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On Track to Success? Returns to Vocational Education Against Different Alternatives*

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ABSTRACT

Many countries consider expanding vocational curricula in secondary education to boost skills and labour market outcomes among non-university-bound students. However, critics fear this could divert other students from more profitable academic education. We study labour market returns to vocational education in England, where until recently students chose between a vocational track, an academic track and quitting education at age 16. Identification is challenging because self-selection is strong and because students' next-best alternatives are unknown. Against this back- drop, we leverage multiple instrumental variables to estimate margin-specific treatment effects, i.e., causal returns to vocational education for students at the margin with academic education and, separately, for students at the margin with quitting education. Identification comes from variation in distance to the nearest vocational provider conditional on distance to the nearest academic provider (and vice-versa), while controlling for granular student, school and neighbourhood characteristics. The analysis is based on population-wide administrative education data linked to tax records. We find that the vast majority of marginal vocational students are indifferent be- tween vocational and academic education. For them, vocational enrolment substantially decreases earnings at age 30. This earnings penalty grows with age and is due to wages, not employment. However, consistent with comparative advantage, the penalty is smaller for students with higher revealed preferences for the vocational track. For the few students at the margin with no further education, we find merely tentative evidence of increased employment and earnings from vocational enrolment.

Keywords: vocational education, returns to education, multi-valued treatment, instrumental variables
JEL Codes: I24, I28, J24

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1 Introduction

Over the last decades, rising demand for high-skilled work has made it increasingly difficult for young workers without tertiary education to secure stable and well-paying jobs (e.g., Autor, 2019; Blundell *et al.*, 2018), widening the social chasm between university graduates and what has been referred to as 'the forgotten half' (Neumark and Rothstein, 2007). At the same time, firms in many (post-)industrial economies lament a lack of skilled workers in fast-growing technical and professional occupations (OECD, 2017), interfering with governments' plans to 're-shore' strategic industries and to decarbonise the economy. In terms of education policy, these developments have led to a heightened interest in improving and expanding vocational curricula in secondary education—particularly so in countries with weaker traditions of providing high-quality vocational education and training (VET) to its students, like the US and UK.[1] Often in reference to apprenticeships-based systems, like those in Germany and Switzerland, VET is heralded as a means to relieve skill shortages, while improving the employment and earnings prospects of non-college-bound students through nurturing non-routine technical and social skills (Fersterer *et al.*, 2008; Pfeiffer, 2018). Nevertheless, considerable disagreement remains on whether vocational education really benefits young people economically—especially in settings where firm-involvement in VET through apprenticeships is rare and where returns to university are high. VET might raise the labour market prospects of low-achieving students, but at the same time it might harm higher-achieving students by diverting them from academic educational routes that lead towards better-paying graduate jobs.

This paper aims to contribute to this debate by delivering causal evidence on labour market returns to vocational upper-secondary education in England, where, until recently, students at age 16 chose between a vocational track, an academic track and quitting education altogether.[2] The setting is interesting because it allows us to study returns to largely classroom-based vocational education for young students facing different alternatives in an economy with high wage inequality. Our research design leverages multiple instrumental variables (IVs) to estimate *margin-specific* treatment effects, i.e., causal returns to vocational education for students at the margin between vocational and academic education and, separately, for students at the margin between vocational and no post-16 education. Using the fact that vocational and academic education are offered by distinct institutions, identification comes from plausibly exogenous variation in distance to the nearest vocational provider conditional on distance to the nearest academic provider (and *vice-versa*), while controlling for granular student-, school- and neighbourhood-level characteristics.

[1] See, e.g., US Department of Education (2012); Jacoby and Dougherty (2016) for the US and Independent Panel on Technical Education (2016) for the UK.

[2] Our analysis focuses on three student cohorts who sat their General Certificate of Secondary Education (GCSE) exams between 2002–2004. For these cohorts, the legal minimum school leaving age (MSLA) was 16 and 14% of students did indeed quit their education at age 16. Since then, the MSLA has been raised to 18 and, despite imperfect compliance with this law, the share of students pursuing no upper-secondary education has declined substantially.

The analysis is based on linked administrative education and earnings data covering three complete cohorts of state-school students in England, which also allows us to closely inspect heterogeneity and potential mechanisms.

The debate on the merits of vocational content in secondary school typically revolves around the types of skills vocational (also known as technical) and academic (also known as general) education provide and their respective value in the labour market. The main benefit of an academic curriculum lies in equipping students with general knowledge and analytical skills that are well transferable across jobs (Goldin, 2001). Compared to the more occupation-specific curricula taught in vocational tracks, this might help students in the labour market through increased flexibility, especially in the long run (Hanushek *et al.*, 2017). This argument is particularly cogent in the face of rapidly changing labour demand due to technological change and globalisation. Advocates of vocational education counter that the general skills taught in academic tracks might, in fact, be too generic to be readily deployable in the labour market unless complemented with tertiary education, which far from all students pursue (Bertrand *et al.*, 2021). Further, the abstract nature of learning in academic tracks might disengage less academically inclined students, leaving them at risk of dropping out of secondary education altogether (Hall, 2016). In contrast, vocational curricula are applied in nature and tightly linked to skill requirements of specific occupations, so that they might both retain more students in education and facilitate students' school-to-work transition.

Despite the long-standing debate on these issues, there is a paucity of compelling empirical evidence on the labour market returns to vocational education. Taken at face value, the descriptive evidence suggests that vocational education involves a trade-off between short-run benefits and long-run costs: studies that compare age-earnings profiles of vocationally and academically educated students generally find that an initial advantage for the former reverses when students are in their (early) thirties (Brunello and Rocco, 2017; Hampf and Woessmann, 2017; Hanushek *et al.*, 2017). While there is some consensus in the empirical literature that vocational education indeed facilitates the school-to-work transition (see, e.g., Shavit and Müller, 2000), whether differences in earnings at later ages are to be interpreted causally remains contested. The selection problems when comparing labour market outcomes between those with and without vocational degrees are severe because, in most settings, vocational students have much lower previous achievement and come from more disadvantaged backgrounds (Ryan, 2001).

A second problem is that treatment effect heterogeneity is likely to be important. Already returns to different *levels* of education generally display a lot of heterogeneity (see, e.g., Carneiro *et al.*, 2011). Returns to different *types* of education can be expected to vary even more strongly and likely correlate with students' education choices (Dahl *et al.*, 2022). Yet, in the presence of selection on gains, the average treatment effect (ATE), which average age-earnings profiles implicitly aim to estimate, is a poor heuristic for judging economic efficiency or guiding policy, because it does not correspond to the effect for marginal students (who are more likely to respond to policy changes).

Note that when there is more than one alternative to vocational education, even among the set of marginal vocational enrollees, returns likely differ depending on students' (typically unobserved) next-best alternative. For example, a student whose alternative to vocational education is quitting education and directly entering the labour market might benefit from enrolling in a vocational track by acquiring additional work-related skills. At the same time, for a student whose alternative to vocational education is enrolling in the academic track, returns might be more ambiguous, especially in the longer run.

Accordingly, it is crucial to identify the most relevant margins of vocational enrolment in a given setting and to estimate margin-specific returns against the respective relevant alternative. This poses a challenge from a methodological standpoint: standard IV based methods, such as two-stage least squares (2SLS) generally fail to recover alternative-specific treatment effects in settings with multiple unordered treatments and effect heterogeneity (Heckman and Urzúa, 2010), even with as many instruments as treatments available (Kirkeboen *et al.*, 2016). Some studies successfully identify alternative-specific effects of education choices by combining data from centralised admission systems, where students' preference orderings can be directly observed, with regression discontinuity designs (RDD) exploiting admission cut-offs generated by over-subscription (Dahl *et al.*, 2022; Kirkeboen *et al.*, 2016; Silliman and Virtanen, 2022). This strategy is not feasible in the English setting where there is neither a centralised admissions system nor systematically oversubscribed education providers in the post-16 sector.

To overcome these challenges and identify the two alternative-specific effects of interest net of self-selection into educational tracks, we apply an identification approach based on multiple IVs proposed by Mountjoy (2022). We exploit the fact that upper-secondary educational tracks in England are linked to specific institutions: the vocational track is primarily offered by vocational colleges ('Further Education Colleges') and the academic track is offered by designated academic colleges ('Sixth Form Colleges'), as well as by secondary schools. By focusing on students from schools that do not offer upper-secondary education, i.e., on students who need to switch to a new institution at age 16 regardless of which track they choose, we can construct two alternative-specific IVs based on students' geographical proximity to the nearest vocational and the nearest academic college. Thus equipped, identification of margin-specific local average treatment effects (LATEs) is secured under intuitive assumptions by 'cross-instrumenting' students' education choices with their distance to a specific alternative of interest in a series of 2SLS regressions, which replace the usual outcome variable with treatment-outcome interactions.

For estimation we leverage unique education administrative data linked to tax records that allow us to follow three full cohorts of state-school educated pupils in England through their school careers, post-compulsory education and into the labour market until age 30. To construct the two required distance instruments we combine geospatial information on students' home addresses with the locations of all post-16 education providers in England. To account for the non-random location of students and education providers, in addition to detailed student- and school-level controls, we directly control for distance to local economic centre, multiple fine-grained measures of neighbourhood quality and region fixed effects. This type of information is typically not available in the classical returns-to-schooling literature employing distance instruments. It allows for comparisons of similar students from similar neighbourhoods who face similar labour market conditions when they make their education choices. We show that the two instruments are empirically well-balanced across a broad range of student characteristics, including nationally administered achievement tests.

We find that the vast majority (about 85%) of marginal students, i.e., of those whose choice to enrol in vocational education is responsive to distance, is choosing between vocational and academic education, not considering the option of no post-16 education. For these students at the margin between vocational and academic education, we estimate that vocational enrolment reduces annual earnings over ages 29–30 by £2,900 or 11% among males and £1,700 or 8% among females. We estimate null effects on the probability of being employed, meaning that the earnings penalty is not due to differences at the extensive margin of working. Rather, vocational education seems to channel these students into lower-paying jobs with worse wage progression: when inspecting returns by age, we find that the earnings effect worsens close to linearly over students' twenties. Together with the arguments that occupation-specific skills may depreciate faster, this trend suggests that the earnings penalty from vocational *vs.* academic education might well continue to grow as students age.

To unpack 'essential heterogeneity' in these average effects, we use our two continuous instruments as local instrumental variables (Heckman and Vytlacil, 2005) and stratify effects across different distances to vocational and academic colleges. This allows us to compare marginal students with different underlying preferences for vocational *vs.* academic education. We confirm that students select into tracks based on their comparative advantage: returns to vocational education increase (i.e., become less negative) with students' preferences for the vocational track (i.e., with distance from vocational college) and decrease with their preferences for the academic track (i.e., with distance to academic college). While returns are negative for most vocational-academic compliers, for those with the highest preferences for vocational education we find positive (though insignificant) effect estimates. This suggests that vocational education might well be beneficial for inframarginal vocational enrollees (i.e., vocational 'always-takers').

To contextualise the effects we characterise compliers and explore potential mechanisms. Students at the margin between vocational and academic education are above-average in terms of previous achievement and socio-economic status and, hence, likely to do well in academic environments. Enrolment in the vocational track slightly reduces these students' upper-secondary achievement, only insubstantially (and insignificantly) increases take-up of apprenticeships and substantially reduces university completion and the quality of universities attended, especially among males. A simple decomposition exercise reveals that about 20% of the earnings penalty from vocational *vs.* academic education can be explained by worse education outcomes. While reduced educational attainment does contribute to the vocational earnings penalty, other channels relating to instructional quality, how vocational skills are remunerated in the British labour market and signalling effects therefore must be at least as important.

Results at the margin between vocational and no post-16 education look very different. Point estimates indicate large returns from pursuing vocational instead of no further education both in terms employment and earnings (e.g., for males a 6 percentage point increase in sustained employment and a £5,000 increase of annual earnings). However, given the low share of compliers at this margin (only 15% of all marginal vocational-track students), the estimates are imprecise and generally not statistically significant. Only the local IV estimates for those with the highest preference for vocational education reach marginal significance.

In conclusion, we find striking heterogeneity in the returns to vocational education in England: for the average student at the margin to academic education, vocational enrolment leads to a large reduction in earnings, whereas for those at the margin of dropping out of education, if anything, it increases earnings. The divergent effects across the two treatment margins highlight the importance of margin-specific identification in this context. Conventional IV methods only identify a pooled LATE of vocational education that combines the two margin-specific effects into a weighted average. We show that this shrouds the large negative effects for the majority of marginal students, giving an ambiguous and more positive impression of vocational education in England than warranted.

In terms of policy, the fact that most marginal vocational students consider the academic track as their alternative, whereas those choosing no post-16 education are largely unresponsive to incentives like distance, warns against expanding enrolment in vocational 'Further Education' colleges. Instead of retaining students in education who would otherwise drop out, policies that seek to increase the attractiveness of the vocational track as is, seem to mainly divert academically able students from more profitable pathways into the labour market. Our results imply that, during our study period, the allocation of students over tracks was economically inefficient: keeping the quality of vocational education fixed, more students ought to go academic. In this regard, our findings support the efficacy of place-based policy interventions that increase post-16 *academic* provision in academic 'cold-spots'. This would draw students from vocational into academic education who benefit greatly from it and could, therefore, also help to combat geographical inequality. Nevertheless, the pattern of sorting on comparative advantage we detect, suggests that vocational education in England has its role to play, likely benefiting inframarginal students with low relative preferences for academic education. To support those students and to alleviate the costs from diversion, education policy in England should focus on establishing a more structured curriculum in the vocational track, including clearer pathways into higher education, while facilitating firm-involvement through apprenticeships.

In addition to its policy relevance, this paper contributes to a small (but growing) literature that aims to discern causal labour market returns to vocational education. Most of the existing evidence comes from continental Europe, where there is a well-established tradition of channelling secondary students into distinct academic and vocational tracks. Starting in the 1970s, a number of countries reformed their vocational tracks by giving more weight to the general curriculum. Evaluations of such reforms in the Netherlands (Oosterbeek and Webbink, 2007), Romania (Malamud and Pop-Eleches, 2011), Sweden (Hall, 2016) and Croatia (Zilic, 2018) all find no effect on students' labour market outcomes. Bertrand *et al.* (2021) consider a similar reform in Norway and find that it increased vocational enrolment and later earnings, especially among disadvantaged men. However, all of these studies estimate general equilibrium effects of curriculum changes that amalgamate impacts on inframarginal vocational students, switchers at the margin between vocational education and dropping out and switchers at the margin between vocational and academic education. As such, they only offer limited guidance for students' education choices or policymakers' allocation problems over existing educational tracks.

Indeed, the empirical evidence suggests that students benefit from vocational education if their alternative is direct labour market entry (e.g., Alfonsi *et al.*, 2020; Bertrand *et al.*, 2021; Birkelund and van de Werfhorst, 2022). Returns at the margin to academic education, in contrast, are much more contested. Based on observational differences, they are commonly believed to be negative, thus fuelling fears of diversion. However, two recent studies that are able to estimate causal effects for students at this margin, challenge this notion. Silliman and Virtanen (2022) exploit admission cut-offs in Finland, where students' preferences over secondary tracks are recorded under a centralised admission system. This allows the authors to estimate causal effects of vocational *vs.* academic education for students marginally admitted to vocational programmes whose next choice would have been an academic programme (and *vice-versa*). Interestingly, they find a positive earnings effect from vocational education that persists until at least age 33 and shows no sign of fading out. Birkelund and van de Werfhorst (2022) study the Danish setting, where students choose between an academic track, a vocational track and no further education, like in England. The authors use a conventional IV strategy, instrumenting students' choices with those of their school peers under the implicit assumption that (unobserved) preferences are weakly ordered. They find positive returns for students at the margin between vocational *vs.* leaving education, and precise null effects for those at the margin between vocational *vs.* academic education.

This paper extends this line of research in two respects. We also employ an IV-based research design to estimate causal returns for marginal students and, in line with the empirical literature's growing awareness of the challenges posed by multiple unordered treatment choices (e.g., Angrist *et al.*, 2019; Dahl *et al.*, 2022; Heckman and Urzúa, 2010; Kirkeboen *et al.*, 2016; Mountjoy, 2022), we disaggregate complier treatment effects into the two relevant margins of choice. We contribute by studying returns to vocational education in a setting with radically different educational and labour market institutions than those in the Nordic countries studied by Bertrand *et al.* (2021), Birkelund and van de Werfhorst (2022) and Silliman and Virtanen (2022). In the UK, much like in the US, firm-involvement in VET is limited, potentially weakening its link with occupations, employers and the skills they demand. Additionally, progression routes through and from vocational education are less established: in both the UK and the US, students are typically expected to build their own curriculum instead of entering well-structured programmes like in the Nordic countries, so that informational asymmetries at the student level can be salient. Finally, both are less egalitarian countries with high levels of wage dispersion and high returns to university. In such settings, diversion from academic education might be particularly costly. While much of the recent policy interest in VET comes from the US and UK, credibly causal empirical evidence on returns to vocational education from these countries is practically absent.[3] Our results suggest that without substantial overhaul of education (and labour market) institutions, the encouraging results from Nordic countries are unlikely to translate.

The paper is structured as follows: section 2 describes the institutional background, the data and observational differences between treatment groups. Section 3 explains the identification strategy. Section 4 presents the main results, including robustness checks and heterogeneity analyses. To better understand the margin-specific LATE estimates, section 5 characterises marginal students, explores mechanisms and probes external validity. Finally, section 6 concludes.

2 Background, Data and Descriptives

2.1 Post-Compulsory Education in England

In England compulsory schooling lasts from age 5 to 16, during which students study a common curriculum. To conclude their compulsory education, all students take a set of standardised exams, the General Certificate of Secondary Education (or GCSEs), in typically eight to ten subjects. Afterwards, they choose if and what type of upper-secondary education to pursue. In the period considered in our analysis, students at age 16 faced three principal alternatives: (i) to pursue upper-secondary education in the academic track, (ii) to pursue upper-secondary education in the vocational track or (iii) to conclude their education and directly enter the labour market.[4]

[3] The only exception we are aware of is Brunner *et al.* (2021). They use admission cut-offs to selective Technical High Schools in Connecticut in an RDD and find that attendance increases earnings for men. However, because these schools are heavily oversubscribed and particularly well-funded the external validity of these results for large-scale implementations of school-based vocational programmes may be limited. Conditioning on multiple observable student characteristics, Kreisman and Stange (2020) report a small positive association between vocational course take-up and wages in the US.

[4] In 2013 and 2015 the so called 'participation age', during which students at least need to engage in some part-time training, was respectively increased from 16 to 17 and from 17 to 18. This implies the option to leave education at age 16 is no longer available and increasingly fewer students pursue this path (despite rather lenient enforcement).

The academic track comprises two years of study towards qualifications known as A-Levels, which are the traditional prerequisite for university entrance. These two years of academic upper-secondary education are referred to as 'sixth form'. They are offered by secondary schools that have their own sixth form (which thus provide lower and upper-secondary schooling) and by designated, publicly funded Sixth Form (SF) Colleges, of which there are 94 across England. For students from schools *with* a sixth form, choosing the academic track at age 16 generally means continuing on one's secondary school. Academic-track students from schools *without* a sixth form generally enrol in SF Colleges. Typically, admission to the academic track requires having achieved a so-called 'Full Level 2', i.e., five GCSEs at grade C or higher, though the exact requirements vary by institution and the specific A-Level subjects students pick (typically they pick three).

In contrast to the academic track and to other European vocational education systems which usually comprise a limited and well-defined number of programmes, the vocational track in England is much less structured. Students can choose '*a la carte*' from a plethora of vocational qualifications that differ in level (from 1 to 3), subject and duration (from 1 to 2 years). Level 3 qualifications are notionally equivalent to A-Levels. They have similar entry requirements in terms of GCSEs, are taught full-time, mostly as two-year courses, and count towards university admission.[5] For students that do not meet the entry requirements for Level 3, there are less demanding vocational qualifications at Level 2 (which count as equivalent to GCSEs) and Level 1 (which count as equivalent to primary school education). At each level the number of courses to choose from is very large: at Level 3 alone, there are more than 3,700 different qualifications (Hupkau *et al.*, 2017). The vast majority of vocational courses for 16–18-year-old learners are classroom-based; apprenticeships offering workplace training typically only start after completion of a classroom-based qualification.

Students choosing the vocational track at age 16 generally enrol in publicly funded Further Education (FE) Colleges, of which there are 247 across England.[6] Similar to community colleges in the US, FE Colleges were historically established to offer adult education. While this function remains important, over the last decades they have increasingly shifted their focus to the education of 16–18-year-old learners pursuing alternatives to purely academic education. Next to vocational courses, FE Colleges offer courses in basic and soft skills (such as employability or communication skills) and some academic courses (remedial courses in English and maths but also A-Levels). Therefore, not dissimilarly to other countries, vocational students typically study a more mixed curriculum than those in the academic track. Note that in England (much like in the US) this is due to students 'mixing and matching' courses instead of a predefined curriculum.

For the empirical analysis, we conceptualise the education choice students face after completing

[5] Though students with vocational qualifications at Level 3 face more restrictions in terms of the degrees and universities they can apply for compared to students with A-Levels.

[6] 80% of all vocational-track students attend an FE college (see Appendix Table B1). The rest is trained by other publicly funded providers, like local authorities, or private providers, both of which are numerous but small (Hupkau and Ventura, 2017). For a map of all FE and SF Colleges, see Appendix Figure A1.

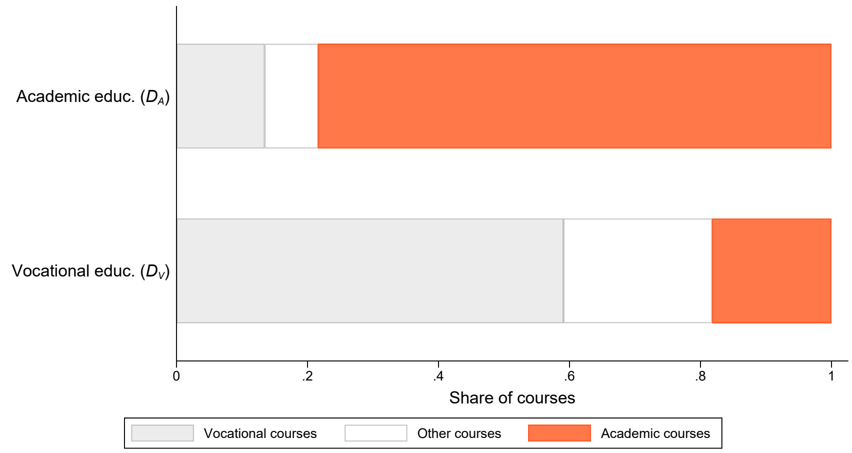


Figure 1. Course contents by educational track.

