.

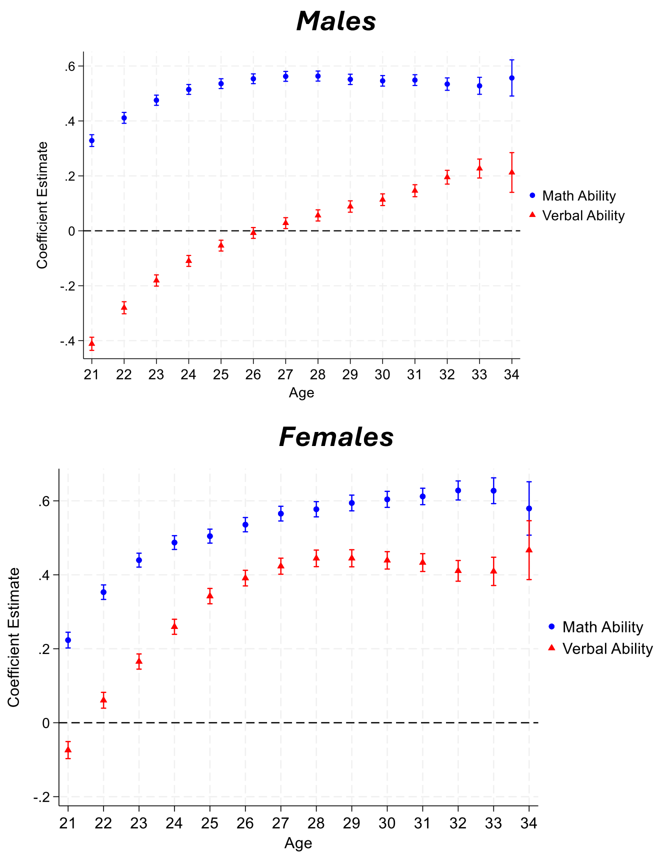
The gender differences in verbal returns are economically substantial. By age 30, the verbal coefficient for women is roughly three times larger than for men, while the mathematics

[15] Consistent with this interpretation, when we restrict the sample to those who leave education with just high school, the negative early-career verbal coefficients disappear (Appendix Figure A3). Likewise, Figure A4 in the appendix shows that the negative returns to verbal skills are much smaller if we restrict the sample to people who are not in education during the year.

coefficients are broadly similar across gender. These results suggest that verbal skills play a much larger role in determining female earnings than male earnings, whereas mathematics skills generate substantial returns for both genders.

More broadly, the life-cycle patterns reinforce our central mechanism. Mathematics skills generate earnings returns early in the career and remain consistently valuable, while the returns to verbal skills emerge later as individuals complete education and enter occupations where communication and analytical writing skills are rewarded. We now examine these gender differences more formally by analysing how skill profiles contribute to gender gaps in education, field choice, and labour market outcomes.

Figure 2 : Effect of Math and Verbal Skills on Log Pay Over the Life Cycle by Gender

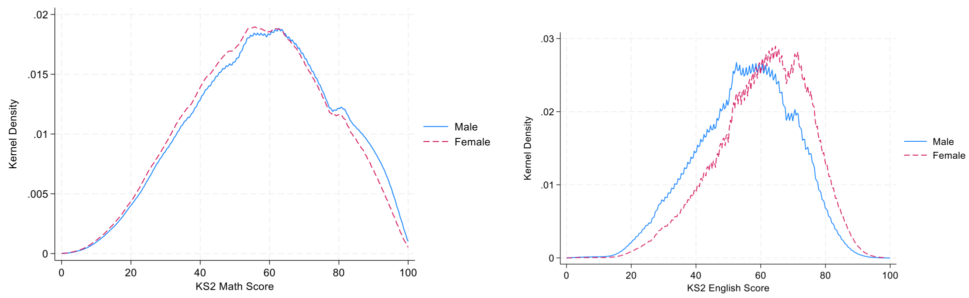


Note: Math and verbal ability refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004. We exclude self-employed earnings since this is only available from 2014 onwards. We also restrict the sample to having real PAYE earnings of at least £5000 and working at least 183 days per year.

