Where versus What

College Value-Added and Returns to Field of Study in Further Education

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ABSTRACT

We use administrative records on educational and labor market trajectories to estimate the value-added of English further education colleges in terms of educational and labor market outcomes and earnings returns to different fields of study taught at these colleges. We find that dispersion in college value-added in terms of labor market outcomes is moderate compared to differences in earnings returns across fields of study. We further show that value-added in labor market outcomes is correlated with value-added in academic outcomes. We conclude that in English further education, what *one studies tends to matter more than* where *one does so.*

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I. Introduction

Technological progress is changing the nature of many occupations. Tasks that traditionally have been executed by workers are increasingly performed by robots. Moreover, the declining costs of automation have accelerated the decrease in the demand for low-skill and routine jobs.[1] Adapting to this new environment will require that many workers acquire new skills in post-secondary education programs (Stromquist 2019). While universities can provide the skills the labor market demands, they are not a feasible option for a large fraction of the population. Many individuals do not have the academic prerequisites, time, or resources to pursue a university degree. Therefore, enrolling in vocational education and training (VET) programs constitutes a natural response to the current dynamics of the labor market for many young people and adults.

In this study, we assess the relevance of two important decisions that prospective students have to make when pursuing vocational studies. We analyze whether *where* one studies is more (or less) relevant for labor market outcomes than *what* one studies. To this end, we estimate how differences in the quality of further education (FE) colleges in England and returns to field of study taught at these colleges contribute to explaining labor market outcomes for young and adult learners. Further, we ask what mechanisms drive heterogeneity in college value–added.

We start by analyzing FE colleges' effects on student human capital accumulation and labor market outcomes by estimating institution's *value-added* (VA) in terms of academic performance, earnings, and employment status.[2] Next, to explore the mechanisms that might be driving heterogeneity in college quality, we correlate college inspection ratings, indicators of resources available to students, and learning formats (for example, distance learning, in the classroom, etc.) with measures of FE college VA. Finally, we estimate returns to fields of study taught at FE colleges and compare them with our VA estimates.

In our empirical strategy, we follow two approaches shaped by the nature of the outcome variables under study. First, to estimate VA in educational outcomes, where no repeated measures over time of the dependent variable exist, we use a cross-sectional strategy where an unusually detailed set of control variables helps to account for many potential confounders. The identifying assumption for this type of empirical specifications is that, conditional on observable characteristics, students are randomly assigned to FE colleges. We discuss the plausibility of this assumption and provide robustness checks supporting it. Second, we implement lagged dependent variable and individual-level fixed-effects models to provide estimates of FE college VA in labor market outcomes and earnings returns to field of study. The fixed-effects analysis corresponds to estimating a treatment-on-the-treated effect, where we compare average gains in the outcome variable after vocational education attendance

1. For example, the world's largest electronics assembler based in Taiwan (Foxcoon Technology Group) reduced its workforce by 30 percent when it included robots in the production process (Saliola, Mohamed Islam, and Winker 2020).

2. As noted by Hoxby (2015), a deep understanding of value-added measures is important to evaluate the potential benefits and costs of any policy that affects individuals' decisions to attend VET.

across different colleges or after specializing in a given sector. This approach allows us to deal with any time-invariant unobserved characteristics that might be related to potential outcomes. We also discuss and address concerns related to potential time-varying selection.

To the best of our knowledge, this study is the first to provide rigorous measures of FE college VA in terms of labor market outcomes for a large set of vocational institutions. The closest studies to ours are Clotfelter et al. (2013), Carrell and Kurlaender (2020), and Kurlaender, Carrell, and Jackson (2016), who estimate VA for community colleges in North Carolina and California. However, their estimates are focused on college outcomes rather than labor market outcomes. Much research in the economics of education has focused on estimating *returns* to vocational degrees or on the returns to attending different *types* of institutions (for example, public vs. for-profit, four-year vs. two-year colleges). For example, Jepsen, Troske, and Coomes (2014) use labor market information prior to and after enrolling in U.S. community colleges in Kentucky to study the returns to different degrees. Cellini and Turner (2019) use a difference-in-difference strategy to analyze the returns to attending for-profit colleges in the United States. Similarly, Andrews, Li, and Lovenheim (2016) analyze the labor market returns to attending community colleges relative to high-quality four-year institutions in Texas.[3] However, none of these studies assesses the degree of heterogeneity in VA across different community colleges. Moreover, our analysis involves estimating VA measures across *all* FE colleges in England, providing a complete picture of this sector. Furthermore, while many papers have studied the mechanisms that make some vocational institutions successful in the United States (Jacoby 2006; Bailey et al. 2006; Calcagno et al. 2008; Stange 2012; Carrell and Kurlaender 2020), most of these analyses relate success only to academic outcomes, while we extend this analysis to labor market outcomes.

Finally, we bring new insights into understanding the relevance of fields of study for labor market outcomes.[4] Our focus on the returns to the number of learning hours *enrolled* in qualifications associated with specific fields of study, rather than achieved hours or completed degrees, provides two main advantages. First, it helps to alleviate endogeneity concerns related to differential selection into completion and achievement of qualifications. Second, the fact that individuals enroll in multiple qualifications from different specializations (that is, not necessarily their main specialization) implies that our identification of the returns to fields of study is also obtained from students specializing in other fields.[5] If instead, we were focusing on estimating returns to completing degrees in different fields of study, these would only be identified from

3. The literature on the returns to vocational degrees in the United States is extensive. For example, Jacobson, LaLonde, and Sullivan (2005a,b); Bahr (2014); Cellini and Chaudhary (2014); Bahr et al. (2015); Dadgar and Trimble (2015); Liu, Belfield, and Trimble (2015); Stevens, Kurlaender, and Grosz (2019); Zeidenberg, Scott, and Belfield (2015); Bettinger and Soliz (2016); Xu and Trimble (2016); Belfield and Bailey (2017a); Mountjoy (2021), among others. Belfield et al. (2018) and Hickman and Mountjoy (2019) provide an extensive analysis of returns in higher education in the UK and Texas.

4. There is a large literature on returns to field of study. See, for instance, Arcidiacono (2004); Arcidiacono, Cooley, and Hussey (2008); Hastings, Neilson, and Zimmerman (2013); Bahr (2016); Kirkeboen, Leuven, and Mogstad (2016); Belfield and Bailey (2017a); Altonji, Arcidiacono, and Maurel (2016); Altonji and Zimmerman (2018); Belfield et al. (2018); Altonji and Zhong (2021).

individuals who completed their studies in the specific field as their major. Furthermore, this is the first study to provide rigorous estimates on the returns to a large number of detailed fields of study in vocational education, as opposed to higher education, in England.

We find substantial heterogeneity in FE colleges' contributions to their students' educational attainment. Compared to the mean in the population, a one standard deviation (SD) increase in college VA increases the number (share) of achieved learning hours by 8.1 percent (6.5 percent). We also find that a one SD increase in college quality increases the likelihood of obtaining a good upper secondary qualification—a pre-requisite for attending university in England—by 4.4 percentage points, or 10.5 percent compared to the sample mean, and increases the likelihood of later attending university by nearly four percentage points, or 10 percent compared to the sample mean. These findings indicate that certain FE colleges are more effective than others at enhancing academic outcomes.

Our findings also indicate a relatively modest dispersion in FE college value-added in terms of earnings, especially for individuals who attend FE college later in life. We show that a one SD increase in FE college VA leads to an increase in daily earnings of around 3 percent for individuals first attending FE college between ages 18 and 20 ("young learners") and by 1.6 percent for individuals attending FE college later in life, between ages 25 and 54 ("adult learners"). Differences in the dispersion of VA between young and adult learners are likely driven by the fact that young learners enroll in and complete substantially more learning hours than adults, making the intensity of the treatment very different between the two groups. To put these numbers into context, Broecke (2012) shows that a one SD increase in university selectivity in the UK leads to a rise in earnings of approximately 7 percent. Relating our findings to returns to associate degrees in the United States, Jacobson, LaLonde, and Sullivan (2005b) find that an additional year of community college increases earnings by 9 percent for men and 13 percent for women, which is substantially larger than the gain that could be obtained from attending a FE college with a one SD higher VA. In summary, while the overall returns to vocational education can be large, the dispersion in FE college value-added in terms of earnings is much smaller. Regarding the effects of FE colleges on improving employment probabilities, we find that a one SD increase in FE college VA increases the likelihood of being employed more than 90 days in a given year by only about 1.7 and one percentage points for young and adult learners, respectively. This represents only a slight increase of 2.3 percent and 1.2 percent, respectively, compared to the mean employment rate in the sample.

The potential mechanisms that could be driving the variability in FE college VA in labor market outcomes include both student achievement at college and college inputs. Our findings suggest a significant correlation between FE college VA in academic outcomes and FE college VA in earnings. Learning modes also seem to play a role in explaining variation in VA, with colleges offering a larger share of their courses in the classroom having higher VA in earnings for young learners. However, we find no correlation between measures of college spending and FE college VA in either earnings or employment.[6] For adult learners, we do not find meaningful

5. For example, a student specializing in engineering and manufacturing technology may also take courses in business administration. Bahr (2014) also relies on credits, but the focus is on credits achieved.

correlations between VA in labor market outcomes and characteristics of colleges, which is likely due to the little variation in VA in labor market outcomes across colleges for this subgroup of the population.

How does the moderate heterogeneity in value-added across colleges in terms of earnings compare to the importance of field of study when it comes to labor market outcomes? We find comparatively large variation in the returns to different fields of study, especially for young learners. For instance, the typical young male learner who chooses engineering and manufacturing technology as his main field of study experiences an increase in average post-FE college daily earnings of 7.7 percent five years after finishing college. In contrast, the typical young male student choosing preparation for life and work experiences negative earnings returns of on average approximately 2 percent five years post-FE, compared to pre-enrollment earnings.[7] These findings are consistent with the literature on returns to field of study in vocational education. According to a review by Belfield and Bailey (2017a), the returns to an associate degree in a STEM field tend to be larger than for other fields.

Disparities in returns to sector are also large among young female learners. Average earnings returns five years post-FE college graduation range from a substantial 16.4 percent for arts, media, and publishing to a mere 0.8 percent for preparation for life and work. Finally, we also find that many specializations present negative returns immediately after finishing VET education that turn positive five years later, indicating that it takes time for positive returns to emerge.

In summary, our results show that there is important variation in returns to field of study, and this variation plays a larger role in labor market outcomes when compared to variation in FE college quality measured by VA. If we order fields of study based on their returns for the typical young male (female) learner, then changing from a field that is in the tenth percentile to one in the 90th percentile would lead to an increase in returns that is approximately 84 percent (43 percent) larger than if we were performing the same exercise based on FE college value-added.

We believe that our findings have relevant practical implications for many students and policymakers. First, they allow prospective FE college students better to understand the variation in quality across different institutions and compare the returns to different fields of study.[8] This is particularly important in light of the evidence suggesting that students tend to be misinformed about the labor market returns of VET qualifications. Baker et al. (2018), for instance, find that only 13 percent of students in a sample of community college students in California correctly rank four broad categories of majors in terms of salary. Second, our findings on mechanisms can inform policymakers about plausible paths to enhance the efficiency of a sector that is

6. Similarly, Stange (2012) finds that instructional expenditure per student has no impact on community college students' educational attainment.

7. Qualifications classified under the field preparation for life and work are usually functional skills qualifications that teach post-16 and adult learners in England how to apply practical math and English skills to real-life and vocational contexts.

8. Value-added estimates for colleges have attracted widespread attention in the United States, following the publication of college score cards by the U.S. Department for Education in 2012 (U.S. Department for Education 2015).

facing significant challenges, such as a perceived decline in quality and student performance, growing demands on their mission, and financial pressures related to increased competition for students and shrinking further education budgets.[9]

In the following, Section II gives an overview of the institutional setting. Section III describes the data. Section IV presents the empirical strategies used. In Section V, we present FE college VA estimates, as well as robustness checks and the analysis of potential mechanisms explaining differences in VA across institutions. In Section VI, we present results on the returns to field of study. Section VII concludes.

II. Institutional Background

Students in England complete compulsory education at the age of 16 (at the end of Key Stage 4, KS4, in year 11) when they take a set of standardized exams (that is, the Graduate Certificate of Secondary Education, GCSEs). All students must take English, math, and science exams at age 16 and are free to choose additional subjects. After compulsory education, students in the sample period we studied were free to choose to stay on in education and follow a further education program. A large fraction of students chooses vocational courses or a combination of vocational and academic courses (Hupkau et al. 2017), which are the subject of this study. Such programs are below a bachelor's degree level and typically take two years or fewer to complete. They are comparable to associate degrees or vocational certificates offered at U.S. community or for-profit colleges. In England, they are mainly offered at FE colleges. Further education colleges are critical because they enroll many more students than universities.[10] They also differ substantially from them. Further education colleges are typically not oversubscribed or selective, meaning they tend to admit all students who apply.[11] They do not tend to offer financial aid, but their courses are typically free to young people up to the age of 19, and many of their courses for adults are also publicly funded.