Notes: This figure plots average shares of academic, vocational or 'other' courses students take by initial enrolment. Shares are constructed considering all courses and modules (of more than one month of length) studied within 24 months of the relevant enrolment (which starts with the first observed study spell after GCSEs). We weight courses by total study time required to complete them ('guided learning hours'). Courses are classified as follows: A(AS)-Levels and GCSE qualifications are classified as academic; non-A-Levels qualifications in vocational subjects are classified as vocational; qualifications whose recorded subject is 'Preparation for Work and Life' (such as qualifications known as Key Skills or Functional Skills) are classified as other.

compulsory schooling as a choice between one of three treatments: the academic track, defined as enrolling in an academic institution (i.e., SF College or a school's sixth form); the vocational track, defined as enrolling in a vocational institution (i.e., FE College or other vocational education provider); and no post-16 education, defined as not enrolling in any upper-secondary education. Importantly, in the analysis we focus on students from secondary schools *without* sixth form, who have to switch institutions at age 16 regardless of whether they want to attend the vocational or the academic track. This is because our identification strategy exploits students' proximity to the closest academic and the closest vocational provider as two alternative-specific instrumental variables that influence students' choices through shifting the respective alternative's costs.

Therefore, our analysis primarily compares vocational-track students on FE Colleges with academic-track students on SF Colleges, largely excluding those on schools. FE and SF Colleges have similar governance and funding structures, are both relatively large institutions and only cater to students above 16, all of which contrasts with secondary schools. Accordingly, this sample restriction allows us to minimise the confounding influence of institutional features in our comparisons despite adopting an institution-based treatment definition.[7] To explore how this maps into the type of qualifications studied, Figure 1 shows the teaching hours-weighted distribution of courses students enrol in by treatment status. On average, students at vocational institutions spend the majority of their time studying vocational subjects, though they also study a substantial amount of basic and soft skills courses and some academic subjects. This sharply contrasts with

[7]Relatedly, Aucejo *et al.* (2022) find little variation between FE Colleges in earnings value-added, suggesting that between-college heterogeneity within the vocational track is limited.

academic-track students who predominantly study academic subjects.

2.2 Data Sources, Sample Construction and Variables

We use a unique ensemble of administrative datasets from England, known as Longitudinal Education Outcomes (LEO), to follow three full cohorts of state-school educated pupils through their school and post-compulsory education into the labour market until the age of 30. The three cohorts we study took their GCSEs in the academic years 2001/02 through 2003/04—these are the earliest cohorts for which we can observe all the required information for our analysis.

To define our base sample we use the pupil census of the National Pupil Database (NPD), which reports information on the universe of students enrolled in state-funded schools in England.[8] For the three above-mentioned academic years, we retain all students in the final year before their GCSEs (year group 11) to define our cohorts of interest.[9] The pupil census includes information on students' gender, ethnicity, special educational need (SEN), language spoken at home and free school meal (FSM) eligibility (indicating economic disadvantage), which we use as controls. Further, we record students' test scores in standardised national end-of-primary-school exams in English, maths and science. These so-called Key Stage 2 (KS2) exams serve as our main ability controls. We also record whether students have achieved Full Level 2, the most important measure of GCSE performance.

The three exhaustive and mutually exclusive treatments of interest are enrolling in the academic track (i.e., SF College or a school's sixth form), enrolling in the vocational track (i.e., FE College or other vocational education provider) and not pursuing any upper-secondary education after compulsory education. To observe all post-16 education choices we link the NPD data with the Individualised Learner Records (ILR), a dataset which covers the universe of publicly-funded education and training activities.[10] Equipped with this information, we define treatment by the institution type of students' first observed enrolment, if any, within a two-year window after completing their GCSEs.[11]

Labour market outcomes come from British administrative tax records (HMRC), which we can link to our student data for the tax years 2004 to 2017. The data covers earnings and employment spells of all employed individuals in England. From 2014 onwards, we also observe earnings from self-employment. We sum the earnings accruing from all employment spells and self-employment in a given year, deflate by the annual UK consumer price index (base year 2017) and winsorise

[8] State-funded schools comprise 93% of the total English student population.

[9] We exclude 3% of students from special educational needs (SEN) schools and 0.5% of students for whom we do not observe a GCSE exam (who mostly are of SEN status).

[10] We thus observe any enrolment at a school's sixth form in the NPD and any enrolment at a SF College, FE College or other private or public vocational education provider in the ILR.

[11] In order to avoid misclassification from short courses or initial enrolments that are subsequently not actually taken up, we ignore learning spells shorter than one month in the treatment assignment.

at the 99^{th} percentile. Our main outcome averages non-missing observations of this measure of real annual earnings within person over ages 29–30.[12] Generally, we include observations without earnings, whether they are unemployed or inactive, because labour market attachment is likely endogenous to education choices.[13] Still, in some analyses we focus exclusively on students with positive earnings who are unequivocally part of the labour market. To disentangle extensive margin effects, we use an indicator for sustained employment, which takes value one if a student was employed more than six months in a given year.[14] To study dynamics, we also construct a student-level panel of employment and earnings over ages 18–30, though this excludes (earnings from) self-employment to ensure comparability across the full age range.

Moreover, we construct a number of educational outcomes. First, using the NPD and ILR, we calculate the share of vocational *vs.* academic courses studied during the first two years of post-compulsory education (see Figure 1). Second, we construct two indicators for upper-secondary attainment: whether students complete any Level 3 qualification (i.e., A-Levels or an equivalent vocational qualification) and whether they obtain a 'Full Level 3' (i.e., two Level 3 qualifications), which is the minimum university entry requirement. Third, using the ILR, we construct an indicator for whether a student ever starts an apprenticeship, seen as a desirable outcome for vocational courses. Fourth, we link our sample to data from the Higher Education Statistics Agency (HESA) containing the universe of university enrolments to construct indicators for starting a 3-year university degree; doing so at a more selective pre-1992 university; and completing a degree.

Our two instrumental variables measure students' proximity to the nearest FE College—as the main provider of vocational upper-secondary education for all students regardless of secondary school—and the nearest SF College—as the main provider of academic upper-secondary education for students from schools without sixth form. In the pupil census, we observe the Lower Super Output Area (LSOA) of students' home address in their final year of compulsory education. LSOAs are small geospatial areas that divide the surface of England into about 33,000 units of 1,000–1,500 inhabitants each. We proxy students' residential location with the population-weighted centroid of their LSOA, calculate ellipsoidal distances in kilometres to all FE and SF Colleges (see Appendix Figure A1 for a map) and take the minimum within each set. Because both distance measures are heavily skewed and the effect of distance on choices is likely to vary with distance, we transform both to natural logarithms for the analysis.[15] Henceforth, we will refer to the two

[12] Earnings for the 2004 cohort, the youngest in the sample, are only available until age 29.

[13] Note that 6% of students cannot be matched to the tax records, meaning they do not show a single earnings spell even 13 years after leaving school. In principle, we retain these observations to avoid selecting our sample on outcomes, but because this group likely includes many individuals that under no circumstance would have entered the labour market (e.g., severely disabled students) we at least exclude those with SEN status or missing KS2 scores (which is often associated with SEN) among the set of unmatched students.

[14] As we do not observe employment spells for the self-employed, we set the sustained employment indicator to one if an individual earned more than £10,000 in a given year.

[15] Furthermore, we apply one final sample restriction and drop the 3% most remote students (who live farther than 63km from any college) as the data becomes sparse and the first stages break down at distances that large.

(logged) instruments as distance to vocational (FE) college, Z_V, and distance to academic (SF) college, Z_A, respectively.[16]

Our use of distance instruments makes it paramount to control for residential sorting. Accordingly, we construct an elaborate control set consisting of student-, school- and neighbourhood-level covariates. At the student level, our control set contains all above-mentioned student demographics, including all their two-way interactions, and cubic polynomials in all three KS2 test scores.[17] Note that we leave out the Full Level 2 indicator measuring GCSE performance from the control set, so we can use it for balance tests later. At the secondary school level, we include indicators for school type, averages of the three KS2 test scores and the shares of FSM eligible, White British and English as a second language students. To measure neighbourhood quality we include cubic polynomials in seven domain-specific Indices of Deprivation (IoD), constructed by the British Ministry of Housing, Communities and Local Government, which vary at the fine-grained LSOA level: IoD income; IoD employment; IoD education, skills and training; IoD health and disability; IoD crime; IoD housing and service; and IoD living environment. On top of these covariates, we include fixed effects for the nine regions of England and for student cohorts to compare students that face similar local labour market conditions when they complete compulsory education. Finally, to alleviate concerns about educational providers concentrating in local centres and families sorting along similar dimensions, we add students' distance to the nearest local economic centre as region-specific cubic polynomials.

2.3 Summary Statistics

As mentioned above, our estimations focus on students from secondary schools without sixth form because, unlike their peers from schools with sixth form, at age 16 these students need to enrol at a new institution for either upper-secondary track. The first two columns of Table 1 compare the full student population to the 40% of students who attend schools without sixth form. Panel A shows that the latter are 11 percentage points (pp) more likely to enrol in vocational, 3 pp more likely to pursue no post-16 education and 13 pp less likely to enrol in the academic track than the average. This might be due to higher barriers to academic track entry when it is not offered by one's secondary school, school quality differences and/or different student body compositions, apparent from the remainder of the table: students from schools without sixth form are more likely to have a special educational need or to be economically disadvantaged (i.e., FSM) (panel B), have lower primary school tests scores (panel C), live in more deprived neighbourhoods (panel D) and earn less at ages 29–30 (panel F). They do not appear to live in more rural areas as evidenced by parity in distance to the closest local economic centre (panel D). However, they do live closer

[16] Appendix Figure A2 shows their distribution in levels and in logs.

[17] As about 10% of students have missing values for at least one KS2 score, we include missing dummies for all three scores.

Table 1. Summary statistics.

	All students	Schools w/o sixth form	Academic education	Vocational education	No post-16 education
	(1)	(2)	(3)	(4)	(5)
A. Treatment choices					
No post-16 education (D_N)	0.14	0.17	0.00	0.00	1.00
Vocational education (D_V)	0.43	0.54	0.00	1.00	0.00
Academic education (D_A)	0.43	0.30	1.00	0.00	0.00
B. Demographic characteristics					
Female	0.49	0.49	0.54	0.49	0.43
White British	0.81	0.81	0.74	0.82	0.86
English as second language	0.09	0.10	0.16	0.09	0.06
Special educational need	0.14	0.16	0.06	0.18	0.28
Free school meal (FSM)	0.13	0.17	0.11	0.18	0.26
C. Previous achievement					
KS2 score English	0.00	-0.13	0.42	-0.29	-0.64
KS2 score Maths	0.00	-0.11	0.41	-0.27	-0.57
KS2 score Science	0.00	-0.11	0.38	-0.25	-0.58
Full Level 2	0.53	0.47	0.81	0.38	0.13
D. Neighbourhood characteristics					
IoD income	0.00	-0.22	0.06	-0.27	-0.54
IoD employment	0.00	-0.25	0.05	-0.33	-0.54
IoD education	-0.00	-0.23	0.16	-0.31	-0.65
IoD environment	-0.00	-0.14	-0.05	-0.15	-0.28
Iod crime	0.00	-0.18	0.01	-0.21	-0.41
IoD housing	-0.00	0.05	-0.03	0.08	0.07
IoD health	0.00	-0.28	0.00	-0.35	-0.53
Distance to local centre in km	8.0	8.1	7.4	8.6	7.6
E. Distance instruments					
Distance vocational college in km	6.1	5.0	5.3	4.9	5.0
Distance academic college in km	15.3	10.7	7.2	12.5	11.2
F. Labour market outcomes at ages 29–30					
Sustained employment	0.74	0.72	0.80	0.72	0.56
Annual earnings in £(incl. 0s)	17,804	16,331	20,944	15,467	10,905
Annual earnings in £(excl. 0s)	21,647	20,180	24,245	18,885	16,029
Observations	1,570,990	618,823	183,269	332,698	102,856

Notes: This table reports means of key variables for different samples: in panel A treatment indicators, i.e., students' education choices, in panels B–D control variables (though we exclude Full Level 2 from the control set), in panel E the distance instruments and in panel F labour market outcomes. KS2 test scores in panel C and the (inverted) indices of deprivation (IoD) in panel D are standardised to mean 0 and standard deviation 1 in the full sample by cohort. Column 1 describes all students enrolled in English state-funded schools who were in their final year of compulsory education in the academic years 2001/02–2003/04, save for minor sample restrictions described in 2.2 (e.g., excluding students from SEN schools). Column 2 describes our estimation sample, i.e., students from secondary schools without a sixth form (i.e., without upper secondary provision). Columns 3–5 split the estimation sample by treatment group.

to academic and vocational colleges, indicating some sorting of these institutions towards their constituencies or *vice-versa* (panel E).

Our estimation sample thus represents a moderately negatively selected group of students in terms of achievement and socio-economic background for whom vocational education plays a particularly important role. Accordingly, they are the group likely most affected by changes in the provision of vocational education, making our estimation sample relevant from a policy perspective, even though it does not cover the whole population. We revisit the question of external validity in section 5.4.

2.4 Selection into Educational Tracks

Columns 3–5 of Table 1 show stark differences in the composition of the three treatment groups. To better understand the selection patterns, Figure 2 plots the distribution of educational choices conditional on different observable student characteristics in our estimation sample.[18]

The treatments of academic and no post-16 education correlate more strongly with observables than that of vocational education. For example, vocational enrolment is very similar between genders, but females are substantially more likely to enrol in the academic track and substantially less likely to pursue no upper-secondary education. Economically disadvantaged students are far less likely to enrol in the academic track, only somewhat more likely to enrol in the vocational track and much more likely to not enrol in either than those without disadvantage. With respect to neighbourhood quality, the enrolment gradient is steepest for academic education, with students from the highest decile more than twice as likely to enrol in the academic track than those from the lowest decile, whereas the no post-16 education and vocational education shares decrease roughly equally over the same range. By far the best predictor of education choices, however, is previous achievement. Academic enrolment monotonically increases with test scores from under 10% in the lowest decile to almost 70% in the highest decile. Conversely, the no post-16 education share monotonically decreases from about 30% to 3% over the same range. Also the vocational share is decreasing in test scores, albeit less steeply.

Altogether, Figure 2 reveals that the group of students in vocational education is more heterogeneous than the other two, who are more clearly either negatively or positively selected. For higher-achieving students, the vocational-academic margin seems most relevant; for lower-achieving students the vocational-no post-16 education margin seems most relevant.

2.5 Differences in Education Outcomes

Figure 3 compares the three treatment groups in our estimation sample in terms of their educational progression and attainment. Differences in upper-secondary attainment between groups are stark: only two-third of vocational-track students ever successfully complete an upper-secondary

[18] Appendix Figure A3 repeats this exercise for students from schools with sixth form. It shows that, while the share of students choosing vocational and no post-16 education is lower and the share choosing academic is higher than in our estimation sample within each covariate cell, next to these level differences the selection patterns are very similar. This suggests that treatment selection is governed by the same process and our complier treatment effect may well be similar for marginal students from schools with sixth form.

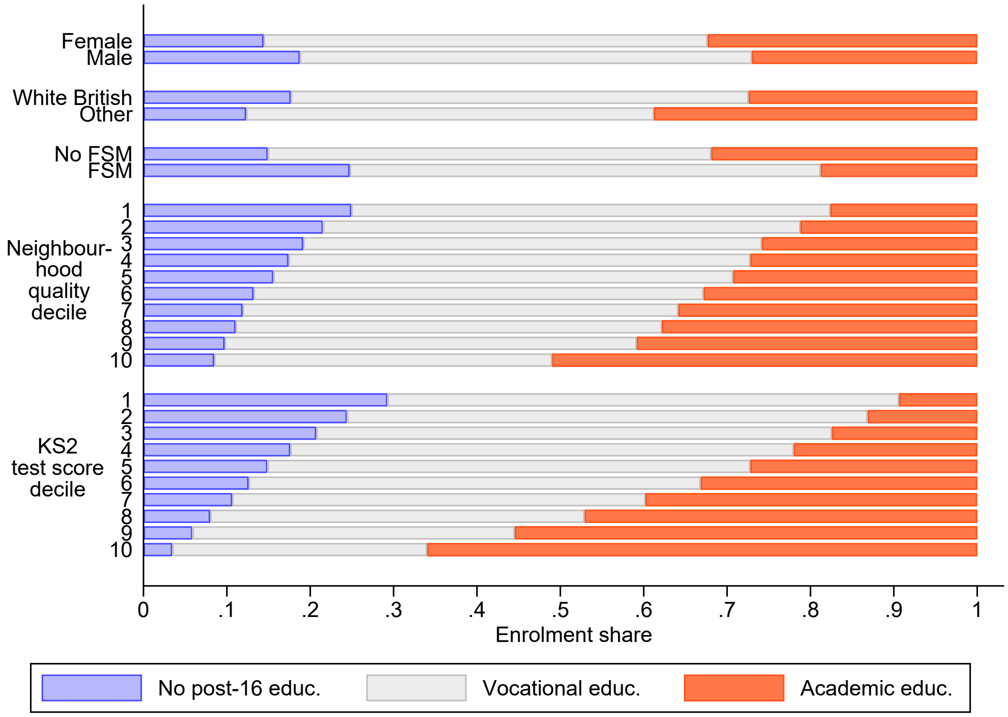


Figure 2. Track choices by observable characteristics.

Notes: This figure shows the distribution of students over treatments by observable characteristics in the estimation sample of students from schools without sixth form. FSM stands for free school meal eligibility. Neighbourhood quality deciles are deciles of the first principal component (PC) of all seven (inverted) IoDs. KS2 test score deciles are deciles of the first PC of all three end-of-primary-school (KS2) test scores. PCs are extracted (and their deciles calculated) in the full sample, so that the deciles refer to the same categories across students from schools with and without sixth form (see Appendix Figure A3.)

(Level 3) qualification and not even one-third manage to reach Full Level 3. This sharply contrasts with the academic track, where these attainment rates lie above 90% and 70%, respectively. Unsurprisingly, upper-secondary attainment of the no post-16 education group is negligible.

Differences in post-secondary education outcomes are equally strong. About one-third of vocational-track students start an apprenticeship, compared to only 9% of academic-track students and around 7% of those who initially chose no post-16 education. While almost two thirds of academic-track students progress to higher education and more than half go on to complete a three-year degree, only around 22% of vocational-track students go to university and only 16% complete a degree. While these difference are large, clearly vocational track attendance does not rule out progression to higher education *per se*. Still, vocational-track students are much less likely to graduate conditional on starting a degree and generally are far less likely to enrol in more prestigious pre-1992 universities.

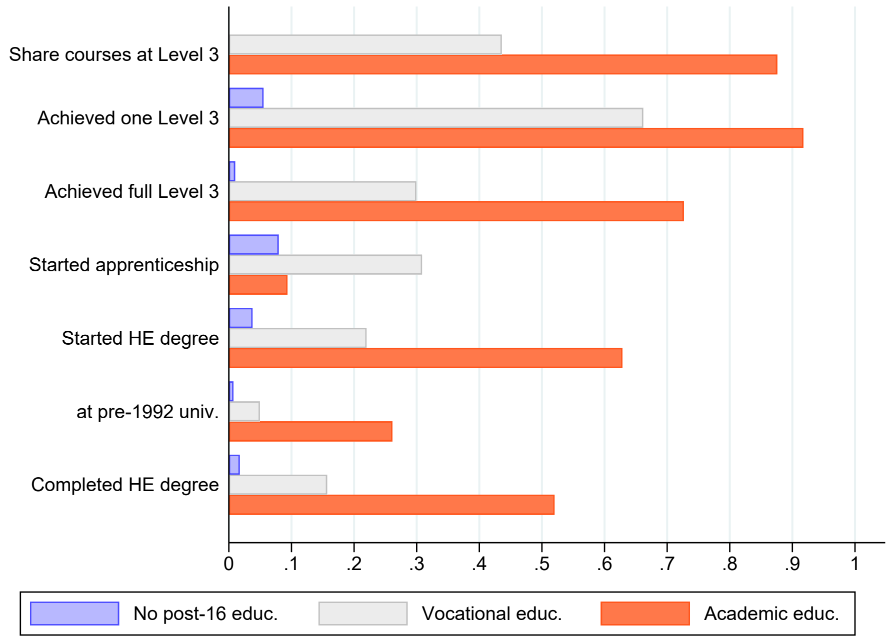


Figure 3. Educational outcomes by initial enrolment.

Notes: This figure shows means for several indicators of educational attainment by treatment group in the estimation sample of students from schools without sixth form. The share of courses at Level 3 is computed over all courses (longer than one month) started within 24 months of the relevant enrolment. The other indicators are measured over the whole period covered by the data (i.e., up to age 29–31 depending on the cohort). 'Full Level 3' stands for successfully passing two Level 3 qualifications (A-Levels or vocational equivalent). Pre-1992 universities are traditionally considered as more selective universities.

2.6 Differences in Labour Market Outcomes

Figure 4 plots raw age-employment (panel A) and age-earnings profiles (panel B) by initial enrolment. All three treatment groups start off with similar employment probabilities at age 18, but in the early years those of vocational- and academic-track students grow at a much faster rate than those of students without post-16 education. An initial advantage of vocational- over academic-track students reverses by age 22 for females and 23 for males, roughly corresponding to the age many academic-track students leave university. For both genders, the raw employment differences have stabilised by age 28 and are much larger between vocational and no-post 16 education than between academic and vocational education.

The earnings trajectories show the expected pattern: those without post-16 education earn slightly more initially but are quickly overtaken by those with vocational education, who in turn are overtaken by those with academic education. In both cases, women tend to experience this overtaking a year earlier than men, as was the case for employment. While the earnings differences between the vocational and the no post-16 education group stabilise rather quickly, those between the academically educated and the rest continue to grow throughout students' twenties—but at a decreasing rate. For women, differences seem to have roughly stabilised by age 29; for men, the

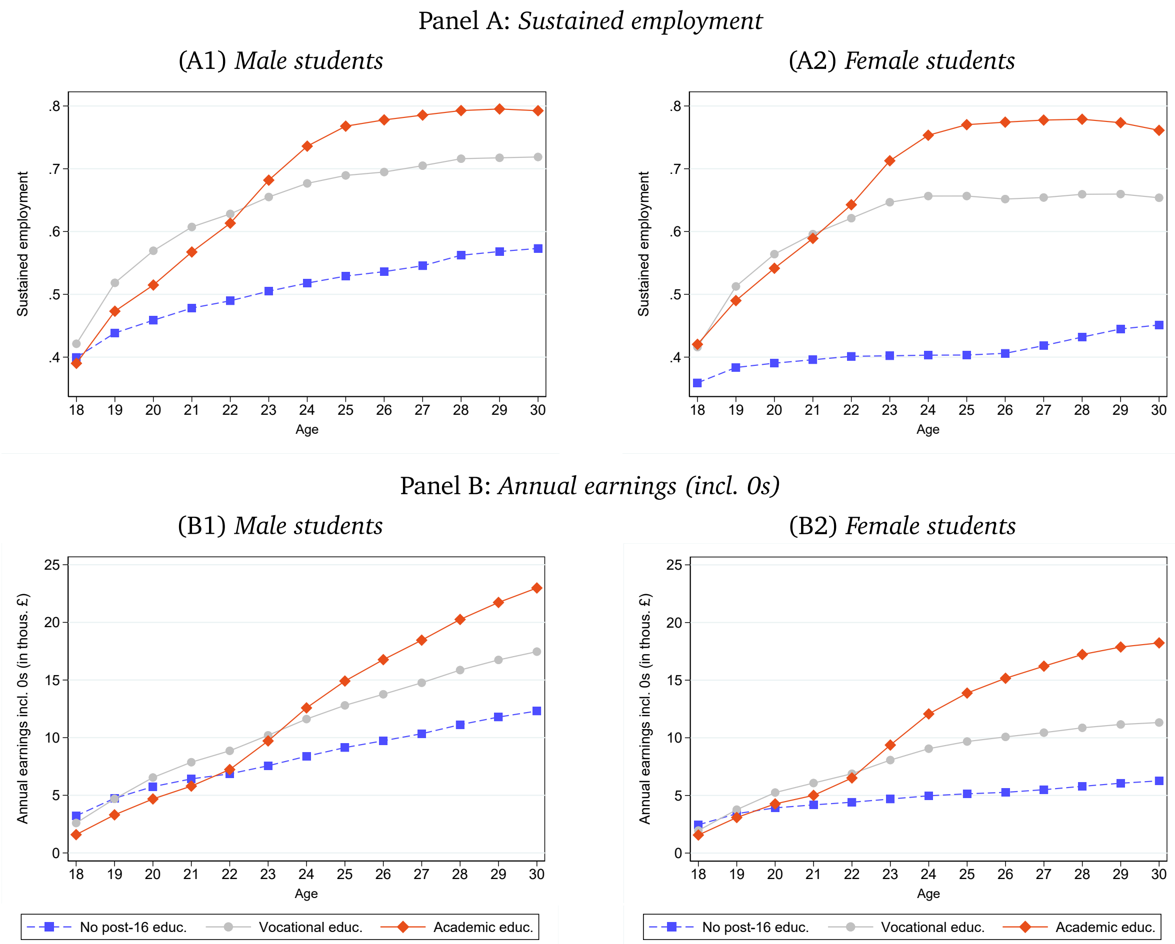


Figure 4. Labour market trajectories by initial enrolment.