Effect on Gender Gaps

Figure 3 presents the distribution of Key Stage 2 scores by gender, illustrating early differences in academic skills that persist through secondary school. Girls outperform boys in English at age 11, with the female distribution noticeably shifted to the right. By contrast, the mathematics distributions are much more similar, with boys showing only a slight advantage in the upper tail. These early skill differences -- girls' substantial advantage in English and boys' marginal advantage in mathematics -- may shape educational choices and labour market outcomes many years later.[16]

Figure 3: Distribution of Key Stage 2 Math and English Scores by Gender



Note: The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range.

Gender differences in educational attainment and labour market outcomes are among the most widely studied topics in economics. However, much of the existing research focuses on selected samples, such as college graduates (Bertrand et al., 2010) or employed workers (Blau and Kahn, 2017), thereby conditioning on outcomes that skills themselves may influence. Our population-level data allow us to examine how gender differences in mathematics and English skills contribute to outcomes along three distinct margins: (1) college enrolment, (2) field choice conditional on enrolment, and (3) earnings conditional on labour market participation. As we show below, skills have very different effects across these margins, with important implications for understanding gender inequality.

[16] We see a similar pattern if we look at GCSE math and English grades.

In Table 5, we show how gender gaps in these outcomes change as we control for math and verbal skills. Column (1) shows that women are 7.5 percentage points more likely than men to enrol in college. However, once we control for verbal skills alone (column 2), this advantage reverses to a 3.1 percentage point disadvantage. This result suggests that women's higher rates of college enrolment are largely explained by their stronger verbal skills. By contrast, controlling for mathematics skills alone has little effect on the enrolment gap (column 3). When both skills are included simultaneously (column 4), the female college enrolment advantage disappears.

The second row shows participation in STEM fields. Here the female disadvantage is substantial -- around 20 percentage points. Controlling for either verbal skills or mathematics skills individually has little effect on this gap. However, when both skills are included simultaneously, the STEM gap falls from 20 to 13 percentage points, a reduction of roughly one-third. This pattern suggests that the STEM gap partly reflects comparative advantage in skills rather than differences in absolute ability: women's strong performance in verbal skills may create attractive alternatives to STEM fields even when their mathematics ability would allow them to enter STEM fields.

These findings for college enrolment and STEM participation are broadly consistent with the results of Aucejo and James (2021), who show that women's relative advantage in verbal ability explains their higher college enrolment and that gender differences in skills account for approximately 35 percent of the gender gap in STEM fields.[17]

The final row examines earnings. There is a raw gender pay gap of −0.37 log points. Controlling for both skills (column 4) slightly increases the gap to −0.41 log points. This pattern reflects two offsetting effects. On the one hand, women's stronger verbal skills support higher

[17] Delaney and Devereux (2019) using Irish data, show that comparative advantage in mathematics and English also helps to explain gender differences in applications to STEM degree programmes.

educational attainment and therefore higher earnings. On the other hand, their comparative advantage in English relative to mathematics encourages sorting into fields with lower average earnings, such as humanities and social sciences, rather than STEM. The small increase in the gender pay gap after controlling for skills reflects the balance of these opposing forces.

Taken together with Figure 3, these results demonstrate that gender differences in skills observable as early as age 11 have long-lasting implications for education and labour market outcomes. Women's advantage in verbal skills helps explain their higher college enrolment, but it may also contribute to occupational sorting away from high-paying fields. Understanding these skill-based pathways is therefore important for designing policies aimed at reducing gender gaps in education and earnings.[18]

Table 5: Effect of Math and Verbal Skills on Gender Gaps in College, STEM and Log Pay

VARIABLES	(1) No Controls	(2) Verbal Skills (IV)	(3) Math Skills (IV)	(4) Both Skills (IV)	(5) Observations
College	0.075***	-0.031***	0.068***	-0.006***	1,252,455
	(0.001)	(0.001)	(0.001)	(0.001)	
STEM	-0.199***	-0.194***	-0.192***	-0.133***	404,870
	(0.002)	(0.002)	(0.002)	(0.002)	
Log Pay	-0.356***	-0.455***	-0.371***	-0.402***	1,107,495
	(0.001)	(0.001)	(0.001)	(0.001)	

Note: The estimates show the coefficients on female from separate regressions of college attendance, UG STEM field of study (conditional on attending college), and log pay on various sets of controls. In column (1) we only include our basic controls including fixed effects for year of birth and calendar year, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. In column (2) we add verbal skills, in column (3) we add math skills and in column (4) we add both math and verbal skills to the regression. We instrument the skills using within–exam-year percentile ranks of Key Stage 2 math and English scores. IV refers to instrumental variables. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$

