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Employment and Earning Outcomes from Train to Gain Extension Analysis

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A report by Frontier Economics and the Institute for Fiscal Studies (IFS)

Annex 3 to 'Reporting on employment and earnings using experimental matched data'

The views expressed in this report are those of the authors and not necessarily the Department for Business, Innovation and Skills or any other Government Departments.

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Contents

Executive Summary

BIS has asked Frontier Economics and the Institute for Fiscal Studies (IFS) to undertake an extension of the analysis of the matched ILR, DWP and HMRC data focusing on Train to Gain (TTG) learners.

In our previous work we found that there was little improvement in the labour market outcomes of this group of learners following training. Since then, more ILR-HMRC/DWP data has become available allowing us to extend the original analysis. BIS is particularly interested in understanding how the outcomes of learning vary across learner cohort and time. We address these questions by comparing the outcomes (measured in the first year after training) of the two learner cohorts in the data, corresponding to the 2006-07 and 2007-08 academic years. We also look at the longer term outcomes (measured in the second year after training) of the first cohort in the data.

Our descriptive analyses reveal that there is little difference between the earlier and later cohorts in terms of employment, benefits and earnings. On the whole, outcomes appear to be slightly poorer for the later cohort but differences are small. Extending the time horizon over which outcomes are measured does not lead to improvements in the estimated outcomes either. Indeed, some of the evidence presented in this report suggests that rather than improve, outcomes may deteriorate over time, particularly earnings and benefit claims. On the other hand there appear to be some gains in employment.

The impact (econometric) analysis we carried out also suggests that TTG has had little impact on labour market outcomes. We ran separate analyses controlling for demographic characteristics and subject studied. There is little pattern in the detailed results and although there appear to be positive effects for some specific learner groups, the overall impacts are small.

The only unambiguously positive impact on pay is for women studying Leisure, Travel and Tourism at FL2. In other cases, although there is no clear impact on pay, there is an increase in employment and decline in benefits. At FL2 this occurs for Health, Public Services and Care; Retail and Commercial Enterprise (for women); Education and Training (for women); Preparation for Life and Work (for women); and Leisure, Travel and Tourism (for men). Given that individuals in TTG are meant to be in continuous employment throughout their learning, this could indicate that they spent a greater part of the 12 months before learning out of work than after learning.

On the whole, employment impacts are often significant while earnings impacts are insignificant or small. It is not clear from our analysis why that might be the case but it may be worth BIS exploring that in more detail through some in-depth case studies or interviews. If significant earnings impacts were to emerge we might expect them to emerge over a longer time period than we have been able to study - a wider review of the literature might help to understand whether in general earnings impacts from training are initially small but then grow, or whether it is difficult to get earnings impacts from training older workers[1].

The results in this report should be viewed in comparison to the impacts of other training programmes - such as FE or apprenticeships. Previous work carried out by IFS/Frontier suggests that training might have significantly higher impacts on students in these funding streams.

A possible explanation for the relatively poor outcomes in TTG, which we are unable to test, is that learners who enter this programme have worse labour market prospects than the rest per se, that is there is some selection bias which is driving the results. Another factor that may be of relevance is that TTG learners are normally already employed before starting and would typically be continuing their current job during training. The continuity of employment may reduce the extent to which individuals are actively changing jobs or seeking higher wages. It may be that an individual entering a new job, where they are expected to then undergo training, may enjoy uplift to their pay before the training has actually commenced. If it were the case that the training was 'bundled' with the job, before and after comparisons would not capture this impact.

[1] A possible explanation for the lack of impacts may be that TTG learners are older (mean age is 38) and at a point in their careers where sizeable changes in labour market performance may not be expected. As we have shown in another report entitled "Age and outcomes"'[1] impacts tend to be strongest for learners aged 25 or less, a group which is under represented in the TTG data

Introduction

Background

The Education and Skills Act 2008 allowed the sharing of data between the Department for Business, Innovation and Skills (BIS), Her Majesty's Revenue and Customs (HMRC) and the Department for Work and Pensions (DWP) in order to analyse how effective training is in improving the employment and earnings outcomes of learners. Consequently BIS received a dataset with personal information removed, containing the employment, earnings and benefit claim data on all those who have undertaken publicly-funded learning in the further education sector and therefore have an Individualised Learner Record.

Objectives and Scope

Previous work conducted by Frontier and the IFS[2] which used the matched data to produce a series of analyses found that the labour market performance of learners varied significantly across a number of dimensions such as funding stream, level of study, subject area and others. In particular, we found that apprenticeships offer the best return in terms of wage increases. That said, all apprentices are young and at a stage of their labour market career where steep increases in earnings can be expected. Outcomes appeared to be poorest for TTG learners. Comparing earnings before and after learning, we found little improvement in the economic performance of TTG learners and in some cases there was evidence of earnings declining.

There are several possible explanations for the observed pattern, including the much greater average age of TTG learners (38) and the possibility that the impact of TTG may take longer to appear. These we can test. On the other hand if there is a selection issue – those with worse labour market prospects engage in TTG – we will not be able to test this.

Since our original work, we have received additional data including an extra year of ILR data and an extra year of matched ILR-HMRC/DWP data. The purpose of this report is to extend the original analysis by exploiting the new data so that:

- We study the outcomes of TTG learners from the 2007-08 cohort one year after learning (i.e. financial year 2009-10);
- We study the outcomes of TTG learners from the 2006-07 cohort two years after learning (i.e. financial year 2009-10); and
- We combine the two years of data and run an impact analysis.

[2] "How to make best use of the new matched data for reporting on the employment and earnings outcomes of training", Report prepared for BIS in April 2010

These analyses allow us to check if the benefits of training differ across cohorts and if they take longer to materialise in this group of learners.

Structure of the Report

This report is structured as follows:

- Chapter 2 provides a short description of our data processing
- Chapter 3 provides a descriptive analysis of the data focusing on how outcomes change for the different age groups within TTG
- Chapter 4 presents the findings from our econometric impact analysis of the data
- Chapter 5 presents our conclusions
- Annex 1 contains a full set of output tables

Data work

This Chapter provides a brief description of the raw data we received and an overview of the data processing we undertook in order to transform it into usable data sets. The methodology used here is exactly the same as the one used in our previous work[3]. The ultimate goal of the data processing was to create a learner-level data set (one record per learner) containing information on learner demographics, type of learning and labour market performance before and after learning. Our focus is only on those who achieved a qualification.

Our analytical strategy is to focus on individuals for whom we can observe *both* pre-training histories (for employment, earnings and benefits) and post-training outcomes for at least 12 months before and after training. The ILR data we received covers two academic years: 2006-07 and 2007-08. The employment and earnings data spans 7 financial years, from April 2003 to April 2010 while the benefits data goes back even longer. Overall, the time period covered by the data is sufficiently long to allow the recording of labour market histories for virtually all learners and outcomes for most learners.

The ILR data records the start and end dates of each course an individual studies. It further specifies if a learner has left their course of study. This allows us to determine whether an individual is in learning at any point in time. Learners start and end their studies at different times, so the learning window will be different for different individuals. However, in order to allow us sufficiently long before/after periods, we only consider learners who are in learning during the academic years (defined as the 12 month period starting from 1 August in the respective year). Students whose learning spells fall outside the window are not included in subsequent analyses, since either their pre- or post-training outcomes are not observed for long enough for our analysis. (For example, some students entering TTG in 2008 may be expected to complete their studies in late 2009, which does not leave a long enough after period during which to measure outcomes).

The following sections describe our data processing in more detail.

ILR data processing

The ILR data we received is at the aims level; that is there is one line for every course individuals undertook in the academic years 2006-07 and 2007-08. There were 217,730 records in 2006-07 and 487,071 in 2007-08. In what follows we describe in detail the steps we took in order to derive a usable learner-level data set which is merged with the HMRC/DWP data. The derivation of the data-set involves the following steps (both 2006-07 and 2007-08 data sets):

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[3] However, we note that the data sets we received for this project were significantly different from those we processed during the earlier work. The ILR data sets contain fewer variables this time round but also have HMRC/DWP identifiers merged in. Also, the HMRC/DWP data sets we received had already been partially 'cleaned' by BIS.

- Deleting the records of learners aged under 16 or over 59;
- Definition of learner highest achievement and its level and subject area;
- Deleting the records of learners who are non-achievers; and
- Condensing the data to one row per learner (keeping the highest achievement only);
- Deleting records with missing identifiers; and
- Definition of a learning window- deletion of learners whose learning falls outside the window;
- Merging the derived ILR data with the clean HMRC/DWP data.

In order to illustrate the process we specify the number of observations dropped at every stage of the process for both data sets, 2007-08 values are in brackets[4].

- Excluding learners aged under 16 and over 59: 5,181 (14,142) records deleted
- Deletion of non-achieving learners (including continuing studies): 157,555 (300,840) records deleted
- Condensing data to one row per learner: 3,677 (12,113) records deleted
- Deletion of records with missing identifiers: 6,382 (13,102) records with no HMRC or DWP identifiers deleted

Once the two data sets are cleaned, we merge them together obtaining a total of 190,868 records- 76.5% appear only in 2007-08, 23% appear only in 2006-07 and 0.5% appear in both years. Finally, we exclude learners whose studies ended (or were expected to end) after 1 August 2008 or start before 1 August 2005. This results in 521 further observations being deleted.

Where learners appear in both years, we take the maximum learning window (spanning the two years) and the highest achievement from the two years.

HMRC/DWP data processing

The HMRC/DWP data we received contains the following elements:

- NBD (benefit spells);

[4] This depends on the sequence in which the steps are taken

- P45 (employment spells);
- P14 (annual earnings).

In this section we describe how the raw data in each of these datasets is used to derive the history and outcome variables used for comparing the effects of different TTG courses. For each dataset there is an initial data cleaning stage, followed by reshaping and reconciling the data.

In terms of processing steps, we have followed exactly the same methodology as we did in our previous work[5]. In terms of methodology, one major difference is that in order to increase the speed with which we process the data, we first remove all non-TTG learners from the data before proceeding with the data cleaning. We also note that the data sets we received this time are different from those received a year ago. The data sets have fewer variables and in the case of P14 and P45 data some data cleaning was already carried out by BIS. For these reasons we are unable to exactly replicate all cleaning steps we took in our previous work.

NBD data

The NBD is a database of benefit spells, which we use to create a benefit history for each an individual, telling us month by month whether that individual was receiving certain types of benefit.