Notes: The figure plots average labour market outcomes over ages 18–30 by treatment group in the estimation sample of students from schools without sixth form. Annual earnings are measured in real 2017 British pounds. Sustained employment indicates being employed more than 6 months in a given year. For comparability across the whole age range only earnings (and employment) from employed, but not from self-employed, work are included. Outcomes at age 30 are not available for the 2004 cohort.

trends suggest that they continue to grow beyond age 30 but at a slower pace. Compared to employment, for earnings the differences between academically and vocationally educated students are more pronounced than those between vocational and no post-16 education students. Note that the raw education premiums in terms of employment and earnings are larger for women than for men, particularly so for the vocational-academic contrast we are most interested in. Accordingly, we will perform all of our analyses separately by gender.

2.7 OLS Results

The raw labour market outcome differences between education groups represent a mixture of causal effects and selection. As a first step towards approximating causal returns to upper-secondary education, we use OLS regressions and our rich background data to estimate *controlled* education

Table 2. OLS regressions for labour market outcomes at ages 29–30.

Dependent variable:	Sustained employment		Annual earnings (incl. 0s)	
	Raw (1)	Controlled (2)	Raw (3)	Controlled (4)
A. Male students				
Academic education (D_A)	0.051***	0.030***	4,548***	1,885***
	(0.002)	(0.002)	(68)	(70)
No post-16 education (D_N)	-0.139***	-0.121***	-4,779***	-3,486***
	(0.002)	(0.002)	(64)	(63)
Dependent var. mean	0.76	0.76	19,311	19,311
Observations	315,217	315,217	315,217	315,217
B. Female students				
Academic education (D_A)	0.112***	0.062***	6,945***	3,792***
	(0.002)	(0.002)	(57)	(56)
No post-16 education (D_N)	-0.218***	-0.182***	-5,318***	-3,788***
	(0.003)	(0.003)	(52)	(51)
Dependent var. mean	0.68	0.68	13,237	13,237
Observations	303,606	303,606	303,606	303,606

Notes: The table results from OLS regressions of labour market outcomes on indicators for academic and no post-16 education (making vocational education the reference category) in the estimation sample of students from secondary schools without a sixth form. The raw specification controls for cohort fixed effects. The controlled specification controls for the full control set described in section 2.2. Standard errors, reported in parentheses, are clustered at the LSOA×cohort level. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

premiums. In particular, we estimate models of the following form:

$$Y = \alpha + \beta_A D_A + \beta_N D_N + \gamma \boldsymbol{X} + \varepsilon, \tag{1}$$

where the dependent variable Y is either employment or annual earnings averaged over ages 29–30, both of which now include self-employment in contrast to Figure 4. D_A and D_N are indicator variables for academic and no post-16 education, respectively, making vocational education the reference category. $\boldsymbol{X}$ is the control set containing student demographics, previous performance, school- and neighbourhood characteristics, described in section 2.2.

The OLS results in Table 2 show that gaps between education groups are large, even after conditioning on observables. Taken at face value, the coefficients in column 4 suggest that choosing vocational instead of academic education at age 16 reduces earnings fourteen years later by roughly £1,900, or 10% of average annual earnings, for men and by £3,800, or 30%, for women. Extensive margin effects play a role in explaining the larger effect for female students, as academically educated women are 6 pp more likely to be employed than vocationally educated women, while for men this coefficient is only half as large. The contrast between vocationally educated students and those without post-16 education is even larger, especially in terms of employment.

3 Research Design

3.1 Limitations of Traditional Approaches

Obtaining meaningful estimates of the returns to vocational education is challenging in the English setting. The first and foremost problem is that student self-selection into educational tracks is strong. With upper-secondary enrolment and admission fully decentralised, students' education choices likely correlate with unobserved traits and preferences that also determine later labour market outcomes. Hence, despite our comparatively elaborate control set, the remaining omitted variable bias in the controlled OLS estimates might well be substantial.

A second challenge to estimating meaningful returns to vocational education is that they likely are heterogeneous, with students sorting into educational tracks with at least partial knowledge of their idiosyncratic returns (Dahl *et al.*, 2022). Accordingly, for many questions the average treatment effects (ATEs) estimated by OLS might not be the most relevant target parameters. For example, in the presence of selection on gains, instead of ATEs we would require effect estimates for students *at the two margins of choice* to judge whether too many or too few students are choosing vocational over academic or no post-16 education from an efficiency standpoint. From a policy perspective, ATEs might well be unrepresentative of effects for students whose education choices are responsive to policy changes, like an expansion or contraction of the vocational sector.

Third, even absent such 'essential' heterogeneity, OLS gives no indication of the relative responsiveness of the two margins of choice, i.e., whether increasing the attractiveness of the vocational track primarily draws in students from no or from academic education. This limits the guidance OLS can give to policymakers. For example, a large ATE of vocational *vs.* no post-16 education is misleading if students at the corresponding margin cannot be reasonably be induced to change their choice, but only students at the vocational *vs.* academic margin react to incentives.

Instrumental variables (IV) are a canonical solution to the problems of OLS. Given a valid instrument, IV eliminates selection bias, allowing for estimation of *causal* returns to vocational education. Further, IV identifies local average treatment effects (LATEs) for marginal students (i.e., compliers with respect to the instrument), which can therefore be more policy-relevant than ATEs (Imbens and Angrist, 1994). However, in our setting there are multiple margins of treatment because students choose between three, instead of only two, unordered alternatives. Among students that are 'marginal' with respect to vocational education, returns will likely systematically differ depending on students' next-best alternatives, i.e., whether they would counterfactually choose academic or no post-16 education. Therefore, a comprehensive description of the returns to vocational education requires the estimation of two separate *margin-specific* LATEs: the effect of vocational *vs.* academic education for students at the corresponding margin; and the effect of vocational *vs.* no post-16 education for students at that margin. However, conventional IV does not identify alternative-specific treatment effects in multi-valued treatment settings, even with as many instruments as treatments available (Kirkeboen *et al.*, 2016).[19] These shortcomings of conventional multivariate IV motivate our use of Mountjoy's (2022) alternative IV-based identification approach.

Before outlining its details, it is worthwhile to highlight that a simple univariate IV—instrumenting the binary indicator for vocational education, D_V, with a single instrument (such as distance to vocational college)—identifies a generic *net* LATE of vocational education against compliers' unobserved next-best alternative. As shown by Kline and Walters (2016), this net LATE decomposes into the two unidentified margin-specific LATEs of interest with weights equal to the share of compliers at each margin:[20]

$$\beta_V^{IV} = \underbrace{\text{LATE}_V}_{\text{Net effect of } V} = \overbrace{\lambda}^{\substack{\text{Complier share} \\ \text{at } V\text{-}A \text{ margin}}} \underbrace{\text{LATE}_{V\text{-}A}}_{\text{Effect of } V \text{ } vs. \text{ } A} + \overbrace{(1-\lambda)}^{\substack{\text{Complier share} \\ \text{at } V\text{-}N \text{ margin}}} \underbrace{\text{LATE}_{V\text{-}N}}_{\text{Effect of } V \text{ } vs. \text{ } N} . \tag{2}$$

Using distance to vocational college as an instrument, we could thus estimate the net effect of vocational education across all marginal vocational education enrollees. While arguably an important parameter, the net LATE offers only a limited understanding of returns to vocational education in England. First, equation (2) shows that it can be composed of many different combinations of margin-specific effects, with potentially very different policy implications. Second, as alluded to above, normative judgment about inefficiencies in the allocation of students to tracks also requires margin-specific effects.

3.2 Empirical Strategy

To identify margin-specific treatment effects we follow an identification approach proposed by Mountjoy (2022). It extends existing theory for identifying complier potential outcomes (POs) in IV settings developed by Imbens and Rubin (1997) and Abadie (2002) to multi-valued treatments by leveraging multiple (alternative-specific) instruments.

To explain our empirical strategy we require some basic notation. Define the three discrete and mutually exclusive treatment conditions as $D = V$ (vocational education), $D = A$ (academic education) and $D = N$ (no post-16 education), with corresponding binary treatment indicators D_V, D_A and D_N. Denote the associated POs as Y_V, Y_A and Y_N, so that observed outcomes are given by

[19] For example, Two Stage Least Squares (2SLS) applied to equation (1), instrumenting the two treatments D_A and D_N with the two distance instruments Z_V and Z_A, does not identify the two margin-specific effects of interest but yields fundamentally uninterpretable quantities that amalgamate all three possible effect margins (Mountjoy, 2022). In particular, it can be shown that: $-\beta_{V\text{-}A}^{2SLS} = \theta_A \text{LATE}_{V\text{-}A} + (1-\theta_A)(\text{LATE}_{V\text{-}N} - \text{LATE}_{A\text{-}N})$ and that $-\beta_{V\text{-}N}^{2SLS} = \theta_N \text{LATE}_{V\text{-}N} + (1-\theta_N)(\text{LATE}_{V\text{-}A} + \text{LATE}_{A\text{-}N})$ where $\text{LATE}_{A\text{-}N}$ is the effect at the margin of academic *vs.* no post-16 education and θ_A and θ_N depend on the multivariate 2SLS first-stage equations.

[20] The weight λ equals the share of Z_V-compliers who are at the vocational-academic margin and is identified by the reduction in $Pr(D = A)$ induced by Z_V as a share of the increase in $Pr(D = V)$. The two margin-specific complier treatment effects, however, are not identified.

$Y = D_V\, Y_V + D_A\, Y_A + D_N\, Y_N$. Further, denote potential treatment choice as $D(z_V, z_A, \mathrm{x}) \in \{N, V, A\}$, representing the education choice a student of type $\boldsymbol{X} = \mathrm{x}$ would make if exogenously assigned to instrument values $(Z_V, Z_A) = (z_V, z_A)$. Corresponding binary indicators are defined analogously.

3.2.1 The Effect of Vocational *vs.* Academic Education

It is well known that IV not only identifies complier treatment effects but also POs (Abadie, 2002). For example, in the simple univariate IV that instruments D_V with Z_V we merely have to replace the outcome variable Y with the treatment-outcome interaction YD_V to identify compliers' mean vocational education PO instead of LATE_V.[21] The intuition behind this is simple: $YD_V = Y_V$ if $D_V = 1$ and $YD_V = 0$ otherwise, so that Z_V-induced changes in YD_V contain information about Y_V for students switching into or out of vocational education in response to changes in distance to vocational college. Yet, as explained above, in our setting these compliers are students who are switching from/to academic education *and* students who are switching from/to no post-16 education. We thus only identify a *net* PO analogous to the net LATE_V in equation (2), i.e., a weighted average of these two complier types' vocational education POs with weights equal to their share. Instead of averaging over these two types of compliers, we would like to focus on one margin at a time.

Mountjoy (2022) shows that, with comparable alternative-specific instruments available, this can be achieved through what may be called 'cross-instrumentation': if in the same IV, instead of using distance to vocational college, we use distance to academic college, Z_A, to instrument the treatment of vocational education, while holding fixed distance to vocational college, we restrict complier flows to the vocational *vs.* academic education margin. This is because, conditional on distance to vocational college, variation in distance to academic college only changes the attractiveness of the academic track, leaving the attractiveness of the other two alternatives unaffected. Hence, any Z_A-induced changes in D_V must be due to students switching between vocational and academic education; movements between vocational and no post-16 education are ruled out. Therefore, the univariate IV for the effect of D_V on YD_V, (cross-)instrumenting D_V with Z_A instead of Z_V, but conditioning on Z_V, identifies the mean vocational education PO for compliers *at the vocational vs. academic education margin only*.[22]

[21] Analogously, with YD_A as the outcome, IV identifies compliers' mean *academic* education PO.

[22] Formally, under assumptions A1, A2 and A3, to be discussed below, the average vocational education PO for vocational-academic compliers at point $(Z_V, Z_A, \boldsymbol{X}) = (z_V, z_A, \mathrm{x})$ is identified as a ratio of partial derivatives as follows:

$$\lim_{z_V' \uparrow z_V} \mathbb{E}\left[Y_V \mid D(z_V', z_A, \mathrm{x}) = V,\, D(z_V, z_A, \mathrm{x}) = A\right]$$
$$= \frac{\partial \mathbb{E}\left[YD_V \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_A} \Bigg/ \frac{\partial \mathbb{E}\left[D_V \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_A}\,.$$

The right-hand side is the local instrumental variables (LIV) estimand (Heckman and Vytlacil, 2005) for the effect of D_V on YD_V, instrumenting D_V with Z_A and conditioning on Z_V and $\boldsymbol{X}$.

By symmetry, the univariate IV for the effect of D_A on YD_A, (cross-)instrumenting D_A with Z_V, while conditioning on Z_A, identifies the mean *academic education* PO for compliers at the vocational *vs.* academic education margin.[23] Under the assumption that Z_V- and Z_A-induced compliers do not systematically differ (to be discussed below), the first margin-specific effect of interest—that of vocational *vs.* academic education for compliers at the vocational-academic margin—is then identified by the difference between these two 'cross-instrumented' univariate IV estimands.

In principle, the identification results in Mountjoy (2022) allow for non-parametric estimation of point-specific marginal treatment effects (MTEs) by using the two continuous instruments as local instrumental variables (LIV) (Heckman and Vytlacil, 2005).[24] Nevertheless, we impose some parametric assumptions to increase statistical power and to obtain readily interpretable LATE estimates for our main results. In particular, we implement both univariate IVs using global linear (in logs) regression models for the reduced form and first stage equations, which control flexibly—but parametrically—for covariates. In section 4.4, we relax these assumptions and estimate more local MTEs across different points of the instrument support to test the robustness of our main results and to inspect effect heterogeneity by unobservables.

Thus, for the (margin-specific) mean vocational education PO, we instrument vocational enrolment with conditional distance to academic college by estimating the following pair of reduced form and first stage equations:

$$YD_V = \alpha_0 + \alpha_1 Z_A + \alpha_2 \boldsymbol{X} + \alpha_3 Z_V + \varepsilon \tag{3}$$

$$D_V = \pi_0 + \pi_1 Z_A + \pi_2 \boldsymbol{X} + \pi_3 Z_V + \nu, \tag{4}$$

to construct the PO's IV estimate as the usual 'Wald' ratio between reduced form and first stage coefficients: $\hat{\alpha}_1/\hat{\pi}_1$ (remember that Z_V is merely a control variable in equations (3) and (4)). Note that this is numerically equivalent to a 2SLS regression of YD_V on D_V instrumented with Z_A and controlling linearly for Z_V and $\boldsymbol{X}$. Further note that the coefficient ratio is simply the global regression analogue to the ratio of local partial derivatives from footnote 22. We think of equations (3) and (4) as (log-linear) first-order approximations to the true reduced form and first

[23] Analogously, under assumptions A1, A2 and A3, the average academic education PO for vocational-academic compliers at point $(Z_V, Z_A, \boldsymbol{X}) = (z_V, z_A, \mathrm{x})$ is identified as a ratio of partial derivatives as follows:

$$\lim_{z'_V \uparrow z_V} \mathbb{E}\left[Y_A \mid D(z'_V, z_A, \mathrm{x}) = V,\ D(z_V, z_A, \mathrm{x}) = A\right] = \frac{\partial \mathbb{E}\left[YD_A \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V} \Bigg/ \frac{\partial \mathbb{E}\left[D_A \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V}$$

[24] The MTE is the limit version of LATE as the instrument shifts tend towards zero. MTE is the continuous instrument analague to LATE because, just like LATE in the binary instrument case, it is defined without parametric assumptions or restrictions on effect heterogeneity (Kennedy *et al.*, 2019). In the binary instrument case (without covariates), 2SLS equals the Wald ratio and thus non-parametrically identifies LATE. This is no longer true in the continuous instrument case, where 2SLS imposes parametric assumptions on the first stage relationship. LIV, in contrast, non-parametrically identifies the point-specific MTE.

stage relationships between distance and outcomes and choices, respectively.

Analogously, for the (margin-specific) mean academic education PO, we instrument academic enrolment with conditional distance to vocational college by estimating the following pair of reduced form and first stage equations:

$$YD_A = \beta_0 + \beta_1 Z_V + \beta_2 \boldsymbol{X} + \beta_3 Z_A + \tilde{\varepsilon} \tag{5}$$

$$D_A = \rho_0 + \rho_1 Z_V + \rho_2 \boldsymbol{X} + \rho_3 Z_A + \tilde{\nu}. \tag{6}$$

to construct the PO's IV estimate as $\hat{\beta}_1/\hat{\rho}_1$.

The estimate for LATE$_{V\text{-}A}$ is then formed by differencing the two margin-specific PO estimates:

$$\widehat{\text{LATE}}_{V\text{-}A} = \frac{\hat{\alpha}_1}{\hat{\pi}_1} - \frac{\hat{\beta}_1}{\hat{\rho}_1}.$$

The share of compliers at the vocational-academic margin, λ, is estimated by the ratio of first stage coefficients $\hat{\rho}_1/-\hat{\pi}_3$, which, intuitively, equals the share of the total reduction in vocational enrolment upon an increase in distance to vocational college ($\hat{\pi}_3$) that is due increased academic enrolment ($\hat{\rho}_1$). To obtain standard errors we block bootstrap at the LSOA×cohort-level (the level at which the instruments vary) with 999 repetitions.

3.2.2 The Effect of Vocational *vs.* no Post-16 Education

Identification at the margin between vocational and no post-16 education proceeds similarly—with one complication. Analogously to the above, the average no post-16 education PO for compliers at this margin is identified by a univariate IV for the effect of D_N on YD_N, (cross-)instrumenting D_N with Z_V.[25] Accordingly, we estimate the following pair of reduced form and first stage equations:

$$YD_N = \gamma_0 + \gamma_1 Z_V + \gamma_2 \boldsymbol{X} + \gamma_3 Z_A + \breve{\varepsilon} \tag{7}$$

$$D_N = \tau_0 + \tau_1 Z_V + \tau_2 \boldsymbol{X} + \tau_3 Z_A + \breve{\nu}, \tag{8}$$

to construct the IV estimate for the no education PO as $\hat{\gamma}_1/\hat{\tau}_1$.

Unfortunately, we cannot apply the same logic to identify the vocational education PO for compliers at this margin. This is because we lack a third instrument shifting only the attractiveness

[25] Analogously, under assumptions A1, A2 and A3, the average no education PO for vocational-no post-16 education compliers at point $(Z_V, Z_A, \boldsymbol{X}) = (z_V, z_A, \mathrm{x})$ is identified as a ratio of partial derivatives as follows:

$$\lim_{z'_V \uparrow z_V} \mathbb{E}\left[Y_N \mid D(z'_V, z_A, \mathrm{x}) = V,\ D(z_V, z_A, \mathrm{x}) = N\right]$$
$$= \frac{\partial \mathbb{E}\left[YD_N \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V} \Bigg/ \frac{\partial \mathbb{E}\left[D_N \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V}$$

of no post-16 education that could be used to (cross-)instrument vocational enrolment. Yet, as discussed by Mountjoy (2022), a workaround is available. Remember that instrumenting vocational enrolment with (conditional) distance to vocational college in the univariate IV for the effect of D_V on YD_V identifies the *net* vocational education PO for all compliers, which decomposes into the two margins with weights equal to the respective complier shares. As we know these shares and the vocational education PO for vocational-academic compliers to be identified from above, we can back out the missing vocational education PO for vocational-no education compliers arithmetically from this decomposition.[26] Only using coefficient estimates from the previous reduced form and first stage equations, the PO estimate can be constructed as $(-\hat{\alpha}_3)/\hat{\tau}_1 - (\hat{\alpha}_1/\hat{\pi}_1)\,(\hat{\rho}_1/\hat{\tau}_1)$. Note how the fact that this PO needs to be backed out propagates uncertainty, reducing statistical power at this margin.

As before, the estimate for $\text{LATE}_{V\text{-}N}$ is then formed by differencing the two margin-specific PO estimates:

$$\widehat{\text{LATE}}_{V\text{-}N} = \left(\frac{-\hat{\alpha}_3}{\hat{\tau}_1} - \frac{\hat{\alpha}_1}{\hat{\pi}_1}\frac{\hat{\rho}_1}{\hat{\tau}_1}\right) - \frac{\hat{\gamma}_1}{\hat{\tau}_1}.$$

We have thus identified all parts of equation (2)'s decomposition of the net effect, LATE_V, into its two margin-specific components, $\text{LATE}_{V\text{-}A}$ and $\text{LATE}_{V\text{-}N}$.

3.3 Assessing the Identification Assumptions

This section discusses the identification assumptions required for Mountjoy's (2022) procedure. We, in turn, state them formally, discuss their interpretation in our setting and empirically assess their plausibility. To simplify notation, we implicitly condition on the control set $\boldsymbol{X}$ in everything that follows.