[18] Hanushek et al. (2015) study the impact on the gender pay gap by looking at the difference in the female coefficient with the addition of numeracy skills. The authors omit literacy skills from the analysis, so our results are not directly comparable. They find the female coefficient falls from 0.186 to 0.149 with the inclusion of numeracy skills. Interestingly, they find that the inclusion of numeracy skills has no effect on the gender pay gap in Ireland, despite large gender differences in skills in Ireland but more than one third of the gender pay gap is explained in the UK by the inclusion of these skills and more than two thirds in Spain.

Non-Linearities

Table 6 examines whether the returns to mathematics and verbal skills vary across the skill distribution. The top panel estimates returns to being in each skill quintile relative to the bottom quintile (the omitted category), using Key Stage 2 (KS2) quintiles as instruments for Key Stage 4 (GCSE) quintiles. The first-stage F-statistics exceed 1,000 for all quintile indicators (Appendix Table A3), confirming that the instruments are very strong. Column (1) shows that earnings returns to mathematics skills are convex. Moving from the bottom to the second quintile increases log earnings by 0.22, the middle quintiles exhibit relatively similar coefficients, with a large jump to 0.56 in the top quintile. This convex pattern implies that high-level mathematics skills yield disproportionately large returns, consistent with a "math superstar" labour market where quantitative expertise commands substantial premiums in finance, technology, and data-intensive occupations.

Verbal returns display an even more pronounced pattern. The coefficients for quintiles two through four are small and often statistically insignificant, while the top quintile yields a coefficient of 0.25. This extreme convexity suggests that only very high verbal skills (top 20%) generate meaningful earnings benefits, while moderate verbal ability provides little advantage over low verbal skills. This pattern likely reflects that communication-intensive high-paying roles (senior management, consulting, law) require exceptional verbal ability, while occupations accessible to individuals with moderate verbal skills offer similar compensation to those requiring only basic literacy.

Column (2) presents results for employment probability. The relationship between skills and employment differs from that for earnings. For mathematics, employment gains are substantial when moving out of the lowest quintile (0.24 for Q2), but the pattern across higher quintiles is less clear. For verbal, the employment effects are relatively modest across the distribution, with the largest effect occurring for the top quintile (0.06). Overall, the employment results suggest that improvements in basic skills can substantially increase employment probabilities, while additional improvements higher in the distribution primarily affect earnings rather than employment.

Taken together, these results indicate that the returns to skills differ across labour market margins. Skill improvements at the bottom of the distribution appear particularly important for employment, while improvements at the top of the distribution generate the largest earnings gains. These patterns suggest that earnings-focused interventions should target high achievers (where returns are convex) while employment-focused programs should target low-skilled individuals (where gains concentrate), creating a tension between efficiency and equity in skill development policy.

Complementarity between verbal and math skills

The bottom panel examines whether mathematics and verbal skills interact in determining labour market outcomes by including an interaction term between the two skill measures, instrumented using the interaction of the corresponding KS2 ranks.[19]

For earnings, the interaction coefficient is positive and highly significant (0.20), indicating strong complementarity between mathematics and verbal skills. Individuals with strong abilities in both domains earn more than would be predicted by the sum of the independent effects of each skill. This result is consistent with evidence from Finland reported by Koivuranta et al. (2023) and suggests that workers with both strong quantitative and strong communication abilities may be particularly well positioned in occupations requiring a combination of analytical and communication skills.

[19] First-stage F-statistics remain strong (>1000), confirming the interaction is well-identified (Appendix Table A4).

For employment probability, the interaction term is negative (−0.39), suggesting that the two skills act as substitutes along this margin. This counterintuitive result likely reflects that employment is primarily about meeting minimum thresholds rather than maximizing combined skills: individuals with high mathematics or high verbal can find employment through distinct pathways (quantitative versus communication-intensive occupations), while having both does not further increase employment probability beyond having either.

Overall, the results suggest that mathematics and verbal skills interact in complex ways across labour market outcomes. While both skills independently contribute to higher earnings and employment, the earnings benefits are greatest for individuals who possess strong skills in both domains.