Table 1 summarizes the qualifications typically obtained by young and adult learners at FE colleges. A set of features characterizes qualifications: the level of the qualification, which is an indicator of depth and difficulty; the intensity and duration of a qualification, typically measured by the number of guided learning hours (that is, the time when students are under the supervision of a teacher, tutor, or lecturer) required to complete the qualification; and the field of study. The main vocational and technical qualifications offered at FE colleges are awards, certificates, and diplomas. Awards are short courses comprising up to 130 guided learning hours, corresponding to about half a semester of study time. Certificates are

9. Further education colleges face a challenging mission, providing VET to learners with very different levels of experience, academic preparation and at very different stages of their professional lives. Further details about these institutions are given in Section II.

10. Over the time period we study, there were around 257 general FE colleges in England. Due to mergers and closures of colleges, this number varies from year to year.

11. Experts at the Association of Colleges, an organization representing FE colleges in England, indicate that general FE colleges, the ones object of this study, do not typically experience oversubscription for their courses.

Table 1
Overview of Qualifications Offered at FE Colleges in England

Qualification Types (1)	Available Levels (2)	Length: Learning Hours (3)	Some Common Examples of Qualifications in General Further Education Colleges (4)
Panel A: Vocational/Technical Qualifications (Job Focused)			
Award	2–8	up to 130 guided learning hours	Award in Food Safety in Catering
			Award in Preparing to Teach in the Lifelong Learning Sector
Certificates			
Certificate	2–8	between 130 guided learning hours and 370 guided learning hours	Certificate in Understanding the Safe Handling of Medicines
			Certificate in Teaching in the Lifelong Learning Sector
Higher National Certificate (HNC)	4		BTEC National Certificate in Sport and Exercise Sciences
			BTEC Higher National Certificate in Construction
Diplomas			
Diploma	2–8	over 370 hours of training	BTEC First Diploma for ICT practitioners Diploma in Accounting
Higher National Diploma (HND)	5		BTEC National Diploma in Art and Design
			BTEC Higher National Diploma in Business

(*continued*)

Table 1 (*continued*)

Qualification Types (1)	Available Levels (2)	Length: Learning Hours (3)	Some Common Examples of Qualifications in General Further Education Colleges (4)
Other			
National Vocational Qualification (NVQ)	2–7	varying sizes/credits, depending on level of study; qualifications are work-based achieved through competency assessment	NVQ in Hairdressing, NVQ in Accounting
Foundation degree	5	2 years full time study	Foundation Degree in Early Years
Panel B: Academic: Subject-Focused			
Functional skills	2	at least 45 guided learning hours	Functional Skills Qualification in English
GCSE	2	120 guided learning hours	GCSE in English
A/AS level	3	360 guided learning hours	A Level in Mathematics
Access to higher education diploma	3	1 year full time study	Access to Higher Education Courses

Notes: The table focuses on the most relevant qualifications that can be undertaken in general FE colleges at Level 2 and above. Entry level and Level 1 qualifications, as well as apprenticeships, are not shown. Most qualifications undertaken in FE colleges are at Level 2 (lower secondary education), Level 3 (upper secondary education and university entry qualifications), and Level 4 (nontertiary postsecondary qualifications). Column 4 shows examples of common qualifications undertaken at those levels.

larger qualifications, comprising between 130 and 370 guided learning hours and taking about one year of full-time study. Diplomas involve at least 370 guided learning hours and usually take up to two years to complete. Another common type of qualification is the National Vocational Qualification, which students take while working. Most of the aforementioned qualifications can be taken at Levels 2–8, meaning that they are available both for 16-year-old school leavers with no further prior education, as well as at tertiary education levels (Levels 4 and above), where individuals need to fulfill some prerequisites.[12] Further education colleges also offer academic qualifications, including GCSEs, A-levels (university entry qualifications), and Foundation Degrees, which are higher education degrees lasting two years and taken by only a small minority of students in our analysis. Note that most qualifications taken at FE colleges do not have a performance indicator akin to a grade associated with them, or if they do, they are often not comparable across different qualifications. Performance is, therefore, typically measured by whether a qualification is achieved.

According to the UK's Department for Education (DfE), students' FE college choices are very localized. Most learners (70 percent) travel less than 10 km from their home to the site of their FE provider, with 50 percent traveling less than 6 km (Snelson and Deyes 2016). This is similar to U.S. community college choices, where students usually attend the one closest to their home (Stange 2012). Accordingly, selection is mainly driven by the sorting of parents (in the case of young learners) and adult learners into different geographic areas and neighborhoods (Gibbons and Telhaj 2007).

While FE colleges are private corporations, the majority of their income comes from government grants, representing, on average, just under 80 percent of revenues in 2015–2016, with only about 14 percent of revenues coming from tuition fees. Because the state funds most of the learning at FE colleges, the courses they provide are regulated by the Office of Qualifications and Examinations Regulation (Ofqual) to ensure certain standards for publicly funded learning.[13] Qualifications are designed by awarding bodies, which are private, for-profit organizations that provide the curricula and assessment framework for different vocational qualifications.[14]

III. Data

For our empirical analysis, we combine several administrative data sets from England. We focus on the universe of more than two million learners for

12. Further education colleges also offer qualifications at lower levels of learning. We do not consider this remedial type of learning in our analysis.

13. The regulatory bodies responsible for further education funding determine which qualifications are eligible for funding, which can change from year to year. To get an idea of the variety of funded learning available for young learners, the list of approved qualifications for 14 to 19-year-olds comprised 12,580 qualifications in 2019 (ESFA 2019).

14. There are many awarding bodies in England, specializing in different kinds of qualifications. In VET, the dominant organizations are Pearson (offering technical qualifications like business and technology qualifications (BTECs)), EAL (offering engineering qualifications) and City & Guilds (offering National Vocational Qualifications in fields such as hairdressing, plumbing, or construction).

four cohorts of school leavers. The data contain comparable measures of prior achievement, from age seven up until the end of compulsory education at age 16, and demographic characteristics (age, ethnicity, language spoken at home, socioeconomic status, neighborhood characteristics, including measures of income and employment deprivation). It also covers every individual who has ever enrolled in publicly funded adult learning and records detailed information on the learning undertaken. Finally, we link educational data to administrative records of labor market outcomes before and after attending FE college.

Because we do not have the same measures of prior attainment and socioeconomic background for all learners, we construct two different data sets for this study. The first data set covers learners aged 16–20 (young learners) when first enrolling in FE colleges. The second data set covers learners aged 25–59 (adult learners). Further details about the data sources, the data set construction for both groups, as well as the sample restrictions can be found in Online Appendix A.1.

Tables 2 and 3 show summary statistics for young learners aged 16–20 and adults aged 25–59, respectively. One of the main differences between young and adult learners is in the duration and intensity of learning. Young learners enroll on average in about 1,049 total guided learning hours, and the average length of study time is about two years (732 days), compared to only 185 guided learning hours for adults and study duration of less than ten months (290 days). In addition, whereas adult learners enroll in about two qualifications on average, young learners take about five courses.

The types of courses studied also differ across the young and adult sample. While more than 60 percent of young learners enroll in at least one course at Level 3, only 31 percent of adult learners do so. Adults are most likely to be observed in learning at Level 2 (62 percent), and a small share (7 percent) are doing advanced courses (Level 4 and above), while almost none of the young learners are enrolled in such higher-level courses. The median distance traveled to the FE college attended for young learners in our sample is about 6 km and around 10 km for adults.

We also present summary statistics for young and adult learners by gender. Online Appendix Tables A1 and A2 correspond to young learners. Young males and females spend about two years on average in FE college learning, and the total number of guided learning hours enrolled is not substantially different across genders.[15] Labor market attachment is also similar across males and females prior to FE college attendance. Among the 18–20 age group, the percent of male and female students that had any employment experience before FE college entry are 75 percent and 76 percent, respectively. However, young males show larger annual earnings than females, with males earning on average £600 more per year than females in the year of FE college entry.

Online Appendix Tables A3 and A4 present similar summary statistics by gender for adult learners. The average duration of further education learning is 319 days for adult females, while for adult males, it is only 257 days. However, females enroll in a similar number of guided learning hours to their male counterparts (195 vs. 173). We also find similar labor market participation rates between males and females, with the employment share before FE college entry being 73 percent and 74 percent,

15. About 40 percent of the gender gap in guided learning hours enrollment is explained by field of study.

Table 2
Summary Statistics for Young Learners

	16–17 (1)	18–20 (2)	Total (3)
Students	838,939	130,009	968,948
FE colleges	258	255	260
Learner characteristics			
Share female	50.34	48.43	50.08
Share max. level enrolled: 2	29.57	33.97	30.16
Share max. level enrolled: 3	61.55	54.48	60.60
Share max. level enrolled: 4	0.35	0.95	0.43
Share observed in HE after FE	30.92	36.61	31.68
Average guided learning hours enrolled	1,115	622	1,049
Duration of learning (days)	767	506	732
Average number of courses enrolled	5.57	2.79	5.20
Median distance KS4 school to FE college (km)	6.43	9.72	6.82
Labor market characteristics			
Share employed before FEC entry[a]	44	76	49
Earnings in FEC entry year	3,779	7,611	4,824
Earnings before FEC entry	3,407	6,915	5,395
Earnings 5 years post FEC	13,264	14,566	13,441

Source: NPD (National Pupil Database, NPD, proprietary data provided specifically for this Project by the UK Department for Education; more information on these data and how to access can be found at https://www.gov.uk/guidance/apply-for-department-for-education-dfe-personal-data), ILR (Individualized Learner Record, ILR, proprietary data provided specifically for this Project by the UK Department for Education; more information on these data and how to access can be found at https://www.gov.uk/guidance/apply-for-department-for-education-dfe-personal-data), HESA (Higher Education Statistics Agency, HESA, proprietary data provided specifically for this Project by the UK Department for Education; more information on these data and how to access can be found at https://www.gov.uk/guidance/apply-for-department-for-education-dfe-personal-data), and LEO (Longitudinal Educational Outcomes, LEO, proprietary data provided specifically for this Project by the UK Department for Education; more information on these data and how to access can be found at https://www.gov.uk/guidance/apply-for-department-for-education-dfe-personal-data).
Notes: The table shows summary statistics for young learners aged 16–20 who enrolled in a further education college at Level 2 and above and first enrolled in a FE college between 2005 and 2010. FEC denotes further education college. Earnings are annual and reported in real terms (in 2015 £).
[a]Employed in at least one of the two years preceding college entry or in entry year.

respectively. Males show substantially higher annual earnings than females in the year they enroll in FE college (£12,681 vs. £8,974). This is probably due to females both working fewer hours and in sectors characterized by lower pay, among other potential reasons.[16]

16. While we observe number of days employed, we do not observe hours worked or the sector or occupation in which individuals are employed.

Table 3
Summary Statistics for Adult Learners

	25–29 (1)	30–39 (2)	40–49 (3)	50–59 (4)	Total (5)
Learners	135,886	293,729	247,086	127,238	803,939
FE colleges	255	255	255	255	255
Learner characteristics					
Share female	51.80	52.86	54.68	51.90	53.09
Share max. level enrolled: 2	59.41	59.81	62.17	66.48	61.52
Share max. level enrolled: 3	32.16	32.37	30.43	27.60	30.98
Share max. level enrolled: 4	8.43	7.82	7.41	5.92	7.50
Average guided learning hours enrolled	248	211	159	106	185
Duration of learnings (days)	320	307	281	236	290
Average number of courses enrolled	2.28	2.17	1.98	1.78	2.07
Median distance to FE college (home)	8.79	9.24	10.64	12.16	10.04
Labor market characteristics					
Share employed before FEC entry[a]	70.79	71.60	74.91	78.28	73.54
Earnings in FEC entry year	8,436	9,724	11,789	13,338	10,713
Earnings before FEC entry	7,891	9,563	11,671	13,559	10,561
Earnings 5 years post FEC	19,850	20,348	21,087	20,265	20,501

Source: ILR (Database, Individualized Learner Record, ILR, proprietary data provided specifically for this Project by the UK Department for Education; more information on this data and how to access can be found at https://www.gov.uk/guidance/apply-for-department-for-education-dfe-personal-data) and HMRC.
Notes: The table shows summary statistics for adult learners aged 25–59, enrolled in a further education college at Level 2 and above, and first enrolling in a FE college between 2007 and 2010. FEC denotes further education college. Earnings are annual and reported in real terms (in 2015 £).
[a]Employed in at least one of the two years preceding college entry or in entry year.

IV. Methodology

The main challenge associated with the identification of FE college value-added and returns to field of study is the problem of selection. Further education colleges tend to admit all of their applicants, and students generally enroll in the institution closest to their home. Therefore, selection into FE colleges is mainly driven by the sorting of individuals into different geographic areas/neighborhoods. A naive approach that just compares the earnings of students enrolled across different institutions is likely to be misleading because it can confound students' prior academic preparation and other background characteristics with FE college inputs. Similarly, selection of students with more motivation or talent into specific fields of study might bias estimates of returns.

