Technical Report

Building a stronger FE college workforce

Methodological appendices

National Foundation for Educational Research (NFER)

Building a stronger FE college workforce: Methodological appendices

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1. Introduction

The existing research and analysis on the further education (FE) workforce in England is limited – particularly so in analysis of pay gaps between FE teaching and industry. This research, commissioned by the Gatsby Charitable Foundation, aims to build upon the existing literature and provide rich new insights on the FE workforce, including new estimates of the magnitude of pay disparities between FE teaching and industry. We provide a detailed summary of the main findings of the research in the main report.

This is an exploratory research project, using a mixed-methods design. The research design involved gathering primary data to explore the main themes in the FE teacher supply landscape, supported by extensive analysis of secondary data sources. We provide a more detailed overview of the project's design and methodology in the main report.

This technical report summarises in detail key aspects of the qualitative and quantitative methodology used in the project to complement, rather than replace, the overview provided in the main report.

This report is arranged into two main sections: Appendix A and Appendix B. Appendix A provides detail on the qualitative analysis used in the project, including interviewee recruitment, sample characteristics and topics covered in the interview. Appendix B provides detail on the quantitative analysis for the project, outlining the different datasets we used, key definitions of samples and variables and our analysis and discussion of self-employment earnings in the Construction, Engineering and Digital industries.

2. Appendix A: Qualitative methodology

The qualitative analysis was integral to the research undertaken in this report. In this section we outlined some of the key details around the recruitment, interviews and sample characteristics used in the analysis.

2.1. Interviewee recruitment

The research team selected Construction, Engineering and Digital as the departments to focus on due to their reputation in the FE sector as being a particular challenge to recruit for. However, it was our intention to use this piece of work as a template for similar research on other FE departments in future. The regions of the North East, South East and West Midlands were selected to provide a range of geography and regional prosperity levels.

All 59 FE colleges with Construction, Engineering and/or Digital departments in these regions were invited to participate in the study. A total of 152 individuals were contacted about participating in the interviews.

Contact details for relevant individuals within those colleges were identified from publicly available sources (such as college websites) or introductions were made via another staff member at the college – including other interviewees. Some teachers were nominated by their Heads of Department, but others were recruited directly. Stakeholders in the research team contacted colleges in advance to alert them of the research and to encourage them to participate.

2.2. Interviewee sample characteristics

The primary qualitative data collection strand of the research involved interviews with a total of 61 members of FE college staff: 27 Heads of Department and 34 teachers[1] from Construction (and the Built Environment), Engineering (and Manufacturing) and Digital departments. Interviewees came from 23 FE colleges across the North East, South East and West Midlands.

While we fell only just short of the target number of interviewees (63), they were not evenly split across departments and regions as had been the initial ambition. This was due to lower levels of engagement with the research among Digital departments and in the South East, and higher levels engagement among Construction departments.

The number of teachers we interviewed was evenly spread across departments and regions. However, study recruitment challenges led us to interview about three times as many Heads of Construction compared to the other two subject areas. We also interviewed significantly fewer Heads of Departments in the South East than in the other regions. See Table 1 for a breakdown by role and department.

[1] While the main focus of the research was on FE lecturers, there were a few lecturers who were in teaching positions but had slightly different job titles. We therefore use the broader term ‘FE teacher’ to refer to interviewees who were in teaching positions.

Table 1 Number of interviewees by role and department

	Heads of Department			Teachers		
	Con.	Dig.	Eng.	Con.	Dig.	Eng.
Total	12	6	9	11	11	12

Source: NFER analysis of primary data collection

While interviews with Heads of Department were intended to provide an overview of the recruitment and retention situation within their department, interviews with teachers looked to understand their own specific journey, attitudes and motivations around working in FE. As a result, more demographic data was collected for the teachers interviewed than the Heads of Department, as it was important to understand the extent to which they could be seen to represent other FE teachers working in their area.

2.2.1. Level of FE experience

Most of the Heads of Department that were interviewed had worked in FE for over 10 years, with the range of FE experience extending from eight to 30 years (see Table 2). Most had either progressed within their departments from teaching to leadership roles or had moved from other colleges for the Head of Department role. In addition to this leadership experience, most of the Heads of Department had worked in industry prior to moving into FE.

The sample of teachers consisted both of those who had worked in FE for a short period and very experienced teachers, with FE experience ranging from just under a year to 30 years, with most falling between 5 and 15 years, as shown in Table 2.

Table 2. Length of time interviewees had spent in FE

Length of time in FE (years)	Number of Heads of Department	Number of teachers
0-4	0	6
5-10	5	10
11-15	7	8
16-20	9	6
Over 20	6	4
Total	**27**	**34**

Source: NFER analysis of primary data collection

The majority of teachers taught qualifications up to level 3. Around a third taught qualifications up to level 5, while a small number taught at level 1 or 2.[2] Around two-thirds of teachers interviewed had an area of responsibility in addition to their teaching role. This included being responsible for a particular subject area or course level, continuing professional development in the department, or a staff support role.

2.2.2. Qualifications

Excluding their teaching qualifications, FE teachers' qualification levels ranged from level 3 to level 8. The majority of teachers in Digital and Engineering had a subject level qualification at degree-level (level 6) or above – including undergraduate, master's and doctorate degrees.

Just over a quarter of teachers had level 5 qualifications, including HNDs and foundation degrees. Around one in five had qualifications below level 5 – all in Construction. A small number had level 4 qualifications, such as HNCs, or level 3 qualifications such as National Vocational Qualifications (NVQs).

2.2.3. Salary

As part of the interviews, teachers were asked if they were willing to provide their salary.[3] We then used this data to calculate an average salary for teachers and compare this to the national picture using data from the FE Workforce Data Collection (FEWDC). We also explored variation in earnings between departments and regions to illustrate some of the factors that influenced salary levels.
The average salary of the whole sample of teachers, including market rate supplements and pay for additional responsibilities (see below), was £36,459. Data from the 2021 FEWDC shows this was broadly in line with the national average. In 2021/22, the median salary for full-time teaching staff working in a general FE college was £36,092 (in 2022 prices) (DfE, 2023).

The average salary for Engineering teachers was lower than for the other two subjects, at £33,425. Construction teachers had the highest average salary at £38,464, with Digital slightly below at £37,487. The FEWDC supports this pattern, as it shows that, in 2021/22, Construction teachers tended to be paid slightly more than Engineering and Digital teachers. However, the earnings reported by our Construction and Engineering teachers were slightly higher than overall median Construction and Engineering earnings in the FEWDC data. We show the variation in earnings across subjects in more detail in Section 3.1 of the main report.

Our primary data suggest that there was only minor regional variation in earnings, with a slightly higher average salary in the South East (£37,800) compared to the West Midlands (£37,325), which was in turn slightly higher compared to the North East (£36,930). Our analysis of FEWDC data suggests that regional variation in earnings was indeed relatively minor in the North East and the South East, where median earnings were within five per cent of overall median earnings.

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[2] There are nine qualification levels in England, ranging from level 1 qualifications (first certificate, GCSE – grades 3, 2, 1) up to level 8 (PhD). See https://www.gov.uk/what-different-qualification-levels-mean/list-of-qualification-levels

[3] In many cases interviewees only provided approximate salaries. Where an interviewee provided only a salary range, the midpoint of this range was used for calculating the average.

However, the FEWDC also suggested that earnings in the West Midlands were slightly higher than overall. We show how earnings varied across regions in more detail in Section 3.1 of the main report.

There was some indication that salary scales between colleges in the North East were more consistent than those in the South East or West Midlands, however sample sizes were too small to draw any definitive conclusions relating to regional differences.

2.3. Interview schedules

The interviews were semi-structured and conducted remotely using Microsoft Teams. Interviews typically lasted between 30- and 45-minutes.

The topics covered by interviews with Heads of Department and teachers respectively can be found in Table 3.

Table 3 Topics covered in the interviews

Topic	Heads of Department	Teachers
Background information: role, length of time in the FE sector, previous roles outside of FE	X	X – plus qualifications
Current role: courses taught, level of satisfaction, pay	-	X
Career plans	-	X
The current staffing situation in their department: existing roles and vacancies	X	X
Experience of recruiting for their department: trends, facilitators and challenges	X	-
Roles staff come from to enter FE teaching	X	Personal experience
Staff retention: rates, reasons for leaving, motivation to remain	X	X
Roles for which staff leave FE teaching	X	X

Source: Interview schedules developed by the NFER project team

3. Appendix B: Quantitative methodology

While much of the analysis for this project was qualitative in nature, we supported our qualitative findings with quantitative analysis of secondary data. We discussed how the qualitative and quantitative components of the research fit together in more detail in section 1.3 of the main report. This section provides additional methodological detail on several key aspects of the quantitative analysis, outlined in each sub-section below.