For this purpose the main elements of each entry are:

- Start and end date of benefit spell;
- Type of benefit;
- Personal identifier (ccorcid)

The raw dataset contains 19,177,335 separate spells on benefits. Of those, only 916,855 spells are retained, as these are matched to TTG learners.

The data has thirteen different types of benefits. Our analysis focuses primarily on out-of-work benefits, but we also retain information on working-age disability benefits, leaving us with the following benefits:

- Disability Living Allowance (DLA),
- Employment and Support Allowance (ESA),

[5] “How to make best use of the new matched data for reporting on the employment and earnings outcomes of training”, IFS/Frontier report prepared for BIS, April 2010

- Incapacity Benefit (IB),
- Income Support (IS),
- Jobseekers' Allowance (JSA),
- Passported Incapacity Benefit (PIB).

To reduce the size of the dataset we have merged PIB, IB and ESA (the successor to IB) into a single category.

Overall, the NBD data is considerably 'cleaner' than the P14 and P45 data, meaning that our data cleaning exercise is relatively straightforward. We found no anomalies in the spell start and end dates. The only significant cleaning we undertook of the NBD data was to drop near duplicate records (in terms of ccorcid cdend cdstart cxben). This resulted in 275,244 observations deleted.

The ultimate aim of the NBD processing was to produce a dataset with one line per individual recording individual's benefit history on a monthly basis. For each month from 2003 to 2010, our data processing code ascertains what proportion of the month an individual spent on each benefit. For example, a spell starting on the 15th of February covers half of February. We reduce the data down to one line per individual, showing the monthly benefit history for IB, IS, DLA and JSA. Table 1 provides a summary of our approach.

Table 1: Reshaping the benefits data

	Start	End	J	F	M	A	M	J	J	A	S	O
Spell A	15 Feb	31 Apr	0	.5	1	1	0	0	0	0	0	0
Spell B	1 Mar	15 Jun	0	0	1	1	1	.5	0	0	0	0
Spell C	1 Aug	31 Dec	0	0	0	0	0	0	0	1	1	1
Employment history			0	.5	1	1	1	.5	0	1	1	1

Source: Stylised example

P14 data

The P14 database contains P14 end of year PAYE information from HMRC. The data contains amounts of earnings and tax, per employment, within individual tax years, for each individual. Records are returned by employers at the end of each tax year. Our objective is to transform the raw P14 data into an individual-level data set showing earnings for each financial year we have data for. The key variables are:

- Personal identifier- we have both HMRC (person_instance_id) and DWP (ccorcid)
- Start and end date of earning spells

- Pay per employment spell
- Flags indicating if more records are expected for an individual in a financial year (ripeness flag)

The raw data contains 76,428,313 records spanning 7 financial years from 2003-04 to 2009-10. Of those, 2,307,202 are matched to TTG learners, i.e. the rest are deleted. Additional cleaning we undertook:

- Deleting spells where payment information is missing: 234,861 records deleted
- Deleting exact duplicates in terms of all variables; 2,831 records deleted
- Deleting spells where the start date is after the end date: 2,135 records deleted
- Deleting spells where payments are negative or equal zero: 54,924 records deleted
- Deleting near duplicates (records where all information is identical except the extract date): 154 records deleted
- Deleting near duplicates (records where there are more than one 'ripe' records and the pay information is identical): 1,362 records deleted

Once the data cleaning is complete, we add pay spells within a year/individual and reduce the data to one record per learner.

P45 data

The P45 data lists the employment spells of an individual. As with the NBD data, the objective is to move from a list of spells to a monthly history for each individual. For each spell we focus on the following information:

- Personal identifier (both 'person_instance_id' for HMRC records and the matching 'ccorcid' for NBD data);
- Start and end date of employment

The following summarises the steps we took to clean the data as it contains records which are irrelevant for our analysis:

- We drop records relating to employment spells before 1 January 2003, which results in the deletion of 903,925 records.
- We next delete employment spells which have negative duration resulting in the deletion of 6,231 records
- We delete records where start date, end date and the person identifiers are identical-28,636 observations deleted

- We remove spells with missing start date-19,624 records deleted or end date-22,706 records deleted

- We adjust uncertain start and end dates (see below)

A serious problem with the P45 data arises from the fact that in many cases start and end dates of employment are not recorded precisely. Suppose an employee leaves their job at some point during a year, but the precise leaving date is not known. In this case, the convention is to use an arbitrary leaving date – the end of that financial year (5th April). Similarly, if the precise start date is not known, it will be recorded as the first day of the financial year (6th April). Uncertain start and end dates therefore lead to an over-estimate of the time an individual is in employment.

In some cases a spell with uncertain start or end dates can overlap with a spell with both certain start and end dates. For example, suppose an individual has a spell running from 1st July to 5th April (i.e. certain start and uncertain end) and another running from 1st July to 31st October (i.e. certain start and certain end). It is reasonable to consider that these are the same spell, and that the individual was not in fact working from 1st November to 5th April. We remove 345,323 such records.

Having cleaned the data, we reduce it to one line per learner, following the same methodology outlined in Table 1.

Reconciling the data

Having processed the NBD and P45 data sets, we seek to reconcile differences in the two before merging them with the earnings data. Overall we view the NBD data as being more reliable than the P45 data. We therefore use it to “correct” inaccuracies in the P45 data. That is, wherever there is inconsistency between the two, we correct the P45 to restore consistency. We do this regardless of the certainty of start and end dates of employment. The mathematical rule we employ is:

Corrected % $\text{Employed}_t = \min[\%\ \text{Employed}_t,\ 1 - \max(\%\ \text{IB}_t,\ \%\ \text{JSA}_t)]$

The worked example below illustrates how this works in practice.

Table 2: Reconciling employment and benefit histories

	J	F	M	A	M	J	J	A	S	O	N	D
Employment	0	.5	1	1	1	.5	0	1	1	1	0	0
IB	0	0	0	0	0	0	0	0	0	0	0	0
JSA	1	0	0	0	0	.75	1	.5	0	0	.5	1
Corrected employment	0	.5	1	1	1	.25	0	.5	1	1	0	0

Source: Stylised example

We can now combine the corrected employment history and annual earnings data to estimate the average pay of an individual for the months they are working. We then multiply this by the proportion of each month worked to get an estimate of earnings per month.

Time in employment per tax year

We need to calculate average time spent in employment for each tax year. We take a relatively simplistic approach to this, adding the proportions of the months and dividing by 12. There are several issues to bear in mind, but which should not have any appreciable impact.

- *Month length and public holidays.* Arguably we should weight months according to number of working days they contain. For simplicity we do not do this.

- *Discrepancy between tax year and calendar month*. The tax year begins on the 6th of April. Arguably we could define months beginning on the 6th so that the tax year and employment months fully correspond. This would be a cumbersome and potentially confusing adjustment, however. Instead we allocate the first sixth of April to the tax year coming to an end and assign the remaining five-sixths of it to the new tax year that starts thereafter.

The approach we take is shown in the table below. This person has worked for half of the year ((0.83 + 1 + 0.5 + 1+ 1+ 1+0.5 +0.17)/12 = 0.5)

Table 3: Calculating proportion of tax year in employment

	A	M	J	J	A	S	O	N	D	J	F	M	A
Employment	1	1	.5	0	1	1	1	0	0	0	0	.5	1
Weight	.83	1	1	1	1	1	1	1	1	1	1	1	.17
Weighted proportion of month worked	. 83	1	.5	0	1	1	1	0	0	0	0	.5	.17

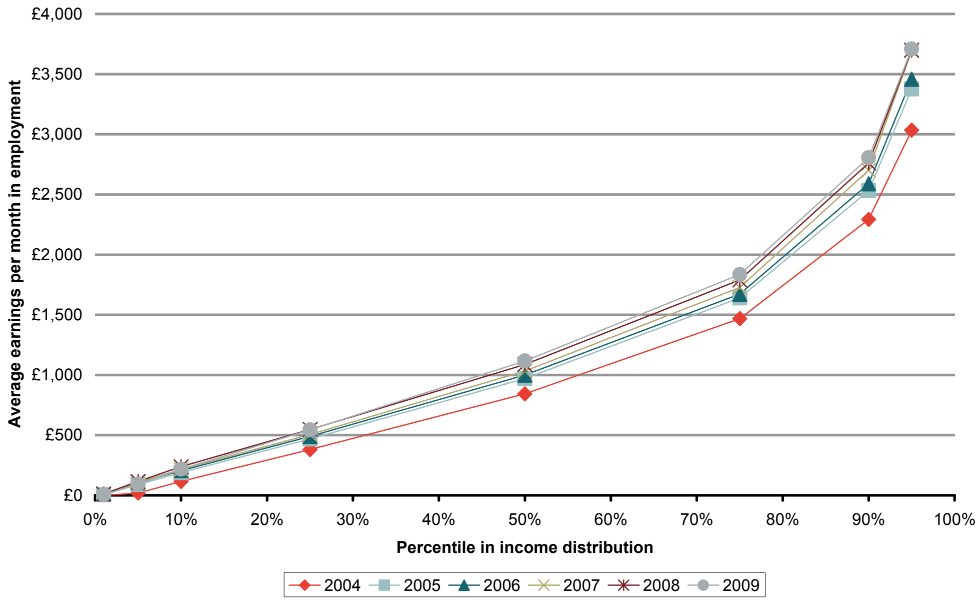
Source: Stylised example

Calculation of average earnings per month worked

Dividing the earnings per tax year by the proportion of the tax year an individual spends in employment, we obtain a yearly estimate of average earnings per month in employment. So if someone has earned £12,000 and worked half the year we would consider them to earn £2,000 per month in employment.

The income distribution for individuals appearing in the P45 is shown overleaf. At the very top of the income distribution are some implausibly high levels of income (in excess of £100,000 per month). The very low incomes in the lower part of the distribution will undoubtedly be driven partly by part-time working.

Figure 1: Distribution of average income per month worked (by year)



Source: Frontier analysis of HMRC/DWP data

Calculation of monthly earnings

We then multiply the earnings per month worked by the proportion of each month in employment to get an estimate of monthly earnings. Since April straddles two financial years, we use a weighted average of the estimated earnings in April according to the rule stated above. This procedure is shown below.