To illustrate how pervasive this problem is among young learners, Figures 1 and 2 plot, respectively, average prior attainment and a measure of socioeconomic status against raw average labor market and educational outcomes by FE college. The prior attainment measure on the horizontal axis of Figure 1 is the average standardized KS4 score by college, while the horizontal axis in Figure 2 is the share of students eligible to receive free school meals by college. As is evident from these figures, there is large heterogeneity across FE colleges in the average characteristics of their student intake, and large and significant correlations between student intake characteristics and ex post educational and labor market outcomes, measured by the number and share of guided learning hours completed, whether or not a Level 3 qualification was obtained, earnings, and employment rates.

To characterize selection into fields of study, Panel A of Figure 3 shows the share of students eligible to receive free school meals (FSM), and Panel B shows the prior academic performance as given by the average standardized KS4 score by field of study chosen at FE college, for young male and female learners.[17] Both panels display notable differences in the sorting of students across fields based on these characteristics.

These empirical regularities show that disentangling the contribution of student characteristics from the effect of institutions and specializations should constitute the main goal of our empirical strategy.

A. *Value-Added Models*

First, we propose a value-added model (VAM) with a very extensive set of control variables and lagged dependent variables, following the spirit of the teacher effectiveness literature. Second, we describe fixed-effects strategies exploiting within-individual variation over time to estimate treatment-on-the-treated effects of the FE college attended and the field of study chosen on employment and earnings outcomes. Using both methods allows us to assess whether our results on VA heterogeneity change under different model specifications.

1. Cross-sectional models with lagged dependent variables

The economics literature on teacher effectiveness (Kane and Staiger 2008; Chetty, Friedman, and Rockoff 2014; Koedel, Mihaly, and Rockoff 2015, among many others) is mainly characterized by the estimation of value-added models with lagged dependent variables in a cross-sectional setting. The key identification assumption of these models translated to our context is that after conditioning on lags of the dependent variable (that is, sufficient statistics) and a large set of controls, individuals are no longer sorted into FE colleges based on unobservable determinants of the dependent variable.[18] The exceptionally rich set of controls that we have available in our data for

17. The KS4 score has been standardized based on the sample of all individuals in a cohort of school leavers, including those going to higher education. Our analysis on returns to fields of study will, however, focus on students that did not enroll in a bachelor's degree after VET in order to ease interpretation of the findings. This explains the negative values on most bars in Panel B of Figure 3.

18. For example, Chetty, Friedman, and Rockoff (2014) argue that, in the context of the teacher value-added literature, a plausible approach to estimating the impact of teachers on wages is to control for lagged wages (that is, prior to college enrollment). However, they do not pursue this route because it is impossible to have information on pre-enrollment wages in their context.

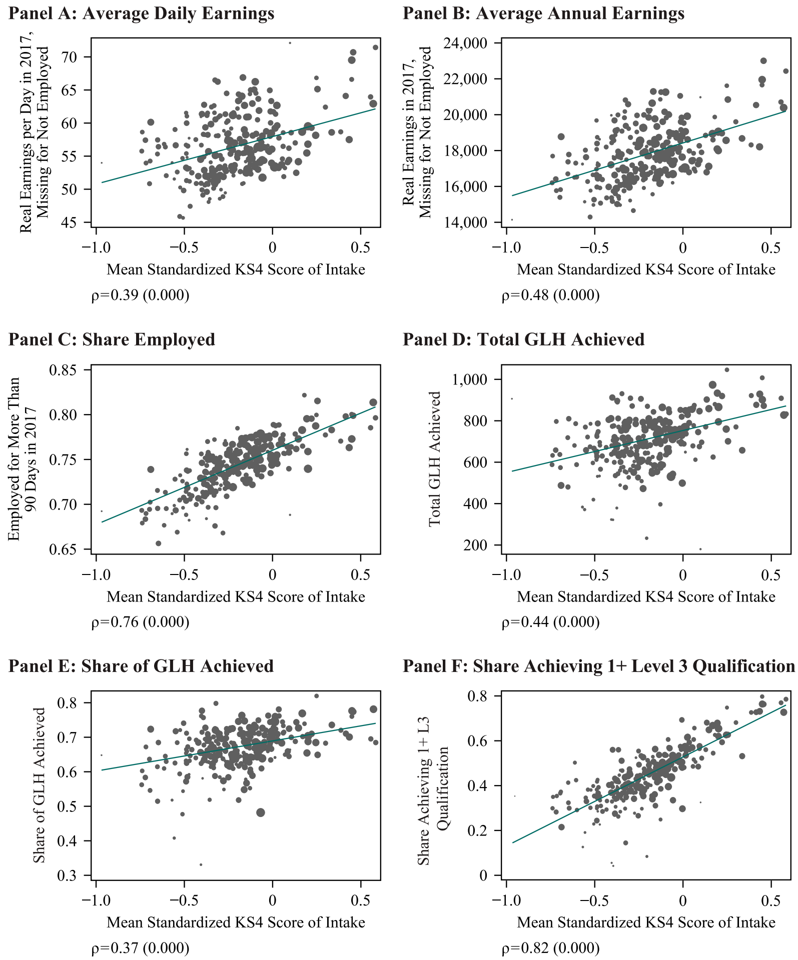

Figure 1

Prior Attainment and Raw Average Outcomes by College

Notes: The graphs plot various labor market outcomes (Panels A–C) and variables of educational achievement (Panels D–F) for students having studied at a college against the average standardized KS4 score (test score at end-of-compulsory schooling) of the intake of that college for cohorts of students having finished compulsory education between 2004 and 2007. The correlation coefficient (ρ) between the two variables is reported at the bottom left of each graph (*p*-value in parentheses).

young learners gives us confidence that we can account for a large array of potential confounders. We describe these controls below.

Equation 1 characterizes our empirical specification. The post-FE college outcome, Y, of individual i, who attended FE college c and is measured at time T (for example, 2017 for labor market outcomes or at the end of FE college attendance for outcomes related to academic achievement), is determined as follows:

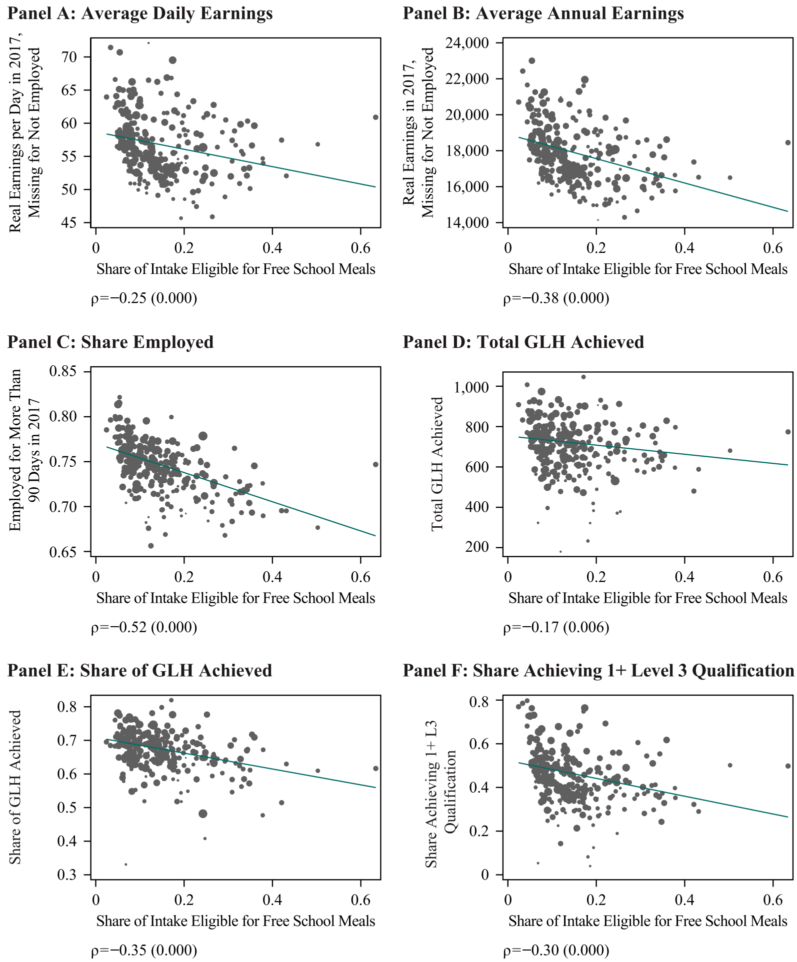

Figure 2

Socioeconomic Status and Raw Average Outcomes by College

Notes: The graphs plot various labor market outcomes (Panels A–C) and variables of educational achievement (Panels D–F) for students having studied at a college against the share of the intake that was eligible for free school meals during compulsory schooling for cohorts of students having finished compulsory education between 2004 and 2007. The correlation coefficient (ρ) between the two variables is reported at the bottom left of the graph (*p*-value in parentheses).

$$(1) \quad Y_{icT} = f_1(Y_{ict-z}) + f_2(\mathbf{X}_{1ict-z}) + f_3(\mathbf{X}_{2ict}) + f_4(\boldsymbol{\rho}_{it}) + \pi_c + \varepsilon_{icT}$$

$f_1(Y_{ict-z})$ is a control function for the lagged outcome (in equations that have labor market outcomes as the dependent variable), with t indicating time while at FE college. For example, earnings specifications include earnings measured prior to FE entry, an indicator for when earnings prior to FE entry were measured, an interaction between

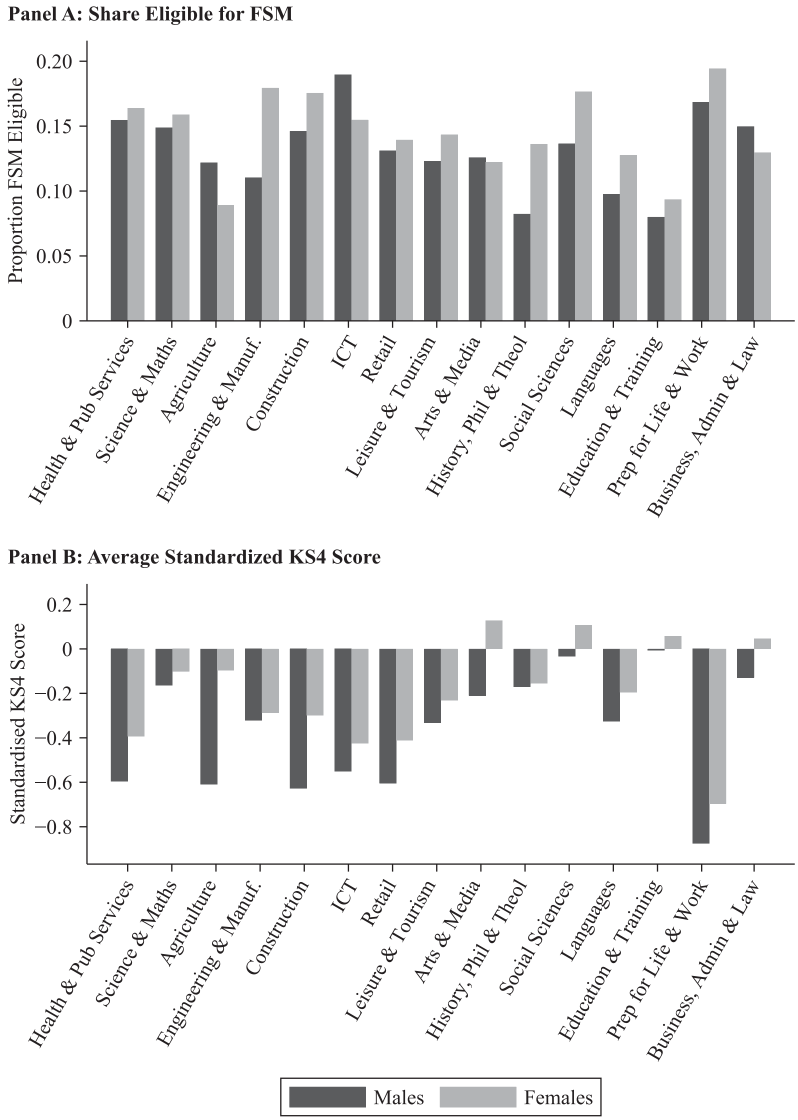

Figure 3

Field of study, Socioeconomic Status, and Prior Attainment

Notes: The graphs plot (Panel A) the share of students eligible for free school meals (FSM) in compulsory education by field of study chosen and (Panel B) the average standardized KS4 score for students choosing a particular field as the main field of study. We exclude students who progress to higher education.

these two variables, and also dummies indicating working status in the years before and at the time of FE college entry.[19] $\mathbf{X}_{1ict-z}$ is a vector of characteristics measured prior to enrolling in the FE college and includes: gender, a series of dummies for ethnicity, a dummy for whether English is spoken at home, a dummy for whether the student had special education needs during compulsory education, a dummy for whether the student was eligible to receive free school meals at the end of compulsory education, the neighborhood IDACI score (that is, a measure of socioeconomic deprivation), the standardized KS4 score, the Ofsted rating of the KS4 school (analogous to school report cards in the US), and student KS2 and KS3 math and English scores.[20] $\mathbf{X}_{2ict}$ is a vector of variables measured at the time of FE college attendance and includes: age when first entered FE college, whether the student attends full-time or part-time, a series of dummies for the main field of study, dummy variables indicating the region where the college is located (to account for different local labor market characteristics), and an additional vector of local deprivation indicators based on the FE college's location and students' area of residence. $f_4(\boldsymbol{\rho}_{it})$ is a flexible vector that includes controls for the academic year compulsory schooling was completed, dummies indicating the last year observed in education, indicators for the number of years since starting FE, and a series of dummies indicating the graduation year from FE college. These controls are included to account for potential earnings drops before FE college enrollment (the "Ashenfelter dip").[21] π_c is the value-added of the FE college attended, and ε_{icT} denotes an idiosyncratic shock.