Table 6: Effect of Non-linearity and Complementarity of Math and Verbal Skills on Log Pay and Employment

VARIABLES	(1) Log Pay	(2) Employment
	Non-Linearities	
Math Q2	0.215***	0.238***
	(0.048)	(0.030)
Math Q3	0.316***	0.027
	(0.040)	(0.026)
Math Q4	0.270***	0.234***
	(0.043)	(0.028)
Math Q5	0.557***	0.133***
	(0.013)	(0.008)
Verbal Q2	0.006	-0.026
	(0.068)	(0.043)
Verbal Q3	0.047	0.054*
	(0.045)	(0.030)
Verbal Q4	0.067	0.034
	(0.046)	(0.029)
Verbal Q5	0.245***	0.059***
	(0.017)	(0.011)
	Complementarity	
Math	0.490***	0.343***
	(0.011)	(0.007)
Verbal	0.200***	0.251***
	(0.010)	(0.007)
Math # Verbal	0.198***	-0.387***
	(0.016)	(0.010)
Observations	1,107,495	1,252,455

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. First stage estimates are in Appendix Tables A3 and A4. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$; * $p<0.10$.

6. Mediation Through Educational Attainment and Field Choice

The previous results show that the effects of skills on earnings differ markedly from their effects on educational attainment. In particular, English skills have stronger effects on educational attainment (Table 2), while mathematics skills generate larger earnings returns (Table 4). One possible explanation is that the returns to skills operate through educational pathways, particularly subject choices at the undergraduate and postgraduate levels. In this section we explore these mechanisms through a mediation analysis.

Table 7 reports regressions of log earnings and employment for individuals aged 30 and above. All specifications include the same demographic and school controls used previously, and we focus on the instrumental variables estimates. Column (1) presents baseline estimates without additional controls for educational outcomes. As in earlier results, mathematics skills have substantially larger earnings effects than English skills: the coefficient on math rank is 0.58 compared with 0.29 for English rank.

In column (2), we add controls for educational attainment, including indicators for taking A-levels, attending college, degree classification, and postgraduate study. Because additional education reduces potential labour market experience at a given age, we also include a control for potential experience. Once these controls are included, the coefficient on mathematics falls modestly to 0.52, while the coefficient on English declines sharply to 0.13. This pattern reflects the strong effect of English skills on educational attainment documented in Table 2. Controlling for education therefore removes an important pathway through which English skills influence earnings, substantially reducing the estimated return to verbal ability, a point previously made by Aucejo and James (2021).

Column (3) further augments the specification by controlling for subject choices, including whether students took mathematics or English A-levels and indicators for undergraduate and postgraduate field of study. Once these controls are included, the coefficient on mathematics declines further to 0.45, while the English coefficient rises slightly to 0.16. This pattern is consistent with the field choice results in Table 3: mathematics skills increase the likelihood of studying high-return fields, while English skills are associated with entry into lower-paying fields. Controlling for subject choice therefore removes an important channel through which mathematics skills increase earnings, while simultaneously removing a negative channel through which English skills reduce earnings. Overall, comparing columns (1) and (3) shows that controlling for educational pathways reduces the estimated effects of both skills by similar magnitudes, indicating that education and field choice mediate the returns to both mathematics and English ability. Unlike Aucejo and James (2021), we conclude that including educational controls (provided they encompass field choices as well as attainment) may lead to an understatement of the effects of math skills on earnings that is similar in magnitude to the understatement of the effects of English skills.

Table 7: Effect of Math and Verbal Skills on Log Pay and Employment

VARIABLES	(1) Log Pay	(2) Log Pay	(3) Log Pay	(4) Employed	(5) Employed	(6) Employed
Math	0.497***	0.385***	0.319***	0.155***	0.124***	0.130***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Verbal	0.350***	0.206***	0.219***	0.124***	0.083***	0.090***
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
R-squared	0.270	0.283	0.295	0.123	0.126	0.131
			Instrumental Variables Estimation			
Math	0.583***	0.521***	0.449***	0.163***	0.135***	0.138***
	(0.007)	(0.007)	(0.008)	(0.005)	(0.005)	(0.005)
Verbal	0.287***	0.131***	0.164***	0.085***	0.025***	0.034***
	(0.008)	(0.009)	(0.009)	(0.005)	(0.006)	(0.006)
Potential experience, A-Levels, College, graduate college, degree class, PG degree	No	Yes	Yes	No	Yes	Yes
A-level math/English and Field of Study in UG and PG	No	No	Yes	No	No	Yes
Observations	1,107,495	1,107,495	1,107,495	1,252,455	1,252,455	1,252,455

