frontier economics

ESTIMATING THE IMPACT OF THE OCTOBER 2015 INCREASE IN THE APPRENTICE RATE

Final report

November 2017

CONTENTS

ACKNOWLEDGMENTS

This report was prepared by Frontier Economics for the Low Pay Commission (LPC).

Authors: Stefano Piano, Danail Popov and Federico Cilauro.

We are grateful for comments from the LPC and from discussants and participants at the LPC Research Workshop in April and the LPC Research Symposium in September 2017.

We also extend our gratitude to Professor Stephen Machin at the London School of Economics, who provided expert methodological advice throughout the study.

Errors and omissions remain the responsibility of the authors alone.

EXECUTIVE SUMMARY

Frontier Economics was commissioned by the Low Pay Commission (LPC) to study the impact of the 2015 increase in the Apprentice Rate (AR) on the number and characteristics of apprenticeships in the United Kingdom. The AR is a minimum wage applicable to all workers in the first year of their apprenticeship, and to apprentices aged 16 to 18 throughout the duration of their apprenticeship. In March 2015, it was announced that the AR would increase from £2.73 to £3.30 per hour, starting in October 2015. This is the first study using an econometric approach to estimate the impact of a minimum wage in the United Kingdom specifically on the number and characteristics of apprentices.

We use a combination of administrative data (the Individualised Learner Record) and survey data (the Apprenticeship Pay Survey) to measure the number of apprentices, their pay, and a number of their characteristics (including demographic characteristics and the completion status of their apprenticeship up to end of September 2016). We focus on the impact of the AR in England, where the data available are richer compared to the other nations of the UK.

We employ an econometric methodology used extensively in the empirical literature on minimum wages: a Difference-in-Differences (DiD) approach exploiting geographical variation in pay across England. Although the AR, like other minimum wages, is applied at the same rate throughout the country, existing differences in pay levels make it more (less) binding in lower (higher)-paying areas. Hence one would expect any effect of the AR to materialise to a greater extent in lower-paying areas, compared to areas where apprentices were more likely to already be paid £3.30 per hour or more prior to October 2015. The DiD approach effectively compares the evolution of the outcome variables between lower and higher-paying areas.

Our main econometric specification finds no statistically significant evidence of a negative impact of the AR increase on apprentice numbers or on completion rates. In contrast, we find positive and statistically significant coefficients on apprentice numbers in January and April 2016. This is robust to a number of robustness checks. However, this effect appears to be driven by course frameworks where relatively few workers would be covered by the AR hike (e.g. Management and Engineering). Therefore, we cannot rule out the possibility that the faster increase in apprentice numbers in low-paying areas is driven by other policy changes, rather than by the AR increase. Specifically, the introduction of the National Living Wage in April 2016 may have decreased the cost to employers of apprenticeships relative to other forms of employment.[1] The positive effect of the AR increase is larger for male apprentices, but this seems to be driven by differences between males and females in the apprenticeship frameworks undertake: males account for the majority of apprentices in frameworks which were positively affected by the increase in the AR. Looking

[1] Other policies may also be driving these results, particularly given the goal to increase the number of apprenticeship to 3 million by 2020, as set out in the 2015 Queen's Speech. However, our estimation strategy aims to control for nation-wide policy changes that would affect relatively low-paying and high-paying areas to the same extent.

specifically at relatively low-paying frameworks, we find suggestive evidence of a negative effect on employment in the Hairdressing framework, where a relatively large proportion of workers (mainly female) were covered by the AR increase. However, the relatively limited sample size available from survey data prevents us from measuring apprentice pay in Hairdressing at sufficiently granular levels of geography to give us confidence of the robustness of this result.

We also find no evidence that the composition of the apprentice population has been affected. Due to data limitations, we could not test whether the AR increase led to apprentices having higher or lower levels of prior educational attainment. We find no effect of the AR increase on the composition of the apprentice population in terms of ethnicity, or in terms of the prevalence of disabilities.

A key limitation of our study is the availability of information on apprentice pay. This report relies on data from the Apprenticeship Pay Survey (APS) in 2014 and 2016, which measure apprentice pay over a year earlier than the AR hike (between July and September 2014) and apprentice pay a year after (between June and July 2016). The APS is the largest data set on apprentice pay in Great Britain, but its sample size is insufficient to explore variation in pay by detailed location and other characteristics (e.g. framework) at the same time. Future studies may wish to explore the feasibility of using administrative sources, such as matching the ILR to the Work and Pensions Longitudinal Study data.