Table 4: Calculation of monthly earnings

	J	F	M	A	M	J
Employment	0	.5	1	1	1	.5
Earnings/month employed, FY ending April 2006	£2000	£2000	£2000	£2000	n/a/	n/a
Earnings/month employed, FY ending April 2007	n/a	n/a	n/a	£2500	£2500	£2500
Corrected employment	0	£1000	£2000	£2417	£2500	£1250

Source: Stylised example

Having cleaned and merged all data sets together, we have a final data set containing 185,553 records of which 93% are FL2, the remaining 7% are Full Level 3 (FL3). We describe the data set in detail in the following section.

Descriptive statistics

Overview

The purpose of this section is to provide a range of descriptions of the earnings, employment and benefit statuses of students who achieved a qualification through the TTG programme. The addition of extra learner and HMRC/DWP data allows us to extend the analysis we undertook previously, and examine whether our findings change over time. Overall our strategy consists of:

- Comparing the demographic characteristics of the two cohorts of learners, 2006-07 and 2007-08;
- Comparing the histories and outcomes (12 months before and after learning) of the two cohorts of learners;
- Comparing the short term and long term outcomes of the 2006-07 cohort (1st year after training vs. 2nd year after training).

The descriptive analysis is interesting and informative but we must stress that observed differences in outcomes by a certain characteristic cannot be taken as evidence that the characteristic has a causal effect on those outcomes. Differences in outcomes may be caused by a variety of omitted factors such as differences in the prior ability or attainment of the students, differences in the average age of the learners, differences in provider locations and differences in the type of qualification studied. The purpose of the descriptive analysis is not to uncover causal relationships but to gain a better understanding of how learner characteristics and outcomes vary over time/subject area.

Before looking at the outputs it is worth discussing some of the limitations of the matched data. In our view, the main weakness of the data is that there appear to be many records with missing earnings information. The matched data contains 185,553 learners. Average employment before learning is 9 months, rising to 9.8 months after learning. However, around half of the learners in the data set have no earnings recorded both before and after learning. There may be genuine reasons why an individual who is in work has no earnings recorded in the P14 data. For example, employers are not required to send earnings data to HMRC on individuals earning below the taxable threshold. However, it is unlikely that this can explain this anomaly in the data fully -given that 76% of individuals in the data worked for 6 months or more in the year preceding learning it is unlikely that many will have earned less than the taxable threshold.

Another unfortunate feature of the data is that it does not allow us to distinguish part-time from full time workers. This means that changes in raw earnings could be the result of a change in working hours (switching from part-time to full-time for example) rather than a genuine pay increase. Therefore, when analysing earnings, we only use individuals in continuous employment and earning reasonable amounts (defined as the range £4,800-£80,000 per year) to generate our summary statistics.

Descriptive statistics

Demographics

The purpose of this section is to establish if learners who completed their studies in 2007-08 are different from those who finished a year earlier. Our previous work[6] on the 2006-07 data showed that TTG learners have rather different characteristics to FE and apprenticeship learners. They are much older, more likely to be male and to live in a deprived area than the rest. The focus of our analysis is on FL2 learners as they make up the vast majority of learners in both years: 97% in 2006-07 and 92% in 2007-08. There are three times as many learners in 2007-08 as there are in 2006-07, giving us a combined sample of 171,867.

We begin by comparing the demographic characteristics of the two cohorts of learners to see if there have been any major changes in demographics. Overall, we find no significant changes. Average age remains 38 in both years and there are no significant shifts in the age distribution of learners over time (see Figure 2).

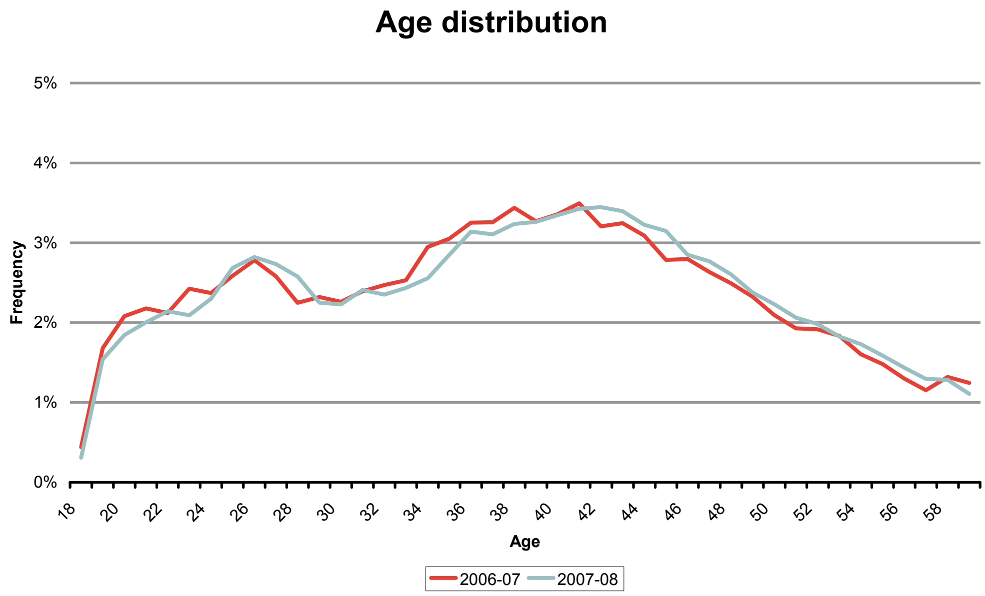
Table 5: Key demographic metrics

	2006-07	2007-08	Difference
% male	56	55	-1%
% ethnic	83	80	-3%
% deprived area	46	41	-5%
mean age	38	38	0

Source: Frontier analysis of ILR-HMRC/DWP data

[6] Frontier/IFS draft report entitled “How to make best use of the matched data for reporting on the employment and earnings outcomes of training”

Figure 2: Learner age histogram 2006-07 and 2007-08



Source: Frontier analysis of ILR-HMRC/DWP data

Subject areas and prior attainment

Learners starting in 2007-08 are not different from those starting a year earlier in terms of prior attainment. In both cases around two-thirds of students have no qualifications and a quarter have qualifications equivalent to Level 1. The remainder is made up of unknown or other qualifications.

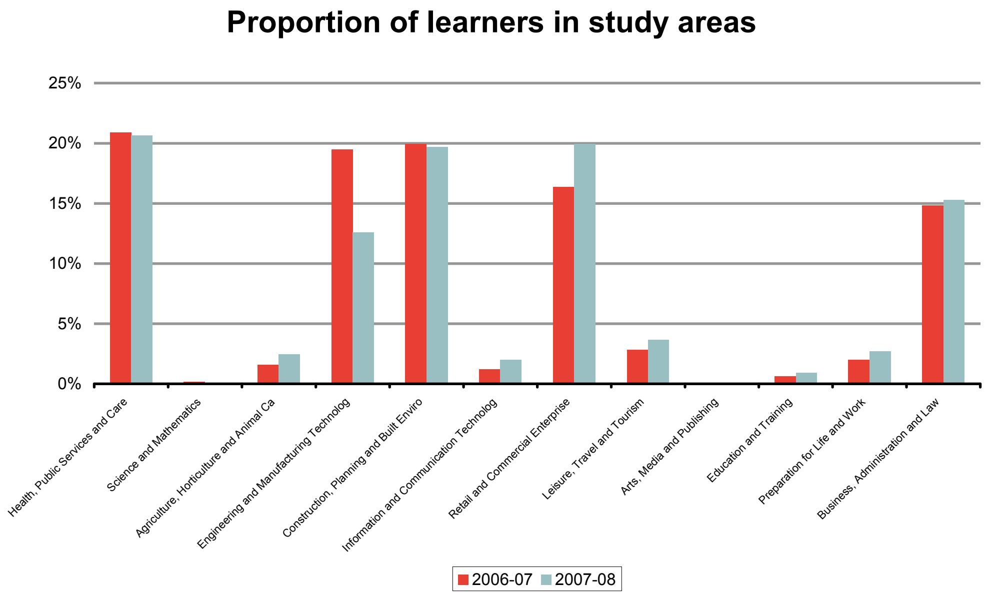
Table 6: Prior attainment

	2006-07	2007-08	Difference
No qualifications	64%	67%	+3%
Level 1	24%	27%	+3%
Other	12%	6%	-6%

Source: Frontier analysis of ILR-HMRC/DWP data

There is also no indication that learners completing the TTG programme in later years study different subjects from those who started in 2006-07. On the contrary, the distribution across subject areas is remarkably consistent. Most students (92% in 2006-07 and 88% in 2007-08) are concentrated in only five subject areas: Health Public Services and Care, Engineering and Manufacturing Technologies, Construction Planning and Built environment, Retail and Commercial Enterprise and Business Administration and Law.

Figure 3: Learner subject areas 2006-07 and 2007-08



Source: Frontier analysis of ILR-HMRC/DWP data

Labour market outcomes

So far we have shown that there have not been any major changes in the profiles of TTG learners over time, both in terms of demographic composition and what they study. We next turn to analysing the economic performance of the two cohorts of learners.

Aggregate statistics

First we compare the outcomes of learners who completed the programme during the 2006-07 academic years with those who did it a year later. In both cases we measure outcomes in the year immediately following achievement in TTG. Second, we explore the extent to which the outcomes of the 2006-07 cohort change over time, by measuring outcomes two years after training finished.