3.1. Analysis of the FE Workforce Data Collection data

Part of the research undertaken for this project involved analysis of the FE Workforce Data Collection (FEWDC). The FEWDC is a new data source, collected by the Department for Education (DfE), comprising a census of all staff working in the FE sector. At the time of analysis, there was one wave of data (for the 2021/22 academic year). The second wave of FEWDC data became available in summer 2024 but was not analysed as part of this project as it was not available when the main statistical analysis work was undertaken.

There are three modules of data within the FEWDC. The modules of interest for this analysis were the workforce module and the vacancies module which collected information about the characteristics and pay of staff working in FE colleges and the number of open teaching vacancies at the college across different subjects.

3.1.1. Analysis of the workforce data

We analysed the workforce module of the FEWDC data to determine how FE staff characteristics and pay varied across subject, region and role.

For this analysis, we considered only staff working in a general FE college. There were two variables recording provider type in the FEWDC data – a 'detailed' and a 'general' provider type. There were about 20 providers where the 'general' provider type was recorded as a general FE college, but the 'detailed' provider type was not – we omitted these providers from the analysis as they were primarily specialised providers outside of the scope of our analysis.

Response rates to the FEWDC data collection were overall sufficient for our analysis to draw generalisable conclusions. While the overall response rate to the FEWDC workforce module was about 75 per cent, it was about 97 per cent for general FE colleges (DfE, 2023).

We identified college staff teaching in our key focus subjects using the variable recording the subject a staff member taught. We included in our analysis those who taught 'Construction, Planning and the Built Environment', 'Design, Engineering and Manufacturing' and 'Digital / ICT.' We grouped other subjects into an 'all other subjects' group that we used to compare findings for our focus subjects to.

Our primary sample for the analysis consisted of those who were recorded as a either a 'lecturer' or a 'teacher' in the data. These were only one two types of teaching roles recorded in the FEWDC (among others such as 'tutor', 'practitioner', etc.). However, we focussed mainly on lecturers and teachers as these were the two largest groups and it aligned with our focus for the interviews. Our tabulations of key characteristics and pay were very similar between our sample of teachers and those in other teaching roles.

The numbers of lecturers and teaching staff in each subject group are provided in Table 4. This represents the total number of unique staff working in general FE colleges in England whose pay was recorded in the FEWDC.[4] However, where lecturers worked across multiple providers, they were recorded as different teachers in the FEWDC data. Therefore, there may have been a degree of double-counting of teachers in the sample.

Table 4 Sample sizes of lecturers and teaching staff by subject

Subject	Number of lecturers	Number of teaching staff
Construction, Planning and the Built Environment	2,380	2,719
Design, Engineering and Manufacturing	1,241	1,463
Digital / ICT	808	897
All other subjects	24,906	28,183

Source: NFER analysis of FEWDC data (for 2021/22).

We also conducted analysis of those working as a Head of Department, in line with our qualitative analysis. However, there were very too few individuals working as a Head of Department in our key focus subjects in the FEWDC to report. This appears to have been because subjects tended to be recorded only for those working in at least one teaching role at their college. Due to these limitations, we did not report any analysis of pay variation for Heads of Departments.

3.1.2. Characteristics of the FE teacher workforce

We analysed the age profile and working patterns for lecturers in our main sample by tabulating the proportion of respondents in each age category and working pattern by subject grouping (i.e. Construction, Engineering, Digital and all other subjects).

We also tabulated the proportion of lecturers in each subject who had a recorded contract end date by July 31, 2022. We used this as a proxy for leaving rates. More robust estimates of leaving rates would involve using the FEWDC to analyse what proportion of FE teachers leave teaching between multiple waves of data, like how leaving rates for state-sector teachers are calculated from the School Workforce Census. However, that will require multiple waves of FEWDC and longitudinal identifiers for staff, neither of which were available at time of publication.

[4] FE providers in the FEWDC are recorded as being in the region where their head office is located. Where a provider operates across multiple regions, this may not be fully reflected by the FEWDC.

3.1.3. FE teacher pay

A key element of our analysis of the FEWDC data involved showing the variation in FE teacher pay by various characteristics. We used the estimates to support the qualitative data analysis and show the variation in industry pay gaps by region.

We analysed pay as either the annual salary or hourly wage earned by FE teachers in the FEWDC. Where a lecturer earned an hourly wage, we calculated an equivalent annual salary by multiplying their hourly wage by 1,924 (i.e. by 37 hours per week and 52 weeks per year). We used 37 hours per week as that was the modal number of hours worked by full-time FE lecturers as per the FEWDC data. This was the same approach used by the DfE in their publicly-available summary statistics to scale up hourly earnings.

Where a lecturer earned an annual salary and worked part-time, we scaled up their earnings to be full-time equivalent (FTE), representing what their annual salary would be if they worked 37 hours per week. This led to some FTE earnings being very high, so we set earnings to missing where they were in the top or bottom one per cent of earnings for their recorded job role (i.e. lecturer or teacher).

The DfE notes that there were challenges in the data collection for staff not working on a permanent or fixed term contract (i.e. a variable hours, zero hours or other contract type) (DfE, 2023). Therefore, earnings for individuals on these contract types were not collected and we were unable to report any estimates of pay for staff on these types of contracts in our analysis.

We generated estimates of median and average FTE-adjusted earnings overall (i.e. for all lecturers in any subject) and split by subject. We also generated additional estimates split by other characteristics such as region, sub-role, role combination and level of experience (in FE and in industry). There were some small sample sizes of lecturers when split by subject and region which meant we were unable to report estimates of median FTE-adjusted earnings for all subjects. We therefore reported average FTE-adjusted earnings instead for our estimates of median subject-specific pay by region.[5]

We also generated estimates of median and average earnings split by working pattern. For these estimates, we did not perform any FTE-adjustment but instead estimated median pay for full-time lecturers only and then for part-time lecturers only, to determine if there were any significant differences across subjects.

The DfE notes that the FE experience and industry experience variables we used for some of the earnings splits were of poor quality (i.e. FE and industry experience were missing for more than half of respondents). We reported earnings split by role experience (i.e. the number of years that staff member worked in the same role at their college) in the main report as there was no missing data. However, we did not report earnings across FE and industry experience due to the issues with missing data.

3.1.4. Vacancies in FE colleges

[5] Where we intended to report median earnings, our minimum threshold for meeting statistical disclosure control rules was four times what was for reporting averages.

We also conducted analysis of the vacancies module in the FEWDC, to provide data on how vacancy rates compared across subjects and regions.

The DfE notes that response rates to the vacancies module of the FEWDC was lower than the workforce module. Specifically, around three-quarters of general FE colleges responded to the vacancies module compared to 97 per cent for the workforce module (DfE, 2023). Indeed, the data contained vacancies information for 114 general FE colleges, which was lower than the 161 general FE colleges we analysed as part of the pay analysis. This may have made our vacancies analysis slightly less representative than our pay analysis.

To mitigate against this, we re-weighted the vacancies data so that the region and provider size profile of FE colleges responding to the vacancies module matched the workforce module. Our analysis suggested that colleges in the North West, West Midlands, South West and South East and in smaller providers (i.e. those with less than 200 teaching staff members) were slightly less likely to respond to the vacancies survey than larger providers and providers in other regions. We therefore re-weighted the data so the region and size breakdowns of responding providers was the same between the vacancies and workforce modules. After applying weights, the number of FE colleges our weighted analysis represented was 151, which was closer in line with the number of FE colleges in our pay analysis. Sensitivity analysis showed that weighting our estimates produced only a slight difference from unweighted estimates.

We calculated vacancy rates by comparing the number of vacancies colleges reported they had in 2021/22 compared to the number of teaching staff positions that college had. We divided the number of vacancies in each subject by the number of teaching staff at the college in the same subject and multiplied by 100 to calculate vacancy rates per 100 members of teaching staff. We calculated unfilled vacancy rates in the same way but only for the number of vacancies that a college reported remained unfilled at the end of the 2021/22 academic year.

The analysis of vacancy rates is based on all general FE colleges, not just the colleges that offered Construction, Engineering and Digital courses. This means that these figures may include some colleges that had zero vacancies because they did not offer a course in our focus subjects that year. However, our analysis showed that virtually every single college in the data had at least one teaching staff member in each of our focus subject areas, so the number of colleges not offering these courses was likely to be extremely small. Some colleges that had no staff members in our key focus areas also reported that they had vacancies in those subjects, which could be indicative of colleges looking to replace staff who had left or who were seeking to establish a course offering in that area.