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. In the lower panel, these scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. Columns (2) and (5) add years of potential experience (defined as age minus years in education minus age left compulsory schooling), fixed effects for doing A-levels, entering college, graduating college, degree class and entering a PG degree. Dummy variables included for entering college as a mature student and if missing degree class or missing PG degree. Columns (3) and (6) subsequently add fixed effects for doing an A-level in math and/or English, and field of UG and PG study. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$.

The final three columns of Table 7 report analogous results for employment probability. In column (4), the baseline IV estimates show that both skills significantly increase the likelihood of employment, although the effect of mathematics skills (0.16) is substantially larger than that of verbal skills (0.09). Once educational attainment controls are added (column 5), the coefficient on mathematics declines modestly to 0.14, while the verbal coefficient falls sharply to 0.03. Adding controls for subject choice in column (6) produces only small additional changes.

These results suggest that verbal skills affect employment primarily through their influence on educational attainment. Mathematics skills, in contrast, continue to have substantial effects on employment even after controlling for education and field of study. This pattern may reflect the broad demand for quantitative skills across occupations or the types of jobs into which mathematically skilled individuals sort.

7. Conclusions

Our paper builds on the important study by Aucejo and James (2021) who used similar UK data to show that verbal skills have a much larger effect on college attendance and graduation probabilities than mathematics skills. Following cohorts completing national exams at age 16 through higher education and into employment until age 34, we show that mathematics and verbal skills operate through fundamentally different pathways. Verbal skills strongly predict educational attainment—including college enrolment, graduation, and postgraduate study—while mathematics skills generate substantially larger earnings returns. At ages 30–34, moving from the 25th to the 75th percentile of the mathematics skill distribution is associated with 31% higher earnings, compared with 16% for verbal skills. This divergence operates partly through field-of-study choice: individuals with stronger verbal skills disproportionately select into fields with higher graduation rates but lower earnings returns, while those with stronger mathematics skills enter STEM and other high-paying majors.

Gender differences in skills explain the female advantage in college attendance and part of the STEM gap but have little effect on the gender earnings gap due to offsetting effects across these pathways: women's verbal advantage facilitates educational access but also steers them toward lower-return fields.

Our findings also highlight an important methodological point: empirical analyses that focus only on college graduates or that control for educational attainment may understate the total returns to skills by conditioning on outcomes that skills themselves influence. Like Aucejo and James (2021), we show that common empirical strategies can distort inference: controlling for educational attainment substantially reduces estimated returns to verbal skills by removing the pathway through which literacy facilitates college access. However, we also demonstrate that conditioning on college field of study attenuates mathematics returns to earnings.

These findings have important policy implications. Policies that focus exclusively on improving mathematics skills may generate substantial labour market returns but may not address inequalities in access to higher education. Conversely, policies aimed at improving literacy may increase educational participation without necessarily improving long-run earnings unless they are accompanied by interventions that affect field of study choices. Understanding how different skills shape educational trajectories and field choices is therefore crucial for accurately estimating the economic returns to human capital and for designing education policies that balance access, equity, and labour market outcomes.

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Appendix

Appendix Tables

Table A1: First Stage Estimates

VARIABLES	(1) Math	(2) Verbal	(3) Math	(4) Verbal	(5) Math	(6) Verbal
	Full Sample		College Sample		Graduation Sample	
KS2 Math	0.548***	0.182***	0.544***	0.115***	0.536***	0.109***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
KS2 Verbal	0.165***	0.488***	0.079***	0.423***	0.073***	0.413***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	1,252,455	1,252,455	404,870	404,870	292,245	292,245
F-Stat	108084.69	93303.54	19768.31	14147.37	13486.11	9276.87

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 (KS2) math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$

Table A2: Effect of Math and Verbal Skills on Log Pay and Employment Excluding Covid Affected Tax Year (2020/2021), Instrumental Variables Estimates

VARIABLES	(1) Log Pay Full Sample	(2) Log Pay Male	(3) Log Pay Female	(4) Employed Full Sample	(5) Employed Male	(6) Employed Female
Math	0.575***	0.536***	0.621***	0.131***	0.110***	0.159***
	(0.007)	(0.010)	(0.011)	(0.004)	(0.006)	(0.007)
Verbal	0.284***	0.174***	0.406***	0.068***	0.014**	0.117***
	(0.008)	(0.011)	(0.012)	(0.005)	(0.006)	(0.007)
Observations	1,081,143	564,417	516,391	1,231,938	628,005	603,540

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$; ** $p<0.05$.