We present a simple before-after comparison of the key labour market variables for the FL2 sample as a whole. The measures we use are:

- Employment: number of months in employment;
- Benefits: number of months on benefits;
- Raw earnings: average annual earnings;

- Filtered earnings: average earnings of individuals who are in continuous employment before and after studies, excluding outliers[7];

Table 7: Labour market performance before and after studies

Labour market outcome	12 months before		12 months after		% change	
	2006-07	2007-08	2006-07	2007-08	2006-07	2007-08
Employment (months)	9.07	8.92	9.45	9.79	4%	10%
Benefits (months)	0.55	0.57	0.40	0.50	-27%	-12%
Raw earnings	£6,936	£6,657	£7,195	£7,029	4%	6%
Filtered earnings	£17,657	£17,695	£18,160	£17,780	3%	0%

Source: Frontier analysis of ILR-HMRC/DWP data

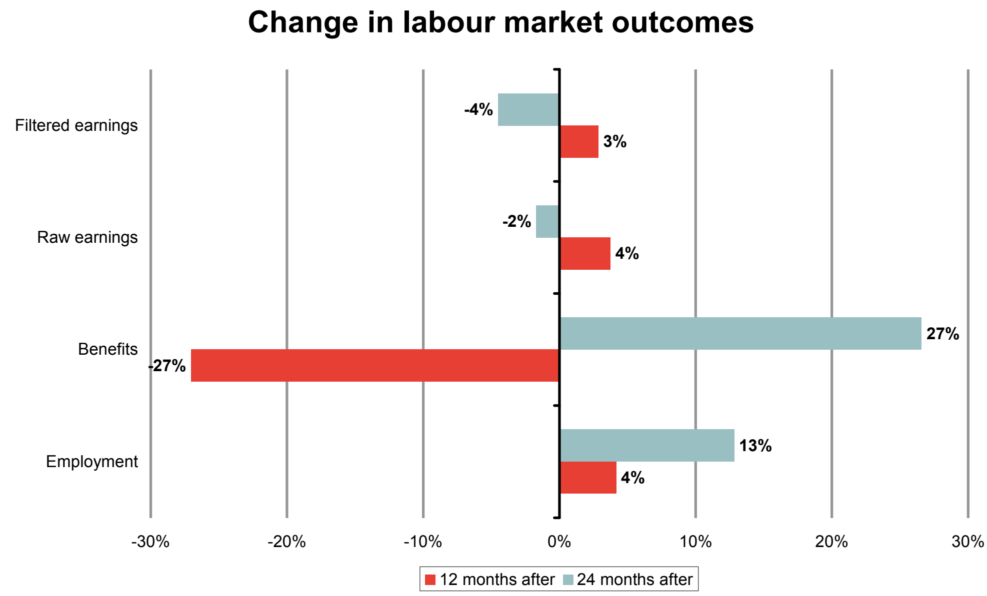
On the whole, labour market performance appears very similar across the two learner cohorts both before and after learning. Learners entering TTG in 2007-08 have slightly worse economic indicators than those entering a year earlier, but the differences are very small indeed. Employment and benefits before training appear virtually identical and raw earnings are around £300 lower for the 2007-08 cohort, relative to the pre-learning baseline.

Following achievement, employment goes up, benefits fall and earnings increase. Other than employment, outcomes appear to improve by more for the 2006-07 cohort, but again differences are small. In term of magnitude, we observe good employment gains and benefit reductions. The earnings increases are very modest (3% for the first cohort and no change for the second cohort). Overall, the data shows that there is little difference between the outcomes of learners who entered TTG at different times.

In order to establish if the benefits of training materialise over a longer time period, we analyse how labour market performance evolves two years after completion of studies rather than one.

[7] We define outliers as individuals whose annual earnings are below £,4,800 or above £80,000

Figure 4: Economic performance over time



Source: Frontier analysis of ILR-HMRC/DWP data

Our results (shown in Figure 4) indicate that outcomes are poorer in the second year after training compared to the first year after training. The exception is employment which is 9 percentage points higher in the second year, but all other indicators worsen. We now see an increase in benefit rates, and falls in real earnings by around 4%.

Table 8: Change in labour market outcomes over time

	12 months before	12 months after	24 months after	% change 12 months after	% change 24 months after
Employment (months)	9.07	9.45	10.23	4%	13%
Benefits (months)	0.55	0.40	0.70	-27%	27%
Raw earnings	£6,936	£7,195	£6,818	4%	-2%
Filtered earnings	£17,657	£18,160	£16,863	3%	-4%

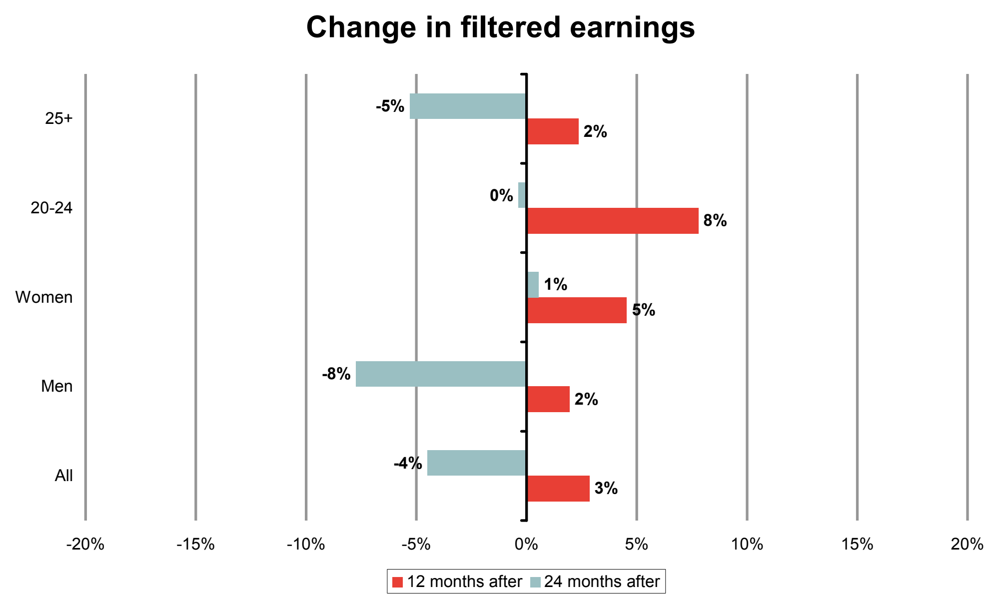
Source: Frontier analysis of ILR-HMRC/DWP data

This overall pattern is consistent across demographic groups. We compare outcomes for men and women and two age bands: those aged between 20 and 24 and the rest. In all groups, we observe better outcomes in the 1st year after training than the 2nd year after training. Within this there are differences between the demographic groups such that women do better than men and younger learners do better than older learners.

Focusing on filtered earnings in the first year after training for example (see Figure 5), we observe increases by 5% for women and 2% for men, relative to their level in the year preceding training. However, while male earnings decline by 8% in the second year after training, female earnings increase slightly by 1% relative to the same baseline. The same pattern holds for employment and benefits.

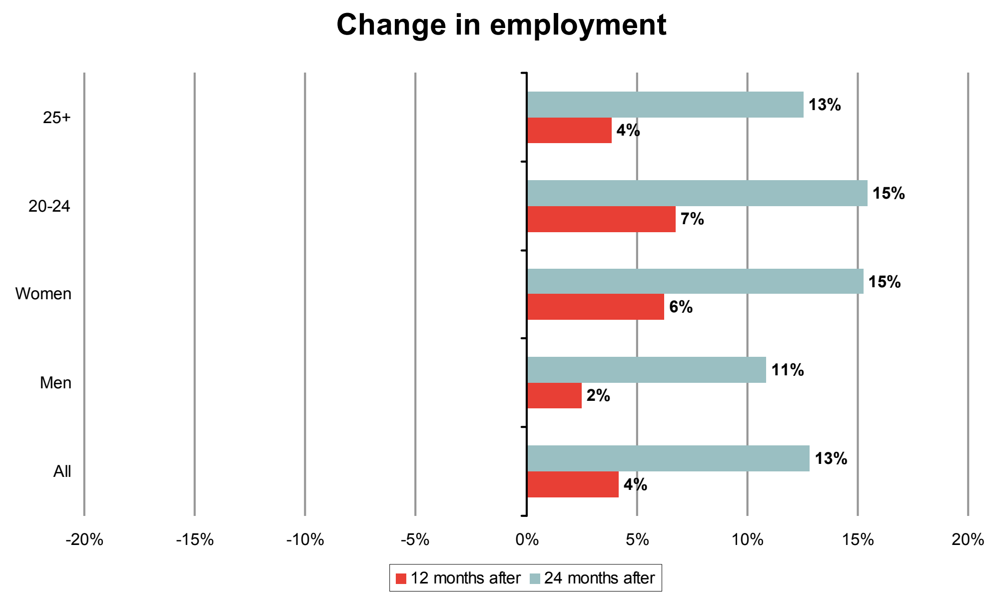
In a similar way, outcomes are consistently better for the 20-24 age group compared with those aged 25 or more. The former group see their filtered earnings remain unchanged while the latter experience a fall of around 5% in the 2nd year after training.

Figure 5: Earnings changes over time



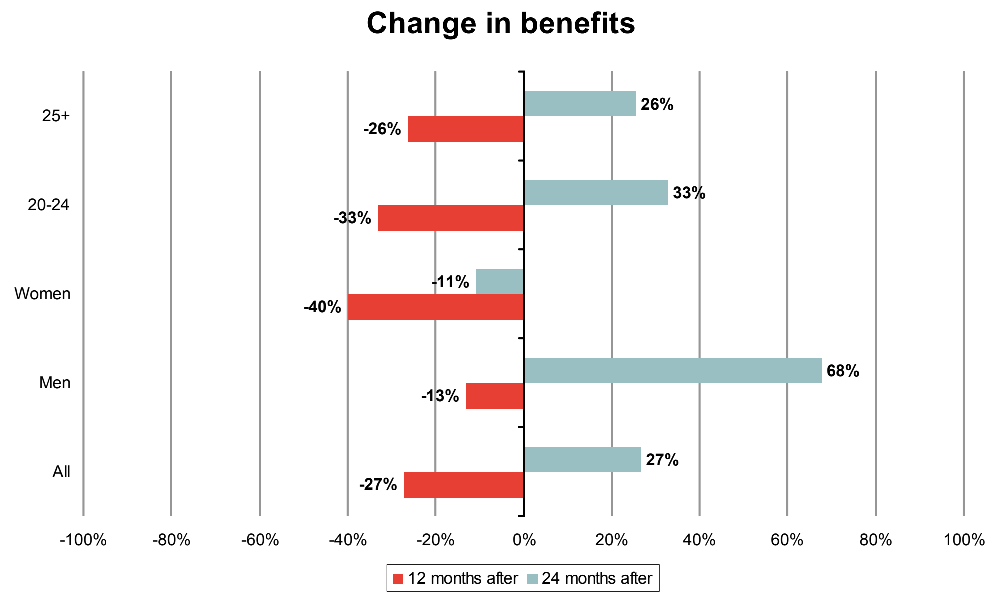
Source: Frontier analysis of ILR-HMRC/DWP data

Figure 6: Employment changes over time



Source: Frontier analysis of ILR-HMRC/DWP data

Figure 7: Benefits changes over time



Source: Frontier analysis of ILR-HMRC/DWP data

Descriptive statistics disaggregated by subject

In this section, we replicate the analysis from the previous section but drill deeper by disaggregating the data in terms of subject studied (note that we only report summary statistics where sample size is greater than fifty observations). This allows us to see if there are interesting variations which can not be uncovered in the aggregate results. Our previous work with the matched data found that certain subject areas such as Construction, Planning and Built Environment had on average better outcomes than the rest in all funding streams. The current data does show that this is the subject area where earnings were highest before learning. However, in terms of changes following training, there appears to be little benefit there. In particular if outcomes are measured in the 2nd year after training, we observe quite large declines in earnings, in the order of 12%. Overall, it remains the case that relative to the baseline (the year before learning), earnings outcomes are better in the first year after training than the second year. This holds for all subject areas with the exception of Education and Training.