Finally, we also analysed what proportion of colleges with unfilled vacancies in each of our focus subject areas said that one or more vacancy was difficult to fill, weighted to ensure representativeness. Of all the colleges with a vacancy that was difficult to fill, we tabulated the reasons colleges reported it was difficult to fill the vacancy. Colleges can report up to six reasons why vacancies were difficult to fill, so we reported the proportion of colleges with a difficult-to-fill vacancy that cited each reason at least once. We weighted the results for representativeness.

3.2. Identifying FE teachers and leavers in the Annual Survey of Hours and Earnings data

To support our analysis of qualitative data on FE teachers, we used data from the Annual Survey of Hours and Earnings (ASHE) in our analysis in order to identify FE teachers each year and draw conclusions about patterns of entry and exit into FE teaching.

The ASHE is a survey dataset collected by the Office for National Statistics (ONS). It is one per cent random sample of the entire labour force in England, based on Pay as You Earn (PAYE) submissions made to His Majesty's Revenue and Customs each year. Once an individual has been selected for inclusion in the ASHE sample, they are re-sampled each subsequent year, meaning that individual respondents' records are longitudinal. This was crucial for our analysis of flows into and out of FE teaching over time.

3.2.1. Identifying FE teachers and their occupational transitions

We identified FE teachers in the ASHE data using the standard occupational classification (SOC) and standard industry classification (SIC) codes of the job respondents were in each year. We used the full series of ASHE data (from 1997 to 2021) in the analysis, so identification of FE teachers in different time periods required different sets of SIC and SOC identifiers, depending on the codes that the ASHE data was coded in that year. The specific SOC code we used to identify FE teachers, and SOC/SIC codes which were excluded from the analysis are provided in Table 5.

Table 5 SOC codes used to identify FE teachers in the ASHE

SOC code	Description	Included?
SOC 2000 (1997 – 2010)		
2312	Further education teaching professionals	Yes
2311	Higher education teaching professionals	No
2314	Education officers, school inspectors	No
2315	Secondary education teaching professionals	No
2316	Primary and nursery education teaching professionals	No
2317	Special needs education teaching professionals	No
2318	Registrars and senior administrators of educational establishments	No
2319	Teaching professionals n.e.c.	No
SOC 2010 (2011 – 2021)		
2312	Further education teaching professionals	Yes
2311	Higher education teaching professionals	No

2314	Secondary education teaching professionals	No
2315	Primary and nursery education teaching professionals	No
2316	Special needs education teaching professionals	No
2317	Senior professionals of educational establishments	No
2318	Education advisers and school inspectors	No
2319	Teaching and other educational professionals n.e.c.	No

The primary data collection for the project focussed exclusively on FE teachers in FE colleges. Within the ASHE data, however, it is not possible to directly determine the type of institution FE teachers worked in (e.g. FE colleges versus sixth-form colleges). However, we used SIC codes to come as close as possible to identifying FE teachers teaching in FE colleges.

We included FE teachers working in a number of different industries in our main sample. This was for several reasons. First, when we included FE teachers working in only one industry (e.g. sub-degree level higher education), this led to small sample sizes. For instance, only about a third of FE teachers in the ASHE are coded in the 'sub-degree level higher education' industry code each year.

There were also inconsistencies in which SIC code the majority of FE teachers were coded to over time. SIC codes are not industry codes that are specific to the education sector, so they do not tend to map neatly to institution type. For instance, while many FE teachers were classified as in sub-degree level HE prior to 2007, the 2007 SIC codeset change led many of these same teachers to be re-classified to general secondary, first-degree level HE and technical and vocational secondary. We therefore included all of these SIC codes in our main sample.

Additionally, SIC codes lack the specificity to identify FE teachers in more complex teaching situations (e.g. those teaching a mixed programme such as delivering a higher education course in an FE college). We did not exclude FE teachers on mixed programmes from our primary data collection and therefore sought to ensure the SIC codes we included in the analysis were broad enough to reflect the sample of FE teachers in our primary data collection as closely as possible.

We specifically excluded, however, FE teachers who were in 'primary education', 'higher education', 'post-graduate level higher education' and 'adult and other education activities.' This is because FE teachers in these settings were unlikely to be reflective of FE teachers in FE colleges and, indeed, the total number of FE teachers in each of these industries was small.[6] The specific SIC codes we used for the analysis are listed in Table 6. We excluded any FE teacher in any other SIC code not listed below.

[6] The largest of these industries by far was 'primary education'. This may reflect how in 2012, the Qualified Teacher Learning and Skills (QTLS) qualification was recognised as equivalent as Qualification Teacher Status (QTS) for teachers working in maintained schools in England, enabling FE teachers to work in primary schools.

Table 6 SIC codes used to identify FE teachers working delivering different programmes

SIC code	Description	Included?
SIC 2003 (1997 – 2007)		
80.10	Primary education	No
80.21	General secondary education	Yes
80.22	Technical and vocational secondary education	Yes
80.30	Higher education	No
80.30/1	Sub-degree level higher education	Yes
80.30/2	First-degree level higher education	Yes
80.30/3	Post-graduate level higher education	No
80.4	Adult and other education activities	No
SIC 2007 (2008 – 2021)		
85100	Pre-primary education	No
85200	Primary education	No
85310	General secondary education	Yes
85320	Technical and vocational secondary education	Yes
85410	Post-secondary non-tertiary education	Yes
85421	First-degree level higher education	Yes
85422	Post-graduate level higher education	No
85510	Sports and recreation education	No

Note: Between 2008 and 2011, the ASHE was dual-coded using both SIC 2003 and 2007. For these years, we included FE teachers in our sample if either their SIC 2003 or 2007 code was listed as in-scope.

This process identified a sample of 3,451 unique FE teachers. Since the ASHE data is a one per cent random sample of the labour force, this meant that our sample of 3,451 teachers was representative of about 345,000 unique FE teachers over the 24-year span we considered.

From this sample, we then identified the jobs FE teachers were working in before and after working in FE teaching. To do this, we exploited the longitudinal nature of the ASHE, which tracks the occupations that the same individuals work in over time.

We began by identifying the first and last year that each FE teacher was identified as such in the ASHE data. For FE teachers who worked in another job prior to joining the FE workforce, we tabulated the occupations that FE teachers tended to work in during the five years before their first FE year. We also counted the number of FE teachers who entered FE teaching in the first year they had an ASHE record. These were teachers who may have either entered straight into FE teaching (e.g. from university), were self-employed prior to entering FE, or otherwise did not have an ASHE record.

Similarly, we also tabulated the occupations that teachers left FE teaching for. Of our full sample of FE teachers, there were 1,144 who left FE teaching and were working in another job within one year. This excluded those who retired from FE, moved into self-employment or who exited the labour force altogether. We first identified an FE teacher's final year in FE teaching (i.e. the last year that an FE teacher was ever recorded as such in the ASHE data). For those who left FE teaching to enter another job (and who did not return to FE teaching later), we tabulated the occupations that teachers worked in during the two years after their final year in FE.

We focussed on a narrower time frame after leaving FE teaching than for our analysis of transitions into FE teaching as we aimed to make the set of occupations FE teachers tend to transition into as relevant as possible to FE teaching. While some FE teachers may transition into industry and over time work their way to, for example, senior management levels in their new career, the job that the ex-FE teacher initially left FE teaching for may be more relevant for understanding which occupations are more relevant for understanding pay disparities with FE.

3.2.2. Setting and imputing the sample of FE teachers

We further refined our sample of FE teachers for analysis by removing records where it was likely that occupation codes for FE teachers had been incorrectly recorded in the data. This occurred mainly around 2011. In that year, the number of FE teachers we identified in the data was considerably higher than in previous years. This was because 2011 was when the SOC codesets used in the ASHE changed from the SOC 2000 framework to the SOC 2010 framework. The spike in FE teachers this year was likely related to the SOC codes changing, rather than any genuine spike in entrants into the profession.

We identified instances where FE teachers may have been assigned to an incorrect occupation by analysing where occupation codes changed in two consecutive years, but where the individual was recorded as having worked in the same job over those same years.

We identified whether an individual was in the same job in two consecutive years using a two-pronged approach. For those working in one job as their main job, we used the *sjob* variable in the ASHE to determine whether that individual was in the same job in two consecutive years. Where an individual was working in more than one job or in a job that was not their main job, we used the *sernol* variable to match jobs together in consecutive years. This was an approach to longitudinal tracking of jobs that was highlighted in ASHE researcher guidance (Forth *et al.*, 2022; Ritchie *et al.*, 2022).