3.3.1 Independence and Exclusion

The first assumption is the canonical IV assumption of independence and exclusion, adapted to the multiple treatments and two instruments setting:

[26] Formally, under assumptions A1, A2 and A3, the average vocational education PO for vocational-no post-16 education compliers at point $(Z_V, Z_A, \boldsymbol{X}) = (z_V, z_A, \mathrm{x})$ is identified as follows:

$$\begin{aligned}
&\lim_{z_V' \uparrow z_V} \mathbb{E}\left[Y_V \mid D(z_V', z_A, \mathrm{x}) = V,\ D(z_V, z_A, \mathrm{x}) = N\right] \\
&\quad = \frac{\partial \mathbb{E}\left[YD_V \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V} \Big/ \frac{\partial \mathbb{E}\left[D_N \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V} \\
&\qquad - \frac{\partial \mathbb{E}\left[YD_V \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_A} \Big/ \frac{\partial \mathbb{E}\left[D_V \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_A} \\
&\qquad\quad * \frac{\partial \mathbb{E}\left[D_A \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V} \Big/ \frac{\partial \mathbb{E}\left[D_N \mid Z_V = z_V, Z_A = z_A, \boldsymbol{X} = \mathrm{x}\right]}{\partial Z_V}.
\end{aligned}$$

A1 Independence and Exclusion:

$$(Z_V, Z_A) \perp\!\!\!\perp \big(Y_N, Y_V, Y_A, \{D(z_V, z_A)\}_{\forall(z_V, z_A)}\big)$$

A1 requires the two distance instruments to be as good as randomly assigned with respect to students' potential outcomes and treatment choices, conditional on the implicit control set $\boldsymbol{X}$. Threats to A1 are residential sorting of students and the non-random location of colleges. If students with a stronger motivation for enrolling in a particular institution type live (or move) closer to it, the exogeneity of distance with respect to education choices would be violated. In this context, we expect residential sorting to be minimal because academic and vocational colleges do not allocate slots based on geographical proximity (nor are they oversubscribed) and generally cater to large regions, so that families' have no incentives to live in their proximity save for shorter travelling times during two years of upper-secondary education. Note that we construct the distance instruments using students' residence a full year before post-16 enrolment and potential relocation decisions are made.

A more serious concern is the non-random location of colleges, which may induce a backdoor association between the distance instruments and students' potential labour market outcomes via local economic conditions (thus violating the exclusion restriction).[27] For this reason the control set $\boldsymbol{X}$ contains detailed neighbourhood controls, including distance to the closest economic centre, next to student- and school-level variables. Accordingly, we only leverage distance variation among similar students, from similar schools, living in neighbourhoods similarly far from economic centres, with similar economic and social characteristics within the same region.

Table 3 assesses the plausibility of A1 empirically by means of balance tests on observed predetermined covariates. In columns 1–5, we sequentially exclude the White British indicator, the FSM indicator and the three test scores from the control set to regress the excluded variable on the two distance instruments and the remaining controls. This way we assess covariate balance with respect to conditional changes in distance. In column 6, we use the full control set to perform the same test with respect to the left-out indicator of whether students have achieved Full Level 2 in their GCSEs, which bears a strong association with students' later earnings.[28] To gauge the economic importance of potential imbalances, in brackets below each coefficient in Table 3 we report how they would translate into changes in annual earnings at ages 29–30. For this we multiply the coefficient on distance with an estimate for the covariate's effect on earnings.[29]

Columns 1–5 show that distance to vocational college correlates significantly only with the White British indicator. But it does so in negligible magnitude: a one percent increase in Z_V is

[27] For example, vocational colleges historically catered for adult workers suggesting they originally might have been located in more disadvantaged areas. Another channel might be any economic (or education) spillover from colleges on their surrounding areas, although we deem it unlikely that these are particularly large.

[28] This is apparent from panel A in Appendix Table B2 which shows that Full Level 2, despite being binary, is the most predictive variable of students' later earnings among all our controls.

[29] These are estimated by an OLS regression of earnings on the covariate of interest (and the rest of the control set). The coefficients are reported in panel B of Appendix Table B2.

Table 3. Instrument balance tests.

Dependent variable:	White (1)	FSM (2)	KS2 English (3)	KS2 Maths (4)	KS2 Science (5)	Full Level 2 (6)
Distance voc. college (Z_V)	0.0024***	0.0000	0.0003	-0.0006	-0.0012	-0.0026***
	(0.0008)	(0.0007)	(0.0015)	(0.0014)	(0.0015)	(0.0009)
	[£1]	[£-0]	[£0]	[£-1]	[£-0]	[£-14]
Distance acad. college (Z_A)	-0.0004	0.0020***	0.0001	-0.0020*	0.0040***	-0.0027***
	(0.0007)	(0.0006)	(0.0012)	(0.0011)	(0.0013)	(0.0007)
	[£-0]	[£-5]	[£0]	[£-4]	[£1]	[£-15]
Controls:						
White British		✓	✓	✓	✓	✓
Free school meal (FSM)	✓		✓	✓	✓	✓
KS2 score English	✓	✓		✓	✓	✓
KS2 score Maths	✓	✓	✓		✓	✓
KS2 score Science	✓	✓	✓	✓		✓
Remaining controls	✓	✓	✓	✓	✓	✓
N clusters	62,560	62,560	61,100	61,192	61,239	62,560
N students	618,823	618,823	563,156	568,866	570,599	618,823

Notes: The table reports results from OLS regressions of selected student characteristics on the two distance instruments and the full control set (see section 2.2), excluding the covariate in question. Results are based on the estimation sample of students from schools without sixth form. Standard errors reported in parentheses are clustered at the LSOA×cohort level. Results in square brackets report how the coefficients translate into earnings (in GBP): this is obtained by multiplying the coefficients of the distance instruments by the coefficients reported in panel B of Table B2. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

associated with a 0.2 pp increase in the probability of being of White British ethnic background, which corresponds to a difference in annual earnings of only £1. Distance to academic college significantly correlates with FSM eligibility and test scores in maths and science but, again, these associations are negligible in size and economic importance: a one percent increase in Z_A is associated with a 0.2 pp increase in the probability of being FSM-eligible (corresponding to -£5 in annual earnings), a 0.2% of a standard deviation decrease in the KS2 maths score (-£4) and a 0.4% of a standard deviation increase in the KS2 science score (£1).

Column 6 shows that both distance instruments retain a small but significant association with students' academic achievement at age 16: a one percent increase in either Z_V or Z_A maps into a 0.3 pp decrease in the probability of attaining Full Level 2. Yet, even though this indicator is the most predictive of students' future earnings, these imbalances merely correspond to annual earnings differences of £14 and £15, respectively. Altogether, while some of the associations are statistically significant, their small size and economic irrelevance suggest that any potential remaining selectivity is negligible.[30]

[30] We do not include the most imbalanced variable 'Full Level 2' (or other GCSEs performance indicators) in our control set $\boldsymbol{X}$ to retain a left-out variable that can be used to assess the validity of A3. Yet, in section 4.2 we show that our main results are unchanged even if Full Level 2 is included in $\boldsymbol{X}$.

3.3.2 Instrument Relevance (First Stages)

Of course, our research design is only feasible if the two distance instruments are strong predictors of education choices. In particular, identification at the vocational-academic margin requires two non-zero first-stage relationships: the conditional effect of distance to closest academic college on vocational education (corresponding to π_1 in equation (4)) and the conditional effect of distance to closest vocational college on academic education (corresponding to ρ_1 in equation (6)). Identification at the vocational-no education margin additionally requires the conditional effect of distance to closest vocational college on no post-16 education to be non-zero (corresponding to τ_1 in equation (8)).[31]

Previous research from England has confirmed that how proximate students live to education providers influences their track choices at age 16 (Dickerson and McIntosh, 2013). This is because students at this age typically do not move out of their family home, making travelling distance a salient financial, temporal and psychological cost. To verify the instruments' relevance in our data, we begin by inspecting the track-specific shares of students enrolling in their closest college. Appendix Table B1 shows that 57% of vocational-track and 59% of academic-track students enrol in their closest FE and SF college, respectively (with 15% and 12%, and 7% and 5% enrolling in the second and third closest colleges, respectively).

Next, Figure 5 directly visualises the three first stage relationships of interest by means of quantile-spaced binned scatter plots, which non-parametrically control for the other distance instrument and the full control set (Cattaneo *et al.*, 2021). Conditional on distance to vocational college (and all other controls), vocational enrolment increases monotonically and approximately linearly in (log) distance to academic college (panel A). A similar picture arises for the relationship between academic enrolment and distance to vocational college (panel B). This visual inspection thus supports the instrument strength conditions for identification at the vocational-academic margin, as well as the chosen linear approximation.

The conditions for identification at the vocational-no education margin are somewhat less favourable. Panel C shows that the choice of no post-16 education is much less responsive to distance to vocational college. Only at distances larger than 3km a positive slope becomes visible. Panel D shows the relationship between vocational enrolment and distance to vocational college, which is the traditional first stage for the net effect of vocational education. Because $D_V = 1 - D_A - D_N$, the decreases in vocational enrolment with distance to vocational college from panel D mirror the increases in academic and no post-16 enrolment from panels B and C. This implies that at closer distances to vocational college the decline in vocational enrolment is entirely at the advantage of academic education; as distance grows, both margins contribute. Still, even at further distances flows across the academic-vocational margin are much more important, meaning that

[31] We formally embed the instrument relevance condition in A2 below.

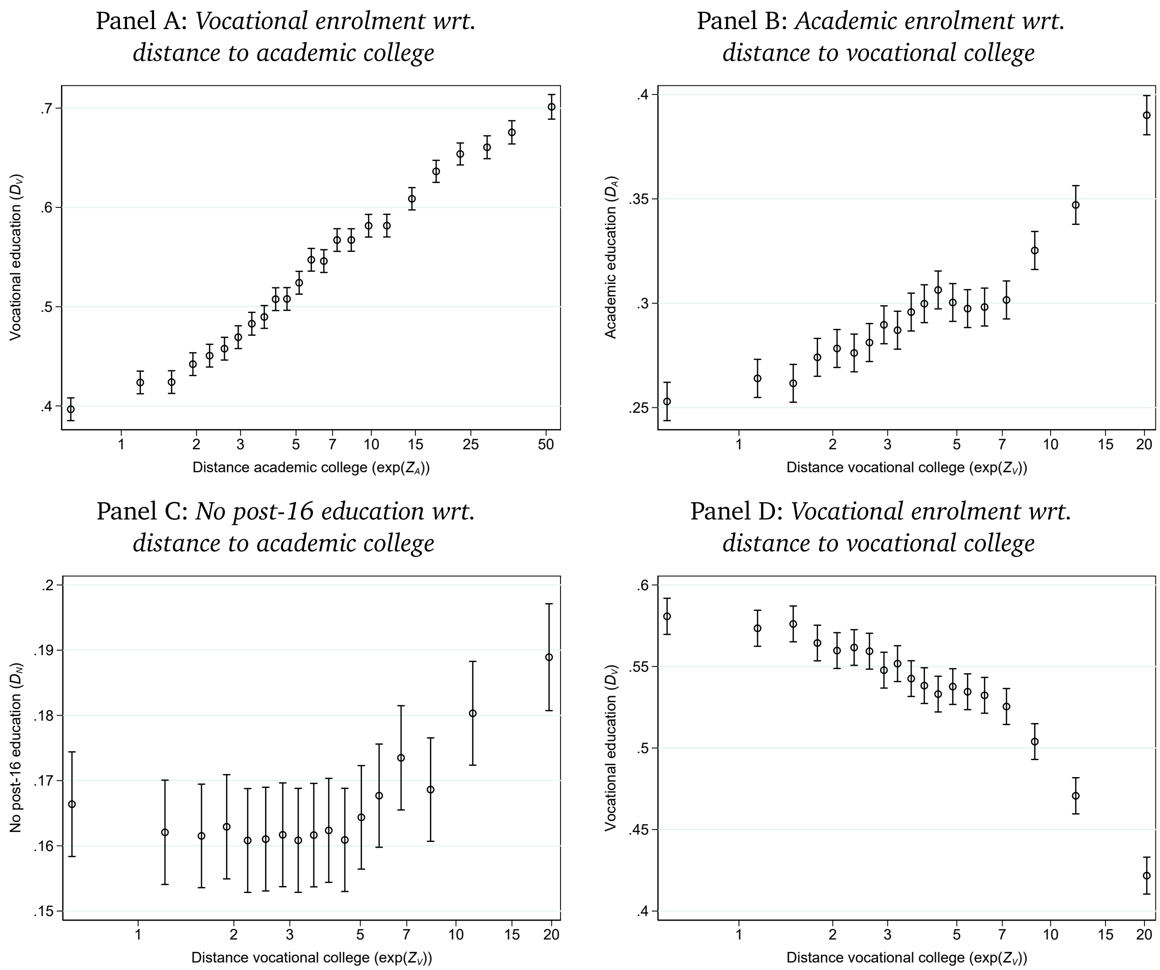


Figure 5. Binned scatter plots of first stage relationships.

Notes: These figures plot the relevant first-stage relationships between students' treatment choices and distance instruments by means of 'binscatters' (Cattaneo *et al.*, 2021). Each panel plots the estimated probability of students choosing a given option (alongside 95% CIs) within quantile-spaced bins of the relevant distance instrument (in natural logs), while controlling non-parametrically for the other distance instrument and the full control set. The figure is based on the estimation sample of students from schools without sixth form.

most marginal students, whose decision to enrol in vocational college is responsive to distance, choose between vocational and academic education.

Finally, Table 4 presents the first stage regression results by gender. Odd columns display our main specifications. All coefficients show their expected signs, consistent with Figure 5: distance to vocational college decreases the probability of vocational enrolment but increases no post-16 education and academic enrolment, while distance to academic college decreases the probability of academic enrolment but increases that of vocational enrolment. To test first-stage strength, we report robust F-statistics for the three coefficients of interest (Olea and Pflueger, 2013).[32]

[32]We report 'Kleibergen-Paap' F-statistics which are robust to heteroskedasticity and clustering and equivalent to the 'effective' F-statistic of Olea and Pflueger (2013) in this case of a single instrument (per first stage).

Table 4. First stage regressions.

Dependent variable:	Vocational educ. (D_V)		Academic educ. (D_A)		No post-16 educ. (D_N)	
	(1)	(2)	(3)	(4)	(5)	(6)
A. Male students						
Distance voc. college (Z_V)	-0.034***	-0.034***	0.027***	0.028***	0.007***	0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
			[F = 455.9]		[F = 39.5]	
Distance acad. college (Z_A)	0.070***	0.070***	-0.077***	-0.076***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[F = 3042]					
R^2	0.08	0.09	0.26	0.32	0.10	0.13
B. Female students						
Distance voc. college (Z_V)	-0.039***	-0.040***	0.035***	0.036***	0.004***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
			[F = 640.8]		[F = 17.5]	
Distance acad. college (Z_A)	0.082***	0.082***	-0.088***	-0.087***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[F = 4103]					
R^2	0.11	0.12	0.26	0.30	0.08	0.11
Full Level 2		✓		✓		✓
Controls	✓	✓	✓	✓	✓	✓

Notes: The table reports results from OLS regressions of treatment indicators on the two distance instruments and the full control set, excluding (odd columns) and including (even columns) an indicator for having achieved Full Level 2. Results are based on the estimation sample of respectively male (panel A) and female students (panel B) from schools without sixth form. Standard errors reported in parentheses are clustered at the LSOA×cohort level. The number of observations is 303,606 (55,079 clusters) in the female sample and 315,217 (55,888 clusters) in the male sample. For the three relevant first stages, in square brackets we present Kleibergen-Paap F-statistics testing first-stage strength in the presence of heteroskedasticity and clustering, whose critical values for a single-instrument 2SLS lie between 5.53 and 16.38 (Olea and Pflueger, 2013). Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For both genders, the F-statistics of the first stages involving D_A and D_V far exceed conventional critical values. The F-statistic for D_N is much lower, confirming that compliers at the vocational-no education margin are few (particularly among female students). The weakness of the first-stage relationship suggests caution when interpreting results at this margin.

As a robustness check, the even columns of Table 4 add the Full Level 2 indicator to the conditioning set of the first stage regressions. Achieving Full Level 2 at the end of compulsory schooling is not only a strong predictor of later earnings but also of students' education choices, which we see reflected in substantial R^2 increases.[33] Nonetheless, the coefficients for the instruments hardly change, confirming that the demographic, school- and neighbourhood-level variables contained in the control set $\boldsymbol{X}$ suffice for purging the distance-choice relationships of confounders, and thus lending further credence to the instruments' independence and exclusion (A1).

[33] In panel C of Appendix Table B2 we show that the Full Level 2 indicator is the strongest predictor of students' post-16 education choices among all our control variables.

3.3.3 Partial Unordered Monotonicity

The next assumption extends the intuition of 'no defiers' from the binary to the multi-valued treatment case, considering only conditional instrumental variation:[34]

A2 Partial Unordered Monotonicity:

For all triples (z_V, z'_V, z_A) with $z'_V < z_V$ we have: $D_V(z'_V, z_A) \geq D_V(z_V, z_A)$ but $D_A(z'_V, z_A) \leq D_A(z_V, z_A)$ and $D_N(z'_V, z_A) \leq D_N(z_V, z_A)$ for all individuals, with each inequality holding strictly for at least some individuals.

For all triples (z_A, z'_A, z_V) with $z'_A < z_A$ we have: $D_A(z_V, z'_A) \geq D_A(z_V, z_A)$ but $D_V(z_V, z'_A) \leq D_V(z_V, z_A)$ and $D_N(z_V, z'_A) \leq D_N(z_V, z_A)$ for all individuals, with each inequality holding strictly for at least some individuals.

A2 requires that a decrease (increase) in the distance to either type of college, holding constant distance to the other, renders the associated education choice weakly more (less) attractive for *all* students.[35] It does not restrict the complier flows to a certain margin, however. For example, as the distance to vocational college decreases ($z'_V < z_V$), but distance to academic college is held fixed, some people may switch into but no one out of vocational education ($D_V(z'_V, z_A) \geq D_V(z_V, z_A)$); whether these compliers come from academic education ($D_A(z'_V, z_A) \leq D_A(z_V, z_A)$) or no post-16 education ($D_N(z'_V, z_A) \leq D_N(z_V, z_A)$) is left unrestricted. However, nobody may switch between no post-16 and academic education in response to this change.

Given their exogeneity, partial unordered monotonicity is a natural assumption for our distance instruments. The only plausible violation would stem from complementarities between the two college types, so that the one's attractiveness is tied to that of the other. However, academic and vocational colleges are substitutes and enrolling in one is not a preparatory step for enrolling in the other at a later stage.

To empirically assess the plausibility of A2 we follow the literature and test whether the first stages are consistent across different subsamples of the data (e.g., Dobbie *et al.*, 2018; Bhuller *et al.*, 2020; Agan *et al.*, 2021). Appendix Table B3 presents estimates for all three first stage of interest across a large variety of covariate-defined data cells. The first stages of D_A and D_V are positive throughout. The weaker first stage of D_N is zero in some subsamples but never negative. Accordingly, we find no evidence for the presence of 'defiers' in our sample.

[34]Heckman and Pinto (2018) develop the general 'unordered monotonicity' condition for the unordered multi-valued treatment case. It requires that treatment responses are uniform across *all* possible shifts in the instruments. Mountjoy's (2022) 'partial unordered monotonicity' relaxes this assumption by looking only at *conditional* variation in the instruments, i.e., focusing on the subset of shifts where one of the two instruments stays constant. This means that we make no assumptions about the behaviour of students in cases where distance to both colleges decreases simultaneously.

[35]And strictly for some students, thus formally embedding an instrument relevance condition.

3.3.4 Complier Comparability

The final assumption is specific to Mountjoy's (2022) framework and draws a connection between the two sets of vocational-academic compliers induced by Z_V and Z_A:

A3 Complier Comparability:

For all pairs (z_V, z_A):

$$\lim_{z'_V \uparrow z_V} \mathbb{E}\left[Y_V \mid D(z'_V, z_A) = V, D(z_V, z_A) = A\right]$$
$$= \lim_{z'_A \downarrow z_A} \mathbb{E}\left[Y_V \mid D(z_V, z'_A) = V, D(z_V, z_A) = A\right]$$

A3 states that compliers shifted from academic to vocational college by a marginal *decrease* in distance to vocational college (left-hand side) must be comparable, in terms of POs, with those shifted by a marginal *increase* in distance to academic college (right-hand side). It is required because we can only identify the right-hand side from the data (using distance to academic college to instrument vocational enrolment, as explained above) but not the left-hand side (because distance to vocational college induces compliers also from the other margin). Given that both are students at a margin of indifference between vocational and academic education and both instruments represent simply the distance to the closest respective provider, *ex ante* it is hard to picture how these two complier types could systematically differ.[36]

The unidentified PO on left-hand side of course prohibits a direct test of A3. Still, we can assess its plausibility by comparing the two complier types in terms of average pre-determined characteristics which are separately identified under A1 and A2 alone.[37] In practice, we compare their performance in the high-stakes GCSEs exams, as measured by Full Level 2 achievement, which we have deliberately excluded from the control set $\boldsymbol{X}$ in order to perform this check. To better gauge the economic magnitude of any potential differences, we also translate Full Level 2 achievement into annual earnings. For this we predict earnings with a simple OLS regression of annual earnings at ages 29–30 (including zeroes) on the Full Level 2 indicator.

Table 5 presents the results from this exercise, separately by gender. Column 1 reports average Full Level 2 achievement and average predicted earnings for vocational-academic compliers induced by Z_V (left-hand side of A3) and column 2 reports the same quantities for those induced

[36] Mountjoy (2022) shows that this condition is implied by a standard Roy-style selection model: both Z_V and Z_A act as costs shifting a single index that governs the relative attractiveness of vocational *vs.* academic education. Hence, students who switch their treatment choice in response to a marginal change in the index are the same regardless of whether this change is induced by a marginal decrease in Z_V or a marginal increase in Z_A (or *vice-versa*).

[37] If in A3, we replace Y_V with some characteristic, C, not determined by D, then also the left-hand side is directly identified. This is because, under A1, $C_V = C_A = C$. Under A2, we can thus estimate Z_V-induced vocational-academic compliers' average C by estimating equations (5) and (6) replacing YD_A with CD_A. Similarly, equations (3) and (4) replacing YD_V with CD_V estimate the average C for the Z_A-induced vocational-academic compliers from the right-hand side of A3.

Table 5. Comparing vocational-academic compliers induced by different distance instruments.

	V-A compliers induced by Z_V	*V-A* compliers induced by Z_A	Difference (1) – (2)
	(1)	(2)	(3)
A. Male students			
Full Level 2	0.71	0.70	0.00
	(0.05)	(0.02)	(0.05)
Predicted earnings	21,696	21,659	37
	(173)	(102)	(192)
B. Female students			
Full Level 2	0.68	0.76	-0.07*
	(0.04)	(0.02)	(0.04)
Predicted earnings	14,800	15,521	-721***
	(168)	(104)	(203)

Notes: The table compares average academic achievement in end-of-secondary-school examinations (Full Level 2) and the associated predicted earnings for two groups of compliers at the vocational *vs.* academic education margin: those induced by conditional variation in distance to vocational college (Z_V) in column 1, and those induced by conditional variation in distance to academic college (Z_A) in column 2. Column 3 reports the estimated differences. All models condition on the full control set. Predicted earnings are first obtained by means of gender-specific regressions of average annual earnings (over ages 29–30) on the Full Level 2 indicator. The number of observations is 303,608 (55,079 clusters) in the female sample and 315,217 (55,888 clusters) in the male sample. Standard errors are block bootstrapped at the LSOA×cohort level using 999 iterations. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

by Z_A (right-hand side of A3). Column 3 reports the difference between the two. For males, the two groups of compliers are perfectly comparable in terms of their GCSE performance and, hence, also in terms of their predicted earnings. For females, in contrast, the two groups appear more different: female compliers who respond to a conditional change in Z_A have higher academic achievement than the group who responds to a conditional change in Z_V, corresponding to a difference in predicted annual earnings of around £720. Accordingly, we conclude that A3 is likely to hold for male students but that caution is required when interpreting the margin-specific IV results for female students. In particular, the results in Table 5 imply that the Z_A-based estimate of their vocational PO is upward biased. In section 4.2 we probe the robustness of our results to correcting the PO (and effect) estimates for these "expected" earnings differences.