Given that the main object of analysis in these lagged dependent variable models is π_c (that is, institution value-added), many covariates that could operate as mediating variables ("bad controls") are excluded from our specifications. These include, for instance, the share of guided learning hours achieved per student, which is a proxy for completion and constitutes an outcome of the FE college.

In terms of estimation, we implement a two-step approach following Guarino et al. (2015). In the first step, we perform an ordinary least squares regression where the institution effect (that is, π_c) becomes part of the error term. The equation we estimate thus becomes:

$$(2) \quad Y_{icT} = f_1(Y_{ict-z}) + f_2(\mathbf{X}_{1ict-z}) + f_3(\mathbf{X}_{2ict}) + f_4(\boldsymbol{\rho}_{it}) + \epsilon_{icT}$$

19. To assess the extent to which pre-FE college earnings reflect the productivity of young learners, in Online Appendix Table A5 we explore the correlation between earnings at age 18 and earnings nine years later among individuals who never attend further education after leaving compulsory education. We find relatively large and statistically significant correlations, even after controlling for a detailed measure of end of secondary school performance, gender, and whether the student was eligible to receive free school meals (see Columns 1–4). For comparison purposes, similar correlations for a subsample of adult learners that were not enrolled in any institution during the period of analysis (that is, between the nine years that separate the earnings outcome and the right-hand-side earnings variable) are presented in Columns 5–8. As would be expected, pre-FE college earnings of adult learners are more predictive of future earnings than those of young learners. However, prior attainment and socioeconomic background data for adults are less precise than for young learners, so the magnitudes of the correlation coefficients are not completely comparable between young and adult learners. Nevertheless, the magnitudes of the correlations for young learners suggest that pre-FE college earnings are capturing important aspects of heterogeneity for this population.

20. KS2 and KS3 scores correspond to standardized measures of student performance at ages 11 and 14.

21. We discuss this in more detail in Section IV.A.2.

with

$$\epsilon_{icT} = \pi_c + \varepsilon_{icT}$$

In the second step, we estimate the population standard deviation of FE college VA and best linear unbiased predictors (that is, shrinkage estimates) of the institution's VA, following Equations 15–21 in Guarino et al. (2015). Models are estimated on the whole sample, by age group on first entering FE college, and separately for males and females.

Despite the rich set of controls included in this cross-sectional setting, unobserved characteristics could still be driving the selection of students into different FE colleges. For labor market outcomes, we can further address this concern by exploiting within individual variation in outcomes before and after attending FE college. The next section describes this approach.

2. Fixed effects model

To further address the concern of possible selection on time-invariant unobservables, we exploit within-individual variation in labor market outcomes by estimating individual fixed-effects models. Compared to the cross-sectional approach presented in Section IV.A.1, the fixed-effects approach has the advantage of potentially further reducing omitted variable bias due to unobserved heterogeneity in ability or other time-invariant factors related to individual success in the labor market.[22]

We estimate the following specification for the two samples of young and adult learners, and also separately by gender:

$$(3) \quad Y_{ict} = f_1(\mathbf{X}_{it}) + f_2(\boldsymbol{\rho}_{it}) + \zeta_i + D_{it}\pi_{ct} + \eta_{ict}$$

where $f_1(\mathbf{X}_{it})$ includes labor market experience up until FE college entry, main field of study, a series of dummies for the region where the FE college is located interacted with the academic year, academic year fixed effects, and a second-order polynomial in age.[23] $f_2(\boldsymbol{\rho}_{it})$ is a flexible vector of control variables that accounts for years since starting and leaving the FE college and whether the individual is enrolled in some form of education in year t. The ζ_is represent individual fixed effects. π_{ct} denotes the effect of the FE college attended on outcome Y_{ict} in period t. Following Jepsen, Troske, and Coomes (2014), π_{ct} is premultiplied by the indicator variable D_{it}, which is equal to one once an individual has finished FE education and zero before.

The key identification assumption for fixed-effects models is the absence of time-variant unobservable characteristics driving selection into FE colleges. While fixed effect strategies cannot handle selection on time-varying unobservables, note that

22. Belfield and Bailey (2017b) provide a thorough discussion of the different empirical strategies that have been implemented in the literature to estimate labor market returns to associate degrees in the United States. They discuss the relative advantages and disadvantages of using fixed-effects strategies. The lagged dependent variable and the fixed-effects empirical strategies complement each other because they rely on different sources of variation in the data. This makes it possible to determine how sensitive the heterogeneity in FE college VA is to different modeling assumptions.

23. The dummies indicating the main field of study take the value one from the year the learner completes FE college education, and zero otherwise.

$f_2(\boldsymbol{\rho}_{it})$ is included to address some potential concerns in this regard. For example, if a wage dip motivates individuals to enroll in FE education, this could lead to an upward bias in our estimates.[24] To overcome these concerns, we take several steps. First, the indicator on whether the individual is enrolled in some form of education accounts for the opportunity cost of students while enrolled in education. Second, the variable capturing the number of years since the individual left the FE college controls for any general post-FE changes in earnings. The third set of controls are dummies for the number of years since entering FE education, which also includes the years before enrolling. This accounts for the "Ashenfelter dip."

In terms of estimation, we also implement a two-step approach. We focus on institution VA corresponding to the year 2017, the last year for which we have earnings and employment data. This implies using all the years when performing the first-step regression, but using only the residuals corresponding to the year 2017 to obtain the population distributions of FE colleges' VA and their shrinkage estimates.

B. Returns to Field of Study

We propose the following empirical model to estimate the returns to learning hours in different fields of study:[25]

$$(4)\quad Y_{ict} = D_{it}\mathbf{Z}_{it}\Upsilon_1 + D_{it}\mathbf{Z}_{it}\tau_t\Upsilon_2 + D_{it}\pi_c + \zeta_i + D_{it}\boldsymbol{\phi}_i + D_{it}\boldsymbol{\phi}_i\tau_t + D_{it}\omega_i + g(\mathbf{X}_{it}) + f(\boldsymbol{\rho}_{it}) + \eta_{ict}$$

Y_{ict} is the outcome of interest (that is, log daily earnings) of individual i, who attended FE college c, measured at time t. D_{it} is an indicator variable that denotes whether the individual has finished FE education at time t. $\mathbf{Z}_{it}$ is a vector representing the number of guided learning hours enrolled in each field of study.[26] The advantage of using enrolled hours rather than achieved hours is that it helps to overcome endogeneity concerns associated with differential selection in terms of who completes them. τ_t indicates the number of years since leaving FE education. $\boldsymbol{\Upsilon}_1$ and $\boldsymbol{\Upsilon}_2$ represent the parameters of interest: the returns to guided learning hours by field of study and the interaction term of years since completing FE college education and guided learning hours by field of study, respectively. This interaction accounts for the fact that returns to certain fields may take time to materialize. π_c denotes further education college fixed effects, which intend to capture the effects of college quality (π_c is

24. Another concern is related to the number of post-FE college outcome observations, which should be uncorrelated with the FE institution attended. For example, if individuals in a certain field of study are more likely to drop out of the sample, we may overstate the impact of that field of study. However, given that the labor market information is coming from the HMRC records, we can follow individuals independently of their field of study or institution attended.

25. This model is estimated separately by age group and gender.

26. Students can enroll in multiple courses in different fields. Therefore, for each student we observe a vector of the total number of guided learning hours enrolled in each field of study. For example, returns to guided learning hours in business are identified from students who specialize in business and those who specialize in social sciences, but were taking some courses in business. Online Appendix Tables A14 and A15 show the share of guided learning hours completed in other fields for an example of a popular main sector for male and female young learners, respectively.

no longer treated as a random effect as in the previous VA specifications). ζ_i denotes individual fixed effects. $\boldsymbol{\phi}_i$ is a vector determining achieved guided learning hours in qualification types (for example, BTEC, NVQ, etc.) and levels (that is, Levels 2–4), which intends to account for selection, difficulty, and signaling effects potentially attached to the different qualifications. $\boldsymbol{\phi}_i\tau_t$ captures differential returns to types of qualifications since finishing FE education. This allows us to control for differential returns to experience that may not be absorbed by individual fixed effects. ω_i denotes the number of guided learning hours achieved by awarding body for each of the different qualifications in which the student has enrolled. $g(\mathbf{X}_{it})$ includes a second-order polynomial for labor market experience, age, and region fixed effects interacted with academic year fixed effects to account for trends in local labor markets. Finally, $f(\boldsymbol{\rho}_{it})$ is a flexible vector that accounts for years since starting FE college, whether the individual is enrolled in some form of education in year t, a linear trend for years since finishing education, and academic year fixed effects.

We are unaware of other studies that intend to estimate returns to field of study based on hours enrolled in each of the different fields of study, while simultaneously controlling for type and awarding body of qualifications achieved, FE college attended, and individual fixed effects. Our approach is similar in spirit to that of Kane and Rouse (1995), who estimate returns to community college credits while conditioning on degree completion. However, they only consider overall achieved credits rather than enrolled credits by field of study. Moreover, returns to field of study in our setting are identified from individuals who specialize and those who do not specialize in a given field of study because individuals tend to complete qualifications not only in their main specialization. Therefore, concerns regarding differential returns to experience for individuals who select into a given main specialization are less of a problem in our setting.

V. Further Education College Value-Added

This section presents value-added estimates for academic and labor market outcomes. We also include robustness checks and discuss plausible mechanisms behind our main findings. As described in Section III, young and adult learners differ substantially in the number of guided learning hours they enroll in while in FE. This suggests that the returns to FE college education for these groups are likely to differ. We therefore present results separately by age group. We also show results by gender due to potential differences in the labor market trajectories of males and females.

A. Academic Outcomes and Progression to Higher Education

First, we assess to what extent some institutions are more successful than others at enhancing students' academic outcomes. These outcomes are only observed once. Therefore, we cannot implement a fixed-effects strategy or control for lags of the dependent variable. However, these empirical models include an extensive set of covariates. We control for several measures of prior academic performance, such as performance in English and math exams at age 16, 14, and 11, and many important background characteristics.[27]

Table 4 reports the population standard deviation of FE college value-added obtained from cross-sectional specifications for young learners that are 18–20 years old when first entering FE college (Column 1), and separately for males (Column 2) and females (Column 3).[28] To determine whether differences in VA across demographic groups are statistically significant, we report bootstrapped standard errors of the VA standard deviations in the second row of each panel.

The first panel of Table 4 focuses on total guided learning hours achieved. A one SD increase in institution value-added is associated with a 33-hour increase in achieved learning hours, and this effect is very similar for males and females. The effect is sizable, representing an 8 percent increase compared to the sample mean of 412 achieved guided learning hours.

The second panel considers the share of guided learning hours achieved, conditional on enrollment. Our findings show that a one SD increase in institution value-added is associated with a 4.5 percentage point increase in the share of guided learning hours achieved. This is equivalent to an increment of about 6.5 percent for the average student. Again, results are similar in magnitude for males and females.

The third panel focuses on achieving at least one Level 3 qualification. Many learners enter FE college with qualifications at or below Level 2. Achieving a Level 3 qualification can therefore be considered an important milestone because it is a requirement for higher education. While these qualifications are taught in FE colleges, they are not awarded by them but by specialized awarding bodies, providing an objective and comparable measure of educational achievement. We find that a one SD increase in FE college value-added increases the probability of obtaining a Level 3 qualification by approximately 4.4 percentage points, which is equivalent to an increase of 10.5 percent when compared to the sample mean. Value-added of colleges in this outcome is higher for males than for females.

Finally, we study progression to higher education in the last panel of Table 4. A one SD increase in FE college value-added raises the probability of progressing to a higher education program by nearly four percentage points (equivalent to a 10 percent increase in terms of the sample mean). This effect is sizable and suggests that some FE colleges are, in fact, better than others at preparing students to enroll in higher education.

Overall, our findings indicate the presence of important variation in FE college value-added in academic outcomes, suggesting that some institutions are more successful than others at enhancing the human capital of their students. Next, we explore whether such heterogeneity is present when considering labor market outcomes.