Between 2010 and 2011, there were a number of FE teachers who were recoded to higher education teaching professionals (SOC 2010 code 2311 versus SOC 2000 code 2312) and vice versa, even though the ASHE indicated they were in the same job in 2011 as in 2010. While FE and HE have separate occupation codes in both SOC 2000 and 2010 frameworks, they are similar education-based occupations. Therefore, the move from SOC 2000 to SOC 2010 may have led some FE teachers to be re-classified as HE and vice versa, when those individuals may in fact have been in HE or FE over the whole time period.

This would lead our analysis of common occupations transitions to over-state the prevalence of transitions into and out of HE. We therefore identified all FE teachers who were re-classified as an HE teacher (while coded as being in the same job) in 2011 and vice versa. We removed the records for these individuals from our sample for all years they were in the ASHE data.

Similarly, there were a number of FE teachers classified as such in 2011, but where the ASHE also said they were in the same (non-FE and non-HE teaching) job that they worked in in 2010. Many FE teachers do indeed move into FE teaching from other non-FE jobs over time. However, the SOC codeset change in 2011 means that there is a much higher chance that these individuals were mis-classified in their job this year than in any other year. This is particularly the case where the ASHE records that these individuals were working in the same job as the previous year. We removed these individuals from our sample.

We did not remove any records for teachers who transitioned into or out of FE teaching in other years when the ASHE records they were working in the same job as the previous year. This is because the SOC codesets were consistent over the 1997-2011 and 2011-2021 periods in our analysis, so there was a relatively low risk of codeset changes leading to a spike in FE teachers being identified in other years.

In addition to the sample setting procedures outlined above, we also imputed a number of records for the year 2008. This is because our analysis showed that there was a significant dip in the number of FE teachers identified in that year relative to 2007 and 2009, suggesting that some records were missing. For FE teachers who were working in FE teaching in 2007 and in 2009, and where the ASHE indicated that the job FE teachers held in 2009 was the same as the previous year, we imputed missing 2008 records.

3.2.3. Inferring subject specialisms

A key limitation of our use of the ASHE data in our analysis is that the ASHE data does not record the subject that FE teachers teach. This was an important consideration for our research, both because we had an explicit focus on FE teachers teaching construction, engineering and digital courses and also because the occupations that FE teachers leave teaching for likely differ significantly by subject.

We therefore attempted to infer subject specialisation using data from the ASHE. We did so by analysing what occupations an FE teacher worked in before, during and after they worked as an FE teacher. We inferred FE teachers who worked predominantly in Construction, Engineering or Digital occupations outside of FE teaching were a Construction, Engineering or Digital FE teacher.

The list of occupations we used for the subject inferences were based on a mapping of SOC 2020 codes to apprenticeship standards.[7] We used the set of occupations mapped to each focus sector to identify FE teachers' specialisms by determining whether an FE teacher worked in at least one

[7] The full list of occupational mappings can be found at: https://occupational-maps.instituteforapprenticeships.org/

mapped occupation for at least one year prior to, during or after working as an FE teacher. For example, 'Carpenters and joiners' (SOC 2020 code 5316) maps to the Construction and the Built Environment sector. If an FE teacher worked in this occupation prior to, during, or after working as an FE teacher we inferred they were a Construction FE teacher.

Some FE teachers may be observed not to have a specialisation at all if none of the occupations they worked in before or during FE teaching map to any of the occupations identified by the SOC-apprenticeship standards mapping as Construction, Engineering or digital. We inferred that these individuals' subject specialisation was outside of Construction, Engineering and Digital.

Some occupations were cross classified across sectors in the SOC to standards mapping. For example, software engineers are considered both an 'Engineering' and a 'Digital' occupation. We therefore further classified some individuals based on other occupations they worked in before or while working as an FE teacher. For example, someone who worked in a software engineering job before becoming an FE teacher, followed by a civil engineering job was classified as an Engineering specialist. We assigned FE teachers to multiple categories if either all of their non-FE occupations were cross classified across disciplines, or if there was no clear 'majority' sector in their recorded non-FE occupations.

This led to a subject classification for some FE teachers. However, there were some important limitations to our approach. For Construction FE teachers, our primary data collection showed that many had worked in self-employment prior to entering FE teaching. Self-employment occupations are not recorded in the ASHE, so it was likely that we were unable to generate inferred subject specialisms for many Construction FE teachers. We were also unable to infer any subject specialisms for those who entered FE teaching as their first job (which our analysis showed was most common for Digital FE teachers). These limitations meant that we were unable to reliably analyse FE teachers in different sectors separately, though the analysis that we were able to conduct across subjects was generally supportive of the findings from our primary data collection. We therefore relied mostly on the full sample of FE teachers for our analysis of occupational transitions.

3.3. List of common occupations FE teachers worked in prior to working in FE teaching

Defining the occupations that FE teachers leave FE teaching for was a critical part of this research, mainly for deriving our measure of earnings in comparator occupations in industry. In the main report, we asserted that the occupations FE teachers worked in prior to and after leaving FE teaching was broadly supported by our quantitative analysis of the ASHE data. The intent of this section therefore is to summarise these key qualitative and quantitative findings in detail.

3.3.1. Common occupations mentioned by interviewees

The occupations that FE teachers worked in prior to entry into FE teaching were varied and depended significantly on the teacher's subject specialisation.

Heads of Departments reported that they generally had a number of years of experience in the FE sector and. Accordingly, most Heads of Department had either progressed within their departments from teaching to leadership roles or had moved from other colleges for the Head of Department role. Most Heads of Departments had also worked in industry prior to joining the FE sector. Common industry experience for Heads of Construction included work as plumbers, carpenters, builders and electricians – often self-employed. Head of Engineering industry experience was more varied, including previous experience in education. Fewer Heads of Digital had worked in industry. Several had worked in other education roles previously, while a small number had moved straight into FE following their studies.

A similar picture emerged for teachers. All the Construction teachers had experience of working in the construction or engineering sector, in roles such as plumbers and gas fitters, bricklayers and electricians, prior to working in FE. Just under half of the Construction teachers mentioned having been self-employed while working in industry. When asked about their colleagues, Construction teachers reported that many came from working ‘on the tools’ in industry like themselves, although a small number came from agencies, independent training providers or – in rare cases – universities. It was considered relatively unusual for industry managers to move into FE.

Nearly all of the Engineering teachers had been employed in industry prior to working in FE, in similar roles and industries to their colleagues (see below). A small number had worked in the education sector prior to FE – in university or secondary.

When asked about their colleagues, Engineering teachers reported that they came from a variety of backgrounds and seniority levels. Broadly, however, they were more likely to come from industry – often in a training or managerial role – than they were to come from another education role - in an FE college, agency, university or independent training provider. The food and drink sector, car manufacturing and maintenance, the armed forces, telecommunications and domestic appliances were particularly common industry areas. Common roles that interviewees mentioned included maintenance, fabrication welders, vehicle technicians and mechanical and electronic engineers.

Fewer Digital teachers had been employed in industry prior to their current roles in FE. Around a third had moved directly into teacher roles with little or no industry experience. IT and technician roles, freelance web and database development, and telecommunications were common areas of work for those who had spent time in industry.

Interviewees reported that it was quite unusual to recruit Digital teachers straight from industry. Most of their colleagues came from other educational roles – primarily other FE colleges, but also secondary schools and universities. Those who did come straight from industry tended to be either IT technicians on the hardware side, or programmers, software/web developers or database administrators on the software side.

3.3.2. Common occupations from the ASHE data

We used data from the ASHE to determine whether the occupations our interviewees told us they had worked in prior to entering FE teaching were representative of the wider population of FE teachers in our focus regions and subjects. The ASHE data shows that there is a wide variety of occupations that FE teachers worked in prior to being an FE teacher. Specifically, the ASHE showed that many FE teachers worked in other education roles, entered into FE as their first job, or moved into FE from lower-skilled occupations (e.g. administrative roles or sales assistants).

This is representative of the entire population of FE teachers in England, many of whom may have subject specialisations outside of our Construction, Engineering and Digital focus. Since the ASHE does not record any information about subject specialisation, it is difficult to determine how common it was for Construction, Engineering or Digital FE teachers specifically to work in occupations that were unrelated to their subject specialisation or lower-skilled before entering FE.

However, for the FE teachers in the ASHE who were able to infer a subject specialisation for, the main occupations our interviewees reported that they worked in prior to working in FE were generally also reflected in the ASHE. In particular, most Construction FE teachers worked in the trades prior to FE. Similarly, many Engineering teachers worked in engineering and science roles, while Digital FE teachers often worked in information technology and media roles.

Indeed, nearly all of the occupations our interviewees reported to us reflected an occupation that some FE teachers in the ASHE had worked in prior to joining the FE workforce, which broadly supports what our interviewees reported to us.