Moreover, further work could aim to investigate the interaction between the AR and other minimum wages, and its impact on the number and characteristics of apprenticeships.

INTRODUCTION

The Low Pay Commission (LPC) has an ongoing remit to: monitor the operation of the National Minimum Wage; assess the impact of any changes to the minimum wage; and make recommendations to the Government on the future level of the minimum wage. In 2009, the LPC recommended that the legal protection of the National Minimum Wage should be extended to apprentices under the age of 19 and to those aged 19 and over in the first 12 months of their apprenticeship. The Apprentice Rate (AR) was introduced in October 2010 at £2.50 an hour, and uprated annually by 1-4% in following years to £2.73 in 2014.

In October 2015, the LPC again recommended a similar rise (to £2.80 an hour). However, the Government decided to reject this recommendation, and to introduce a substantially larger uplift of the AR, to £3.30 an hour. This represented a 21% increase, in contrast to the LPC's recommendation of a modest 2.6% increase. A stated aim of the policy was to improve the relative attractiveness of apprenticeships, particularly for young people, by reducing the gap between the AR and the under-18 National Minimum Wage set at £3.87 per hour.

The Department for Business, Innovation and Skills' (BIS) assessment of the likely impact of the AR increase to £3.30 estimated that 67,000 apprenticeships would be affected by the policy, resulting in a cost to businesses of £93 million.[2] Sectors with low pay would be particularly affected – for example, across the UK, the median hourly pay for Level 2 and 3 apprentices in Hairdressing was only £2.94 in 2014. However, this impact assessment assumed that the increase would have no significant effect on the total number of apprenticeships provided. This was partly due to a lack of evidence on how the supply of apprenticeships responds to the AR. The impact assessment argued that existing evidence on the impact of minimum wage changes (in particular, estimates of the elasticity of labour demand) cannot be robustly applied to apprenticeships, as the characteristics and employment statuses of apprentices differ substantially from those of low paid workers in general.

Against this backdrop, the LPC commissioned Frontier Economics to carry out new research to address gaps in existing knowledge. The specific aims of the research are to analyse the effects of the increase in the AR on the number of apprentices and as far as possible examine how this may vary for different groups. This is a challenging exercise, because during the same period there also considerable changes relating to apprentice policy that were aimed at increasing numbers.

We have drawn on a range of data sources such as the Apprentice Pay Survey (APS) and the Individualised Learner Record (ILR), which were analysed econometrically in a difference-in-differences (DiD) framework to address the study questions.

The rest of this report is organised as follows:

[2] Department for Business, Innovation and Skills (2015).

- Chapter 2 provides an overview of the broader context for apprenticeship policy and gives a brief summary of existing research in the area.
- Chapter 3 presents our analytical approach including data sources and econometric methodology.
- Chapter 4 presents the findings from our econometric work.
- Chapter 5 concludes and suggests areas for future research.

1 BACKGROUND AND CONTEXT

1.1 Apprenticeship Policy in England

Apprenticeships are structured training programmes which are undertaken in a working environment. They combine on-the-job training with classroom based development of skills and knowledge. Apprenticeships can be beneficial for businesses if they provide programmes which satisfy specific employer needs. The benefit for the learner is that they gain real world experience while earning a wage and gaining recognised qualifications.

In the United Kingdom, apprenticeship policy is devolved and the systems differ across nations. We focus on the developments in Apprenticeship Policy which are relevant to England, because they are more important for understanding the econometric results in section 3.

In England, apprenticeships can be undertaken by anyone aged over 16. There are intermediate apprenticeships (Level 2 – equivalent to five good GCSE passes – A* to C), advanced apprenticeships (Level 3 – equivalent to two A-level passes) and higher apprenticeships (Level 4 or higher – equivalent to National Vocational Qualification Level 4 or Foundation Degrees).

Until recently, apprenticeships were organised in frameworks. These defined the requirements for an apprenticeship programme, setting out: the qualifications which have to be completed; the key skills targets; and any other requirements. The frameworks also include information on job roles, entry routes, apprenticeship length and the career paths available upon completion.