Table A3: First Stage Estimates for Non-linear Specification

VARIABLES	(1) Math Q3	(2) Math Q4	(3) Math Q5	(4) Verbal Q3	(5) Verbal Q4	(6) Verbal Q5
KS2 Math Q2	0.132***	0.067***	0.002***	0.040***	0.030***	0.005***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
KS2 Math Q3	0.198***	0.171***	0.042***	0.042***	0.071***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
KS2 Math Q4	0.146***	0.266***	0.150***	0.028***	0.100***	0.058***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
KS2 Math Q5	0.014***	0.198***	0.413***	-0.009***	0.078***	0.157***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
KS2 Verbal Q2	0.060***	0.017***	-0.003***	0.133***	0.068***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
KS2 Verbal Q3	0.092***	0.050***	0.009***	0.160***	0.192***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
KS2 Verbal Q4	0.089***	0.070***	0.048***	0.093***	0.285***	0.122***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
KS2 Verbal Q5	0.035***	0.053***	0.148***	-0.018***	0.198***	0.378***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Observations	1,107,582	1,107,582	1,107,582	1,107,582	1,107,582	1,107,582
F-Stat	3217.08	6132.89	12467.44	2444.87	7869.55	11512.33

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$
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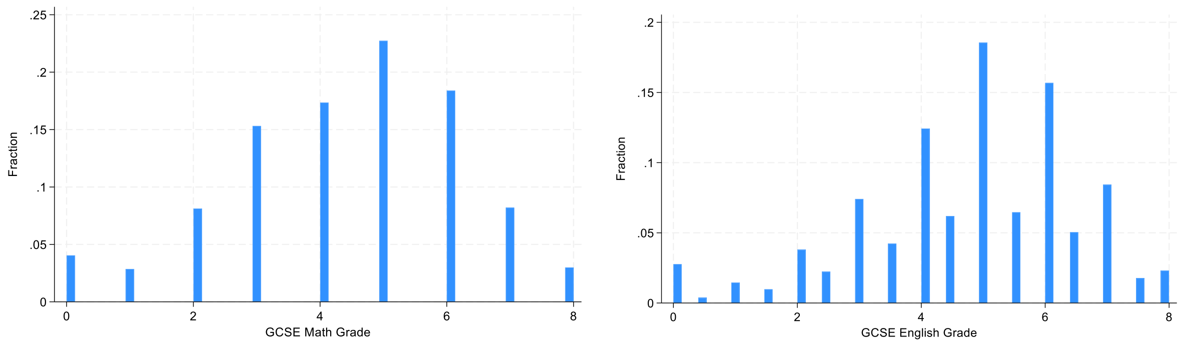
Table A4: First Stage Estimates for Complementarity Specification

VARIABLES	(1) Math # Verbal
KS2 Math	0.063***
	(0.001)
KS2 Verbal	0.008***
	(0.001)
KS2 Math # KS2 Verbal	0.568***
	(0.002)
Observations	1,107,582
F-Stat	73974.71

Note: Math and verbal refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range. Robust standard errors are reported in parentheses. *** $p < 0.01$