We provide the list of the most common occupations FE teachers worked in prior to joining the FE workforce in Tables 7 and 8. Table 7 shows the 20 most common occupations for all the FE teachers we identified using the ASHE data. Table 8 shows all the common occupations for FE teachers who had an inferred specialisation (i.e. either Construction, Engineering or Digital).

We do not report any individual occupations where the number of unique FE teachers who worked in that occupation prior to joining the FE workforce was less than 10. Additionally, the sum of the number of FE teachers who worked in each individual occupation prior to entering FE does not sum to the total number of unique FE teachers identified in the ASHE data as many FE teachers worked in multiple occupations prior to joining the FE workforce.

The lists of common occupations show each occupation's SOC 2010 code and description. Over the time period of our analysis, occupations in the ASHE data were coded using both the SOC 2000 and SOC 2010 frameworks. We converted each occupation's SOC 2000 code to SOC 2010 codes.[8] This was partly to ensure consistency in the occupational lists in our analysis and to ensure sufficient sample size to analyse patterns in the data.

We also reported three-digit rather than four-digit occupation codes in the lists. This was because the four-digit occupation codes that FE teachers worked in before and after working in FE teaching were in many cases very specific jobs, and there was insufficient sample size using four-digit occupation codes to identify patterns in the individual four-digit occupations.

[8] ONS produced versions of the Labour Force Survey and the 2001 Census dual-coded to both SOC 2000 and SOC 2010. This enabled us to use the 'minor group' cross-tabulations to provide a sensible mapping between each framework's occupational codes. See https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2010.

Table 7 Common prior occupations – all FE teachers

SOC code	Description	Unique teachers
-	FE teaching was first ASHE record	1,329
231	Teaching and Educational Professionals	1,226
612	Childcare and Related Personal Services	177
711	Sales Assistants and Retail Cashiers	159
415	Other Administrative Occupations	121
323	Welfare and Housing Assoc. Professionals	118
416	Administrative Occupations: Office Managers and Supervisors	117
356	Public Services and Other Assoc. Professionals	116
242	Business, Research and Administrative Professionals	92
614	Caring Personal Services	84
211	Natural and Social Science Professionals	80
412	Administrative Occupations: Finance	70
927	Other Elementary Services Occupations	70
113	Functional Managers and Directors	67
213	IT and Telecommunications Professionals	54
344	Sports and Fitness Occupations	50
223	Nursing and Midwifery Professionals	50
353	Business, Finance and Related Assoc. Professionals	49
354	Sales, Marketing and Related Assoc. Professionals	49
421	Secretarial and Related Occupations	45

Note: Reflects the 20 most common prior occupations for all FE teachers.

Source: NFER analysis of ASHE data for 1997 to 2021.

Table 8 Common prior occupations – FE teachers with any inferred specialisation

SOC code	Description	Unique teachers
416	Administrative Occupations: Office Managers and Supervisors	117
415	Other Administrative Occupations	113
231	Teaching and Educational Professionals	90
213	IT and Telecommunications Professionals	44
353	Business, Finance and Related Assoc. Professionals	28
354	Sales, Marketing and Related Assoc. Professionals	25
523	Vehicle Trades	23
413	Administrative Occupations: Records	22
711	Sales Assistants and Retail Cashiers	21
113	Functional Managers and Directors	19
125	Managers and Proprietors in Other Services	19
356	Public Services and Other Assoc. Professionals	18
323	Welfare and Housing Assoc. Professionals	16
412	Administrative Occupations: Finance	15
524	Electrical and Electronic Trades	15
242	Business, Research and Administrative Professionals	14
243	Architects, Town Planners and Surveyors	14
211	Natural and Social Science Professionals	13
712	Sales Related Occupations	12
531	Construction and Building Trades	11
612	Childcare and Related Personal Services	10

Source: NFER analysis of ASHE data for 1997 to 2021.

The results suggest that there were a significant number of FE teachers who entered FE teaching having not worked in another occupation beforehand. While this could suggest that there are substantial numbers of FE teachers who enter teaching straight from university, it may also reflect FE teachers who worked in self-employment or whose previous employer had otherwise not filled out the survey.

The results also suggest that administrative and sales-related occupations are common for FE teachers to work in prior to joining the FE workforce. This was true both overall and for FE teachers with an inferred subject specialisation.

While many FE teachers likely to do indeed work in administrative and sales-related occupations prior to entering FE teaching, limitations in how we identify subject specialisation meant that it was not clear the extent to which this was likely to be true for Construction, Engineering and Digital FE teachers specifically. Nonetheless, it was reassuring that most of the occupations our Construction, Engineering and Digital interviewees told us they had worked in prior to FE (e.g. the trades, IT, etc.) were also present in the ASHE data.

3.4. List of common occupations after leaving FE teaching

In the main report we discussed the occupations our interviewees told us they knew colleagues had left FE teaching for or would consider leaving FE teaching for themselves. This was generally supported by our analysis of the ASHE data.

Table 9 shows the 20 most common occupations for FE teachers to leave teaching for, according to the ASHE. Table 10 then shows all of the common occupations for FE teachers who had an inferred specialisation (i.e. either Construction, Engineering or Digital).

The number of FE teachers we identified working in each occupation after leaving FE teaching was broadly lower than the counts of teachers working in each occupation prior to entering FE teaching (in Tables 7 and 8). This was for two main reasons. First, there were a significant number of FE teachers who, in the time period we included in our analysis, did not leave FE teaching at all, or who left FE teaching and had no subsequent records in the ASHE.[9] Secondly, there were a number of FE teachers who left FE teaching and moved to occupations which few other FE teachers left FE teaching for. We only report occupations in Tables 10 for which there were at least 10 unique FE teachers who left FE teaching to move into that occupation.

The most common occupation that FE teachers worked in after leaving teaching were other education occupations, which included primary and secondary school teachers, higher education and other education-related occupations (e.g. technical and vocational instructors, driving and flying instructors, etc.). Other occupations included many of those that were common occupations for FE teachers to work in prior to joining the FE workforce: sales and business professional roles, administrative occupations, IT and telecommunications and occupations in the sciences. This was true both overall and for teachers who we inferred had a Construction, Engineering or Digital specialisation.

Given the overall small sample sizes of FE teachers who leave FE teaching for another job, it was generally difficult to analyse the patterns in the destinations for FE teacher leavers. This was particularly the case for FE teachers who we inferred had a subject specialisation as sample sizes were even smaller than overall. There were also broader limitations in how we inferred FE

[9] This would reflect FE teachers who moved into self-employment, retired, left the workforce or the UK or whose employer stopped responding to the survey.

teachers' subject specialisations which meant it was not clear whether these occupations were indeed common destination occupations for Construction, Engineering and Digital FE teachers.

Table 9 Common occupations after leaving – all FE teachers

SOC code	Description	Unique teachers
231	Teaching and Educational Professionals	776
356	Public Services and Other Associate Professionals	65
612	Childcare and Related Personal Services	48
323	Welfare and Housing Associate Professionals	47
242	Business, Research and Administrative Professionals	40
415	Other Administrative Occupations	37
213	Information Technology and Telecommunications Professionals	32
614	Caring Personal Services	32
113	Functional Managers and Directors	25
416	Administrative Occupations: Office Managers and Supervisors	24
211	Natural and Social Science Professionals	21
354	Sales, Marketing and Related Associate Professionals	20
221	Health Professionals	19
341	Artistic, Literary and Media Occupations	18
311	Science, Engineering and Production Technicians	17
223	Nursing and Midwifery Professionals	17
711	Sales Assistants and Retail Cashiers	16
112	Production Managers and Directors	16
244	Welfare Professionals	15
412	Administrative Occupations: Finance	14

Note: This table reflects only the 20 most common prior occupations for all FE teachers.
Source: NFER analysis of ASHE data for 1997 to 2021.

Table 10 Common occupations after leaving – FE teachers with an inferred specialisation

SOC code	Description	Unique teachers
231	Teaching and Educational Professionals	117
356	Public Services and Other Associate Professionals	29
415	Other Administrative Occupations	20
213	Information Technology and Telecommunications Professionals	16
416	Administrative Occupations: Office Managers and Supervisors	14
612	Childcare and Related Personal Services	14
354	Sales, Marketing and Related Associate Professionals	12

Source: NFER analysis of ASHE data for 1997 to 2021.

3.5. List of comparator occupations

To analyse how earnings in FE teaching compare to earnings in industry, we selected the most-relevant 'comparator' occupations outside of FE teaching. We did this separately for occupations in industry and other occupations in the education sector.