27. The full set of controls is reported in the footnotes of Table 4.

28. We focus on learners aged 18–20 because this is our main sample for the analysis of VA in labor market outcomes and because most students show a pre-FE college labor market experience. For completeness, we report analogous results for the 16–20 age sample and adult learners in Online Appendix Table A6. The results for the 16–20 sample are very similar (see row four for every outcome, where the SD in VA is expressed as the percent of the mean of the dependent variable). The same exercise for the adult sample shows bigger VA estimates in this subsample. However, the lack of many background characteristics and prior attainment measures in the adult sample calls for extra caution when interpreting these estimates.

Table 4
Value-Added in Academic Outcomes

	All (1)	Male (2)	Female (3)
Panel A: Total GLH achieved			
SD value-added (A)	33.454	35.013	33.624
SE	(1.118)	(1.256)	(1.381)
Mean dep. var. (B)	412	417	407
(A)/(B)	0.081	0.084	0.083
Observations	94,559	48,728	45,654
Colleges	228	221	227
Panel B: Share of GLH achieved			
SD value-added (A)	0.045	0.049	0.044
SE	(0.001)	(0.002)	(0.002)
Mean dep. var. (B)	0.689	0.686	0.693
(A)/(B)	0.065	0.072	0.063
Observations	94,424	48,661	45,587
Colleges	228	221	227
Panel C: Achieved 1+ Level 3 Qualification			
SD value-added (A)	0.044	0.048	0.043
SE	(0.001)	(0.002)	(0.002)
Mean dep. var. (B)	0.417	0.378	0.458
(A)/(B)	0.105	0.127	0.095
Observations	94,559	48,728	45,654
Colleges	228	221	227
Panel D: Progression to Higher Education[a]			
SD Value-Added (A)	0.038	0.044	0.038
SE	(0.001)	(0.002)	(0.002)
Mean dep. var. (B)	0.376	0.343	0.411
(A)/(B)	0.102	0.127	0.091
Observations	94,559	48,728	45,654
Colleges	228	221	227

Notes: The table shows summary statistics of value-added measures based on estimations of Equation 2 (without lagged dependent variables). The reported standard deviations of value-added measures are adjusted for sampling error. Bootstrapped standard errors on the standard deviations are reported in lines denoted SE.

[a]Denotes observed in a higher education institution at the bachelor's degree level and above. Estimates based on cross-sectional data for young learners include the following controls: a series of dummies for region where FE college is located, fixed effects for academic year compulsory schooling was completed, a series of dummies for the last year observed in education (FE or higher education, HE), dummy variables indicating the number of years since starting FE, age first entered FE college, whether student attends full-time or part-time, a series of dummies indicating the last year observed in FE college, a series of dummies for main sector, gender, a series of dummies for ethnicity (white, mixed, Asian/Chinese, Black), a dummy for whether English spoken at home, a dummy capturing whether student had special education needs during compulsory schooling, dummy for whether student was eligible to receive free school meals in KS4 year, neighborhood IDACI score based on postcode prior to joining FE college, standardized KS4 score, OFSTED rating dummies of KS4 school, KS3 math result, KS3 English result, KS2 English result, KS2 math result, series of dummies indicating whether the student had worked before FE college (never worked before college, worked in year of entry, worked one year before entry, worked two years before entry), and a series of deprivation indicators (crime, employment, health, income) based on FE college postcode and based on student's postcode coming from ILR.

B. Labor Market Outcomes

We now turn to the estimation of college value-added in labor market outcomes: log daily earnings, log annual earnings, daily earnings in levels (including zeros for those not employed), and whether the individual was employed for more than 90 days, all measured in 2017 (the last year for which we have labor market data). While annual log earnings condense the effect of FE college value-added on employment intensity and earnings, daily earnings in levels allow us to incorporate into the analysis those individuals who are not working after finishing FE education, combining extensive and intensive margin effects.

Table 5 presents the results. The first three columns correspond to lagged dependent variable specifications using cross-sectional data for young learners (Equation 2), while the last six columns correspond to individual fixed-effects specifications (Equation 3) for young (Columns 4–6) and adult learners (Columns 7–9). The top panel shows that a one SD increase in college value-added increases daily earnings by around 3 percent to 3.6 percent for young learners, depending on the specification, and by 1.6 percent for adult learners.[29]

We also explore whether heterogeneity in FE college VA in log daily earnings varies by field of study. To this end, we estimate specifications allowing institution VA to interact with field of study, grouping subjects into two broader groups of STEM and non-STEM fields. We find that the standard deviation of institution VA conditional on STEM fields is 2.8 percent, while in non-STEM fields, it is 3.6 percent.[30]

Analysis by gender, summarized in Figure 4, shows that college VA tends to matter more for females than males among young learners. A one SD increase in college value-added increases daily earnings by 4.1 percent for females and 3.1 percent for males. These estimates are statistically significantly different from each other. For adult learners we do not observe the same gender disparities in value-added.

The second panel of Table 5 shows that results are similar to our previous specification for young and adult learners when considering log annual earnings. The third panel of Table 5 shows results corresponding to daily earnings in levels, which include individuals not in employment. Again, these estimates provide a similar picture as for log daily earnings or log annual earnings. For example, a one SD increase in FE college value-added increases daily earnings for young learners by approximately £1.7, which corresponds to a 3.8 percent increase in mean daily earnings, where the estimates are slightly higher for young females than for males (5 percent vs. 3.7 percent). For older learners, a one SD increase in value-added increases daily earnings by around £1, equivalent to a 1.9 percent increase in their mean daily earnings.

Finally, we find little dispersion in terms of FE college's contribution to employment outcomes. The fourth panel of Table 5 shows that a one SD increase in FE college value-added is associated with an increase in the probability of being employed at least 90 days in 2017 of 1.7 percentage points for the young and one percentage

29. Given that estimates are very similar across model specifications for young learners, moving forward, we describe the results based on our preferred specification of panel estimates for this group (Columns 4–6).

30. While aggregation in two broad categories may mask other types of heterogeneities across sectors, sample size limitations related to having enough observations per sector and college prevent us from further disaggregating the results into finer fields of study. Note that these estimates are not reported in Table 5.

Table 5
Value-Added in Labor Market Outcomes in 2017

	18–20-Year-Olds						25–29-Year-Olds		
	Cross-Section			Panel			Panel		
	All (1)	Male (2)	Female (3)	All (4)	Male (5)	Female (6)	All (7)	Male (8)	Female (9)
Panel A: Log Daily Earnings in 2017									
SD value-added	0.036	0.026	0.044	0.030	0.031	0.041	0.016	0.018	0.019
SE	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	70,321	36,331	33,729	87,449	45,695	41,506	459,816	203,861	255,902
Colleges	227	218	224	248	242	243	252	250	252
Panel B: Log Annual Earnings in 2017									
SD value-added	0.035	0.024	0.041	0.040	0.048	0.051	0.020	0.025	0.024
SE	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
Observations	70,321	36,331	33,729	87,449	45,695	41,506	459,816	203,861	255,902
Colleges	227	218	224	248	242	243	252	250	252
Panel C: Daily Earnings in Levels in 2017 (Incl. Zeros for Not Employed)									
SD value-added (A)	1.748	2.106	1.972	1.705	1.855	1.967	0.923	1.202	0.899
SE	(0.230)	(0.383)	(0.333)	(0.163)	(0.220)	(0.200)	(0.044)	(0.077)	(0.039)
Mean dep. var. (B)	45.273	50.316	39.839	44.830	49.742	39.460	48.760	56.501	42.270
(A)/(B)	0.039	0.042	0.050	0.038	0.037	0.050	0.019	0.021	0.021
Observations	90,033	46,602	43,260	112,891	58,982	53,748	551,440	251,483	299,957
Colleges	228	221	227	250	246	246	252	252	252
Panel D: Employed > 90 Days in 2017									
SD value-added (A)	0.008	0.013	0.000	0.017	0.023	0.012	0.010	0.009	0.011
SE	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.000)

(continued)

Table 5 (*continued*)

	18–20-Year-Olds						25–29-Year-Olds		
	Cross-Section			Panel			Panel		
	All (1)	Male (2)	Female (3)	All (4)	Male (5)	Female (6)	All (7)	Male (8)	Female (9)
Mean dep. var. (B)	0.749	0.744	0.754	0.742	0.739	0.745	0.852	0.833	0.869
(A)/(B)	0.010	0.018	0.000	0.023	0.031	0.017	0.012	0.011	0.013
Observations	94,552	48,724	45,651	118,846	61,795	56,882	668,967	306,742	362,225
Colleges	228	221	227	250	246	246	252	252	252

Notes: The table shows summary statistics of value-added measures based on estimations of Equation 2 for cross-sectional data and Equation 3 for panel data. The reported standard deviations of value-added measures are adjusted for sampling error. Bootstrapped standard errors (SE) for the standard deviations are reported in parentheses. Estimates based on cross-sectional data for young learners include the following controls: earnings measured prior to FE entry, indicator for when earnings prior to entry were measured, interaction between pre-FEC earnings measure and timing of measurement (for earnings specifications), series of dummies for region where FE college is located, fixed effects for academic year compulsory schooling was completed, a series of dummies for the last year observed in education (FE or higher education, HE), dummy variables indicating the number of years since starting FE, age first entered FE college, whether student attends full-time or part-time, a series of dummies indicating the last year observed in FE college, a series of dummies for main sector, gender, a series of dummies for ethnicity (white, mixed, Asian/Chinese, Black), a dummy for whether English spoken at home, a dummy capturing whether student had special education needs during compulsory schooling, dummy for whether student was eligible to receive free school meals in KS4 year, neighborhood IDACI score based on postcode prior to joining FE college, standardized KS4 score, OFSTED rating dummies of KS4 school, KS3 math result, KS3 English result, KS2 English result, KS2 math result, a series of dummies indicating whether the student had worked before FE college (never worked before college, worked in year of entry, worked one year before entry, worked two years before entry), and a series of deprivation indicators (crime, employment, health, income) based on FE college postcode and based on student's postcode coming from ILR. Estimates based on panel data for young learners include the following controls: individual fixed effects, a series of dummies indicating the main sector (taking the value one from the year of completing FE college education and zero before), a series of dummies for region where FE college is located interacted with the academic year, years of work experience prior to entering FE college, age, age-squared, a dummy indicating whether the individual is in any form of learning in a given academic year (FE or HE), dummy variables capturing the number of years prior to FE entry, and the number of years since finishing further education. Estimates based on panel data for adult learners include the following controls: individual fixed effects, academic year fixed effects, series of dummies indicating the main sector (taking the value one from the year of completing FE college education), series of dummies for region where FE college is located interacted with the academic year, years of cumulative work experience up to FE entry, age, age-squared, dummies indicating whether the learner is undertaking any learning in a given year (whether observed in the Individual Learner Records or Work Based Learning collection), dummy indicating whether the learner is doing an apprenticeship in that year, the number of years since finishing further education, and a series of dummy variables indicating the number of years since starting FE.

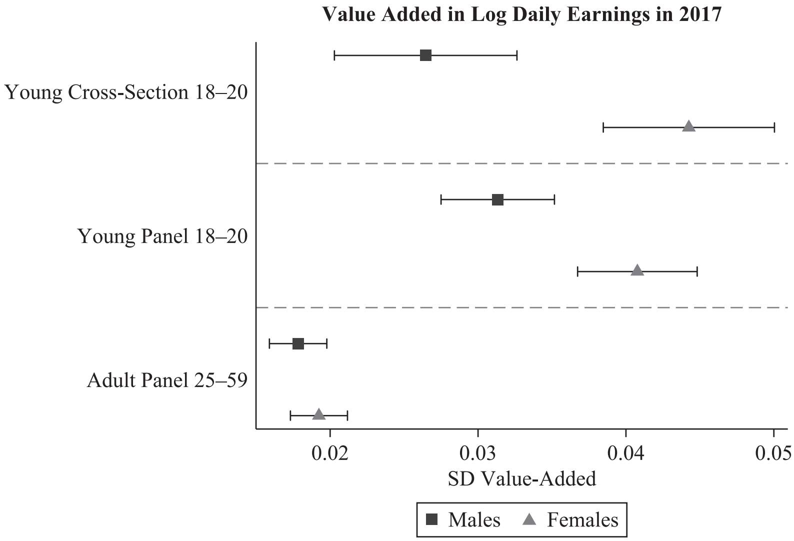

Figure 4

Value-Added in Log Daily Earnings, by Gender

Notes: The graph plots VA estimates corresponding to VA in log daily earnings for males and females separately for the young cross-section, the young panel, and the adult panel. The whiskers represent the 95 percent confidence intervals derived using bootstrapped standard errors.

point for the adult sample. This corresponds to a 2.3 percent increase with respect to the mean for the young and a 1.2 percent increase for adults.[31]

Our results do not imply that colleges do not add value or that there are no returns to attending college. Instead, they imply that overall, the variation in these returns is relatively modest. However, as shown in Online Appendix Figure A1, which plots college-level VA estimates in log daily earnings on the vertical axis, ordered by institutions' percentile rank in VA, the differences between extremes, high versus low VA institutions, are less modest.

In summary, two main findings emerge from the value-added analysis. First, heterogeneity in labor market returns of attending different FE colleges can be characterized as more moderate when compared to the variability in academic outcomes. This suggests that other factors, such as field of study, might be important to explain heterogeneity in labor market outcomes among vocational education students. Second, the effects of college quality on adult learners are about half the size of those on young learners. These differences are likely driven by the lower intensity of treatment (that is, the lower number of courses and guided learning hours completed) among adult learners.