Further, learners in the earlier cohort appear to have better outcomes than those in the 2007-08 cohort (see Table 10) with the exception of two subject areas: Leisure, Travel and Tourism and Education and training. On the whole, however we do not observe major earnings changes in any of the subject areas.

Table 9: Change in filtered earnings over time: 2006-07 cohort

Subject area	12 months before	12 months after	24 months after	% change 12 months after	% change 24 months after
Health, Public Services and Care	£13,216	£14,330	£14,018	8%	5%
Science and Mathematics					

Subject area	12 months before	12 months after	24 months after	% change 12 months after	% change 24 months after
Agriculture, Horticulture and Animal Care	£18,457	£18,689	£17,395	1%	-5%
Engineering and Manufacturing Technologies	£19,991	£20,105	£18,443	1%	-7%
Construction, Planning and Built Environment	£23,917	£24,439	£21,076	2%	-12%
Information and Communication Technology	£19,045	£20,099	£19,177	6%	1%
Retail and Commercial Enterprise	£15,472	£15,959	£15,328	3%	-2%
Leisure, Travel and Tourism	£18,798	£19,257	£17,805	2%	-7%
Arts, Media and Publishing					
History, Philosophy and Theology					
Social Sciences					
Languages, Literature and Culture					
Education and Training	£12,262	£12,825	£13,097	5%	9%
Preparation for Life and Work	£16,124	£16,822	£15,782	4%	-4%
Business, Administration and Law	£16,443	£16,729	£15,783	2%	-5%

Source: Frontier analysis of ILR-HMRC/DWP data. Blank cells indicate small samples (fewer than 50 observations)

Table 10: Change in filtered earnings across cohort

Labour market outcome	12m before		12m after		% change	
	2006-07	2007-08	2006-07	2007-08	2006-07	2007-08
Health, Public Services and Care	£13,216	£13,997	£14,330	£14,694	8%	5%
Science and Mathematics						
Agriculture, Horticulture and Animal Care	£18,457	£18,816	£18,689	£18,804	1%	0%
Engineering and Manufacturing Technologies	£19,991	£20,017	£20,105	£19,804	1%	-1%
Construction, Planning and Built Environment	£23,917	£24,330	£24,439	£23,663	2%	-3%
Information and Communication Technology	£19,045	£19,273	£20,099	£18,957	6%	-2%
Retail and Commercial Enterprise	£15,472	£16,302	£15,959	£16,421	3%	1%
Leisure, Travel and Tourism	£18,798	£17,029	£19,257	£17,730	2%	4%
Arts, Media and Publishing						

Labour market outcome	12m before		12m after		% change	
	2006-07	2007-08	2006-07	2007-08	2006-07	2007-08
History, Philosophy and Theology						
Social Sciences						
Languages, Literature and Culture						
Education and Training	£12,262	£11,069	£12,825	£11,685	5%	6%
Preparation for Life and Work	£16,124	£15,412	£16,822	£15,673	4%	2%
Business, Administration and Law	£16,443	£16,880	£16,729	£16,993	2%	1%

Source: Frontier analysis of ILR-HMRC/DWP data. Blank cells indicate small samples (fewer than 50 observations)

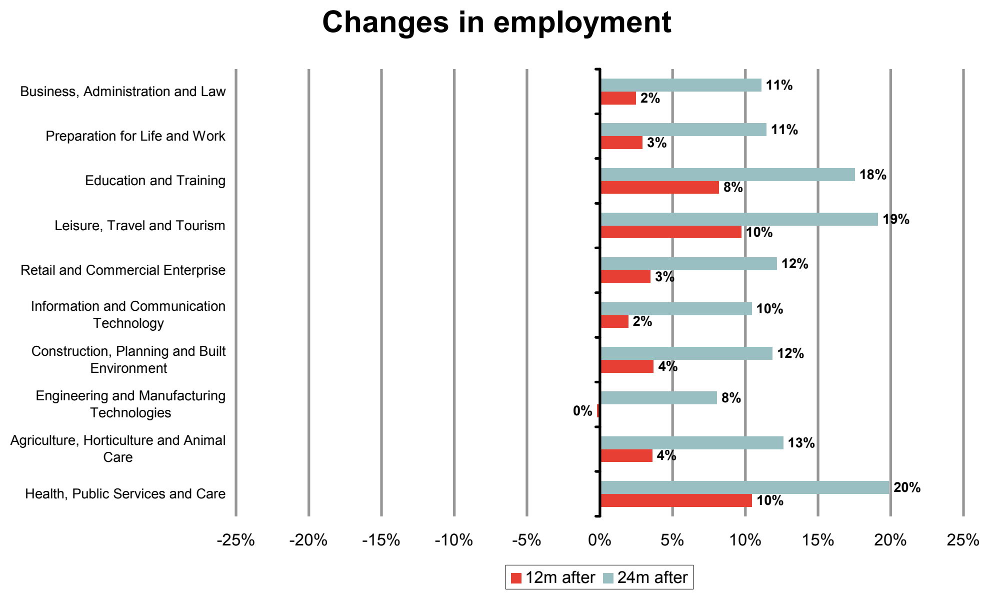
The data reveals the same pattern in terms of benefits- that is benefit claims are higher two years after training than one year after training. In addition, training appears to have a smaller effect on benefits in the second cohort of learners relative to the first.

Employment follows exactly the opposite pattern. It is greater in the second year after training and in the second cohort of learners (those who started training in 2007-08). This is consistently the case for all subject areas.

We must stress that these descriptive before-after comparisons do not take into account general economic conditions which may well drive the results. For example the worsening of benefit claims in the 2007-08 cohort (12 months after training) and the 2006-07 cohort (24 months after training) may simply be a consequence of the recession- the timing period will coincide with financial years 2008-09 and 2009-10 which saw rises in general unemployment in the UK relative to 2007-08[8]. We remove the influence of general economic conditions in our impact analysis section. This is an unfortunate feature of before-after comparisons: the lack of a contemporaneous comparison group means the estimated outcomes can be confounded by unobservable aggregate trends.

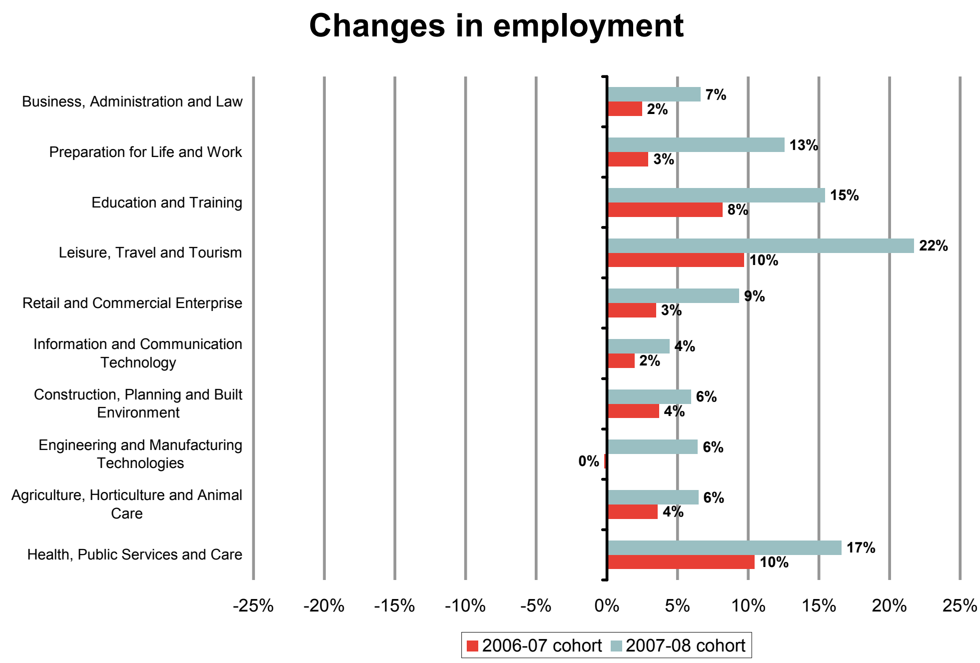
[8] National Statistics Online data shows that the unemployment rate for individuals aged 16-64 in March 2008 was 5.2% but this increased to 7.4% in March 2009 and 8% in March 2010. (http://www.statistics.gov.uk/statbase/TSDdownload2.asp)

Figure 8: Employment changes over time: 2006-07 cohort



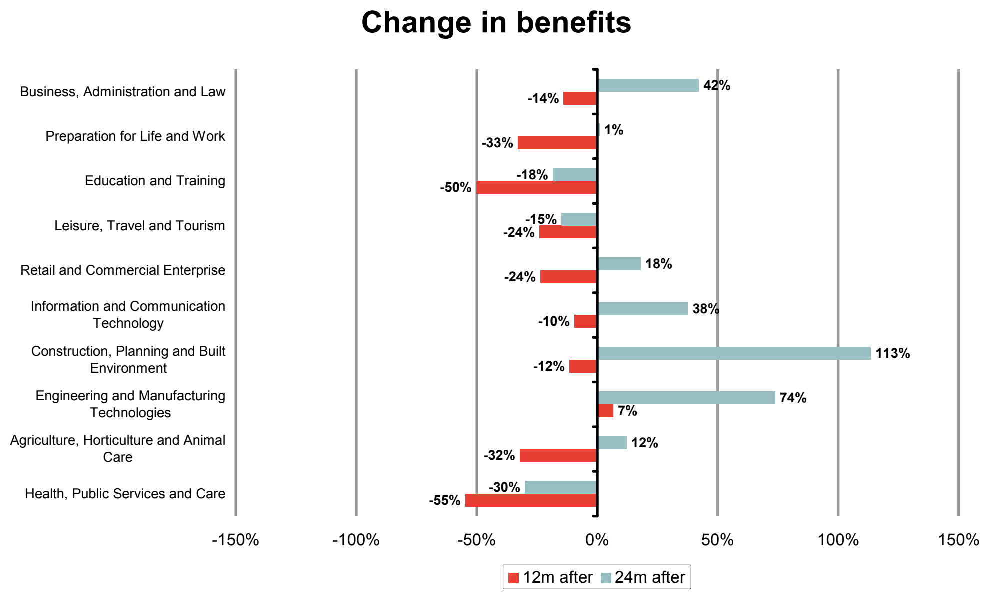
Source: Frontier analysis of ILR-HMRC/DWP data