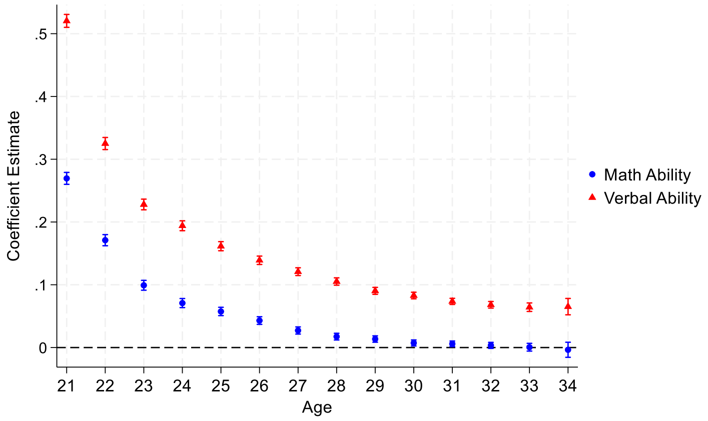
Appendix Figures

Figure A1: Distribution of Math and English GCSE Grades



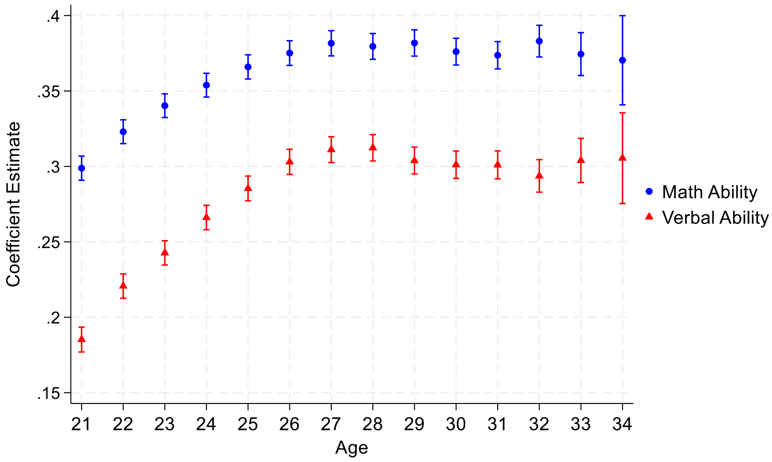
Note: Math and English GCSE grades ranging from A* to U are mapped on to an 8 to 0 scale. English is calculated as the average of English literature and language grades. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and to individuals observed between ages 30 and 34, using the maximum observed age within this range.

Figure A2: Effect of Math and Verbal Skills on University Attendance by Age



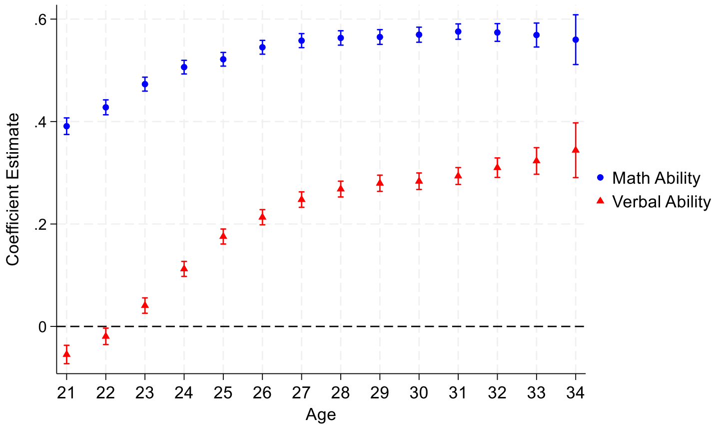
Note: Math and verbal ability refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004. We exclude self-employed earnings since this is only available from 2014 onwards. We also restrict the sample to having real PAYE earnings of at least £5000 and working at least 183 days per year.

Figure A3: Effect of Math and Verbal Skills on Log Pay for High School Graduates



Note: Math and verbal ability refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and those with highest education is high school. We exclude self-employed earnings since this is only available from 2014 onwards. We also restrict the sample to having real PAYE earnings of at least £5000 and working at least 183 days per year.

Fig A4: Effect of Math and Verbal scores on Log Pay Conditional on Not Being in Education



Note: Math and verbal ability refer to within–exam-year percentile ranks of GCSE math and English scores. These scores are instrumented using within–exam-year percentile ranks of Key Stage 2 math and English scores. Controls include fixed effects for year of birth and calendar year, gender, quintiles of the IDACI area deprivation rank, an indicator for ever being eligible for free school meals, ethnicity (mixed, Chinese, Black, Asian, White or other), and secondary school fixed effects. The sample is restricted to cohorts completing GCSEs between 2002 and 2004 and for those who are not in education. We exclude self-employed earnings since this is only available from 2014 onwards. We also restrict the sample to having real PAYE earnings of at least £5000 and working at least 183 days per year.