3.5.1. Industry occupations

We selected the most-relevant comparator occupations mainly via the primary data collection. Specifically, we asked interviewees what occupations they had colleagues that had left FE teaching for. We also asked interviewees whether there were (hypothetically) any occupations they would consider leaving FE teaching for should they ever leave the profession. We then aggregated occupations listed by interviewees into one list of relevant comparator occupations, but treated the 'hypothetical' occupations slightly differently in the analysis if no interviewee told us that they knew one or more colleague who had transitioned into that occupation.

We matched the occupations that our interviewees mentioned to a standard occupational classification (SOC) code and aggregated them all together into one list. We then assigned a subjective prevalence rating to each occupation, based on how common that occupation was cited during the interviews. The prevalence ratings used were 'very common', 'common', 'uncommon' and 'very uncommon'.

We then cross-checked this list of occupations against data from the ASHE to ensure that the list of occupations reflected the broader patterns of destination occupations for ex-FE teachers. As we discussed in the main report, it was not straightforward to establish what the main destination occupations are for FE teachers who leave teaching. Nonetheless, the ASHE broadly supported the list of comparator occupations we used in the analysis.

However, some of the comparator occupations mentioned to us by interviewees had very few people working in them in the ASHE data. This was partly because there were a number of occupations in which many people work in self-employment and hence are not recorded in the ASHE. This included occupations such as bricklayers and plasterers.

There were also several lower-skilled manufacturing occupations in the ASHE data which were extremely uncommon outside of certain regions in the country. This included paper and wood machine operatives, textile process operatives and plastics process operatives. We excluded all such occupations as sample sizes were too small to analyse and, since the ASHE data suggests that these are small occupations, they are unlikely to be significant destinations in industry for FE teachers.

We also included a small number of additional occupations that the ASHE data suggested were key destination occupations in industry for FE teachers, but which were not mentioned in the ASHE. Specifically, this involved including the few industries in which the ASHE data suggested that more than 20 FE teachers had left FE teacher for, and which had not been mentioned as a comparator occupation by interviewees.

Finally, we estimated median earnings in industry using this list of relevant comparator occupations in industry. We included a weight in our estimates to put more emphasis on occupations which were more frequently mentioned as a destination occupation in the interviews. For example, if a significant number of Construction FE teachers reported ‘electrician’ as a comparator occupation, but very few reported that ‘project manager’ was a comparator occupation, we would assign a higher weight to electricians than project managers.

The weights also put more emphasis on those occupations that interviewees told us they knew one or more colleague had actually moved into (i.e. the occupation was not a ‘hypothetical’ comparator occupation) and where our qualitative analysis suggested it was a common transition. The weights we used as part of the analysis, and the scenario in which each weight value was applied, are provided in Table 11.

Table 11 Weights used for the comparator occupations in the analysis

Weight value	Description
5	Occupation was not ‘hypothetical’ and was a ‘common’ or ‘very common’ destination
4	Occupation was not ‘hypothetical’ and was ‘uncommon’ or ‘very uncommon’
3	Occupation was ‘hypothetical’ and was ‘common’ or ‘very common’
2	Occupation was ‘hypothetical’ and was ‘uncommon’ or ‘very uncommon’
1	ASHE data suggested more than 20 FE teachers had transitioned into this occupation but it was not mentioned as a destination by any of our interviewees

The list of Construction, Engineering and Digital comparator occupations, along with the weight assigned to each, are provided in Table 12.

Table 12 Key comparator occupations

SOC code	Description	Weight
Construction comparator occupations		
1139	Functional managers and directors n.e.c.	5
1251	Property, housing and estate managers	5
2436	Construction project managers and related professionals	5
3563	Vocational and industrial trainers and instructors	5
5221	Metal machining setters and setter-operators	5
5241	Electricians and electrical fitters	5
5314	Plumbers and heating and ventilating engineers	5
5315	Carpenters and joiners	5
8149	Construction operatives n.e.c.	5
2121	Civil engineers	4
2129	Engineering professionals n.e.c.	4
2434	Chartered surveyors	4
3422	Product, clothing and related designers	4
3565	Inspectors of standards and regulations	4
5319	Construction and building trades n.e.c.	4
5323	Painters and decorators	4
5330	Construction and building trades supervisors	4
5231	Vehicle technicians, mechanics and electricians	3
1121	Production managers and directors in manufacturing	2
2462	Quality assurance and regulatory professionals	2
3567	Health and safety officers	2
5250	Skilled metal, electrical and electronic trades supervisors	2
4159	Other administrative occupations n.e.c.	1
4162	Office supervisors	1
Engineering comparator occupations		
2121	Civil engineers	5
2122	Mechanical engineers	5
2123	Electrical engineers	5
2126	Design and development engineers	5

2129	Engineering professionals n.e.c.	5
5221	Metal machining setters and setter-operators	5
2127	Production and process engineers	4
2424	Business and financial project management professionals	4
2434	Chartered surveyors	4
2461	Quality control and planning engineers	4
3113	Engineering technicians	4
5213	Sheet metal workers	4
5231	Vehicle technicians, mechanics and electricians	4
5249	Electrical and electronic trades n.e.c.	4
3563	Vocational and industrial trainers and instructors	3
3122	Draughtspersons	2
3213	Paramedics	2
3545	Sales accounts and business development managers	2
3562	Human resources and industrial relations officers	2
4124	Finance officers	2
5319	Construction and building trades n.e.c.	2
4159	Other administrative occupations n.e.c.	1
4162	Office supervisors	1
Digital comparator occupations		
2136	Programmers and software development professionals	5
2137	Web design and development professionals	5
3132	IT user support technicians	5
2133	IT specialist managers	4
2423	Management consultants and business analysts	4
3563	Vocational and industrial trainers and instructors	4
2134	IT project and programme managers	3
3131	IT operations technicians	3
2139	Information technology and telecommunications professionals n.e.c.	2
3421	Graphic designers	2
3543	Marketing associate professionals	2
5242	Telecommunications engineers	2
4159	Other administrative occupations n.e.c.	1
4162	Office supervisors	1

Source: NFER analysis of primary data and NFER analysis of ASHE data for 1997 to 2021.

3.5.2. Education comparator occupations

We also conducted analysis of how pay for FE teachers compares to pay for those working in other occupations in the education sector. This involved a similar process of selecting key comparator industries in education.

We selected education comparator occupations similarly to how we selected industry comparator occupations. Our interviewees and ASHE analysis of the common destination occupations for FE teachers outside of teaching suggested that a significant proportion of FE teachers who leave teaching move into other education occupations (i.e. three-digit SOC code 231). We therefore included all occupations in our analysis which were in this SOC code grouping (excluding FE teaching).

We also included two other education-related occupations outside of the main education grouping but which our analysis of the ASHE data suggested was a common destination occupation for FE teachers (i.e. more than 20 FE teachers in our analysis transitioned left FE teaching to enter that occupation). The list of occupations we included in the analysis is provided in Table 13.

Similarly to our industry comparator occupations, we applied weights to our analysis of pay in education comparator occupations. However, since transitions from FE teaching into each of these education-related occupations are much more well-defined in the ASHE data than for industry comparator occupations (i.e. do not suffer from the same self-employment challenges), we did not have to use qualitative weights. Instead, we estimated what proportion of FE teacher who left teaching each year moved into each education comparator occupation, which we used as each occupation’s weight.

Table 13 List of education comparator occupations

SOC code	Description
2311	Higher education teaching professionals
2314	Secondary education teaching professionals
2315	Primary and nursery education teaching professionals
2316	Special needs education teaching professionals
2317	Senior professionals of educational establishments
2318	Education advisers and school inspectors
2319	Teaching and other educational professionals n.e.c.
3563	Vocational and industrial trainers and instructors
6126	Educational support assistants

Source: NFER analysis of primary data and NFER analysis of ASHE data for 1997 to 2021.

3.6. Constructing our measure of pay gaps in comparator occupations

To calculate our measure of pay gaps between FE teaching and industry, we took the difference between median earnings in FE teaching and median earnings in our industry and education comparator occupations.

In this section, we provide further details on how we constructed each of the components of our measure of pay gaps; that is, earnings for FE teachers and earnings in industry and education comparator occupations.

3.6.1. Estimating FE teacher pay over time

Of the two key components of our pay gaps measure, median pay for FE teachers was the more complex to measure. This was mainly because of the paucity of data on FE teacher earnings over time.

Data on FE teacher earnings are available from several sources, including the Staff Individualised Records (SIR) data, the FE Workforce Data Collection (FEWDC), DfE Teacher Pension Scheme data[10] and the ASHE. Each of these data sources has a number of advantages and disadvantages, which are summarised in Table 14.