Figure 9: Employment changes: cross cohort comparison



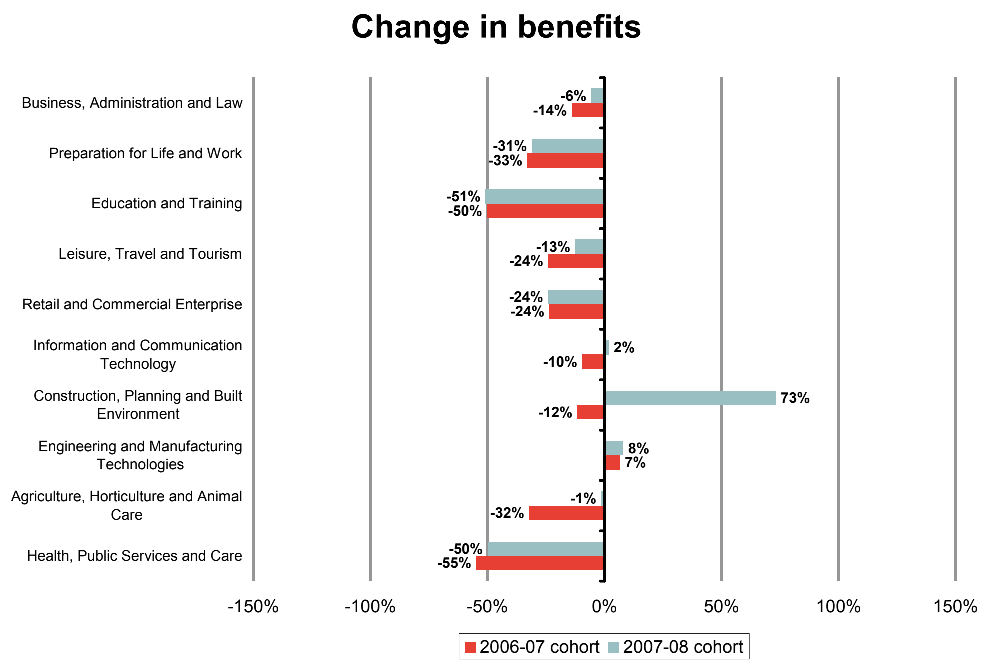
Source: Frontier analysis of ILR-HMRC/DWP data

Figure 10: Benefits changes over time: 2006-07 cohort



Source: Frontier analysis of ILR-HMRC/DWP data

Figure 11: Benefit changes: cross cohort comparison



Source: Frontier analysis of ILR-HMRC/DWP data

Impact analysis

Methodology

The methodology we employ in analysing the impact of learning follows on from that developed in our previous report 'How to make best use of the new matched data for reporting on the employment and earnings outcomes of training'.

In the absence of a clear control group we have compared the outcomes of individuals who have completed training with the outcomes of those same individuals before they had embarked upon training. This is known in the programme evaluation literature as a before-after comparison. We view it as the only meaningful comparison that can be made given the data sources.

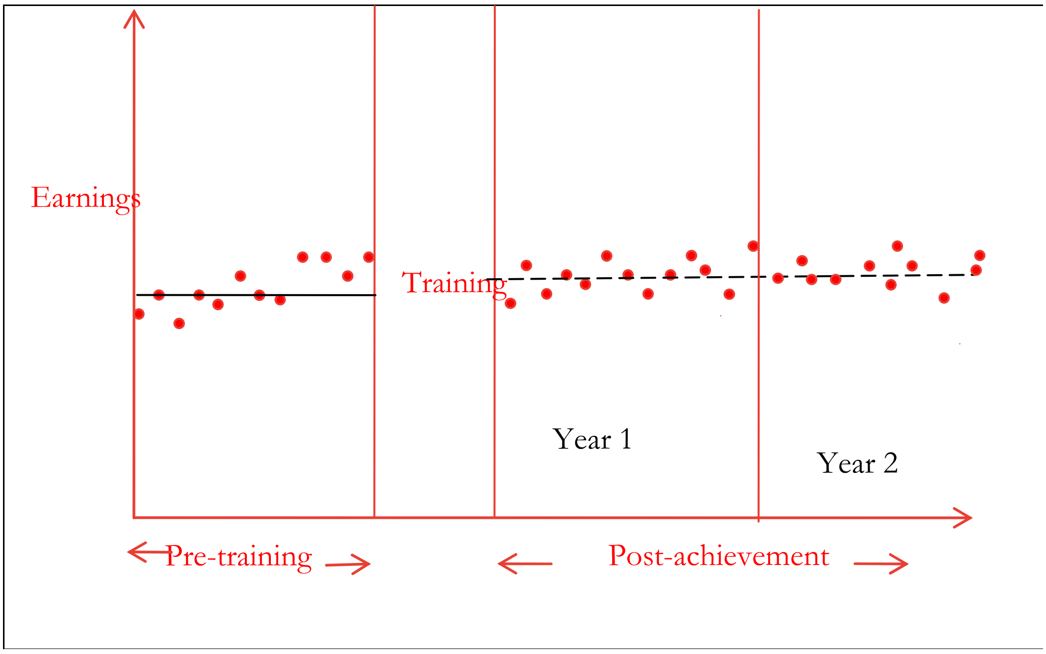
Our approach uses the longitudinal information on labour market outcomes to compare the employment and earnings of the learners before and after training took place, after taking into account inflation and macroeconomic factors which may also have affected earnings. We distinguish between the following time periods:

- 12 months before training;
- Time spent in training;
- 12 months immediately after training[9] (year 1);
- Second year after training, i.e. months 13 to 24 (year 2).

These are shown in the figure overleaf.

[9] Note that we have not used a 3 month buffer period (which was the case in previous work we undertook looking at the impacts for FE students in this analysis. This is because train to gain students are older and in established jobs unlike FE students many of whom will be leaving full-time education for the first time.

Figure 12: Impact analysis methodology



Source: Stylised example

Our analysis in the previous report compared the 12 months pre-training with the first 12 months post-achievement (“1-year impacts”). A similar analysis is performed here. However, we also analyse the impacts in the second year post achievement. (“2 year impact”). That is, we compare the pre-training period with months 13 to 24 post achievement. This is to test whether, in addition to any immediate impact from training, there might be an element of the impact which takes longer to manifest itself. As previously discussed due to data coverage we focused our 2-year analysis on learners in the 2006/07 academic year.

As before, we look at two measures of impact. The first measure of ‘impact’ we consider is simply the raw difference between pre-and post-training outcomes. However, a crucial issue here is whether there are any unobserved factors that (a) influence labour market outcomes and (b) change over time. Any such factors (aggregate economic fluctuations, earnings inflation, etc.) need to be separately accounted for in order to prevent them from contaminating the estimated impact of training. To do this we put in year dummy variables (binary variables equal to one if an observation occurs in a given financial year, and zero otherwise) which capture underlying yearly variation in labour market conditions in a flexible way. This should absorb as much of the variation in outcomes caused by changes in overall economic conditions as possible[10]. We are able to do this with our data as the before and after periods vary by individual, and hence for a number of years we observe individuals both before and after training. This allows us to separately identify the impact of the training program as well as macroeconomic year effects.

[10] We also adjust the earnings information for inflation in order to focus on real-terms earnings.

Two other points about the methodology are worth emphasising:

- *Fixed effects*. In labour market evaluations it is important to control for individual-specific characteristics that might affect wages and employment. For example, gender, ethnicity and region are all likely to be correlated with both earnings and training. However, it will not be possible to control for every single relevant characteristic. A potentially more effective technique is to strip out the effect of all individual characteristics (both observed and unobserved) that do not vary over time, such as demographics or underlying "ability". This is known in the evaluation literature as a 'fixed effect' approach as it controls for all fixed individual-specific effects on outcomes.

- *Clustering*. Our statistical models allow for any remaining unobserved factors to be correlated over time for the same individual. This allows the 'shocks' that a person receives in each time period to their labour market outcome to be persistent over time, rather than necessarily completely independent of each other. For example, if someone has unexpectedly low wages this month because of a negative shock, our methodology allows this shock to persist to the next month. This technique, known as 'clustering', does not affect our estimates of the impact of training, but it does affect the significance levels of the estimates. In particular, it will reduce the statistical significance of any estimated impacts, thus making the resulting inferences more conservative.

Discussion of results

In this section we present a general summary of the results of this analysis. Our overall finding is that TTG has had little impact on labour market outcomes. The results are set out in full in the following section.

Before diving into the results it is important to emphasise that in some areas we can only draw limited conclusions on the impacts, due to the sample sizes of some of the groups.

- The majority of TTG learners are FL2. Sample sizes are generally too small for FL3 learners.

- For many study areas the number of learners is small.

- There were many more learners in 2007/08. Since our sample for estimating 2-year impacts is from 2006/07 learners, the sample sizes for this analysis are generally not very large.

- The filtering of earnings also has a substantial impact on sample sizes.

As a result of this, only a subset of impact analyses will be meaningful. The impacts to focus on are 1 year impacts at FL2:

- Health, Public Services and Care;

- Agriculture, Horticulture and Animal Care (men);

- Engineering and Manufacturing Technology;
- Construction, Planning and Built Environment (men);
- Retail and Commercial Enterprise;
- Leisure, Travel and Tourism (men);
- Business, Administration and Law.

In terms of the results there is little overall pattern. Most of the impacts are statistically insignificant. Some are negative.

In many cases there are significant changes in pay outcomes in terms of the raw difference, but these differences lose statistical significance in the regression models. In these cases, although there is a before/after change, it is due to more general labour market conditions rather than the specific impact of training. This is the case with Health, Public Services and Care; Agriculture, Horticulture and Animal Care (for men); Retail and Commercial Enterprise; Leisure, Travel and Tourism (for men); Education and Training (for women); and Preparation for Life and Work (for women).

The only unambiguously positive impact on pay is for women studying Leisure, Travel and Tourism at FL2.