31. The number of observations for daily earnings in the third panel is lower than the number of observations for employment because we drop outliers from our earnings observations, for example, those positive but very low daily earnings (less than £10) or very high daily earnings (more than £1,000). Individuals who were not employed in a given year are coded as having zero earnings.

C. Robustness Checks

The analysis for young learners presented so far includes students who attend higher education after FE college. Value-added estimates may, therefore, partially be picking up the effect of earning a university degree. To determine the extent to which this matters for our results and to get a sense of the importance of FE college value-added among those students whose final educational goal is to achieve a vocational degree, we present VA estimates for those who never attend university after leaving FE college (nearly 70 percent of the sample of young learners) in Online Appendix Table A7. Individual fixed-effects estimates using panel data indicate that increasing FE college value-added by one standard deviation increases daily log earnings by 2.6 percent for this subsample, which is similar in magnitude to estimates for the full sample reported in Table 5 (3 percent).

Individuals who first enter college at the ages of 16 or 17 are less likely to have prior labor market experience, which is why we have left them out of our main analysis above. However, this may compromise the external validity of our findings. To address this concern, Online Appendix Table A8 reports the variation in FE college value-added estimates for the 16–20 (Columns 1–3) and 16–17 (Columns 4–6) age groups. Reassuringly, the results are very similar to our main estimates in Table 5.

To better understand the richness of our control variables in the cross-sectional setting, Online Appendix Table A9 shows how adding different controls sequentially affects the variation in VA estimates across colleges. The first column shows that a one SD increase in FE college VA leads to an almost 8 percent increase in earnings when no controls are included. Controlling for gender (Column 2) reduces this estimate to 7.2 percent, whereas adding the learner's age and year of FE study in Column 3 reduces it to 5.2 percent. Further including controls for learners' socioeconomic status, local neighborhood deprivation, and prior school attainment at ages 11, 14, and 16 reduces the estimate to 4 percent (Column 6). Finally, adding lagged earnings (Column 7), main sector dummies (Column 8), and whether the student studies full-time versus part-time (Column 9) further reduces the estimate to 3.6 percent. Overall, we believe that our rich set of control variables is quite powerful in addressing selection.

Despite our rich set of controls, cross-sectional models with lagged dependent variables cannot completely rule out selection on unobservables. If the large set of controls is not extensive enough to account for sorting into FE colleges, we will be confounding students' characteristics with the quality of the institution. To indirectly assess the likely importance of selection on unobservables in the cross-section specifications, we follow Chetty, Friedman, and Rockoff (2014) and the teacher value-added literature and analyze to what extent VA estimates correlate with a priori important observable student characteristics (that is, prior performance—KS2 and KS3 scores—and free school meal eligibility) when the latter are left out intentionally from the empirical specifications. A strong correlation could indicate that selection on unobservables could still be an important driver of our findings. Figures 5 and 6 show, respectively, correlations of value-added measures in earnings and employment estimated in this way with measures of average prior academic preparation (that is, average student performance in KS2 and KS3 at the college level) and socioeconomic status (that is, the share of the FE college's intake that had been eligible to receive free school meals in the year they completed compulsory education). Reassuringly, our value-added estimates

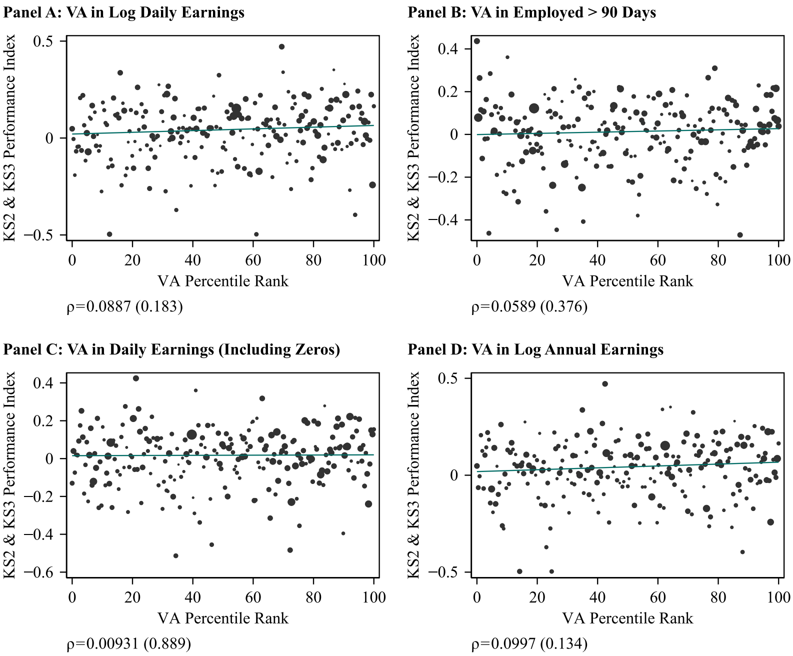

Figure 5

Value-Added in Labor Market Outcomes and Test Scores at Ages 11 and 14

Notes: The graph plots the average score on an index for KS2 and KS3 performance in math and English at a college against the college's ranking in terms of value-added in different dimensions, estimated using cross-sectional data for individuals aged 18–20 when first enrolling in the college with the same control variables as reported in Table 5, but excluding KS2 and KS3 performance. A higher rank indicates high value-added. Value-added by college is weighted by the number of observations for the college. The correlation coefficient (ρ) between the two variables is reported at the bottom left of each graph (*p*-value in parentheses).

show no correlation with either KS2 and KS3 performance nor with the share of enrolled free school meal eligible students.[32] In contrast, recall that in Figures 1 and 2, we saw that average raw daily earnings of graduates at FE colleges were significantly positively correlated with average school performance and negatively correlated with the share of the student intake that was eligible to receive free school meals. The absence of correlation between our FE value-added measures and a priori important variables that characterize the background of the learner suggests that selection on unobservables is not driving our cross-sectional results.

32. A similar test would be to estimate the correlation of FE college value-added when we include and exclude prior performance and free school meal eligibility (FSM). Our results show, for example, that the correlation of FE value-added in log daily earnings between these models is 0.998 when we include and exclude FSM from the preferred specification.

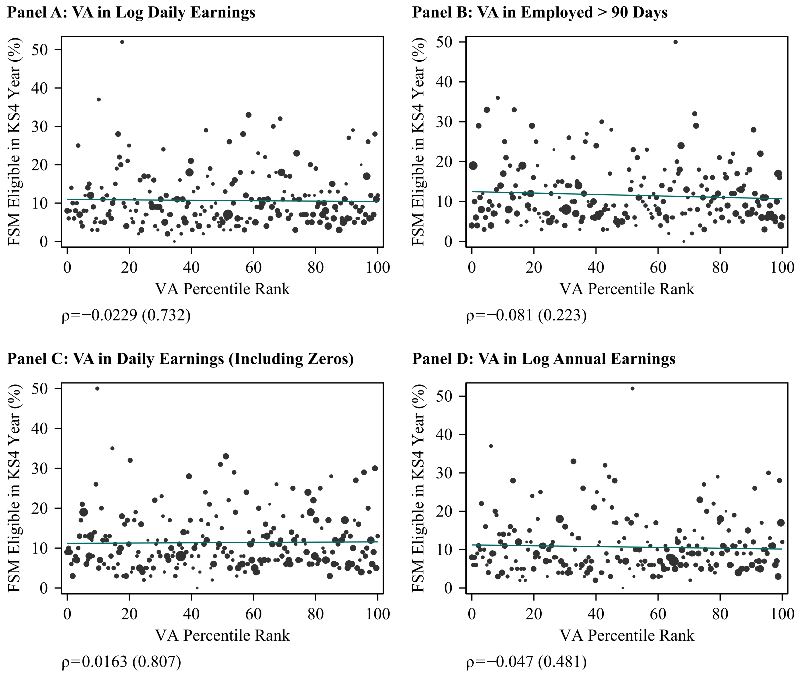

Figure 6

Value-Added in Labor Market Outcomes and Socioeconomic Status

Notes: The graph plots the share of students at a college having been eligible for free school meals at some point during compulsory schooling against the college's ranking in terms of value-added in different dimensions, estimated using cross-sectional data for individuals aged 18–20 when first enrolling in the college with the same control variables as reported in Table 5, but excluding free school meal eligibility. Value-added by college is weighted by number of observations for the college. The correlation coefficient (ρ) between the two variables is reported at the bottom left of each graph (*p*-value in parentheses).

D. Mechanisms

To provide a better understanding of what might be driving FE college VA, we regress these measures on a set of potential mediating variables: college inspection ratings, value-added measures on academic outcomes (representing proxies for human capital accumulation), indicators for resources available to students, and the share of students enrolled in different types of learning formats in each institution (for example, percent of subjects set in the classroom).[33]

Table 6 shows results corresponding to three college-level regressions where the dependent variables are VA in log daily earnings, employment, and enrollment in

33. College inspection ratings are performed on a regular basis and colleges receive a grade between one and four, where four means that the college requires improvement, and one means that the college is outstanding (Ofsted reports). We recoded the measure so that four means "outstanding" and one means "requires improvement."

Table 6
Value-Added for Young Learners and College Characteristics

	VA ln Earnings (1)	VA Employment (2)	VA HE (3)
Average OFSTED rating[a]	0.002	−0.002	−0.001
	(0.003)	(0.001)	(0.003)
VA in achieved Level 3	0.109**	0.009	0.104*
	(0.051)	(0.021)	(0.060)
VA in % of GLH achieved	0.167***	−0.005	0.200***
	(0.048)	(0.019)	(0.056)
Teacher salary cost/Total staff cost	0.039	−0.000	0.065*
	(0.034)	(0.014)	(0.039)
Total expenditure over FTE students	0.003	−0.000	−0.000
	(0.002)	(0.001)	(0.002)
% aims set in workplace	−0.227*	−0.011	−0.138
	(0.128)	(0.052)	(0.150)
% aims classroom/provider	0.098***	0.025*	0.007
	(0.033)	(0.013)	(0.039)
Observations	225	226	226
R^2	0.213	0.047	0.113

Notes: The table shows regressions of value-added measures in labor market outcomes and progression to higher education (HE) on college-level characteristics. VA in log daily earnings (Column 1) and employment (Column 2) derived using panel data and individual fixed-effects strategy for the sample of 18−20-year-olds. VA in progression to higher education (Column 5) was derived using cross-sectional data for the sample of 18–20-year-olds. Standard errors in parentheses. *$p < 0.5$, **$p < 0.01$, ***$p < 0.001$. GLH, guided learning hours; FTE, full-time equivalent.
[a]Average between 2005 and 2010.

higher education. We focus the analysis on young learners, given that variation in FE college VA for adult learners is relatively small. Column 1 indicates that VA in log daily earnings is positively and statistically significantly correlated with VA in achievement of Level 3 qualifications and VA in the share of achieved guided learning hours. We also find that different learning formats significantly correlate with VA in earnings. For example, institutions with a larger share of students taking in-person classes (note that the excluded alternative is distance learning) tend to exhibit higher VA in earnings. Finally, college inspection ratings (that is, average grade received in Ofsted reports) and measures of available resources do not seem to correlate with VA in earnings. Column 2 focuses on explaining VA in employment, and the only significant correlate is the percent of aims set in the classroom. The relatively low explanatory power of the mediating variables is somewhat unsurprising, given that we do not find much variation in VA in employment. Finally, Column 3 studies plausible mechanisms behind FE college variation in increasing the probability of attending higher education. Results show that value-added measures in achievement of Level 3 qualifications and share of achieved guided learning hours are positively and significantly correlated with VA in progression to higher education. This is expected, given that achieving a Level 3 qualification is a prerequisite for higher education. Finally, we also find that the share of total staff cost spent on teachers is positively, though only marginally significantly, correlated with VA in progression to higher education, but not with VA in labor market outcomes.

Overall, our findings indicate that VA in academic outcomes (which are directly linked to human capital formation) are significantly correlated with VA in earnings. This suggests that the human capital accumulation channel is important to explain why some colleges are better than others at improving the labor market outcomes of their students. We also find that learning formats may play a role in explaining quality. However, like Stange (2012), we do not find strong evidence indicating that college expenditure levels are associated with FE college quality.

VI. Returns to Field of Study

In this section, we first present the results on returns to field of study and then provide a discussion of the results and several robustness checks.

A. Results

Tables 7–10 reports the full set of results. Column 1 displays the level effect of enrolled guided learning hours in each field of study, while Column 2 reports their interaction with years since finishing FE college.[34] Column 3 reports mean GLH in a given sector when that field is the main field of study. Columns 4 and 5 provide an approximation of the marginal effect of specializing in each field one and five years after finishing FE education. We report the share of individuals specializing in each field in Column 6. Finally, for each of the subsamples, we summarize the marginal effects of specializing in each field one and five years after finishing FE education in Figure 7, focusing on the fields representing at least 5 percent of enrollment of the respective sample.