Table 14 Sources of FE teacher pay data

Data source	Advantages	Disadvantages
SIR data	• Based on a census of FE teachers • Provides mean and median earnings for FE teachers in different types of institutions • Time series of comparable data back to 2012/13	• Only provides estimates of average and median earnings • No data from 2019/20 onwards
FEWDC data	• Based on a census of FE teachers • Detailed data on FE teacher earnings, including providing earnings by subject, region, type of institution, type of working pattern and role • Provides mean and median earnings for FE teachers in general FE colleges and other types of institutions	• Only one year of data available (2021/22) at the time of analysis
DfE Teacher Pension Scheme data	• Long time series of comparable data on earnings (back to 1998/99) • Provides estimates of mean and median earnings for FE teachers in general FE colleges and other types of institutions	• Based on estimates from pensions data, not a census of FE teachers • Data only available to 2019/20.

[10] This is published publicly online at: https://www.gov.uk/government/publications/further-education-college-workforce-analysis

Data source	Advantages	Disadvantages
	• Provides details of the earnings distribution of earnings (for 2019/20 only)	
ASHE data	• Long time series of data (back to 1997) • Provides details on the distribution of FE teacher earnings for all years • Provides details on how FE teacher earnings differs by region	• Difficult to separately analyse FE teachers teaching in different types of institutions • SOC codes may sometimes be recorded inconsistently over time, leading to difficulties identifying FE teachers • Based on a random sample of the entire labour force in England • Relatively small sample sizes of FE teachers, particularly when split by year

Despite the key differences between these datasets, estimated earnings for FE teachers from each of these data sources were broadly similar. Specifically, between 2012 and 2018 (the only years that the SIR data, Teacher Pension Scheme data and the ASHE data overlap), median FE teacher earnings across these three data sources were within five per cent (£1,000) of each other.

Since each individual data source covers only a limited number of years, generating an estimate of FE teacher pay over time involves combining different sources of data. To ensure the comparability of our estimates, we used just two data sources to generate our time series of FE teacher pay: the DfE's Teacher Pension Scheme data and the FEWDC. This is because both provide estimates of median FE teacher earnings for those working in general FE colleges and the Teacher Pension Scheme data provides more years of available earnings estimates than other sources such as the SIR.

Since the Teacher Pension Scheme data only provides earnings estimates up to 2019/20 and the FEWDC (at the time of analysis) had data only for 2021/22, this meant that there was a gap for 2020/21. We estimated FE teacher earnings for 2020/21 by first estimating the average real growth in FE teacher pay scales between 2019/20 and 2020/21. To do this, we used the recommended pay scales for FE teachers in England,[11] from which we subtracted the annual inflation rate for 2020, based on the Consumer Price Index with Housing (CPI-H). We then used this real growth rate to scale up earnings from 2019/20.

Repeating the same procedure for other years yielded median FE teacher earnings which tracked reasonably closely to the actual figures, so this was likely to have led to a realistic estimate. This was a similar approach to that used in existing research (Sibieta and Tahir, 2023).

[11] See https://www.ucu.org.uk/fescales_england.

Once we constructed our time series of FE teacher pay, we adjusted median earnings estimates to reflect 2021 prices using the CPI-H.

For our analysis of pay gaps by region, we used data from the FEWDC only, rather than from the Teacher Pension Scheme data. This was because this part of the analysis focussed only on 2021/22 only, and data was available on FE teacher earnings by region in the FEWDC, unlike the Teacher Pension Scheme data. We estimated average FE teacher pay in 2021/22 separately by region, rather than the median. This is because sample sizes of FE teachers by subject and region were too small to report medians. We provide more detail on how we estimated average and median FE teacher pay from the FEWDC in Section 3.1 of this appendix. To generate our measure of region-specific pay in comparator occupations, we then compared our estimates of region-specific average FE teacher pay to our estimates of region-specific average pay in comparator occupations.

3.6.2. Estimating a time series of pay in comparator industries

To construct our estimate of median pay in comparator industries, we first identified everyone in the ASHE data who were working in the key comparator industries in Table 12. We then estimated median and third quartile earnings (both excluding and including overtime pay) for all those working in each comparator industry in each year. We excluded those on 'trainee' or 'junior' pay scales, those who were working temporary jobs or whose earnings were impacted by employee absence.

We adjusted earnings to represent full-time equivalent earnings. For those working part-time, we scaled earnings up to the modal number of hours worked by full-time workers in each occupation. For example, if a part-time mechanical engineer worked 20 hours per week, but the modal full-time hours worked per week in their occupation was 40, we doubled their earnings. We did not adjust earnings for anyone working full-time or anyone working more than the modal number of full-time hours. We also used the Consumer Price Index with Housing (CPI-H) to adjust for inflation, so our estimates reflected 2021 prices. Finally, we weighted our earnings estimates using the ASHE calibration weight to ensure our estimates were representative of the entire workforce in each occupation each year. An example is provided in Table 15 for 2021.

Table 15 Median earnings in comparator occupations for 2021

SOC code	Description	Median earnings (2021 £)	Third quartile earnings (2021 £)	Count
Construction (overall comparator industry median earnings = £34,428)				
1139	Functional managers and directors n.e.c.	58,189	76,135	197
1251	Property, housing and estate managers	36,803	49,063	336
2436	Construction project managers and related professionals	40,201	49,331	75
3563	Vocational and industrial trainers and instructors	29,897	36,540	430

5221	Metal machining setters and setter-operators	28,462	31,840	207
5241	Electricians and electrical fitters	32,466	37,073	454
5314	Plumbers and heating and ventilating engineers	31,863	35,915	170
5315	Carpenters and joiners	27,625	31,559	220
8149	Construction operatives n.e.c.	25,559	30,111	334
2121	Civil engineers	41,156	53,317	148
2129	Engineering professionals n.e.c.	42,423	52,380	423
2434	Chartered surveyors	39,317	49,552	185
3422	Product, clothing and related designers	28,177	33,983	119
3565	Inspectors of standards and regulations	31,009	42,674	60
5319	Construction and building trades n.e.c.	26,200	31,791	114
5323	Painters and decorators	-	-	60
5330	Construction and building trades supervisors	36,139	42,458	157
5231	Vehicle technicians, mechanics and electricians	28,192	33,228	411
1121	Production managers and directors in manufacturing	48,529	70,836	1,361
2462	Quality assurance and regulatory professionals	44,846	57,802	341
3567	Health and safety officers	35,877	43,374	111
5250	Skilled metal, electrical and electronic trades supervisors	35,967	41,000	133
4159	Other administrative occupations n.e.c.	23,088	30,207	3,785
4162	Office supervisors	26,948	31,786	155
Engineering (overall comparator industry median earnings = £37,251)				
2121	Civil engineers	41,156	53,317	148
2122	Mechanical engineers	40,844	57,566	70
2123	Electrical engineers	50,825	61,040	90
2126	Design and development engineers	43,920	50,950	250
2129	Engineering professionals n.e.c.	42,423	52,380	423
5221	Metal machining setters and setter-operators	28,462	31,840	207
2127	Production and process engineers	39,952	49,743	149
2424	Business and financial project management professionals	51,352	67,938	878
2434	Chartered surveyors	39,317	49,552	185

2461	Quality control and planning engineers	38,684	45,743	155
3113	Engineering technicians	35,743	43,849	246
5213	Sheet metal workers	-	-	23
5231	Vehicle technicians, mechanics and electricians	28,192	33,228	411
5249	Electrical and electronic trades n.e.c.	33,734	39,796	337
3563	Vocational and industrial trainers and instructors	29,897	36,540	430
3122	Draughtspersons	30,256	37,854	111
3213	Paramedics	41,421	47,200	57
3545	Sales accounts and business development managers	47,142	64,606	1,686
3562	Human resources and industrial relations officers	27,904	34,880	449
4124	Finance officers	26,948	31,723	110
5319	Construction and building trades n.e.c.	26,200	31,791	114
4159	Other administrative occupations n.e.c.	23,088	30,207	3,785
4162	Office supervisors	26,948	31,786	155
Digital (overall comparator industry median earnings = £37,146)				
2136	Programmers and software development professionals	45,461	56,374	721
2137	Web design and development professionals	34,880	39,863	158
3132	IT user support technicians	28,893	35,877	526
2133	IT specialist managers	49,522	64,137	593
2423	Management consultants and business analysts	42,853	57,652	527
3563	Vocational and industrial trainers and instructors	29,897	36,540	430
2134	IT project and programme managers	52,093	63,453	95
3131	IT operations technicians	29,897	37,895	382
2139	Information technology and telecommunications professionals n.e.c.	43,139	56,010	408
3421	Graphic designers	28,213	33,029	130
3543	Marketing associate professionals	28,486	35,279	434
5242	Telecommunications engineers	33,168	39,863	43
4159	Other administrative occupations n.e.c.	23,088	30,207	3,785
4162	Office supervisors	26,948	31,786	155

Note: Cells marked ‘-‘ were suppressed as sample sizes in one or more years were too small to report.