In other cases, although there is no clear impact on pay, there is an increase in employment and decline in benefits. At FL2 this occurs for Health, Public Services and Care; Retail and Commercial Enterprise (for women); Education and Training (for women); Preparation for Life and Work (for women); and Leisure, Travel and Tourism (for men). Given that individuals in TTG are meant to be in continuous employment throughout their learning, this could indicate that, before these courses, they had spent a greater part of the 12 months before learning out of work than after.

An important factor in explaining the overall lack of impact is that TTG learners tend to be older than learners in other funding streams. As we have shown in another report entitled ‘Age and returns to training’, the strongest impact of training happens for those who are under 25. For older age groups the impacts tend to be much smaller.

Another factor that may be relevant is that learners are normally already employed before starting and would typically be continuing their current job during training. The continuity of employment may reduce the extent to which individuals are actively changing jobs or seeking higher wages. It may be that an individual entering a new job, where they are expected to then undergo training, may enjoy an uplift to their pay before the training has actually commenced. If it were the case that the training was ‘bundled’ with the job, a before-after comparison would not capture this impact.

Conclusions

This report builds on previous work conducted by IFS and Frontier looking at the outcomes of training in the different funding streams of Further Education. The availability of more learner and labour market data has allowed us to build on our earlier work in two ways:

- By extending the time horizon during which we monitor the labour market performance of learners post-training; and
- By examining the extent to which outcomes vary across learner cohort, that is how 2007-08 learners perform in the labour market relative to 2006-07 learners;

The findings in this report are consistent with our previous work. Overall, there is little improvement in the labour market outcomes of TTG learners following training. We found some differences in the outcomes of the two cohorts of learners, but these are relatively small. Generally they appear to show the later cohort performing worse than the earlier cohort. We also found that the labour market performance of the 2006-07 cohort does not get better over time- earnings and benefits appear to worsen while employment improves. On the whole, our preferred econometric model revealed no substantive impacts for this group of learners.

There are several possible explanations for the lack of impacts we find. TTG learners are older (mean age is 38) than FE and apprenticeship learners and at a point in their careers where sizeable changes in labour market performance are perhaps not to be expected. As we have shown in another report entitled “Age and outcomes”[11] impacts of training tend to be strongest for learners aged 25 or less, a group which is under-represented in the TTG data. An alternative explanation, which we are unable to test, is that learners who enter TTG have poor labour market prospects per se, that is there is some selection bias which is driving the results. Finally TTG learners are normally already employed before starting learning and would typically be continuing their current job during training. The continuity of employment may reduce the extent to which individuals are actively changing jobs or seeking higher wages. It may be that an individual entering a new job, where they are expected to then undergo training, may enjoy an uplift to their pay before the training has actually commenced. If it were the case that the training was ‘bundled’ with the job, before and after comparisons would not capture this impact.

[11] “Age and outcomes”, report prepared for BIS by IFS/Frontier, 2011

Annex 1: Econometric data tables

We present data tables for the following impact analyses:

- Men, FL2, 1 year impacts (06/07 and 07/08);
- Women, FL2, 1 year impacts (06/07 and 07/08);
- Men, FL3, 1 year impacts (06/07 and 07/08);
- Women, FL3, 1 year impacts (06/07 and 07/08);
- Men FL2, 2 year impacts (06/07);
- Women FL2, 2 year impacts (06/07);
- Men FL3, 2 year impacts (06/07);
- Women FL3, 2 year impacts (06/07).

For each impact analysis we focus on the following types of outcome:

- Earnings (raw);
- Earnings (filtered);
- Employment rate;
- Benefit rate.

In each case we report the sample size (the number of individuals), the pre-learning outcome, the change in outcome post-learning (i,e, the raw difference) and the impact attributed to the learning.

The statistical significance of the impacts is summarised as follows:

*** = statistically significant at the 1% level.

** = statistically significant at the 5% level

* = statistically significant at the 10% level.

Table 11: Men, FL2, 1 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	5,109	612.27	111.94***	22.03	1,376	1410.63	89.06***	-13.2
Agriculture, Horticulture and Animal Care	3,745	627.93	81.69***	7.97	1,066	1573.87	29.23*	-28.24
Engineering and Manufacturing Technology	19,902	696.57	3.5	-42.68***	5,126	1736.42	18.73**	-13.1
Construction, Planning and Built Environment	33,872	630.97	-.81	-38.16**	5,990	2032.31	-4.97	-2.33
Information and Communication Technology	1,204	665.23	12.54	-44.45	288	1776.96	-2.24	-123.9**
Retail and Commercial Enterprise	15,488	700.51	38.09***	-11.13	4,617	1632.33	34.16***	2.55
Leisure, Travel and Tourism	4,728	429.49	43.41***	4.39	695	1528.52	52.7**	-13.68
Education and Training	42	525.00	55.13	36.39	13	1024.51	132.71	66.47
Preparation for Life and Work	1,647	608.55	19.89	-48.99**	400	1571.72	43.02	48.95
Business, Administration and Law	9,946	677.59	12.47*	-39.6***	2,705	1670.93	14.2	-32.22

Source: Frontier analysis of ILR-HMRC/DWP data

Table 12: Men, FL2, 1 year impacts (employment and benefits)

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	5,109	0.75	.098***	.038***	5,109	0.06	-.025***	-.014***
Agriculture, Horticulture and Animal Care	3,745	0.82	.05***	-.003	3,745	0.03	-.002	.001

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Engineering and Manufacturing Technology	19,902	0.80	.032***	-.01***	19,902	0.03	.002*	.006***
Construction, Planning and Built Environment	33,872	0.64	.035***	-.002	33,872	0.04	.017***	.006***
Information and Communication Technology	1,204	0.80	.049***	.031**	1,204	0.04	.005	-.003
Retail and Commercial Enterprise	15,488	0.81	.054***	.006	15,488	0.04	-.004***	-.002
Leisure, Travel and Tourism	4,728	0.59	.12***	.058***	4,728	0.13	-.02***	-.014***
Education and Training	42	0.80	.001	-.151**	42	0.05	-.026	.018
Preparation for Life and Work	1,647	0.76	.045***	-.017	1,647	0.05	.001	.009
Business, Administration and Law	9,946	0.82	.042***	.002	9,946	0.03	.001	.005**

Source: Frontier analysis of ILR-HMRC/DWP data

Table 13: Women, FL2, 1 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	30,601	427.56	94.83***	4.59	6,684	1112.90	77.09***	1.81
Agriculture, Horticulture and Animal Ca	152	540.82	49.1	-62.34	39	1413.55	2.34	-113.58**
Engineering and Manufacturing Technology	4,593	552.87	-6.95	-54.16***	1,189	1407.08	-20.16	-14.8
Construction, Planning and Built Environment	122	462.23	-35.78	-18.3	19	1329.45	174.89	234.17
Information and Communication Technology	1,931	509.83	33.28***	-9.38	461	1502.71	31.02	-4.47

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Retail and Commercial Enterprise	17,397	401.73	41.25***	-8.61	4,162	1052.24	33.73***	-13.36
Leisure, Travel and Tourism	1,257	370.21	77.43***	49.04**	223	1226.26	135.07***	142.99**
Education and Training	1,446	286.81	78.21***	25.59	294	948.24	61.28***	29.15
Preparation for Life and Work	2,715	421.99	89.02***	-11.	611	1119.17	49.42**	1.76
Business, Administration and Law	16,221	514.25	39.62***	-31.22***	4,539	1251.15	39.8***	-34.43***

Source: Frontier analysis of ILR-HMRC/DWP data

Table 14: Women, FL2, 1 year impacts (employment and benefits)

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	30,601	0.73	.114***	.024***	30,601	0.07	-.035***	-.015***
Agriculture, Horticulture and Animal Care	152	0.79	.033	-.007	152	0.05	-.011	-.026**
Engineering and Manufacturing Technology	4,593	0.79	.039***	-.018***	4,593	0.03	.005**	.006**
Construction, Planning and Built Environment	122	0.70	.002	-.025	122	0.08	.004	.021
Information and Communication Technology	1,931	0.84	.023***	-.002	1,931	0.03	-.003	.0
Retail and Commercial Enterprise	17,397	0.77	.074***	.02***	17,397	0.05	-.017***	-.011***
Leisure, Travel and Tourism	1,257	0.63	.094***	.021	1,257	0.15	-.014**	-.006
Education and Training	1,446	0.78	.113***	.053***	1,446	0.06	-.033***	-.021***

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Preparation for Life and Work	2,715	0.73	.1***	.026**	2,715	0.08	-.034***	-.021***
Business, Administration and Law	16,221	0.81	.049***	-.006**	16,221	0.04	-.005***	.0

Source: Frontier analysis of ILR-HMRC/DWP data

Table 15: Men, FL3, 1 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	911	590.05	113.25***	8.32	249	1408.49	146.58***	159.93**
Agriculture, Horticulture and Animal Care	30	415.57	89.86	103.34	-	-	-	-
Engineering and Manufacturing Technology	1,057	1123.32	35.56	-305.09***	249	2315.44	98.14*	-234.96***
Construction, Planning and Built Environment	1,507	688.46	5.57	-11.13	283	2422.15	-51.93	19.43
Information and Communication Technology	22	720.43	38.92	211.96	-	-	-	-
Retail and Commercial Enterprise	359	691.59	-32.74	1.6	98	1688.64	-22.72	-35.26
Leisure, Travel and Tourism	48	420.55	13.46	-237.78	-	-	-	-
Education and Training	27	498.46	111.08	-72.56	-	-	-	-
Preparation for Life and Work	90	776.66	15.41	-3.27	28	1733.69	42.72	-164.71
Business, Administration and Law	625	790.13	-19.89	-238.24**	178	1990.64	-21.22	-265.55**

Source: Frontier analysis of ILR-HMRC/DWP data. Cells which are potentially disclosive have been marked with "-".

Table 16: Men, FL3, 1 year impacts (employment and benefits)

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	911	0.74	.108***	.025	911	0.06	-.02***	-.019**
Agriculture, Horticulture and Animal Care	30	0.90	-.04	-.044	30	0.00	.022	.016
Engineering and Manufacturing Technology	1,057	0.80	.033***	-.028**	1,057	0.03	.013***	.031***
Construction, Planning and Built Environment	1,507	0.74	.03***	.01	1,507	0.02	.016***	.006**
Information and Communication Technology	22	0.85	-.028	.056	22	0.05	-.004	-.012
Retail and Commercial Enterprise	359	0.83	.036**	.001	359	0.02	.004	.01
Leisure, Travel and Tourism	48	0.79	.07	-.015	48	0.04	-.02	.05
Education and Training	27	0.73	.097	.04	27	0.02	-.024	-.03
Preparation for Life and Work	90	0.78	.042	-.05	90	0.02	.027**	.012
Business, Administration and Law	625	0.84	.031***	-.043**	625	0.01	.013**	.009

Source: Frontier analysis of ILR-HMRC/DWP data. Cells which are potentially disclosive have been marked with “-“.