4 Results for Labour Market Outcomes

4.1 Main Results

Table 6 presents the main results for the alternative-specific effects of vocational education on students' labour market outcomes averaged over ages 29–30. We present all results separately by gender: columns 1–3 pertain to men and columns 4–6 to women.[38]

[38] Appendix Table B4 presents the estimation results for the pooled sample.

Table 6. IV estimates for margin-specific effects of vocational education.

	Male students			Female students		
	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)
	(1)	(2)	(3)	(4)	(5)	(6)
Net effect vocational education						
LATE_{V}	0.022	-851	-1,155	0.017	20	-313
	(0.032)	(1,125)	(1,103)	(0.031)	(842)	(857)
Academic education margin						
Complier share	*0.80*	*0.80*	*0.80*	*0.90*	*0.90*	*0.90*
	(0.03)	*(0.03)*	*(0.03)*	*(0.02)*	*(0.02)*	*(0.02)*
$\text{LATE}_{V\text{-}A}$	0.014	-2,267**	-2,952***	0.014	-419	-1,171*
	(0.021)	(868)	(853)	(0.020)	(679)	(686)
No post-16 education margin						
Complier share	*0.20*	*0.20*	*0.20*	*0.10*	*0.10*	*0.10*
	(0.03)	*(0.03)*	*(0.03)*	*(0.02)*	*(0.02)*	*(0.02)*
$\text{LATE}_{V\text{-}N}$	0.057	4,958	6,158	0.042	3,796	7,737
	(0.149)	(5,028)	(4,653)	(0.288)	(6,762)	(7,787)
Test of $\text{LATE}_{V\text{-}A} = \text{LATE}_{V\text{-}A}$	$p = 0.77$	$p = 0.16$	$p = 0.06$	$p = 0.92$	$p = 0.49$	$p = 0.20$
N students	315,217	315,217	268,222	303,606	303,606	232,565
N clusters	55,888	55,888	54,003	55,079	55,079	52,179

Notes: The table reports IV estimates of the net complier treatment effects of vocational education on the three indicated labour market outcomes (top panel), as well as its decomposition into the two margin-specific effects of vocational *vs.* academic education and vocational *vs.* no post-16 education, alongside the estimated complier share at each margin (bottom panels). The details of the estimation are explained in the text. Results are based on the estimation sample of respectively male students (columns 1–3) and female students (columns 4–6) from schools without sixth form. Standard errors are block bootstrapped at the LSOA×cohort level using 999 iterations. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Net effect.—The upper panel reports estimates for the net effect of vocational education, LATE_{V}, which pools the treatment effects for vocational-academic compliers and vocational-no education compliers into one weighted average. Not a single net effect estimate is statistically significant at conventional levels. Taken at face value, the point estimates suggest small positive effects on employment, moderate negative effects on earnings for men and null effects for women, though the level of imprecision is such that we cannot rule out large negative or even moderately positive effects for either gender. To move beyond these inconclusive results, the remainder of the table decomposes the net effects into their constituent margin-specific components, $\text{LATE}_{V\text{-}A}$ and $\text{LATE}_{V\text{-}N}$, as outlined in the previous section.

Academic education margin.—We first turn our attention to the vocational-academic education margin, where the vast majority of marginal vocational education students appear to be found: the complier shares in the second row of the table indicate that for 80% of male compliers and 90% of female compliers the alternative to the vocational track is academic education and not direct labour market entry. For these students, we find (near) zero effects of choosing vocational education on sustained employment for both men (column 1) and women (column 4). For men, we find that enrolment in vocational education reduces earnings: in the full sample, we estimate a highly significant effect of -£2,270, corresponding to a 9% reduction in annual earnings (column 2). The estimate is precise enough to rule out small negative effects. Restricting the sample to individuals with positive earnings to approximate those unequivocally part of the labour force, the negative effect grows to -£2,950 (column 3) corresponding to a reduction of 11%.[39] For women, the effect on earnings appears to be less pronounced: in column 4 we find a small and insignificant effect of vocational enrolment on earnings in the full sample. However, once we restrict the sample to women with positive earnings to capture those who partake in the labour market, we find a negative earnings effect of £1,170 that is significant at the 10% level. This corresponds to a 6% reduction in annual earnings.

No post-16 education margin.—The bottom panel of Table 6 reports results for the vocational-no education margin, i.e., for compliers whose alternative to vocational enrolment is no further education. As discussed above, students' decision to leave the education system at age 16 is much less responsive to vocational college proximity than the other two alternatives. Only 20% of male compliers and 10% of female compliers are to be found at this margin. The weaker first stages for no post-16 education, together with the fact that the expression for $\text{LATE}_{V\text{-}N}$ involves four different coefficient ratios, amount to rather imprecise results. The point estimates hint at large positive effects of vocational *vs.* no post-16 education on employment and earnings for both males and females. However, we are unable to confidently rule out null or even negative effects. In the remainder of the paper, we therefore concentrate on results for the more relevant academic education margin, referring the interested reader to the appendix for some complementary results for the no post-16 margin.

Discussion.—The results in Table 6 carry a number of important insights. First, the vast majority of students whose choice to enrol in vocational education is responsive to incentives like distance, is choosing between vocational and academic education, not considering the option of no post-16 education. This suggests that policies that seek to increase vocational enrolment by increasing the attractiveness of vocational colleges, might do so mainly at the expense of academic enrolment. It follows that understanding the alternative-specific return of vocational *vs.* academic education is of paramount importance for policy. Second, for these vocational-academic compliers, vocational education has no discernible effect on labour market attachment at ages 29–30, but large negative effects on earnings, especially so for men. Third, given the absence of extensive margin effects, negative earnings impacts must be due to wages or intensive margin responses (i.e., working hours). However, given that in England full-time employment is by far the most common working arrangement among males, differences in working hours are unlikely to be an important driver

[39] Note that, given the absence of extensive margin effects, conditioning on positive earnings should not bias the estimates.

of these results.[40] This suggests that choosing vocational over academic education at age 16 substantially lowers students' wages 14 years later.

Fourth, the results reveal striking heterogeneity in the returns to vocational education: for male students at the margin with academic education, vocational enrolment unequivocally leads to a large reduction in earnings, whereas for those at the margin with no post-16 education, if anything, it appears to increase earnings. Among male students with positive earnings, despite the imprecision surrounding the estimates at the no post-16 education margin, we can confidently rule out returns at the two margins are equivalent (as shown by the p-value at the bottom of the table). While less pronounced, the same pattern is visible for female students. The fact that the net effect is composed of two apparently divergent alternative-specific effects highlights the importance of margin-specific identification in this context. The conventional single-instrument IV estimate is contaminated by large but very imprecise (unidentified) point estimates for a small group of compliers at the no post-16 education margin. This shrouds negative effects for most compliers, thus nurturing an ambiguous and more positive impression of vocational education in England than warranted. Incidentally, the fact that the two alternative-specific LATEs diverge also implies that a conventional two-instrument IV would be no remedy. We illustrate this in Appendix Table B5 by showing effect estimates obtained from a 2SLS regression that instruments D_A and D_N with Z_V and Z_A and decomposing those into their constituent effect and bias terms.

4.2 Sensitivity Checks

This subsection presents a number of sensitivity checks probing the robustness of the main results.

Different sample restrictions.—First, we illustrate the robustness of the results to different sample restrictions. Columns 1–3 in Appendix Table B6 keep all students from secondary schools without a sixth form, including all students not found in the earnings data, regardless of missing KS2 scores or SEN status, as well as the 3% most remote students. Columns 4–6 take the opposite approach and exclude all 6% of students who are never observed in the earnings data. None of these changes to the sample definition alter our main conclusions: for men, the share of compliers at the *V-A* margin remains unchanged and, if anything, the negative earnings effect is stronger. For women, the share of compliers at that margin becomes slightly higher and the effect on earnings conditional on being in the labour market is only slightly smaller.

Including Full Level 2.—Second, in columns 7–9 of Appendix Table B6 we show results when including the Full Level 2 indicator in the control set. Again, this barely affects the effect estimates at the *V-A* margin and leaves our overall conclusions unchanged. While perhaps unsurprising given the results shown in Tables 3 and 4, this result is encouraging because it confirms that our results

[40] Additionally, from a theoretical viewpoint, we expect education choices to affect the level and type of skills students acquire, and hence the type of job or occupation they can perform or how productively they can perform it. It is less clear how education choices would affect the intensive margin (or in which direction).

do not hinge on conditioning on GCSE performance. Hence, we can confidently leave out the Full Level 2 indicator in order to assess and correct for complier differences (see below).

Different distance instruments.—Third, in columns 10–12 of Appendix Table B6 we show estimates based on instruments defined in terms of driving distance between students' homes and the closest education providers rather than using geographical distance.[41] This slightly decreases the magnitude of the negative earnings effects at the *V-A* margin but without affecting our qualitative conclusions.[42]

Adjusting for complier differences.—Finally, we address concerns about potential violations of A3, which requires compliers shifted from academic to vocational education by a decrease in distance to vocational college (i.e., Z_V-compliers) to have the same mean vocational education PO than those shifted by a marginal increase in distance to academic college (i.e., Z_A-compliers). When assessing this assumption in Table 5, we found significant differences in Full Level 2 achievement between the two complier types among females. These mapped into non-negligible differences in predicted earnings, suggesting their potential outcomes may not be perfectly comparable. This section gauges how these differences affect our effect estimates.

To do so, we repeat the exercise from Table 5 for all three labour market outcomes: for each outcome, we calculate the differences in mean outcomes between Z_V- and Z_A-compliers at the vocational-academic margin as predicted by their underlying differences in achievement of Full Level 2. Then, we adjust the Z_A-compliers-based vocational education PO estimate by this difference and recalculate LATE$_{V\text{-}A}$ with the adjusted PO. Table 7 reports the results from this exercise.[43] The odd columns report the original PO estimates, which underlie the main results in Table 6. The even columns report the adjusted POs.

Unsurprisingly, the correction has no effect on the results for males in panel A, so that any conclusion we drew above remains unchanged. For example, we originally (i.e., using Z_A-compliers) estimated that, under vocational education, net annual earnings for male compliers are £21,513 (column 3). According to our procedure, taking into account differences in pre-determined characteristics and how they translate into outcome differences, this estimate should be upward-adjusted to better approximate the PO of Z_V-compliers, who are used to estimate the counterfactual academic education PO. Doing so yields an adjusted vocational education PO estimate of £21,549 which, in turn, yields an imperceptibly smaller LATE$_{V\text{-}A}$ of -£2,230 (column 4).

In contrast, the results for females in panel B are markedly affected by the correction resulting

[41] Driving distances were obtained using the HERE Routing API to compute the shortest route between the population-weighted centroids of students' residential LSOAs and the coordinates of relevant educational institutions (link). See also Weber and Péclat (2017) on how to compute driving distance.

[42] We do not use driving distance in the main models because the first stages are slightly weaker than when using geographical distance. This is likely because the modes of transport typically used by 16–18-year-old students especially in (semi-)urban areas are rail-based public transport or bicycles, which are less well approximated by driving distance.

[43] Appendix Table B7 repeats the exercise for the no post-16 education margin. Note that the net effect LATE$_V$ is unaffected by this because adjustments at the two margins mechanically offset each other.

Table 7. Correcting IV estimates at the academic educ. margin for complier differences.

Dependent variable:	Sustained employment		Annual earnings (incl. 0s)		Annual earnings (excl. 0s)	
	Raw IV (1)	Corrected (2)	Raw IV (3)	Corrected (4)	Raw IV (5)	Corrected (6)
A. Male students						
Vocational PO	0.837	0.838	21,513	21,549	23,993	24,058
	(0.009)	(0.010)	(328)	(371)	(325)	(358)
Academic PO	0.823		23,779		26,945	
	(0.018)		(807)		(808)	
$LATE_{V\text{-}A}$	0.014	0.015	-2,267**	-2,230***	-2,952***	-2,887***
	(0.021)	(0.021)	(868)	(857)	(853)	(840)
	p = 0.85		p = 0.85		p = 0.76	
B. Female students						
Vocational PO	0.746	0.730	15,877	15,156	19,334	18,775
	(0.009)	(0.010)	(225)	(272)	(227)	(285)
Academic PO	0.731		16,296		20,505	
	(0.017)		(628)		(652)	
$LATE_{V\text{-}A}$	0.014	-0.001	-419	-1,140*	-1,171*	-1,729***
	(0.020)	(0.020)	(679)	(647)	(686)	(671)
	p = 0.00		p = 0.00		p = 0.00	

Notes: For each of the three outcomes, the table shows vocational-academic complier potential outcome (PO) and $LATE_{V\text{-}A}$ estimates, as they were originally estimated (odd columns) and when corrected for complier differences (even columns), separately by gender. The vocational education PO is corrected by adding to the original estimate the predicted outcome difference between compliers induced by variation in distance to vocational college and compliers induced by distance to academic college. The corrected $LATE_{V\text{-}A}$ is obtained by subtracting the original academic PO from the corrected vocational PO. In square brackets we report p-values testing against the null hypothesis that the corrected and original $LATE_{V\text{-}A}$ estimates are identical. The number of observations is the same as in Table 6. Standard errors are block bootstrapped at the LSOA×cohort level using 999 iterations. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in a statistically significant difference (see bottom row). To better match the complier group used to estimate the academic POs, female students' vocational PO estimates are to be downward-adjusted across all three outcomes. This leaves the conclusion of a zero effect on employment unchanged, but yields larger negative estimates for earnings. In the full female sample, the effect of enrolling in vocational instead of academic education is now estimated to be -£1,140, significant at the 10% level (column 4). In the sample of women with positive earnings, the adjusted estimate now points to an even stronger earnings reduction of £1,730, significant at the 1% level (column 6). Accordingly, for females the original IV estimates of $LATE_{V\text{-}A}$ from Table 6 are upper bounds: the true earnings effects likely are more negative, closer to the effects for males. In the remainder of the paper we therefore use the adjusted estimates when referring to our main results and also adjust all our subsequent estimates accordingly.

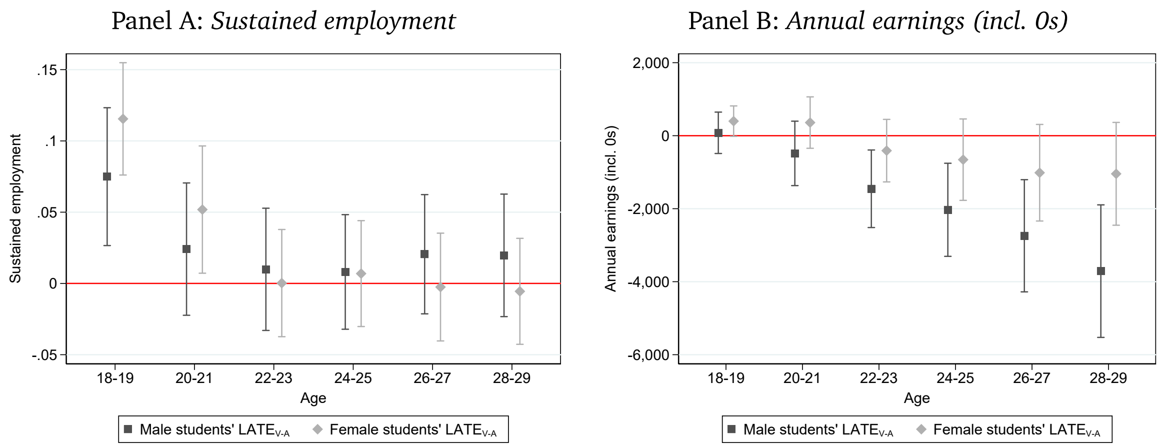


Figure 6. Age-effect profiles at the vocational-academic margin.

Notes: These figures plot estimates of the margin-specific effect of vocational *vs.* academic education, LATE$_{V\text{-}A}$, on sustained employment (panel A) and annual earnings (panel B) across different ages by gender. For each two-year age bin, we average annual earnings and sustained employment (if observed) over the two successive years. For comparability across the whole age range only earnings (and employment) from employed, but not from self-employed, work are included. The LATE$_{V\text{-}A}$ estimates are corrected for estimated differences in predicted outcomes between compliers groups as illustrated in 4.2. 95% confidence intervals are based on block bootstrapped standard errors at the LSOA×cohort level using 500 iterations.

4.3 Effects by Age

So far, we have focused on labour market outcomes averaged over ages 29–30. In Figure 6 we inspect effect dynamics over students' early careers, plotting the estimated effects of vocational *vs.* academic education on the probability of sustained employment (panel A) and net annual earnings (i.e., including observations with zero earnings) (panel B) across all two-year age bands from 18–19 to 28–29.[44] The figure reveals that vocational education confers an initial employment advantage: male and female vocational-track graduates are respectively 10 and 12 pp more likely to be in sustained employment at ages 18–19. This halves by ages 20–21 and essentially disappears by ages 22–23, after which the effect remains close to and statistically indistinguishable from zero (positive point estimates suggest that, if anything, vocational education continues to confer a small employment advantage). Correspondingly, vocational education also confers a small initial advantage in terms of net earnings. However, the earnings premium deteriorates close to linearly over the observed age range with point estimates for both genders turning negative by students' mid-twenties. The negative trend is more pronounced for men for whom the earnings penalty becomes statistically significant at age 22–23.

Initial employment and earnings advantages for the vocationally educated are in line with what theory predicts: the occupational skills acquired in the vocational track facilitate the school-

[44] We focus on earnings including zeros to keep the sample consistent across different ages. The outcomes exclude (earnings from) self-employment to ensure comparability across the age range, because those we only observe from 2014 onward. Comparison with the estimates from Table 7 suggests that this decreases the magnitude of the effect for women but increases it for men.

to-work transition, leading to earlier labour market entry and hence higher earnings early on. However, here these initial returns are extremely short-lived. Therefore, their erosion is unlikely to be driven by faster depreciation of specific human capital and lower labour market adaptability for the vocationally educated, as predicted by theory and found in other studies. Over the age range we observe, it is more plausible that students with academic education enter the labour market later but in higher-paying jobs with better wage progression. Note that the estimated effect dynamics make it likely that earnings differences continue to grow. Earlier obsolescence of occupation-specific skills will only add to these differences as students grow older. Consequently, we conceive of our effect estimates for ages 29–30 as a lower bound of how the earnings differential between vocational and academic education will develop as students' careers progress.

4.4 Effects across the Distance Grid

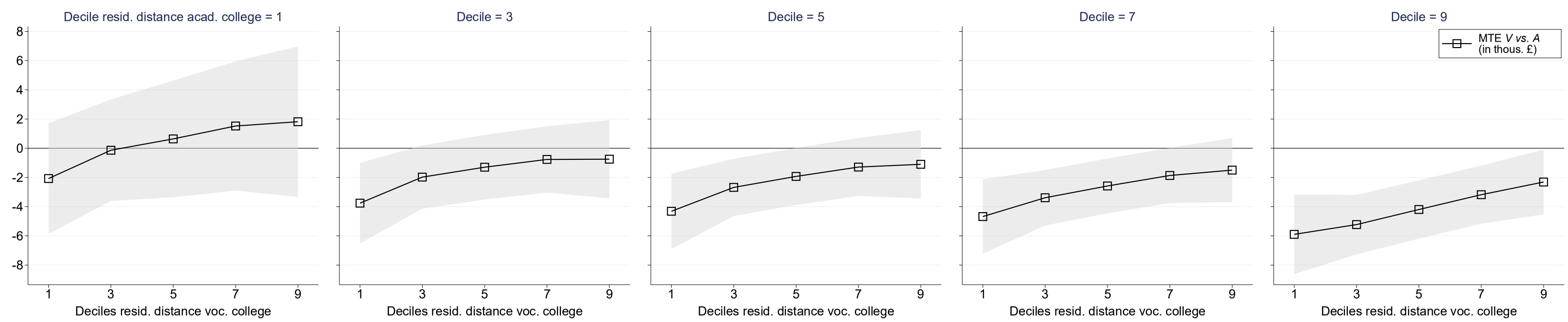
The results presented thus far are based on global regression models for the reduced form and first stage equations that restrict the effect of the distance instruments to be constant and linear (in logs). This implies that any heterogeneity in the effect of vocational education among compliers is muted. In this section, we relax the parametric restrictions and let the coefficients vary across different values of the distance instruments, (Z_A, Z_V), thus allowing us to study how the effect of vocational education varies for marginal students who live at different distances from their closest academic and vocational colleges. This is interesting because compliers living further away from a particular option (e.g., academic college) need to have higher underlying preferences for that option (i.e., academic education) for the higher costs of enrolling to be offset—otherwise they would not be marginal. Accordingly, local estimates at different distance points allow us to test whether preferences reflect individuals' comparative advantage for different types of education.

To do so, we estimate the reduced form and first stage equations (3)–(8) as local linear regressions across a two-dimensional grid defined by the first, third, fifth, seventh and ninth deciles of the residualised distances to academic and vocational college.[45] This yields 25 grid point-specific decompositions of net MTEs into their margin-specific constituents, analogous to the decomposition of LATE_V from above. We focus on the margin-specific effect of vocational *vs.* academic education (i.e., $\text{MTE}_{V\text{-}A}$) on net annual earnings (incl. 0s).

Figure 7 presents the results for male students. Each of the five diagrams in panel A of plots $\text{MTE}_{V\text{-}A}$ estimates across different distances to vocational college, holding distance to academic college fixed at the first, third, fifth, seventh and ninth decile, respectively. Consistent with students

[45] We residualise the distance instruments with respect to the control set $\boldsymbol{X}$ to ensure that evaluation points only differ in education choices' costs due to differences in distance but not due to compositional changes. Note that, to keep the dimensionality manageable, our estimates are local with respect to the two residualised distances only: we estimate locally weighted regressions, where all variables enter additively but with coefficients that are allowed to vary arbitrarily across different $(Z_V = z_V, Z_A = z_A)$ evaluation points. We weight observations by their distance to the evaluation point using a two-dimensional Epanechnikov kernel function with bandwidth set to two standard deviations of the respective residualised distance.