Source: NFER analysis of ASHE data for 2021

To construct our overall measure of earnings in comparator industry occupations, we then estimated a weighted average of all the median earnings estimates across comparator occupations, using the weights outlined in Table 12. We used the same approach to generate an overall measure of third quartile earnings.

Regional earnings in comparator occupations were also constructed in a similar way, but were based on average earnings in comparator occupations for those working in each region. We used average earnings rather than median earnings because sample sizes when split by region were small and in order to match our estimates of average FE teacher earnings which we generated from the FEWDC. Crucially, we used the same comparator industries in our regional estimates, so that any differences in regional comparator earnings do not reflect differences across regions in the composition of the occupations considered.

We also combined the North East with Yorkshire and the Humber for our region-specific pay gap measures. This was because the North East is a small region and the number of workers per year in the North East in many of the key comparator occupations was below 10. We combined the North East with Yorkshire and the Humber as this was the region that bore the closest demographic and geographic resemblance to the North East in the Census 2021 data.[12]

3.7. Self-employment earnings

Our qualitative analysis revealed that FE teachers considered pay in industry to be superior to pay in FE teaching. This was particularly the case for Construction FE teachers, where our interviewees emphasised a culture of high pay and long hours. This is somewhat at odds with our analysis of industry pay gaps, which showed that the pay gap between FE teaching and Construction comparator industries was smaller than for Engineering or Digital.

As we outlined in the main report, however, a key reason for this is likely to have been that, as our interviewees told us, self-employment was common in most of the key Construction comparator occupations, including for bricklayers, electricians and plumbers. This is supported by data from the Labour Force Survey which shows that, despite a fall in self-employment numbers since the Covid-19 pandemic, in 2022 the construction sector had the highest number of people in self-employment of any industry (ONS, 2022).

However, we were unable to observe self-employment earnings in the ASHE data. Indeed, our analysis of the ASHE data suggested that there were so few bricklayers in the ASHE data (and who were therefore in employment rather than self-employed) that we were unable to include bricklaying in our analysis of earnings in comparator occupations at all. This meant that our analysis of industry pay gaps for construction excluded a significant part of the industry landscape, and may have led us to under-estimate earnings in Construction comparator occupations.

[12] For example in age, ethnicity, population density and common industries. See https://www.nomisweb.co.uk/sources/census_2021

For instance, Table 15 shows that median annual earnings for those working in the construction trades was about £26,000. However, estimates from Hudson Contract, a payroll service provider in the construction industry, estimates that average weekly earnings for self-employed tradespeople in August 2023 was £1,012 (equating to more than £50,000 annually), which is about double our estimates for employed construction workers in the ASHE data (Hudson Contract, 2023).

The problem was also not unique to Construction comparator industries – there were some comparator industries for Digital FE teachers which our interviewees told us were common self-employment occupations as well, such as programming and marketing.

Given this significant limitation of the data, we explored a number of secondary data sources to determine whether it would be possible to generate estimates of median earnings in the key self-employment occupations that our interviewees shared with us.

3.7.1. Estimates of earnings in self-employment comparator occupations

Estimating earnings in self-employment is a considerable challenge, for several reasons. Part of the challenge is that there are few secondary data sources recording reliable, detailed information on self-employment earnings. Self-employment earnings are also often complex to define and measure. Earnings can be irregular and come in different forms. They can also not always, or not always consistently, account for a worker's expenditures, which can often be written off against tax owed (Department for Business Innovation & Skills, 2016).

We explored several different data sources which collect information on the self-employed to varying degrees. We first explored the Labour Force Survey (LFS) and the Family Resources Survey (FRS) to determine whether they contained useful information on self-employment earnings. However, neither was suitable for our purposes. While the LFS collects information on the number of people in self-employment, it does not collect information on self-employment earnings. The FRS, meanwhile, does collect information on self-employment earnings of surveyed households. However, we found that sample sizes were small and the occupational classifications collected by the survey were too coarse to be used in the analysis.

We also explored the UK Household Longitudinal Study (UKHLS) for our analysis. The UKHLS data contains both records of self-employment earnings of responding households in addition to respondents' occupations at a sufficient level of granularity for our analysis. Records of respondents' self-employment earnings are primarily based on the profit they claim through their business with HMRC in each financial year. A net gross conversion is then applied to this figure to yield net gross income from self-employment. If a respondent has not yet prepared their tax claim when they respond to the survey, self-employment earnings are estimated based on a respondent's revenue and business expenditure, and adjusted to reflect net gross income (Fisher *et al.*, 2019).

We used the data from the UKHLS to identify people working in self-employment in the key Construction comparator occupations which our interviewees told us were typically self-employment occupations. These occupations are listed in Table 16.

We only considered individuals who reported that they worked in self-employment as their main job. We also excluded individuals who worked zero hours in self-employment and, similarly to our main analysis, we adjusted earnings to full-time equivalent earnings. We did this by scaling up net earnings for those who worked less than 40 hours per week to reflect what they would have earned had they worked a full week. Finally, we applied the cross-sectional UKHLS weights provided in the data to ensure the representativeness of the results.

Due to small sample sizes, we were unable to construct an estimate of median earnings in self-employment occupations separately by year. We therefore combined all self-employed workers in our occupations of interest that we identified in the survey between 2011 and 2021 into one sample, adjusting our estimates using the CPI-H to reflect real 2021 earnings. Our estimates of median earnings in our main occupations of interest are provided in Table 16.

The results suggest that self-employment earnings in our selected occupations were all considerably lower than median earnings in employment (we showed median earnings in employment in each of these industries based on data in the ASHE in Table 15). Ostensibly this appears to contradict our interviewees' assertions about high pay in self-employment in industry. However, there are a number of reasons why the data from the UKHLS provides lower estimates of self-employment than employment earnings.

One reason is that the distribution of self-employment earnings is highly skewed. In particular there are a considerable number of individuals who earn very low or even negative net income in their self-employment job. Removing those who made negative profits in their business raises our estimate of median self-employment earnings considerably, but even so, our estimates were still lower than median earnings in employment for the same occupations.

The skewed distribution also meant that there was a significant difference between average and median self-employment earnings in these occupations – with the average much higher than the median. This is a known challenge inherent in working with self-employment earnings data (Department for Business Innovation & Skills, 2016). In order to maintain consistency with the rest of our analysis, we reported median earnings in Table 16, rather than the higher averages.

Table 16 Estimates of earnings in the industries in which self-employment was particularly prevalent

SOC code	SOC description	Median earnings – overall	Median earnings – positive gross earnings only	Count - overall	Count – positive gross earnings only
2136	Programmers and software development professionals	35,868	40,844	300	280
3543	Marketing associate professionals	21,570	27,477	158	146
5241	Electricians and electrical fitters	18,027	22,320	427	377
5312	Bricklayers and masons	22,621	25,770	298	262

SOC code	SOC description	Median earnings – overall	Median earnings – positive gross earnings only	Count - overall	Count – positive gross earnings only
5314	Plumbers and heating and ventilating engineers	17,894	24,325	470	392
5319	Construction and building trades n.e.c.	14,847	20,028	796	648

Note: Median earnings refer to FTE-adjusted, real earnings using 2021 prices. The column for 'positive gross earnings only' excludes those who reported or were estimated to have turned a loss on their self-assessment return each year.

Source: NFER analysis of UKHLS data for 2011 to 2021.

There is another possible explanation for why earnings in self-employment appear to be lower than for the same occupations in employment. Random audits of the nearly third of UK taxpayers who file self-assessment tax records with HMRC suggest that 36 per cent of self-assessment tax filers had errors in their tax return leading to an under-statement of earnings and therefore of tax owed. This was found to be considerably higher in the construction industry than in other industries, where around 60 per cent of tax returns filed by self-employed construction workers contained an understatement of earnings. Construction was the second-highest industry for under-reporting earnings, behind only the hospitality industry (Advani, 2022).

Indeed, the evidence shows that the average self-employed construction worker who under-reports their income does so by £2,200 per year (Advani, 2022). Assuming an annual income below £50,000, this implies about £11,000 of under-reported income per year. This is roughly similar to the difference between our estimates of earnings in employment and self-employment in our key self-employment occupations in Table 15, which could suggest that under-reporting of income accounts for a significant part of this gap. However, this is impossible to estimate with any precision or certainty.

Given the overall uncertainties and challenges with estimating self-employment earnings, we have not included these estimates in our overall estimate of earnings in Construction comparator occupations. While excluding self-employment excludes a key part of the labour force in the construction industry, there are too many caveats and uncertainties associated with the analysis to ensure it is sufficiently reliable to report.

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