Table 17: Women, FL3, 1 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	4,397	456.60	88.17***	-55.49	1,034	1245.49	118.63***	32.77
Agriculture, Horticulture and Animal Care	16	337.83	-26.57	118.99	-	-	-	-

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Engineering and Manufacturing Technology	31	492.44	-36.	-785.63**	-	-	-	-
Construction, Planning and Built Environment	-	-	-	-	-	-	-	-
Information and Communication Technology	54	388.08	-32.17	-140.	-	-	-	-
Retail and Commercial Enterprise	577	511.58	8.06	-44.54	146	1310.08	-21.61	-73.24
Leisure, Travel and Tourism	42	318.18	122.99*	-55.67	12	957.44	77.53	29.95
Education and Training	534	261.82	65.43***	2.05	105	946.30	122.48***	10.77
Preparation for Life and Work	190	436.78	72.4	24.12	44	1084.83	118.44	-117.37
Business, Administration and Law	2,241	531.61	38.36***	-35.05**	572	1483.97	37.89	-43.97

Source: Frontier analysis of ILR-HMRC/DWP data. Cells which are potentially disclosive have been marked with "-".

Table 18: Women, FL3, 1 year impacts (employment and benefits)

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	4,397	0.76	.084***	.017**	4,397	0.04	-.011***	-.005
Agriculture, Horticulture and Animal Care	16	0.66	.113	-.155	16	0.00	0.00	0.00
Engineering and Manufacturing Technology	31	0.79	.108*	-.077	31	0.00	0.00	0.00
Construction, Planning and Built Environment	-	-	-	-	-	-	-	-
Information and Communication Technology	54	0.86	.033	.087	54	0.02	-.017	-.036

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Retail and Commercial Enterprise	577	0.82	.03**	-.009	577	0.03	.008	.009
Leisure, Travel and Tourism	42	0.78	.11**	-.076	42	0.03	-.01	.012
Education and Training	534	0.79	.082***	.011	534	0.04	-.018***	-.006
Preparation for Life and Work	190	0.83	.058**	.047	190	0.05	-.024**	-.018
Business, Administration and Law	2,241	0.84	.05***	.01	2,241	0.02	.0	.007**

Source: Frontier analysis of ILR-HMRC/DWP data. Cells which are potentially disclosive have been marked with "-".

Table 19: Men, FL2, 2 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	1,388	569.34	74.03***	-80.49	335	1368.48	44.01	11.35
Agriculture, Horticulture and Animal Care	876	653.34	10.96	-85.79	245	1556.98	-54.31*	-253.88**
Engineering and Manufacturing Technology	7,533	738.49	-69.45***	-165.05	1,812	1768.48	-52.95***	44.23
Construction, Planning and Built Environment	10,608	618.92	-40.81	-62.96**	1,550	2017.42	-77.77***	73.22
Information and Communication Technology	249	702.02	29.26	-141.68	64	1590.14	-83.89*	-392.11***
Retail and Commercial Enterprise	4,340	677.94	-26.16**	-69.78**	1,124	1609.81	-25.92	-175.49**
Leisure, Travel and Tourism	1,179	469.72	-5.03	103.53	164	1589.26	-41.23	166.4
Education and Training	10	456.72	-97.75	-153.78	-	-	-	-

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Preparation for Life and Work	372	674.79	-80.72**	-147.48	82	1806.60	-40.92	38.69
Business, Administration and Law	2,714	688.25	-40.06***	11.86	693	1663.34	-79.16***	267.77**

Source: Frontier analysis of ILR-HMRC/DWP data. Cells which are potentially disclosive have been marked with “-“.

Table 20: Men, FL2, 2 year impacts (employment and benefits)

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	1,388	0.75	.073***	-.028	1,388	0.05	-.003	.006
Agriculture, Horticulture and Animal Care	876	0.79	.053***	-.091***	876	0.04	.007	.012
Engineering and Manufacturing Technology	7,533	0.82	.008*	-.025**	7,533	0.03	.022***	.016**
Construction, Planning and Built Environment	10,608	0.63	.008**	-.021**	10,608	0.04	.052***	.041***
Information and Communication Technology	249	0.83	.032	.017	249	0.04	.017*	-.016
Retail and Commercial Enterprise	4,340	0.81	.031***	-.037**	4,340	0.03	.022***	.026**
Leisure, Travel and Tourism	1,179	0.66	.09***	-.036	1,179	0.10	-.014**	.006
Education and Training	10	0.85	-.052	-.049	-	-	-	-
Preparation for Life and Work	372	0.81	-.01	.004	372	0.04	.021**	-.021
Business, Administration and Law	2,714	0.83	.029***	-.04	2,714	0.03	.016***	.038**

Source: Frontier analysis of ILR-HMRC/DWP data. Blank cells indicate that statistics can not be calculated due to small samples (dividing by zero etc). Cells which are potentially disclosive have been marked with "-".

Table 21: Women, FL2, 2 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	9,660	423.53	81.23***	-107.1**	1,979	1086.15	78.38***	-65.87
Agriculture, Horticulture and Animal Care	38	549.80	-23.22	675.92**	-	-	-	-

Engineering and Manufacturing Technology	1,904	607.28	-68.28***	-84.29	502	1426.43	-87.98***	-50.8
Construction, Planning and Built Environment	38	453.03	56.2	-729.25**	-	-	-	-
Information and Communication Technology	462	487.94	17.87	-76.47	108	1352.27	82.13*	-92.05
Retail and Commercial Enterprise	4,541	418.24	23.99***	-45.84	1,049	1030.10	30.36**	-24.02
Leisure, Travel and Tourism	323	344.59	43.23	56.44	44	1337.17	22.75	-291.75
Education and Training	334	320.50	62.68**	194.04	63	990.92	98.4	220.6***
Preparation for Life and Work	676	423.69	18.58	6.71	139	1181.39	-35.41	417.51**
Business, Administration and Law	4,875	529.09	6.42	-71.77**	1,291	1239.75	21.7	4.46

Source: Frontier analysis of ILR-HMRC/DWP data. Cells which are potentially disclosive have been marked with "-".

Table 22: Women, FL2, 2 year impacts (employment and benefits)

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	9,660	0.74	.102***	.014	9,660	0.07	-.02***	-.011
Agriculture, Horticulture and Animal Care	38	0.79	.053	.007	38	0.05	-.022	-.086
Engineering and Manufacturing Technology	1,904	0.80	.027***	.014	1,904	0.03	.016***	.013
Construction, Planning and Built Environment	38	0.78	-.031	-.261***	38	0.05	.025*	.032
Information and Communication Technology	462	0.86	.032*	.018	462	0.01	.002	-.003
Retail and Commercial Enterprise	4,541	0.78	.053***	-.065***	4,541	0.05	.0	.03**

	Employment rate				Benefit rate			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Leisure, Travel and Tourism	323	0.65	.093***	.019	323	0.11	.004	-.025
Education and Training	334	0.79	.108***	.071	334	0.04	-.021**	.002
Preparation for Life and Work	676	0.75	.061***	-.048	676	0.07	-.008	.017
Business, Administration and Law	4,875	0.82	.034***	-.038**	4,875	0.04	.012***	.02

Source: Frontier analysis of ILR-HMRC/DWP data

Table 23: Men, FL3, 2 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	133	546.7591	102.05	371.51**	27	1378.747	153.39	890.75***
Construction, Planning and Built Environment	284	538.4262	36.12	49.44	34	2301.2	144.25	118.9
Information and Communication Technology	-	-	-	-	-	-	-	-
Retail and Commercial Enterprise	39	681.384	224.54*	360.43	10	1974.579	197.96	121.63
Preparation for Life and Work	-	-	-	-	-	-	-	-
Business, Administration and Law	81	758.7676	-155.75**	-207.78	16	1951.888	-343.77**	-179.58

Source: Frontier analysis of ILR-HMRC/DWP data. Blank cells indicate that statistics can not be calculated due to small samples (dividing by zero etc). Cells which are potentially disclosive have been marked with "-".

Table 24: Men, FL3, 2 year impacts (employment and benefits)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	133	0.666	.118***	.105**	133	0.077	-.02	-.026
Construction, Planning and Built Environment	284	0.719	.041	-.023	284	0.016	.026***	.007
Information and Communication Technology	-	-	-	-	-	-	-	-
Retail and Commercial Enterprise |	39	0.895	.042	.065	39	0.003	.033	.001
Preparation for Life and Work	-	-	-	-	-	-	-	-
Business, Administration and Law	81	0.890	-.029	-.074	81	0.002	.038**	.095

Source: Frontier analysis of ILR-HMRC/DWP data. Cells which are potentially disclosive have been marked with "-".

Table 25: Women, FL3, 2 year impacts (earnings)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	612	457.41	41.26*	191.11**	141	1248.30	114.98**	42.73
Retail and Commercial Enterprise	51	773.06	-73.77	126.74	12	1497.80	5.36	486.33***
Education and Training	85	188.88	8.29	-36.88	11	1018.88	-112.1	144.36

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Preparation for Life and Work	38	339.35	124.31**	-88.89	10	812.42	315.45**	407.08**
Business, Administration and Law	260	569.19	25.19	-50.46	71	1438.46	2.83	56.37

Source: Frontier analysis of ILR-HMRC/DWP data

Table 26: Women, FL3, 2 year impacts (employment and benefits)

	Earnings - all				Earnings – filtered			
	Sample size	Before	Raw difference	Impact	Sample size	Before	Raw difference	Impact
Health, Public Services and Care	612	0.772	.041**	.019	612	0.048	.009	-.021
Retail and Commercial Enterprise	51	0.848	-.08	-.062	51	0.031	.011	.023
Education and Training	85	0.784	.093**	.087**	85	0.024	.024	.025
Preparation for Life and Work	38	0.819	.019	.014	38	0.092	-.023	-.019
Business, Administration and Law	260	0.851	.04**	-.008	260	0.020	.001	.002

Source: Frontier analysis of ILR-HMRC/DWP data

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