Panel A: *Marginal Treatment Effects*



Panel B: *Potential Earnings*

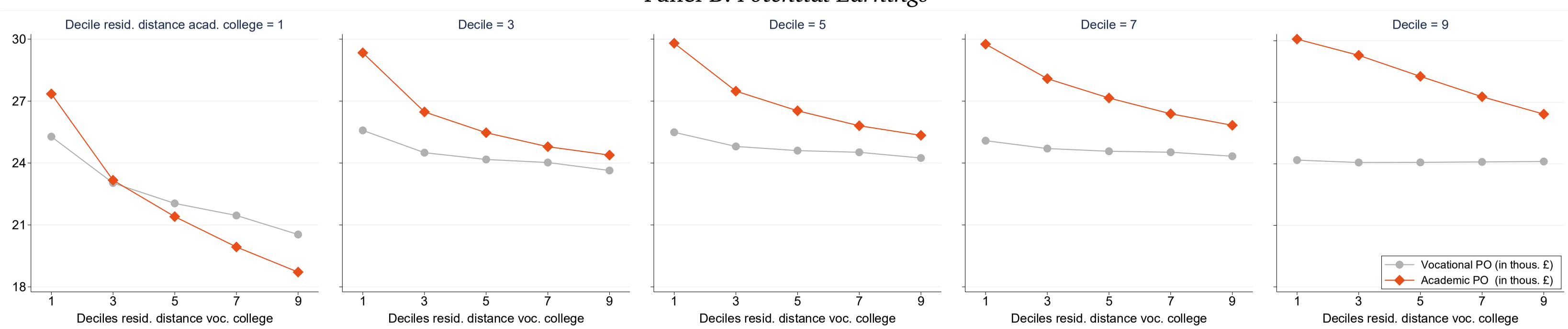


Figure 7. MTEs and earnings POs of vocational *vs.* academic education across the distance grid for male students.

Notes: This figure plots estimates for MTE$_{V\text{-}A}$ and associated average potential earnings for male students across 25 points of a two-dimensional grid defined by the two residualised distance instruments. The figure is constructed as follows: First, we residualise the two distance instruments, Z_V and Z_A, with respect to the control set, $\boldsymbol{X}$. Second, we define a 5-by-5 distance grid corresponding to the 1st, 3rd, 5th, 7th and 9th deciles of the two residualised distances. Third, we estimate a series of local linear reduced form and first stage regressions for each gridpoint, weighting observations by their distance to the grid point using a two-dimensional Epanechnikov kernel function with a bandwidth of two standard deviations in either dimension. Finally, we construct the MTE and PO estimates from the local regression coefficients analogously to the global main estimates above (see section 3.2.1). 90% confidence intervals are based on 500 block-bootstrap iterations clustering at the LSOA×cohort level.

selecting into tracks based on gains, we find that returns to vocational education increase with distance to vocational college and decrease with distance to academic college. To exemplify this, first consider the rightmost effect estimate in the leftmost diagram, i.e., deciles ($z_V^d = 9$, $z_A^d = 1$), pertaining to vocational-academic compliers who live closest to an academic college and furthest from a vocational college. Since they are willing to travel the longest distance to enrol in vocational education, these marginal students must have the strongest preferences for vocational education (or, equivalently, the strongest dislike for academic education). There is some tentative evidence these compliers may experience positive returns to vocational education (of a magnitude of around £2,000 although imprecisely estimated). Staying within the same diagram, returns decrease as distance to vocational college becomes smaller, i.e., as we consider compliers with a weaker underlying preference for vocational education. Next, consider the opposite grid point, i.e., the leftmost effect estimate in the rightmost diagram, corresponding to deciles ($z_V^d = 1$, $z_A^d = 9$). This effect pertains to vocational-academic compliers with the strongest preferences for academic education, given that they would travel the furthest to enrol in academic college. These students experience large negative returns to vocational education of around -£6,000. Again, if within the same diagram, we consider larger distances to vocational college, the estimated returns become less negative.

To better understand the source of students' selection on gains, in panel B we plot the PO estimates that underlie the effect estimates in panel A. Interestingly, the results show that the heterogeneity in $\text{MTE}_{V\text{-}A}$ is primarily driven by differences in gains from studying in the academic track: the academic education POs increase with students' preferences for academic education and decrease with preferences for vocational education. In contrast, the vocational education POs remain essentially flat across most points of the distance grid, with the exception of students living very close to an academic college (which are also by far the least precisely estimated).

The results for female students are displayed in Appendix Figure A5. Among female compliers, returns to vocational *vs.* academic education are more consistently negative. Their effects also decrease with distance to academic college, though we do not find systematic variation in returns with respect to distance to vocational college.

Overall, this analysis confirms that for most students at the vocational-academic margin returns to vocational education are negative. However, it also reveals substantial treatment effect heterogeneity that systematically relates to students' selection into treatments: especially for men, returns to vocational education are less negative, and even positive (though insignificant), for compliers with stronger preferences for vocational compared to academic education. Therefore, vocational education might not be detrimental for all students, but inframarginal students with the strongest relative preferences for the vocational track (i.e., vocational 'always-takers') might well benefit from it. Nevertheless, we note that, since returns appear to flatten at the highest levels of vocational preferences, it is unlikely that they become much higher than what is observed here even for always-takers. Finally, the analysis of the POs reveals that students' preferences for the two tracks reflect how well they would do after attending the academic track but are unrelated to how they would fare after attending the vocational track. The fact that students do not seem to understand their comparative advantage with respect to vocational education points to a lack of information, potentially reflecting problems of the vocational track that have been noted in previous research, such as the absence of a structured curriculum and a lack of effective career guidance (Wolf, 2011).

5 Understanding $\text{LATE}_{\text{V-A}}$

5.1 Characterising Compliers

Our IV estimates pertain to marginal vocational education students who would have made a different post-16 education choice had they lived at closer or further from a vocational college. We found that the vast majority of these students are choosing between vocational and academic education and subsequently focused on effects of vocational education for this group, i.e., on $\text{LATE}_{V\text{-}A}$. To better understand how representative the LATE is for effects in the wider population, this section characterises the group of compliers along several dimensions.

We first assess the size of the complier population. Dahl *et al.* (2014) show that it can be estimated by comparing treatment take-up at the instrument's extreme values: the share of students who choose D_V at maximum distance to vocational college equals the share of always-takers, while the share of students who do not choose D_V at minimum distance to vocational college equals the share of never-takers. The rest are compliers would have chosen a different post-16 education at at least some point of the distance distribution. We estimate the share of always-takers as the mean of D_V at the 99^{th} percentile of the residualised Z_V distribution and the share of never-takers as the mean of $(1 - D_V)$ at the 1^{st} percentile. The share of vocational always-takers is 50% for males and 48% for females and the share of never-takers is 39% for both genders. Accordingly, compliers make up about 11% and 13% of our estimation samples for males and females respectively. Of these, 80% and 90% are at the vocational-academic education margin, respectively.

Next, we characterise vocational-academic compliers by observables. Figure 8 plots estimates for *V-A*-compliers' mean predetermined characteristics along with means for all vocational- and academic-track students (separately for females and males).[46] Marginal students are more likely to be White British and, on average, of higher socio-economic status than both vocational- and academic-track students, as indicated by a lower prevalence of FSM eligibility and higher average neighbourhood income. In terms of previous achievement, the average marginal student lies in

[46] Remember that *V-A*-compliers' average value in some scalar predetermined characteristic, C, can be estimated the same way we estimate the academic education PO for vocational-academic compliers (from equations (5) and (6)) after replacing YD_A with CD_A in equation (5).

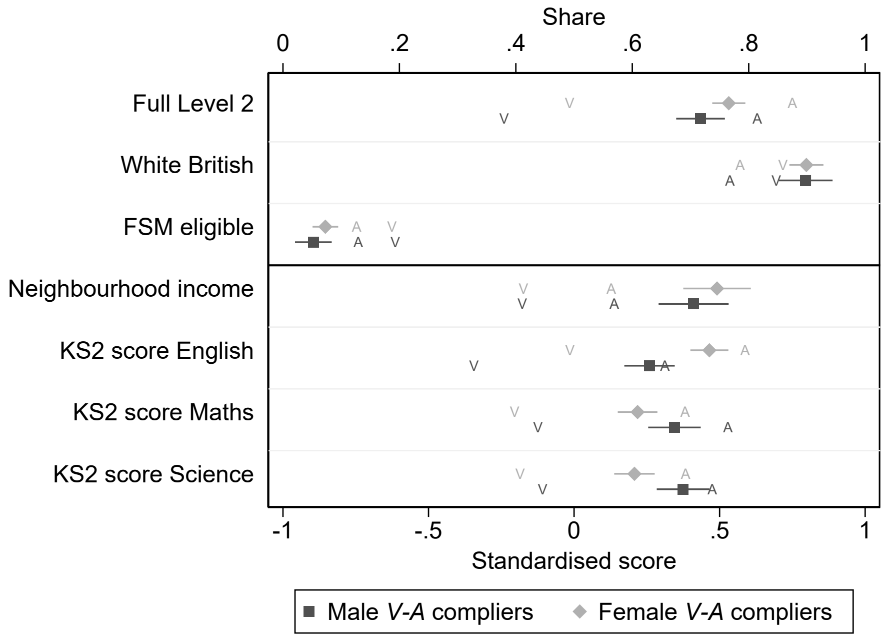


Figure 8. Complier characteristics.

Notes: The figure shows estimated mean characteristics of vocational-academic compliers with associated 95% CIs, alongside the sample means for the vocational (V) and academic (A) treatment groups, separately by gender. The figure is based on the estimation sample of students from schools without sixth form. Characteristics plotted in the lower part of the panel are standardised within the total student population. Neighbourhood income refers to the inverted index of neighbourhood income deprivation, so that higher values indicate less deprived neighbourhoods.

between typical students from the two tracks, though much closer to academic than vocational ones. This is true for their KS2 test scores in English, maths and science, as well as for their GCSE performance, as measured by achievement of Full Level 2. The latter is unsurprising because students who are considering academic upper-secondary education in Sixth Form Colleges need to meet the minimum GCSE requirements to be eligible for admission, which typically is Full Level 2, whereas many vocational students study courses at lower levels without strict entry requirements (i.e., Level 2 and 1 courses). Overall, the vocational-academic compliers for whom we estimate causal effects are academically apt students from socio-economically advantaged backgrounds, likely to do well in academic environments.

5.2 Comparison to OLS

From a policy perspective, returns for marginal students are important because their treatment choices are responsive to incentives—and thus likely also to a broad set of policies. While the previous section showed that this group represents a non-negligible portion of the population, it also showed that compliers are not representative of the average student. When stratifying effects along the distance grid, we found that within the subgroup of *V-A*-compliers there is heterogeneity

Table 8. Comparing OLS and IV estimates of the effect of vocational *vs.* academic education.

Dependent variable:	Sustained employment			Annual earnings (incl. 0s)		
Estimation method:	OLS (1)	rw-OLS (2)	IV (3)	OLS (4)	rw-OLS (5)	IV (6)
Effect for males	-0.030 (0.002)	-0.023 (0.002)	0.015 (0.021)	-1,885 (70)	-1,960 (94)	-2,230 (857)
Effect for females	-0.062 (0.002)	-0.057 (0.002)	-0.001 (0.020)	-3,792 (56)	-3,878 (70)	-1,140 (647)

Notes: The table reports estimates of the effect of vocational *vs.* academic education on employment and earnings by gender from three different models: Columns 1 and 4 report the effects as estimated with a conventional OLS regression (same estimates as in Table 2); columns 2 and 5 report the effects as estimated by an OLS regression where observations are reweighted to be comparable with *V-A*-compliers; finally, columns 3 and 6 report the corrected IV estimates of $\text{LATE}_{V\text{-}A}$ from Table 7. Standard errors, reported in parentheses, are clustered at the LSOA×cohort level.

in the return to vocational education. Accordingly, it would be premature to dismiss the efficacy of vocational *vs.* academic education for all students solely on the basis of the negative IV estimates for $\text{LATE}_{V\text{-}A}$.

OLS has potential for learning about returns in the broader population because, absent remaining unobserved confounders, it estimates alternative-specific ATEs. Accordingly, it is worthwhile to compare our plausibly causal but local IV estimates with the possibly biased but global OLS results from Table 2. If treatment effects were homogeneous, comparison of IV and OLS estimates would allow one to directly infer the severity of selection bias. However, if treatment effects are heterogeneous, like shown to be the case here, the estimates can differ even in the absence of selection bias, simply because the average causal effect among compliers differs from that among the overall population. Part of this heterogeneity may be associated with differences in observed characteristics and, indeed, the previous section revealed that *V-A*-compliers are of above-average academic ability and socio-economic status. To facilitate the comparison between OLS and IV, we therefore reweight the OLS sample to better resemble *V-A*-compliers following the procedure outlined in Bhuller *et al.* (2020): first, we split both gender-specific samples into 25 mutually exclusive and exhaustive subgroups based on quintiles of previous achievement and neighbourhood income. Next, we separately estimate the relevant first-stage equation (6) for each subgroup, allowing us to calculate its share of *V-A*-compliers. Finally, we reweight the sample so that the weight each subgroup receives in the OLS estimation corresponds to its proportion of compliers.

Table 8 compares regular controlled OLS estimates, OLS using the complier-reweighted sample ('rw-OLS') and our margin-specific IV estimates for the effect of vocational *vs.* academic education on employment and earnings, separately by gender. The results suggest that the differences between the IV and the OLS estimates cannot be accounted for by heterogeneity in effects, at least due to observables. The effect estimates from reweighted OLS are generally very close to those from regular OLS. The most striking differences between OLS and IV are to be found in terms of employment: OLS suggests that vocational education substantially reduces students' probability to be in sustained employment, but IV shows that this is an artefact of selection as causal employment effects are null (or even positive). In terms of earnings, the selection patterns differ by gender: for females, OLS substantially overestimates the earnings penalty, while for males, if anything, OLS underestimates it. This suggests that self-selection into the vocational track is more negative for females.

5.3 Mechanisms: Educational Attainment and Progression

While standard human capital (and signalling) models would predict that vocational education is an improvement over no upper-secondary education—a prediction consistent with the large (though imprecise and insignificant) earnings premium we find at the vocational *vs.* no post-16 education margin—the relative merits of vocational *vs.* academic upper-secondary education are much less clear in theory. They crucially depend on the types of skills that students acquire in the respective educational tracks and on the opportunities for higher education they face afterwards. To get a better understanding of the mechanisms behind the earnings penalties from vocational education we find at this margin, in this section we investigate how vocational enrolment affects students' educational attainment and progression.

First, we study the types of courses *V-A*-compliers choose when enrolled in either institution type. Figure 9 plots the margin-specific vocational PO and academic PO estimates for the share of Level 3 courses and the share of academic courses of students' curriculum. For male compliers, academic education increases the share of Level 3 courses from 92% to 98%. For female compliers, a tiny increase from 83% to 85% is insignificant. Beyond the positive effect for males, these numbers show that vocational-academic compliers mainly study Level 3 courses *regardless of track choice*, highlighting their positive selection compared to the average vocational-track student (who studies only 43% of Level 3 courses; see Figure 3). Similarly, at approximately 60%, the share of academic courses is high even when these students attend a vocational college (the average for vocational-track students is 18%; see Figure 1). Nevertheless, academic enrolment substantially increases this share to almost 90% for males and to approximately 77% for females. The greater impact academic *vs.* vocational enrolment has on the curriculum of male students offers a potential explanation for the larger earnings penalty they experience from vocational education.

Second, we study how these education choices translate into upper-secondary attainment. We consider two outcomes: attainment of at least one qualification at Level 3 and of Full Level 3. The former is the expected educational level by age 18 and required for many jobs. The latter is crucial for entering higher education. The first two rows of Figure 10 plot complier PO estimates for these outcomes, next to the implied margin-specific treatment effect, $\text{LATE}_{V\text{-}A}$, separately for males and females. We find that males are about 4–5 pp more likely to achieve these outcomes if they enrol in the academic track whereas females are almost equally likely to achieve them in either track.

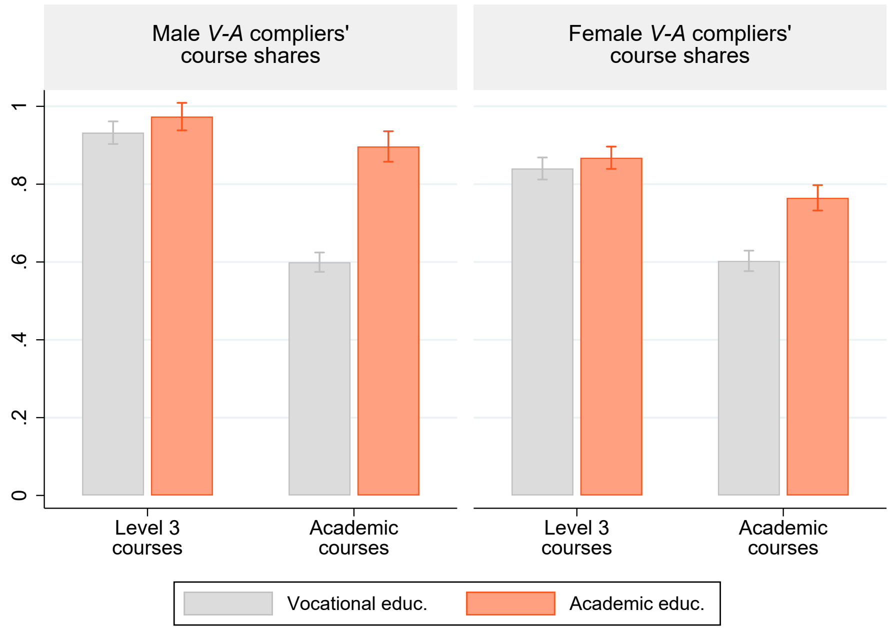


Figure 9. *V-A*-compliers' course enrolment potential outcomes.

Notes: This figure plots, separately by gender, the estimated mean academic and vocational education potential outcomes (POs) for the share of Level 3 courses and the share of academic courses for vocational-academic compliers. The shares are based on all courses (of more than one month) started by students within 24 months or their first studying spell and are weighted by the recorded number of teaching hours. Academic courses refer to A(AS)-level and GCSEs qualifications. The figure is based on the estimation sample of students from schools without sixth form, restricted to individuals with positive earnings at ages 29–30. The vocational education POs are corrected for differences in predicted outcomes between complier groups (as illustrated in 4.2). 90% CIs are based on block bootstrapped standard errors at the LSOA×cohort level using 999 iterations.

This confirms that male compliers' upper-secondary educational experience is more sensitive to track choices than that of females.

Finally, we study students' educational progression to post-secondary education. First, we consider apprenticeships which are commonly perceived as a positive outcome for vocational-track students and have been shown to yield substantial returns in the English labour market (Cavaglia *et al.*, 2020). Surprisingly, for neither gender we find strong evidence that vocational education increases take-up of apprenticeships. Second, we consider the canonical academic pathway of higher education (HE). For both genders, point estimates suggest that vocational education slightly reduces the probability to enrol in university, though these effects are not statistically significant. Still, for males we find a substantial (and significant) 5 pp (or 11%) reduction of the probability to complete an HE degree. Most strikingly, we find that vocational education almost halves students' probability to attend more selective ('pre-1992') universities, which have been shown to yield much higher earnings returns than less prestigious ('post-1992') universities (Britton *et al.*, 2020).

From this analysis a couple of conclusions follow. First, students at the vocational-academic margin attain relatively high levels of education even when attending the vocational track. Still,

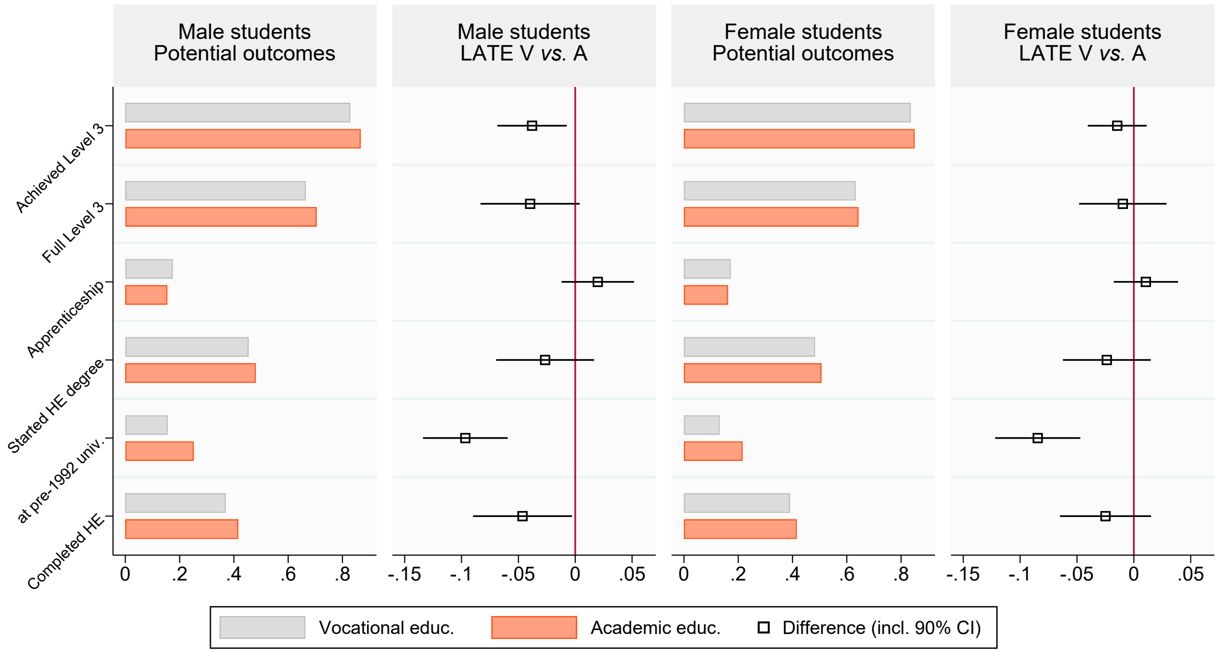


Figure 10. *V-A* effects and potential outcomes for educational attainment.

Notes: This figure plots estimates for vocational-academic compliers' mean potential outcomes (POs) and the associated LATEs$_{V\text{-}A}$ for a range of indicators of educational attainment, separately by gender. The figure is based on the estimation sample of students from schools without sixth form, restricted to individuals with positive earnings at age 29-30. The vocational education POs are corrected for differences in predicted outcomes between complier groups (as illustrated in 4.2). 90% CIs are based on block bootstrapped standard errors at the LSOA×cohort level using 999 iterations.

its effects on upper-secondary and tertiary attainment levels are negative, especially among male students. Some arguments for expanding access to VET assume that students at the margin between vocational and academic education do not end up in university anyway and would therefore benefit from a more occupation-specific curriculum. Our findings suggest that in England, where university participation has greatly expanded over the last 25 years, this argument is not particularly salient. The average marginal student is relatively apt academically and, while far from all marginal students who attend the academic track go on to complete university, more than 40% do—half of them even study in more selective pre-1992 universities. Notably, vocational education drastically decreases the probability of attending such a high-quality institution. Second, the English vocational track fails to channel its graduates into apprenticeships, potentially indicating a lack of involvement by employers. Third, corresponding to the earnings results, the negative educational consequences from vocational enrolment are more pronounced for males than for females. This is likely explained by the fact that their upper-secondary curriculum is more affected by track choice.