1. Young male learners

The top left panel of Figure 7 shows that the two fields of study that present the largest returns five years after graduation are engineering and manufacturing technology, and business administration and law. The average young male learner specializing in these fields experiences an increase of 7.7 percent and 5.8 percent in daily earnings, respectively. Many specializations present negative returns immediately after graduation that turn positive five years after graduation. Some fields, such as preparation for life and work, exhibit negative returns even five years after graduation. The differences in returns among the top three majors in terms of enrollment are substantial.

34. The coefficients on the interaction terms correspond to Υ_2 in Equation 4.

Table 7
Earnings Returns to Field of Study—Males (Young Learners)

	Coefficients			Estimated Return		
Field of Study	Υ_1 (1)	Υ_2 (2)	Mean GLH if Main Field (3)	1-Year Post FE (4)	5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
Health, public services, and care	0.001	0.001***	402	0.010	0.027***	8.1%
	(0.002)	(0.000)		(0.007)	(0.006)	
Science and mathematics	–0.005	0.002***	447	–0.012	0 030*	2.2%
	(0.003)	(0.001)		(0.014)	(0.012)	
Agriculture, horticulture, and animal care	–0.007*	0.001*	633	–0.036*	–0.010	1.7%
	(0.003)	(0.000)		(0.018)	(0.016)	
Engineering and manufacturing technology	0.002	0.002***	622	0.025***	0 077***	20.4%
	(0.001)	(0.000)		(0.006)	(0.005)	
Construction, planning, and the built environment	–0.004***	0.002***	614	–0.014*	0 035***	18.3%
	(0.001)	(0.000)		(0.007)	(0.006)	
Information and communication technology	–0.007***	0.002***	706	–0.030**	0 037***	6.7%
	(0.002)	(0.000)		(0.010)	(0.009)	
Retail and commercial enterprise	–0.003	0.001***	477	–0.010	0.015	4.6%
	(0.002)	(0.000)		(0.010)	(0.009)	
Leisure, travel, and tourism	–0.010***	0.003***	570	–0.039***	0.036***	8.8%
	(0.001)	(0.000)		(0.008)	(0.007)	
Arts, media, and publishing	–0.009***	0.002***	926	–0.063***	0.016*	10.8%
	(0.001)	(0.000)		(0.009)	(0.008)	

(*continued*)

Table 7 (*continued*)

	Coefficients			Estimated Return		
Field of Study	Υ_1 (1)	Υ_2 (2)	Mean GLH if Main Field (3)	1-Year Post FE (4)	5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
History, philosophy, and theology	−0.022**	0.004*	411	−0.077**	−0.018	0.5%
	(0.008)	(0.001)		(0.030)	(0.025)	
Social sciences	−0.008	0.003*	356	−0.018	0.030	0.3%
	(0.011)	(0.002)		(0.037)	(0.033)	
Languages, literature, and culture	−0.009	0.004*	118	−0.006	0.014	0.7%
	(0.013)	(0.002)		(0.014)	(0.012)	
Education and training	0.022	0.006**	197	0.057*	0.108***	0.3%
	(0.015)	(0.002)		(0.027)	(0.023)	
Preparation for life and work	−0.014***	0.001	154	−0.020***	−0.017***	9.4%
	(0.003)	(0.000)		(0.004)	(0.004)	
Business administration and law	0.000	0.002***	551	0.010	0.058***	7.3%
	(0.002)	(0.000)		(0.009)	(0.008)	
Observations	286,935					

Notes: The $\boldsymbol{\Upsilon_1}$s are coefficients from individual fixed-effects regressions of log daily earnings on the total number of guided learning hours (in hundreds) enrolled in a particular field of study (Equation 4). The $\boldsymbol{\Upsilon}_2$s are the interaction terms between guided learning hours enrolled (in hundreds) and years since finishing FE college education. The estimated returns reported in Columns 4 and 5 are the marginal effects one and five years after leaving the college, respectively, of choosing the sector as the main sector. The regression controls for guided learning hours achieved by awarding body and type/level of qualification, plus the interaction term between GLH achieved by type/level of qualification and years since finishing FE college, college fixed effects, and cumulative experience, in addition to the controls reported in Section IV.B. Sample: male learners aged 18–20 who were enrolled in FE college between 2005 and 2010 and who study towards qualifications at Level 2 or above.

Table 8
Earnings Returns to Field of Study—Males (Adult Learners)

	Coefficients			Estimated Return		
Field of Study	Υ_1 (1)	Υ_2 (2)	Mean GLH if Main Field (3)	1-Year Post FE (4)	5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
Health, public services, and care	−0.009*** (0.001)	0.003*** (0.000)	73	−0.005*** (0.001)	0.004*** (0.000)	19.0%
Science and mathematics	−0.035*** (0.002)	0.007*** (0.000)	215	−0.061*** (0.004)	−0.001 (0.003)	1.1%
Agriculture, horticulture, and animal care	−0.019*** (0.002)	0.003*** (0.000)	182	−0.029*** (0.003)	−0.006* (0.002)	1.5%
Engineering and manufacturing technology	−0.004*** (0.001)	0.002*** (0.000)	207	−0.003** (0.001)	0.015*** (0.001)	19.0%
Construction, planning, and the built environment	−0.008*** (0.001)	0.002*** (0.000)	284	−0.018*** (0.002)	0.007*** (0.001)	10.7%
Information and communication technology	−0.019*** (0.001)	0.005*** (0.000)	166	−0.025*** (0.001)	0.006*** (0.001)	7.9%
Retail and commercial enterprise	−0.005*** (0.002)	0.001*** (0.000)	88	−0.003** (0.001)	0.002 (0.001)	6.9%
Leisure, travel, and tourism	−0.031*** (0.002)	0.003*** (0.000)	134	−0.037*** (0.002)	−0.018*** (0.002)	3.7%
Arts, media, and publishing	−0.021*** (0.001)	0.004*** (0.000)	342	−0.059*** (0.003)	−0.010*** (0.002)	2.3%

(*continued*)

Table 8 (*continued*)

	Coefficients			Estimated Return		
Field of Study	Υ_1 (1)	Υ_2 (2)	Mean GLH if Main Field (3)	1-Year Post FE (4)	5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
History, philosophy, and theology	−0.076***	0.012***	389	−0.250***	−0.070***	0.5%
	(0.003)	(0.001)		(0.010)	(0.007)	
Social sciences	−0.049***	0.008***	348	−0.142***	−0.033**	0.1%
	(0.005)	(0.001)		(0.016)	(0.011)	
Languages, literature, and culture	−0.005	0.001	113	−0.004	0.000	1.6%
	(0.003)	(0.001)		(0.003)	(0.003)	
Education and training	0.004**	0.001***	119	0.006***	0.011***	6.8%
	(0.001)	(0.000)		(0.001)	(0.001)	
Preparation for life and work	−0.026***	0.005***	109	−0.023***	−0.003*	4.7%
	(0.002)	(0.000)		(0.002)	(0.001)	
Business administration and law	0.003**	0.001***	131	0.005***	0.009***	14.2%
	(0.001)	(0.000)		(0.001)	(0.001)	
Observations	2,695,465					

Notes: The Υ_1s are coefficients from individual fixed-effects regressions of log daily earnings on the total number of guided learning hours (in hundreds) enrolled in a particular field of study (Equation 4). The Υ_2s are the interaction terms between guided learning hours enrolled (in hundreds) and years since finishing FE college education. The estimated returns reported in Columns 4 and 5 are the marginal effects, one and five years after leaving the college, respectively, of choosing the sector as the main sector. The regression controls for guided learning hours achieved by awarding body and type/level of qualification, plus the interaction term between GLH achieved by type/level of qualification and years since finishing FE college, college fixed effects, and cumulative experience, in addition to the controls reported in Section IV.B. Sample: male learners aged 25–59 who were enrolled in FE college between 2006–2007 and 2009–2010 and who study towards qualifications at Level 2 or above.

Table 9
Earnings Returns to Field of Study—Females (Young Learners)

Field of Study	Coefficients Υ_1 (1)	Coefficients Υ_2 (2)	Mean GLH if Main Field (3)	Estimated Return 1 Year Post FE (4)	Estimated Return 5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
Health, public services, and care	−0.002	0.002***	514	0.000	0.036***	25.3%
	(0.001)	(0.000)		(0.006)	(0.005)	
Science and mathematics	−0.008*	0.005***	369	−0.009	0.071***	2.8%
	(0.004)	(0.001)		(0.013)	(0.012)	
Agriculture, horticulture, and animal care	−0.002	0.003***	796	0.014	0.122***	2.5%
	(0.002)	(0.000)		(0.017)	(0.015)	
Engineering and manufacturing technology	0.002	0.002***	555	0.024	0.073***	1.2%
	(0.004)	(0.001)		(0.020)	(0.017)	
Construction, planning, and the built environment	−0.006	0.003***	630	−0.018	0.052*	0.8%
	(0.005)	(0.001)		(0.029)	(0.025)	
Information and communication technology	−0.007	0.003***	351	−0.013	0.036***	3.0%
	(0.004)	(0.001)		(0.012)	(0.011)	
Retail and commercial enterprise	−0.004*	0.003***	590	−0.006	0.055***	25.0%
	(0.002)	(0.000)		(0.009)	(0.008)	
Leisure, travel, and tourism	−0.002	0.003***	611	0.011	0.095***	5.6%
	(0.002)	(0.000)		(0.011)	(0.010)	
Arts, media, and publishing	−0.004**	0.004***	877	0.007	0.164***	11.3%
	(0.001)	(0.000)		(0.010)	(0.009)	

(*continued*)

Table 9 (*continued*)

	Coefficients			Estimated Return		
Field of Study	Υ_1 (1)	Υ_2 (2)	Mean GLH if Main Field (3)	1 Year Post FE (4)	5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
History, philosophy, and theology	−0.018**	0.007***	432	−0.048	0.071***	1.0%
	(0.007)	(0.001)		(0.026)	(0.021)	
Social sciences	0.003	0.007***	336	0.034	0.123***	0.4%
	(0.010)	(0.002)		(0.032)	(0.028)	
Languages, literature, and culture	−0.017	0.004**	133	−0.017	0.006	1.2%
	(0.009)	(0.001)		(0.011)	(0.009)	
Education and training	0.031***	0.001	165	0.053***	0.062***	1.5%
	(0.009)	(0.001)		(0.013)	(0.011)	
Preparation for life and work	−0.022***	0.005***	175	−0.029***	0.008	5.9%
	(0.004)	(0.001)		(0.007)	(0.006)	
Business administration and law	0.004*	0.004***	430	0.036***	0.103***	12.5%
	(0.002)	(0.000)		(0.007)	(0.006)	
Observations	226,524					

Notes: The Υ_1s are coefficients from individual fixed-effects regressions of log daily earnings on the total number of guided learning hours (in hundreds) enrolled in a particular field of study (Equation 4). The Υ_2s are the interaction terms between guided learning hours enrolled (in hundreds) and years since finishing FE college education. The estimated returns reported in Columns 4 and 5 are the marginal effects, one and five years after leaving the college, respectively, of choosing the sector as the main sector. The regression controls for guided learning hours achieved by awarding body and type/level of qualification, plus the interaction term between GLH achieved by type/level of qualification and years since finishing FE college, college fixed effects, and cumulative experience, in addition to the controls reported in Section IV.B. Sample: Female learners aged 18–20 who were enrolled in FE college between 2005 and 2010 and who study towards qualifications at Level 2 or above.