As a back-of-the-envelope calculation to quantify how these differences in educational attainment and progression could contribute to the negative earnings effect of vocational education, we perform partial Oaxaca-Blinder decomposition. In particular, we multiply the differences in

Table 9. Decomposition of *V-A* earnings effect by educational attainment.

Sample:	Male students	Female students
	(1)	(2)
Total earnings effect (LATE$_{V\text{-}A}$)	-2,887	-1,729
Predicted effect due to educational attainment	-530	-423
Share of total effect	0.18	0.24

Notes: The table reports, separately by gender, the IV estimate of the margin-specific effect of vocational *vs.* academic education, LATE$_{V\text{-}A}$, on annual earnings (excl. zeroes) from column 6 of Table 7, as well as the component of this effect that can be explained by differences in educational attainment (Level 3, Full Level 3, apprenticeship, pre-1992 university, HE degree). The latter is computed by first multiplying the IV-estimated margin-specific effect of vocational education on each education outcome with the earnings return associated with the education outcome and then summing all these indirect effects. The earnings returns are estimated from a controlled OLS regression of earnings on all education outcomes, reweighting the sample to resemble compliers like in Table 8. The final row reports the share of the total effect that can be explained by the indirect effect on education outcomes.

Level 3 attainment, Full Level 3 attainment, starting an apprenticeship, completing a university degree and doing so at a pre-1992 university from Figure 10 by the observational (gender-specific) earnings premiums associated with these outcomes. These we estimate using an OLS regression of earnings on the education outcomes (and the full control set), weighting by the complier weights from the previous section. Table 9 reports the results from this exercise. For both genders we find that, keeping their OLS-estimated, i.e., observational, returns constant, the estimated changes in educational attainment predict about one fifth in the earnings penalty from vocational education. Reduced educational attainment and progression alone cannot fully explain the earnings loss students at the vocational-academic margin suffer from vocational education, but it does contribute to these effects.

5.4 External Validity

In this section, we explore to what extent our results are informative of the returns to vocational education for the population of English students attending secondary school *with* sixth form who are excluded from the main analysis. Because these students can attend the academic track on their own secondary school, their post-16 education choice does not respond to distance to academic college and, hence, for them we cannot recover alternative-specific effects. Even so, their decision to enrol in the vocational track is affected by distance to vocational college, Z_V, because schools do not offer vocational courses. Accordingly, for them the *net* complier treatment effect of vocational education, LATE$_V$, is identified by the univariate IV that instruments vocational education, D_V, with Z_V. Identification of the share of compliers at the vocational-academic margin, λ, does not rely on Z_A either, so that it is identified in this sample, as well. Hence, to gauge to what extent our estimates for the margin-specific returns of vocational *vs.* academic education extrapolate to students from schools with sixth form, we compare estimated net returns and margin-specific complier shares between the two samples to at least infer plausible magnitudes for the margin-specific effect that

Table 10. Net effect of vocational education across secondary school samples.

	Male students			Female students		
	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)
	(1)	(2)	(3)	(4)	(5)	(6)
A. Students from schools without sixth form (main analysis sample)						
Sample share compliers (both margins)	0.11	0.11	0.12	0.13	0.13	0.14
Of those at *V-A* margin	0.80	0.80	0.80	0.90	0.90	0.90
Implied sample share *V-A*-compliers	0.09	0.09	0.10	0.12	0.12	0.12
Net effect vocational educ. (LATE_V)	0.022	-851	-1,155	0.017	20	-313
	(0.032)	(1,125)	(1,103)	(0.031)	(842)	(857)
B. Students from schools with sixth form (excluded from main analysis)						
Sample share compliers (both margins)	0.07	0.07	0.07	0.07	0.07	0.06
Of those at *V-A* margin	0.63	0.63	0.66	0.79	0.79	0.82
Implied sample share *V-A*-compliers	0.04	0.04	0.04	0.05	0.05	0.05
Net effect vocational educ. (LATE_V)	0.006	-3,897	-5,378	0.110	-1,418	-4,586
	(0.042)	(1,653)	(1,615)	(0.047)	(1,424)	(1,544)

Notes: This table compares the net effect of vocational education (LATE_V) and complier shares between the estimation sample containing only students from secondary schools without a sixth form (panel A) and students from secondary schools with a sixth form that are excluded from the main analysis (panel B). The first row of each panel reports the overall share of vocational education compliers in the sample; the second rows report the share of those at the vocational *vs.* academic margin (λ); the third rows report the implied proportion of *V-A* compliers in the sample obtained from multiplying the first two rows. Finally, the fourth rows report LATE_V estimated by a 2SLS regression that instruments the vocational treatment indicator D_V with Z_V (while controlling linearly for Z_A and the control set). Standard errors for LATE_V are reported in parentheses.

we cannot estimate directly.

Table 10 reports the results from this exercise: panel A refers to students from schools without sixth form (i.e., the main analysis sample) and panel B refers to students from schools with sixth form (i.e., those excluded from the main analysis). The first three rows in each panel quantify the size of the complier population: the first reports the overall share of vocational education compliers in the population, the second the complier share at the vocational-academic margin, λ, and the third reports the product of those two shares, i.e., the implied population share of *V-A*-compliers. There are substantially more marginal students in our analysis sample (11% and 13% of males and females, respectively) than in the excluded part of the population (7% of both genders). As expected, the majority of students whose post-16 education choice is responsive to changes in the attractiveness of the vocational track due to distance, attends schools without sixth form where the option of vocational education is more salient.

For sustained employment, the net treatment effect for male compliers is close to zero in both samples. For females, it is much larger for students in schools with sixth form than in our estimation sample. For earnings, in contrast, the net effect of vocational education is much more negative for (female and male) students from schools with sixth form, especially when conditioning on positive earnings. At the same time, the share of compliers at the vocational-academic margin, for whom we would expect a negative effect of vocational education given the previous results, is smaller in this part of the population. Because we deem it highly unlikely that the effect of vocational *vs.* no post-16 education is strongly negative for these students, this suggests that the negative earnings effect of vocational *vs.* academic education is even more pronounced for students from schools with sixth form. This is plausible because the quality of the academic track might be higher in secondary schools than in (academic) Sixth Form Colleges and students on those schools might be more academically apt. Accordingly, our main estimates are likely to be a lower bound for the average earnings penalty from vocational education for all marginal students in the English student population.

6 Discussion and Conclusions

In recent years, many countries have witnessed a renewed policy interest in expanding and improving vocational education to make education systems more inclusive and fit for changing economic needs. Internationally, systems with widespread firm-based vocational education provision, like Germany and Switzerland, are examples of the merits of vocational education. It is less clear how effective such policies would be in more market-oriented economies with weaker traditions of vocational education, like the UK and the US. Our paper contributes to this debate by delivering plausibly causal estimates of alternative-specific returns to vocational education in England.

Compelling evidence on returns to vocational education is scant because self-selection into vocational programmes is typically strong. An additional challenge to identifying policy-relevant effects is that in most settings students face more than one alternative to vocational education. Upon completing compulsory education at age 16, until recently students in England were indeed able to choose to enrol in an academic track, enrol in a vocational track or leave education. For identification, we exploit that the academic and the vocational tracks are linked to distinct post-16 institutions to construct two alternative-specific IVs based on students distance to the nearest respective provider. Thus equipped, we estimate the returns of vocational *vs.* academic education and of vocational *vs.* no post-16 education among compliers at the two respective margins of treatment, using an identification strategy proposed by Mountjoy (2022).

Our analysis shows that the vast majority of marginal vocational students are choosing between vocational and academic, not considering the option of no post-16 education. For these students, we find large negative effects of vocational education on earnings at ages 29–30, especially among males, and null effects on the probability of employment. Given that returns are negative from students' early twenties onwards, they are not due to faster depreciation of occupation-specific skills but likely due to students entering lower-wage jobs with weaker wage progression. Characterising the group of marginal vocational-academic students by observables reveals that they are on average higher achieving and from more advantaged backgrounds than typical vocational students, which might make them more likely to do well in academic environments. In line with this, these compliers achieve rather highly in either track. Still, especially among males, enrolling in the vocational track lowers upper-secondary and tertiary educational attainment. Strikingly, compliers of either gender are far less likely to progress to higher-quality universities from the vocational track. A decomposition exercise suggests that at least 20% of the negative earnings effect of vocational *vs.* academic education can be explained by worse education outcomes.

While we find that returns are negative for most students at the vocational-academic margin, we detect effect heterogeneity that is consistent with comparative advantage: marginal students living further away from vocational colleges (who must have higher unobserved preferences for the vocational track) exhibit more modest negative returns. For males, we even find suggestive evidence of positive returns to vocational *vs.* academic education among compliers with the lowest relative preferences for the vocational track, suggesting that it may well be beneficial for a large share of inframarginal vocational students. Interestingly, this comparative advantage is solely rooted in students' understanding of their labour market performance after attending the academic track: while we find a correspondence between students' preferences and their academic potential outcomes, no such correspondence exists with respect to vocational ones which are seemingly more difficult to anticipate.

Our findings at the margin between vocational and no post-16 education are less conclusive. This is the result of the involved nature of the identification procedure and the small proportion of marginal students at this margin (particularly among females), which also make the results less relevant from a policy perspective. Nevertheless, the point estimates at least suggest that students who enrol in vocational education as opposed to dropping out of education benefit, with significant results for marginal male students with highest unobserved preferences for vocational education. Perhaps more importantly, the fact that the two alternative-specific returns diverge, limits the value of a conventional IV strategy which only identifies the *net* effect of vocational education (a weighted average of the two margin-specific effects). We show that this yields a smaller and insignificant estimate of the returns to vocational education, thus shrouding the large negative effects for the majority of marginal students and nurturing an ambiguous and more positive impression of vocational education in England than warranted.

Overall, these results stand in marked contrast with other recent quasi-experimental studies. Also focusing on returns to vocational *vs.* academic education, these papers tend to find either positive or at least non-negative effects for average marginal students at comparable ages. However, with the exception of Brunner *et al.* (2021) who study a small number of selective and particularly well-resourced vocational schools in Connecticut, these studies focus on Nordic countries characterised by very different education and labour market institutions than those in the UK (Bertrand *et al.*, 2021; Birkelund and van de Werfhorst, 2022; Silliman and Virtanen, 2022). In these settings, upper-secondary vocational education is better integrated with firm-based training (the predominant learning mode in Denmark) and offers more equal pathways into tertiary education. For example, Silliman and Virtanen (2022) find that, unlike in England, the Finnish vocational track does not impair progression to university.

Accordingly, our results might be due to problems specific to the English vocational track. Those include an extremely wide course offer with (too) many narrow qualifications, hard to navigate for students and without clear recognition among employers, the absence of good career guidance and a lack of clear progression routes into higher (vocational) education and work-based learning opportunities, such as apprenticeships (Musset and Field, 2013; Wolf, 2011). All these factors have also contributed towards deep-rooted negative perceptions about vocational education in England, so that, graduation from a vocational college might also be read as a negative signal by employers (Wolf, 2011). Yet, signalling cannot explain the pattern of effect heterogeneity we uncover and so it is unlikely to be the primary mechanism at play.

Nevertheless, it is also likely that labour markets in countries like England and the US are less favourable for vocational education, more generally. Through learning different types of skills, vocational graduates are likely to enter different occupations. For example, Birkelund and van de Werfhorst (2022) find that the Danish vocational track channels students into occupations with lower prestige compared to the academic track. However, in Denmark this does not translate to differences in earnings. The authors attribute this to strong trade unions and widespread collective wage agreements, which compress wage differentials between occupations. For a comparison, collective bargaining coverage in the UK in 2015 stood at 28% compared to 83% and 89% in Denmark and Finland respectively, with figures for trade union density similarly far apart.[47] Accordingly, one interpretation of our results is that in less egalitarian countries with high levels of wage dispersion across occupations and firms, occupational sorting resulting from curricular tracking into vocational and academic programmes can more easily translate into substantial earnings penalties later on—especially, if exacerbated by differences in educational quality.

In terms of education policy, our findings dissuade from an expansion of vocational education in England in its current form, as this would primarily divert students from the academic track and associated higher earnings. Instead, policymakers first need to reform the vocational track to tackle the problems mentioned above, i.e., consolidating the curriculum into fewer well-defined programmes, strengthening the emphasis and availability of apprenticeships and establishing clearer pathways into (good) universities or other post-secondary institutions. Encouragingly, recent reforms by the British government seem to go in this direction—although it it is premature

[47] Source: OECD Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, available at https://stats.oecd.org/Index.aspx?DataSetCode=CBC.

to say whether they will improve the system. In the face of grave regional inequality in the UK and elsewhere, public debate has focused on the need for place-based policy interventions. Our findings point to academic 'cold-spots' where marginal students would benefit a lot from increased post-16 academic provision—for these students with strongest preferences for academic education the earnings gain from switching from the vocational to the academic track likely exceeds any improvement in vocational returns.

Such a mix of policies would likely improve student sorting across tracks and improve labour market prospects of those enrolled in vocational education. Yet, whether vocational education really has the potential to bring about sweeping improvements with respect to labour market inequality and workforce productivity in the UK (and US) remains unclear. For a large part this will depend on the exact skills students acquire in different educational tracks and how productively these can be put to use across the occupations and industries students work in afterwards. Hence, unravelling these mechanisms is a fruitful avenue for future research.

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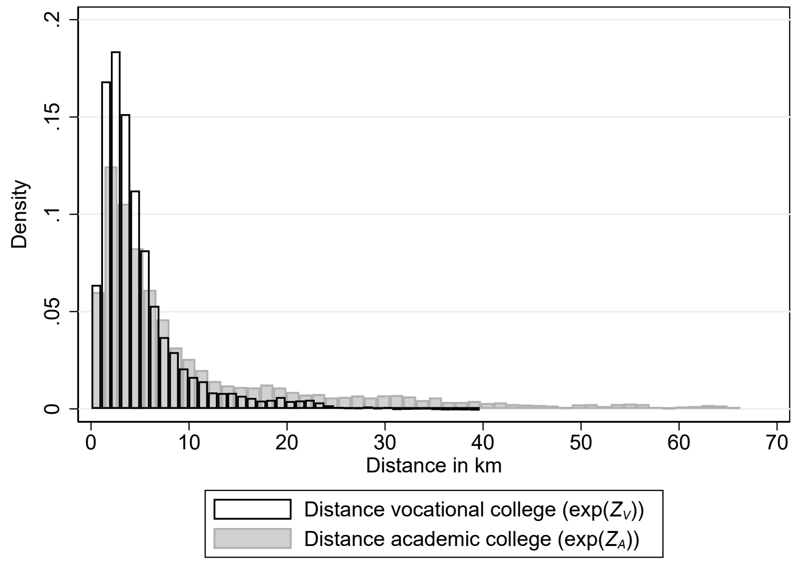
Appendix for Online Publication

A Additional Figures

Figure A1. Locations of vocational and academic colleges.

Notes: This map shows the location of Sixth Form (academic) colleges and Further Education (vocational) colleges in England.

Panel A: *Distances in levels*



Panel B: *Distances in logs*

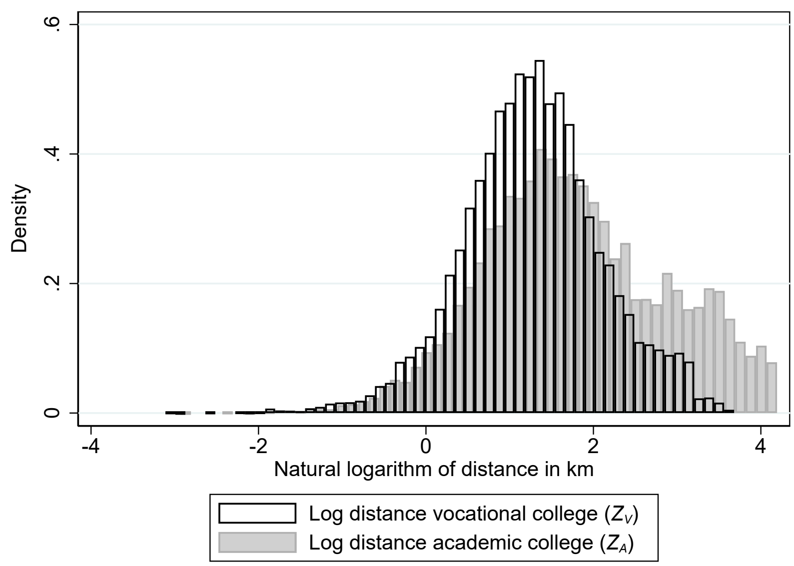


Figure A2. Distributions of the distance instruments in levels and logs.

Notes: This figure plots histograms of the distribution of students' distance (in km) to their closest vocational and academic college in levels (Panel A) and natural logarithms (Panel B).

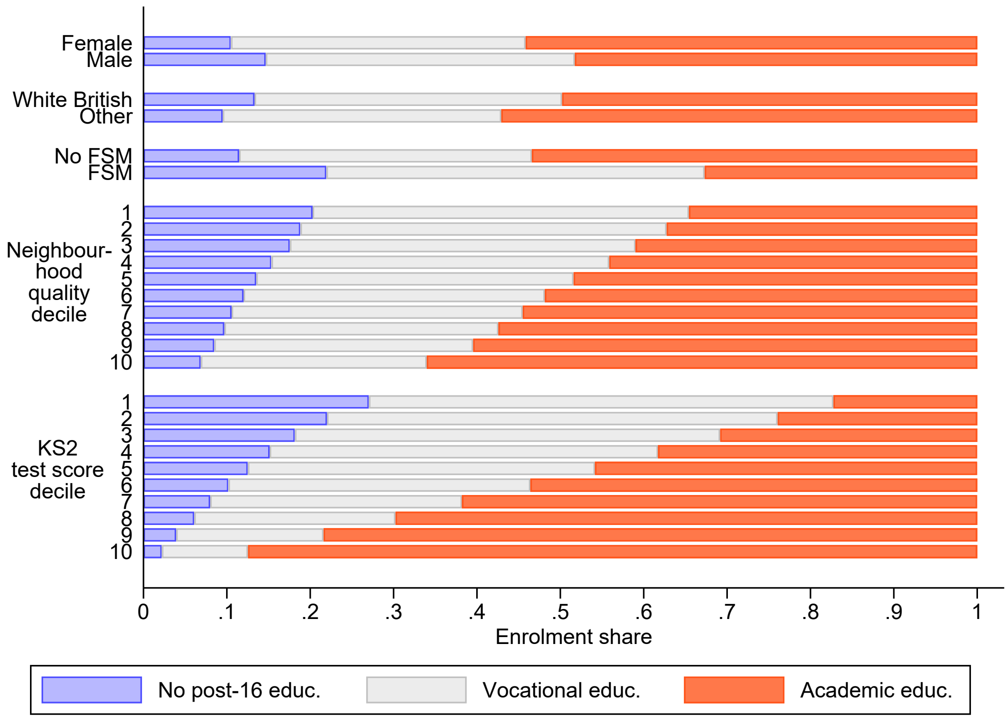
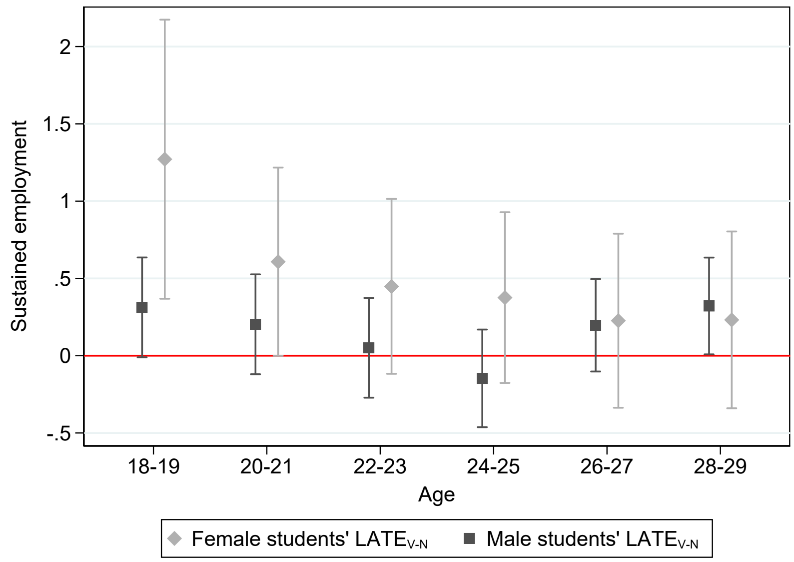


Figure A3. Track choices by observable characteristics among students from schools with sixth form.

Notes: This figure shows the distribution of students over treatments by observable characteristics. The figure is based on students from schools with sixth form (i.e., those excluded from the estimation sample). FSM stands for free school meal eligibility. Neighbourhood quality deciles are deciles of the first principal component (PC) of all seven (inverted) IoDs. KS2 test score deciles are deciles of the first PC of all three end-of-primary-school (KS2) test scores. PCs are extracted (and their deciles calculated) in the full sample, so that the deciles refer to the same categories in the estimation sample as for students from schools with sixth form (see Figure 2.)

Panel A: *Sustained employment*



Panel B: *Annual earnings (incl. 0s)*

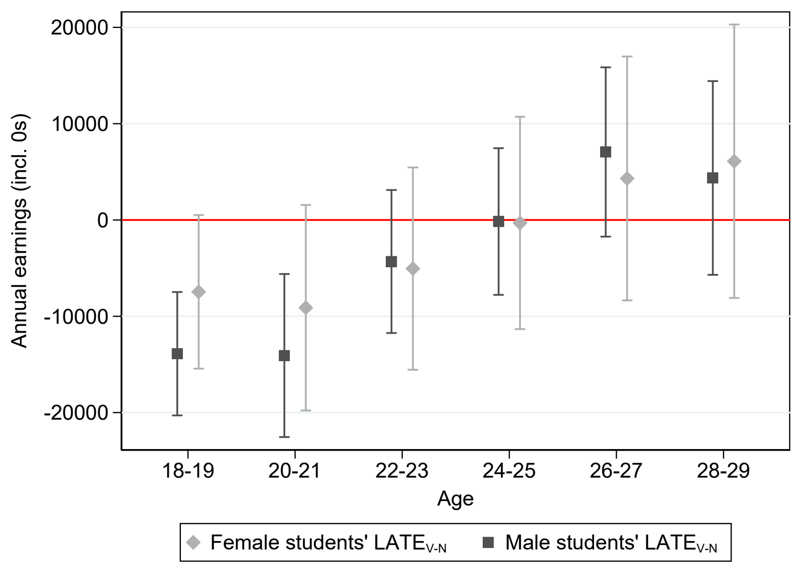
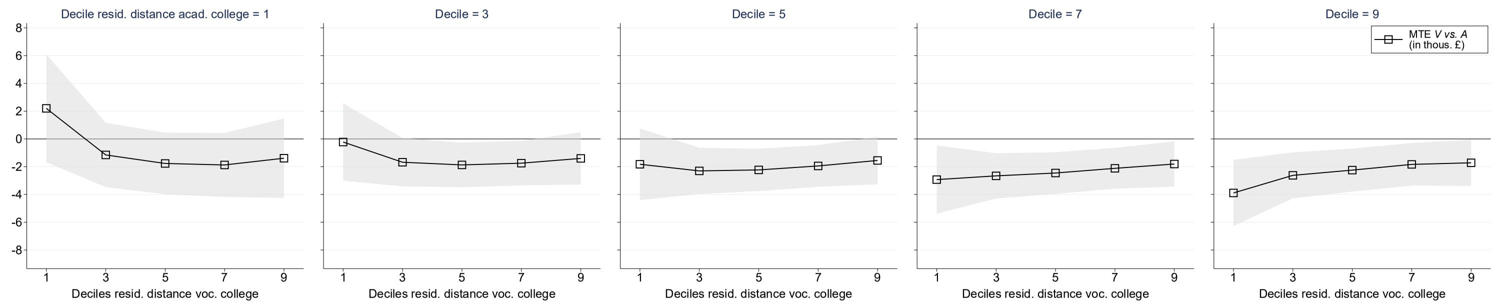


Figure A4. Age-effect profiles at the vocational-no post-16 education margin.