Table 10
Earnings Returns to Field of Study—Females (Adult Learners)

Field of Study	Coefficients Υ_1 (1)	Υ_2 (2)	Mean GLH if Main Field (3)	Estimated Return 1 Year Post FE (4)	5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
Health, public services and care	–0.009***	0.005***	136	–0.006***	0.019***	34.3%
	(0.001)	(0.000)		(0.001)	(0.000)	
Science and mathematics	–0.028***	0.009***	177	–0.034***	0.027***	2.2%
	(0.002)	(0.000)		(0.003)	(0.002)	
Agriculture, horticulture, and animal care	–0.012***	0.001**	343	–0.038***	–0.028***	1.1%
	(0.001)	(0.000)		(0.004)	(0.003)	
Engineering and manufacturing technology	–0.005*	0.001***	172	–0.007*	0.003	1.2%
	(0.002)	(0.000)		(0.003)	(0.002)	
Construction, planning and the built environment	–0.004**	0.003***	398	–0.006	0.038***	0.5%
	(0.002)	(0.000)		(0.006)	(0.005)	
Information and communication technology	–0.023***	0.005***	134	–0.024***	0.002	7.2%
	(0.001)	(0.000)		(0.002)	(0.038)	
Retail and commercial enterprise	–0.021***	0.002***	218	–0.041***	–0.025***	11.3%
	(0.001)	(0.000)		(0.002)	(0.002)	
Leisure, travel, and tourism	–0.017***	0.001***	176	–0.028***	–0.020***	1.7%
	(0.002)	(0.000)		(0.003)	(0.002)	
Arts, media, and publishing	–0.017***	0.002***	291	–0.043***	–0.018***	2.7%
	(0.001)	(0.000)		(0.002)	(0.002)	

(*continued*)

Table 10 (*continued*)

Field of Study	Coefficients Υ_1 (1)	Coefficients Υ_2 (2)	Mean GLH if Main Field (3)	Estimated Return 1 Year Post FE (4)	Estimated Return 5 Years Post FE (5)	Share of Individuals Specializing in Field (6)
History, philosophy, and theology	−0.052***	0.013***	431	−0.169***	0.056***	1.1%
	(0.002)	(0.000)		(0.006)	(0.005)	
Social sciences	−0.026***	0.007***	429	−0.082***	0.039***	0.3%
	(0.002)	(0.000)		(0.009)	(0.007)	
Languages, literature, and culture	−0.005**	0.001*	130	−0.006*	−0.001	2.5%
	(0.002)	(0.000)		(0.002)	(0.002)	
Education and training	−0.009***	0.006***	140	−0.005***	0.026***	12.7%
	(0.001)	(0.000)		(0.001)	(0.001)	
Preparation for life and work	−0.021***	0.009***	139	−0.017***	0.030***	6.5%
	(0.001)	(0.000)		(0.002)	(0.001)	
Business administration and law	0.002*	0.001***	187	0.006***	0.017***	14.8%
	(0.001)	(0.000)		(0.001)	(0.001)	
Observations	3,194,471					

Notes: The Υ_1s are coefficients from individual fixed-effects regressions of log daily earnings on the total number of guided learning hours (in hundreds) enrolled in a particular field of study (Equation 4). The Υ_2s are the interaction terms between guided learning hours enrolled (in hundreds) and years since finishing FE college education. The estimated returns reported in Columns 4 and 5 are the marginal effects, one and five years after leaving the college, respectively, of choosing the sector as the main sector. The regression controls for guided learning hours achieved by awarding body and type/level of qualification, plus the interaction term between GLH achieved by type/level of qualification and years since finishing FE college, college fixed effects, and cumulative experience, in addition to the controls reported in Section IV.B. Sample: female learners aged 25–59 who were enrolled in FE college between 2006–2007 and 2009–2010 and who study towards qualifications at Level 2 or above.

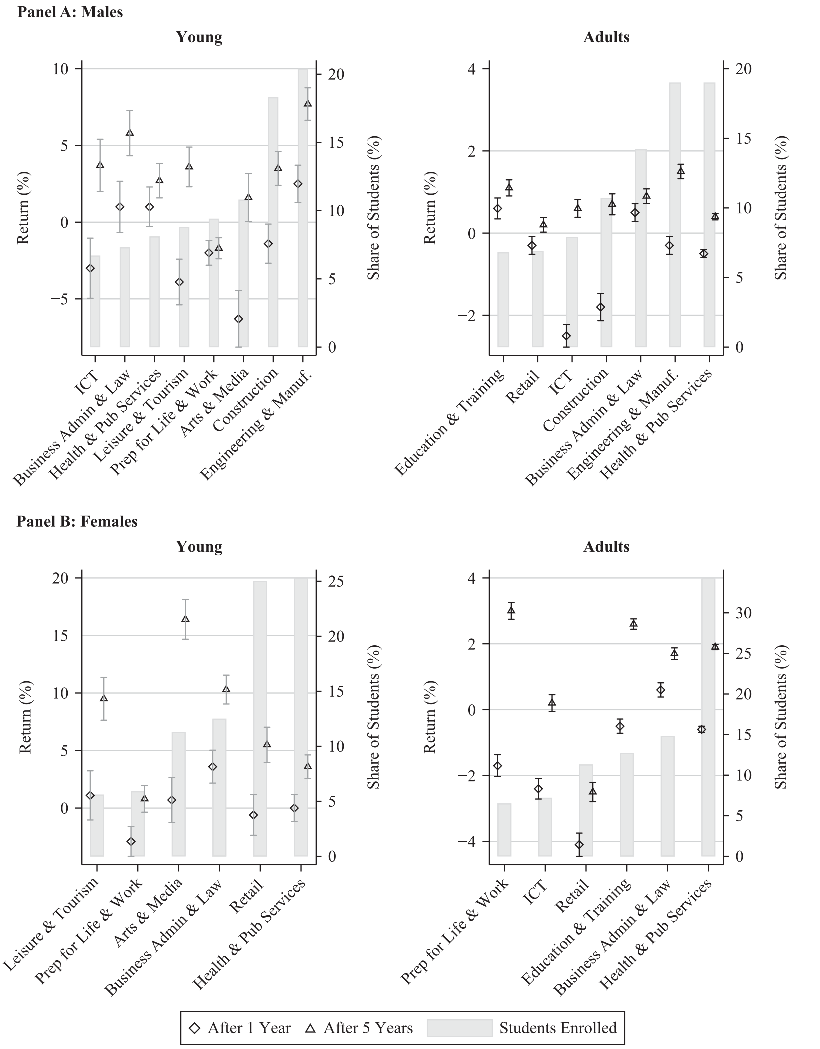

Figure 7

Daily Earnings Returns to Field of Study

Notes: The graph plots estimates for the marginal returns to field of study one and five years after FE college graduation for the average learner specializing in these fields. These are obtained by multiplying the average guided learning hours taken among those that specialize in a given field reported in Column 3 of Table 7 for young males (Table 8 for adult males, Table 9 for young females, and Table 10 for adult females), multiplied by the returns per 100 hours one and five years after leaving FE education (Columns 1 and 2 of the respective tables). The whiskers represent the 95 percent confidence intervals. Only fields with at least 5 percent of enrollment are shown. The bars represent the enrollment shares in each field. Sample: individuals aged 18–20 (25–54) when first enrolling in FE college for young (adult) learners.

The average student in engineering and manufacturing technology will experience a return between 2.2 and 4.8 times larger than the average student in the two other specializations (Table 7 also reports these results).[35]

2. Adult male learners

The top right panel of Figure 7 shows that engineering and manufacturing technology, education and training, and business administration and law are among the fields that lead to the largest returns five years after FE college attendance for male adult learners. The average adult specializing in these fields shows an increase in daily earnings five years after graduation of 1.5 percent, 1.1 percent, and 0.9 percent, respectively. As noted earlier, the overall lower returns compared to young learners are potentially driven by the fact that adult learners enroll in a substantially lower number of guided learning hours overall. Finally, most sectors lead to returns close to zero five years after completion. Some sectors, such as history, philosophy, and theology, even exhibit negative returns, but these are mostly insignificant, as they represent very small enrollment shares (Table 8 also reports these results).

3. Young female learners

This demographic group experienced statistically significant positive returns five years after graduation across almost all fields, as seen in the bottom left panel of Figure 7 and Table 9. For example, the average female specializing in arts, media, and publishing experiences an increase in daily earnings of 16.4 percent five years after graduation, while those specializing in business administration or health experience returns of 10.3 percent and 3.6 percent, respectively. If we compare returns between young males and females, it is not clear what drives these differences. A possible explanation could be gender disparities in matching between FE college specialization and occupation. An alternative explanation could be gender differences in work intensity in the years before and after enrolling in FE college. Finally, it is worth highlighting that the enrollment of young females across fields is very different from their young male counterparts. For example, while 1.2 percent of females pursue engineering and manufacturing as their main field of study, 20.4 percent of young males do so. To conclude, similar to young male learners, the differences in returns among the top three majors for females in terms of enrollment are significant. The average young female student in business administration and law will experience a return that is between 1.9 to 2.9 times larger than the average student in the two other specializations.[36]

4. Adult female learners

These learners mainly specialize in health, public services, and care (34.3 percent), business administration and law (14.8 percent), and education and training

35. Engineering and manufacturing technology, construction, planning and the built environment and arts, media, and publishing represent approximately 50 percent of the total enrollment of male young learners.

36. Health, public services, and care; retail and commercial enterprise; and business administration and law represent approximately 60 percent of the total young female enrollment.

(12.7 percent). All these fields show returns between approximately 2 percent and 3 percent five years after graduation for the average learner (see bottom right panel of Figure 7 and Table 10). Those specializing in retail and commercial enterprise experience a negative return five years after completion of –2.5 percent. Overall, returns for adult females are larger in magnitude than for adult males, mirroring the findings for young learners. Note that while in our main specifications we tend to find higher returns to specializations for females than for males, this does not imply that females overall have higher earnings post FE-college attendance. As can be seen from the summary statistics in Online Appendix Tables A1–A4, women have consistently lower average earnings five years after FE college attendance.

Four main conclusions emerge from these results. First, there are important heterogeneities in the returns to fields of study. Second, adults experience smaller overall returns to field of study. Third, engineering and manufacturing technology and business administration and law are not only showing large enrollment levels among young and adult male learners, but they are also among the fields that lead to the largest positive returns. Finally, business administration and law and health, public services, and care are the fields that show both high levels of enrollment and consistently positive returns for females across age groups.

B. Discussion and Robustness Checks

In our main analysis, we estimate the returns to field of study while simultaneously controlling for achieved qualifications by type, level, and awarding body. This allows us to estimate returns to GLH in different fields net of completion effects, which is important because many students do not finish their studies. To get an understanding of potential sheepskin effects (that is, the value of qualification achievement above and beyond the value of enrolling and studying a given amount of GLH by sector), Online Appendix Tables A10–A13 show returns estimates when controlling for *enrolled* rather than *achieved* qualifications by type, level and awarding body. Estimates are generally similar across the two specifications, suggesting that sheepskin effects are not very important in this setting. However, we find some larger differences for young females, for instance, in health, public services and care and retail and commercial enterprise. These findings are consistent with Kane and Rouse (1995), who find only small returns to degree completion over and above the value of the credits completed, except for the case of females, which is mainly driven by nursing.

Our estimates of returns to field of study are, in general, smaller than those found elsewhere in the literature for community colleges in the United States (see, for instance, Belfield and Bailey 2017a; Stevens, Kurlaender, and Grosz 2019). Unlike most of these other studies, which include dummy variables to capture returns to field of study, the granularity of our data allows our identification strategy to estimate returns to field of study by exploiting information on the number of guided learning hours enrolled in each of the specific fields while holding constant enrolled guided learning hours in other fields. Moreover, our specifications control for qualification achievement. These two features are likely to make some of our estimates lower than in other studies.[37]

Finally, we explore the importance of learning in one's main sector versus other fields. We do this in specifications where we include a variable indicating GLH in the main field of study and a variable measuring GLH in other fields. We find that returns to GLH in the main field of study are 20 percent and 35 percent larger than returns to GLH in other fields for young male and female learners, respectively.[38]

VII. Conclusions

In this study, we estimate FE college value-added in terms of several academic and labor market outcomes and returns to field of study in vocational education for young and adult learners in England. Our findings show that variability in FE college VA is larger for young than adult learners, which is likely driven by differences in the intensity of the treatment—adults tend to enroll in fewer, shorter, and less intense courses in terms of learning hours. We find moderate variability in college value-added in terms of earnings and employment probabilities. However, there is more heterogeneity across institutions when considering completion of learning hours and progression to higher levels of learning.

We present indicative evidence that certain characteristics of the FE colleges correlate with institution VA in labor market outcomes. Value-added in earnings presents a statistically significant positive correlation with college VA in terms of the share of GLH achieved, VA in achieving a good (Level 3) upper secondary qualification, and with in-person (as opposed to distance) learning. While these correlations cannot be interpreted as causal, they provide potential avenues for further research into the drivers of college value-added.

The moderate variation in institution VA on earnings contrasts with the larger heterogeneity in returns to field of study, suggesting that *what* one studies rather than *where* one does so is more relevant for labor market outcomes. For instance, if we order fields of study based on their returns for the typical young male (female) learner, then changing from a specialization that is in the (bottom) 10th percentile to one in the (top) 90th percentile would lead to an increase in returns that is approximately 84 percent (43 percent) larger than if we were performing the same exercise but based on FE college value-added. The larger heterogeneity in returns to field of study is not driven by "niche" fields with low enrollment levels. Differences in returns to field of study among the most popular specializations (in terms of enrollment) are also substantial. These findings also imply that rather than colleges not producing human capital that is valued in the labor market, many of them do not seem to be enrolling students in the programs with the highest returns.

Overall, our findings can help prospective FE learners make more informed decisions on how to confront important trade-offs in post-secondary education. These

37. In fact, we run the analysis with main field dummies, and the returns to field of study in those specifications tend to be larger. Results are available upon request.

38. Results are available upon request.

results are particularly relevant in light of the evidence suggesting that students tend to be misinformed about the labor market returns of VET qualifications. For example, Baker et al. (2018) find that only 13 percent of students in their sample of community colleges in California correctly rank four broad categories of majors in terms of salary. Since the typical student attending FE is relatively immobile, policymakers should focus particularly on ensuring appropriate career advice to students regarding the field of study they choose.

Our findings are also relevant since most students attending FE college tend to be from a disadvantaged socioeconomic background and have low prior attainment. Therefore, providing information so that these students can achieve high labor market returns after completing vocational qualifications could be crucial for reducing inequality.

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