Notes: This set of figures plot the estimates of LATEs of vocational *vs.* no post-16 education on sustained employment (Panel A) and annual earnings (Panel B) and the associated 95% CIs at different age points by gender. For increased precision and computational ease we combine outcomes from two successive age points; we do so by taking the average of annual earnings (if observed) between two successive years and the average of whether students were in sustained employment. For comparability across the whole age range only earnings (and employment) from employed, but not from self-employed, work are included. LATE$_{V\text{-}N}$ estimates are corrected for estimated differences in predicted outcomes across compliers groups as illustrated in section 4.2. Confidence intervals are based on block bootstrapped standard errors at the LSOA×cohort level using 500 iterations.

Panel A: Marginal Treatment Effects



Panel B: Potential Earnings

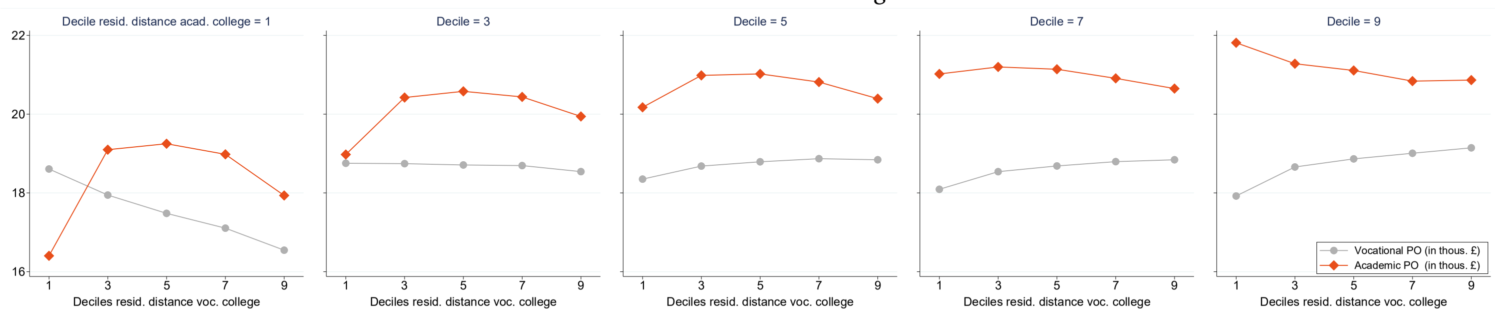


Figure A5. MTEs and earnings POs of vocational *vs.* academic education across the distance grid for female students.

Notes: This figure plots the $MTE_{V\text{-}A}$ and average potential earnings for female students estimated at different locations of the two-dimensional grid defined by the two residualised distance instruments. We first residualise the two distance instruments Z_V and Z_A with respect to the control set. Then, we define a 5-by-5 distance grid corresponding to the 1st, 3rd, 5th, 7th and 9th deciles of the two residualised distances. Finally, we estimate a series of local linear reduced form and first stage regressions for each gridpoint, weighting observations by their distance to the grid point using a two-dimensional Epanechnikov kernel function with a bandwidth of two standard deviations in either dimension. The MTE and average potential earnings estimates are constructed from the local regression coefficients analogously to the main estimation. 90% confidence intervals are based on 500 block-bootstrap iterations clustering at the LSOA×cohort level.

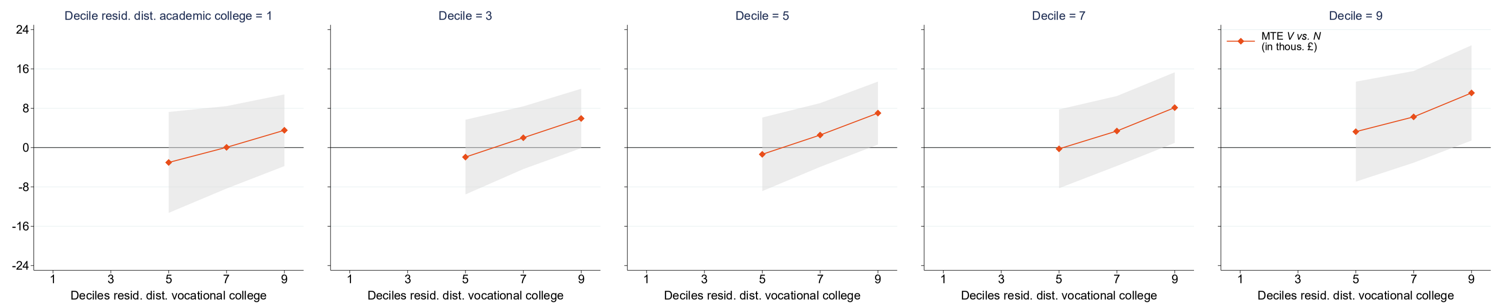
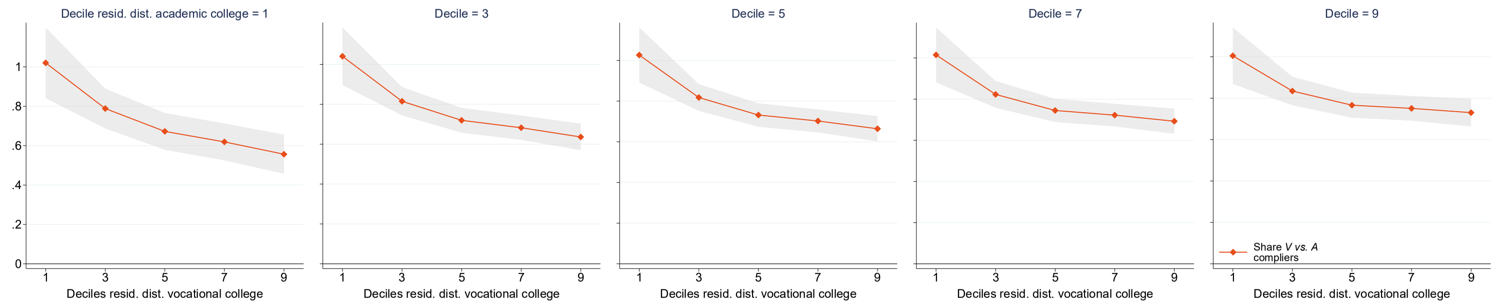


Figure A6. MTEs of vocational *vs.* no post-16 education on earnings across the distance grid for males.

Notes: This figure plots, only for males, the $\text{MTE}_{V\text{-}N}$ estimated at different locations of the two-dimensional grid defined by the two residualised distance instruments. We first residualise the two distance instruments Z_V and Z_A with respect to the control set. Then, we define a 5-by-5 distance grid corresponding to the 1st, 3rd, 5th, 7th and 9th deciles of the two residualised distances. Finally, we estimate a series of local linear reduced form and first stage regressions for each gridpoint, weighting observations by their distance to the grid point using a two-dimensional Epanechnikov kernel function with a bandwidth of two standard deviations in either dimension. The MTE estimates are constructed from the local regression coefficients analogously to the main estimation. 90% confidence intervals are based on 500 block-bootstrap iterations clustering at the LSOA×cohort level. To improve the visualisation of the estimates at the gridpoints when they are more relevant, we choose to consistently omit estimates at the 1st and 3rd deciles of residualised Z_V: at close distance to vocational college, students at the *V-N* margin are not responsive to changes in distance as shown by a too weak first stage resulting in inflated estimates and CIs. The implication is that estimates of $\text{MTE}_{V\text{-}N}$ for students leaving close to vocational colleges are not as relevant since the proportion of compliers at the *V-N* margin is particularly low as shown by A7. Results for females are not reported for similar reasons: in line with the global specification, first stages are too weak across all gridpoints so that ensuing estimates cannot be meaningfully interpreted or visualised. They remain available on request.

(A) *Panel A: Male students*



(B) *Panel B: Female students*

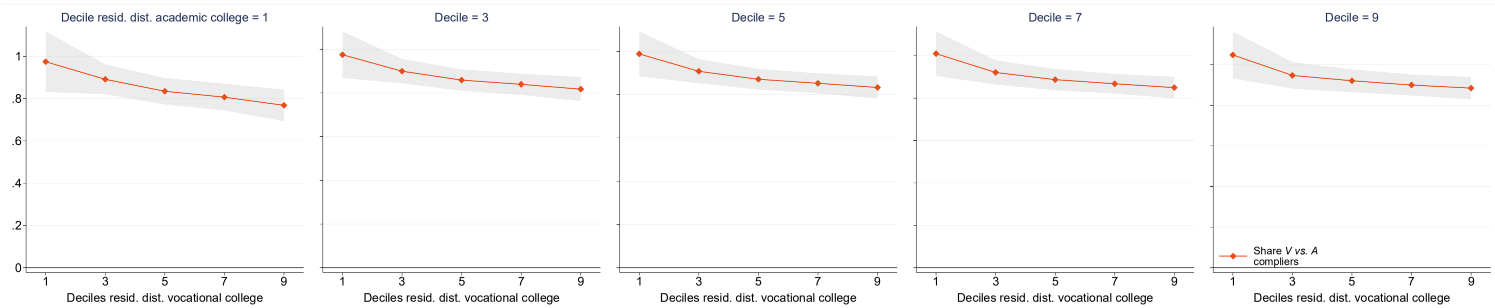


Figure A7. Compliers shares across the distance grid.

Notes: This figure plots the share of *V-A*-compliers estimated at different locations of the two-dimensional grid defined by the two residualised distance instruments. The share estimates are constructed from the local regression coefficients analogously to the main estimation. See the notes from Figure 7. 90% confidence intervals are based on 500 block-bootstrap iterations clustering at the LSOA×cohort level.

B Additional Tables

Table B1. Institutional enrolment of vocational and academic students.

	Vocational	Academic
Proportion enrolled in:		
FE Colleges	0.82	.
Sixth Form Colleges	.	0.81
Of which in:		
First closest	0.57	0.59
Second closest	0.15	0.12
Third closest	0.07	0.05

Notes: The upper panel reports the proportion of vocational-track and academic-track students enrolled in each track's main institution type (FE Colleges for vocational and Sixth Form Colleges for academic), which are used to build the distance instruments. For the vocational track, the residual category consists of small independent training providers and instiutions in th public sector; for the academic track, the residual category are schools' sixth forms. Conditional on enrolling in the track's main institution type, the bottom panel reports the proportion of students enrolling in the first, second and third closest FE and Sixth Form College, respectively.

Table B2. Effects of various covariates on education choices and outcomes.

Independent variable:	White British	Free school meals	KS2 English	KS2 Maths	KS2 Science	Full Level 2
	(1)	(2)	(3)	(4)	(5)	(6)
A. Raw relationship with earnings						
Coefficient	725	-5860	2851	3822	3366	8203
	(55)	(45)	(19)	(18)	(18)	(37)
R^2	0.00	0.02	0.04	0.07	0.06	0.08
B. Controlled relationship with earnings						
Coefficient	-809	-2764	834	1968	363	5536
	(86)	(59)	(27)	(29)	(27)	(43)
C. Raw relationship with education choices						
Coefficient w/ vocational	0.060	0.033	-0.079	-0.078	-0.066	-0.180
as dependent variable	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.00	0.00	0.02	0.02	0.02	0.03
Coefficient w/ academic	-0.114	-0.131	0.154	0.147	0.134	0.406
as dependent variable	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
R^2	0.01	0.01	0.11	0.10	0.09	0.20

Notes: For each of the covariates indicated in the column header, panel A reports the variable's coefficient from a bivariate regression of earnings at ages 29–30 on the covariate (and a constant); panel B reports the variable's coefficient from a multivariate regression of earnings on the covariate and the remaining control set; panel C reports the variable's coefficients from two separate bivariate regressions: one for vocational enrolment and one for academic enrolment.

Table B3. First stages in different subsamples: testing monotonicity.

First stage(s) for:	Net LATE	Margin-specific LATEs		
	D_V wrt Z_V	D_V wrt Z_A	D_A wrt Z_V	D_N wrt Z_V
	(1)	(2)	(3)	(4)
Female	-0.0393***	0.0822***	0.0352***	0.0041***
	(0.0015)	(0.0013)	(0.0014)	(0.0010)
	303,606	303,606	303,606	303,606
Male	-0.0341***	0.0700***	0.0274***	0.0067***
	(0.0015)	(0.0013)	(0.0013)	(0.0011)
	315,217	315,217	315,217	315,217
White British	-0.0406***	0.0753***	0.0338***	0.0068***
	(0.0013)	(0.0011)	(0.0011)	(0.0008)
	498,226	498,226	498,226	498,226
Other ethnicity	-0.0142***	0.0823***	0.0133***	0.0009
	(0.0028)	(0.0023)	(0.0026)	(0.0017)
	120,597	120,597	120,597	120,597
Free school meal (FSM)	-0.0217***	0.0527***	0.0152***	0.0065***
	(0.0025)	(0.0021)	(0.0019)	(0.0021)
	107,607	107,607	107,607	107,607
No FSM	-0.0394***	0.0809***	0.0344***	0.0051***
	(0.0013)	(0.0011)	(0.0012)	(0.0008)
	511,216	511,216	511,216	511,216
Bottom 25% KS2	-0.0243***	0.0374***	0.0177***	0.0066***
	(0.0018)	(0.0015)	(0.0012)	(0.0016)
	183,738	183,738	183,738	183,738
Second 25% KS2	-0.0326***	0.0584***	0.0236***	0.0089***
	(0.0020)	(0.0017)	(0.0016)	(0.0015)
	145,026	145,026	145,026	145,026
Third 25% KS2	-0.0421***	0.0945***	0.0377***	0.0044***
	(0.0021)	(0.0018)	(0.0019)	(0.0013)
	145,032	145,032	145,032	145,032
Top 25% KS2	-0.0520***	0.1232***	0.0504***	0.0016*
	(0.0023)	(0.0019)	(0.0023)	(0.0010)
	145,027	145,027	145,027	145,027
Bottom 25% IoD	-0.0148***	0.0578***	0.0133***	0.0015
	(0.0025)	(0.0021)	(0.0020)	(0.0019)
	154,706	154,706	154,706	154,706
Second 25% IoD	-0.0186***	0.0680***	0.0169***	0.0017
	(0.0024)	(0.0020)	(0.0020)	(0.0016)
	154,706	154,706	154,706	154,706
Third 25% IoD	-0.0446***	0.0825***	0.0346***	0.0100***
	(0.0023)	(0.0019)	(0.0021)	(0.0014)
	154,752	154,752	154,752	154,752
Top 25% IoD	-0.0624***	0.0981***	0.0555***	0.0068***
	(0.0025)	(0.0023)	(0.0024)	(0.0012)
	154,659	154,659	154,659	154,659

Notes: The table reports the relevant first stage coefficients as estimated in different covariate-defined subsamples. Standard errors, clustered at the LSOA level, are reported in parentheses. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4. IV estimates for margin-specific effects of vocational education pooling both genders.

	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)
	(1)	(2)	(3)
Net effect vocational education			
LATE_V	0.021	-399	-705
	(0.022)	(722)	(698)
Academic education margin			
Complier share	*0.86*	*0.86*	*0.86*
	(0.02)	*(0.02)*	*(0.02)*
$\text{LATE}_{V\text{-}A}$	0.015	-1,257**	-2,062***
	(0.014)	(559)	(551)
No post-16 education margin			
Complier share	*0.14*	*0.14*	*0.14*
	(0.02)	*(0.02)*	*(0.02)*
$\text{LATE}_{V\text{-}N}$	0.057	4,687	7,373*
	(0.139)	(4,043)	(4,068)
Test of $\text{LATE}_{V\text{-}A} = \text{LATE}_{V\text{-}A}$	$p = 0.75$	$p = 0.14$	$p = 0.03$
N students	618,823	618,823	500,787
N clusters	62,560	62,560	60,419

Notes: The table is analogous to Table 6, except for not splitting the sample by gender. Standard errors are block bootstrapped at the LSOA×cohort level using 999 iterations. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5. Decomposition of multivariate 2SLS.

	Male students	Female students
Multivariate 2SLS estimates		
$\beta^{2SLS}_{V\text{-}A}$	-1140	-630
	(521)	(395)
$\beta^{2SLS}_{V\text{-}N}$	338	5600
	(4144)	(5078)
Margin-specific LATE estimates		
$\text{LATE}_{V\text{-}A}$	-2267	-418
$\text{LATE}_{V\text{-}N}$	4958	3774
$\text{LATE}_{A\text{-}N}$	-9837	9460
First-stages derived weights		
θ_A	0.934	0.960
θ_N	0.729	0.653

Notes: The upper panel of the table reports, separately by gender, the estimated coefficients of a 2SLS regression where indicators for academic enrolment and no post-16 enrolment are instrumented with both distance instruments simultaneously. These estimates cannot be interpreted as causal returns to education choices because they represent a mixture of effects from multiple treatment margins. In particular, it can be shown that $-\beta^{2SLS}_{V\text{-}A} = \theta_A \text{LATE}_{V\text{-}A} + (1-\theta_A)(\text{LATE}_{V\text{-}N} - \text{LATE}_{A\text{-}N})$ and $-\beta^{2SLS}_{V\text{-}N} = \theta_N \text{LATE}_{V\text{-}N} + (1-\theta_N)(\text{LATE}_{V\text{-}A} + \text{LATE}_{A\text{-}N})$, where $\text{LATE}_{A\text{-}N}$ is the effect at the margin of academic *vs.* no post-16 education and the wheights θ_A and θ_N depend on the multivariate 2SLS first-stage equations (Mountjoy, 2022). The bottom panel of the table reports empirical estimates of the relevant elements of this decomposition, explaining why empirically the 2SLS estimates would appear to be considerably different from our estimated effects.

Table B6. Robustness checks for IV estimates of margin-specific labour market effects.

	No sample restrictions			Excluding unmatched students			Controlling for Full Level 2			Instruments ≡ driving distance		
	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)	Sustained employment	Annual earnings (incl. 0s)	Annual earnings (excl. 0s)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Male students												
V-A-compl.	0.80	0.80	0.80	0.80	0.80	0.80	0.82	0.82	0.81	0.79	0.79	0.79
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\text{LATE}_{V\text{-}A}$	0.000	-2424***	-3098***	0.021	-2163**	-2976***	0.015	-2207**	-2895***	0.022	-1648*	-2436***
	(0.022)	(881)	(832)	(0.021)	(907)	(872)	(0.021)	(889)	(847)	(0.022)	(923)	(894)
$\text{LATE}_{V\text{-}N}$	0.147	6701	6624	0.067	4781	6142	0.024	3512	4964	-0.101	-495	1748
	(0.159)	(5196)	(4615)	(0.141)	(4935)	(4614)	(0.149)	(5282)	(4903)	(0.143)	(4747)	(4361)
B. Female students												
V-A-compl.	0.91	0.91	0.91	0.90	0.90	0.91	0.91	0.91	0.91	0.87	0.87	0.89
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\text{LATE}_{V\text{-}A}$	0.009	-359	-1104*	-0.005	-846	-1155*	0.014	-431	-1147*	0.023	156	-560
	(0.019)	(615)	(636)	(0.018)	(654)	(696)	(0.019)	(676)	(677)	(0.021)	(705)	(717)
$\text{LATE}_{V\text{-}N}$	-0.016	3613	9765	0.069	4840	8060	-0.070	-410	4310	0.044	2204	4613
	(0.491)	(8849)	(8920)	(0.285)	(7036)	(7241)	(0.366)	(7944)	(8227)	(0.236)	(5443)	(7045)

Notes: This table reports, separately by gender, estimates of the *V-A* complier share and the two margin-specific effects of vocational education on three labour market outcomes across four different robustness checks. In columns 1–3, we use the full sample of students from secondary schools without a sixth form, relaxing the sample restrictions used to construct the main estimation sample (see 2.2); in columns 4–6, we exclude students for whom we do not observe a single earnings spell in the tax records throughout our observation period; in columns 7–9, we include the indicator for having achieved Full Level 2 in the GCSE exams as an additional control variable; in columns 10–12, we redefine the instruments in terms of logged driving distance (instead of logged geographical distance) between students' home address and the closest academic/vocational college. Otherwise, the estimations are identical to the main results reported in Table reftab:main. Standard errors are block bootstrapped at the LSOA×cohort level using 500 iterations. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B7. Correcting the IV estimates at the No Post-16 education margin for complier differences.

Dependent variable:	Sustained employment		Annual earnings (incl. 0s)		Annual earnings (excl. 0s)	
	Raw IV	Corrected	Raw IV	Corrected	Raw IV	Corrected
	(1)	(2)	(3)	(4)	(5)	(6)
A. Male students						
Vocational PO	0.877	0.875	26,201	26,049	29,473	29,210
	(0.125)	(0.125)	(4,646)	(4,660)	(4,410)	(4,450)
No Post-16 PO	0.821		21,242		23,315	
	(0.089)		(2,628)		(2,208)	
$LATE_{V\text{-}N}$	0.057	0.054	4,958	4,807	6,158	5,894
	(0.149)	(0.149)	(5,028)	(5,041)	(4,653)	(4,675)
	$p = 0.85$		$p = 0.85$		$p = 0.76$	
B. Female students						
Vocational PO	0.707	0.844	14,222	20,424	22,469	27,707
	(0.249)	(0.251)	(6,209)	(6,651)	(7,658)	(8,613)
No Post-16 PO	0.664		10,425		14,732	
	(0.145)		(2,671)		(2,960)	
$LATE_{V\text{-}N}$	0.042	0.179	3,796	9,999	7,737	12,975*
	(0.288)	(0.281)	(6,762)	(6,844)	(7,787)	(8,401)
	$p = 0.04$		$p = 0.04$		$p = 0.06$	

Notes: For each of the three outcomes, the table shows vocational-no education complier potential outcome (PO) and $LATE_{V\text{-}N}$ estimates, as they were originally estimated (odd columns) and when corrected for complier differences (even columns), separately by gender. The vocational PO is corrected by taking into account the estimated difference in the associated predicted outcome between the two groups of compliers respectively induced by conditional variation in one of the two instruments. The corrected $LATE_{V\text{-}N}$ is obtained by subtracting the original academic PO from the corrected vocational PO. In square brackets we report p-values testing against the null hypothesis that the corrected and original $LATE_{V\text{-}N}$ estimates are identical. The number of observations is the same as in Table 6. Standard errors are block bootstrapped at the LSOA×cohort level using 999 iterations. Stars indicate significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.