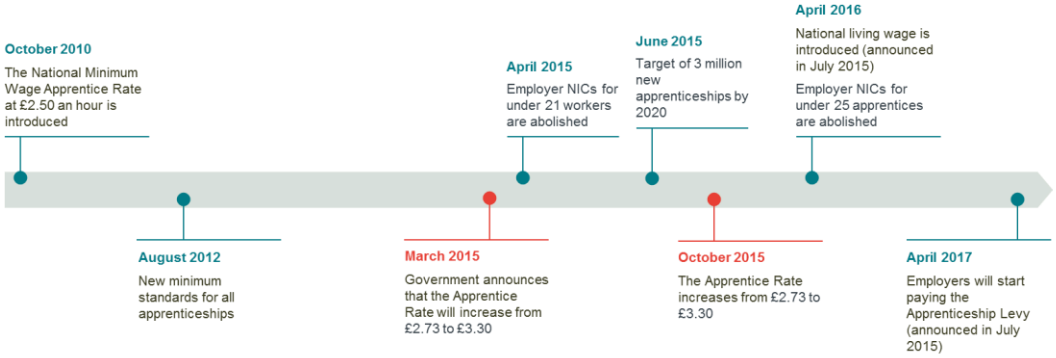
The government has introduced a range of reforms to apprenticeship policy in recent years to meet its manifesto pledge of 3 million new apprenticeships by 2020 – a commitment which is enshrined in law. A timeline of recent reforms is given in Figure 1. A number of policies aiming to boost apprenticeships were announced or introduced around the time of the Apprentice Rate increase.

Some have made apprenticeships more attractive for employers – for example, the abolition of employer National Insurance Contributions (NICs) for 16-24 year old apprentices introduced in April 2016 reduced the effective cost of employing young apprentices making it more attractive for employers to hire apprentices. More recently, the government introduced the Apprenticeship Levy in April 2017. The Apprenticeship Levy is equivalent to 0.5% of employers' pay bills[3] and can be used to cover training costs by employers. Other policies have sought to generate additional demand for apprenticeships. For example, the legal protection of the term 'apprenticeship' under the Enterprise Bill and ongoing media attention and promotional events have aimed to generate interest in the area. The new apprenticeship standards, which aim to make apprenticeships more relevant for employers, can have both demand- and supply-side effects.

[3] Applied to employers with pay bill greater than £3m.

Other policy changes that could have affected the number of apprenticeships and their characteristics also took place around the time of the AR increase. Although none of these changes took place in October 2015, it is worth bearing in mind this wider policy context, including policies that have a wider labour market scope. For example, the introduction of the new national minimum wage (for adults aged over 25) in April 2016 – the National Living Wage – at a rate of £7.20 would have altered employers' incentives to hire apprentices somewhat and likewise affected incentives for adults who may be considering applying for an apprenticeship.

Figure 1. Timeline of apprenticeship policy reforms



1.2 Related literature

There are a few studies looking at how the Apprentice Rate in the UK affects apprentice pay or the uptake of apprenticeships. On the supply side, existing studies have found that pay levels were not the primary reason for starting an apprenticeship. On the demand side, and also have not impacted significantly on employer offers of apprenticeships.

Higton et al. (2012) aimed to understand how the introduction of the Apprentice Rate (AR) affected apprenticeship take-up, provision of training places, and the distribution of pay among apprentices. The study involved a review of existing literature, a survey of apprentices and employers, group discussions with apprentices and qualitative in-depth interviews with stakeholders such as training providers. The study found that average minimum pay for apprentices was £5.41 per hour and around five percent of employers paid apprentices below the £2.50 AR. Overall the study found that the introduction of the AR had relatively little impact on the demand and supply of apprenticeships. Employers reported the AR made little difference to their decision to offer apprenticeship places and demand for apprenticeships from young people was perceived to be strong.

Behling and Speckesser (2013) carried out an econometric study looking at the introduction of the AR on levels of gross hourly apprentice wages using data from 2007-2011. The study used a difference-in-differences (DiD) approach with two alternative control groups: non-apprenticeship learners in employment studying towards similar qualifications; apprentices who earn above the AR. The authors found that the AR is more binding for certain groups, such as young people (aged 16-18) and apprentices in low paying sectors, such as hairdressing. Further, the study found evidence that pay for young people (aged under 25) increased in low paying sectors following the introduction of the AR.

Broader research looking at the effects of minimum wage policy on young people has found some evidence that employment is responsive to wage rates. For example, London Economics (2015) looked at the effect on their employment outcomes of the relative reduction and then freeze of minimum wages for young people. They used a DiD analysis to determine whether any employment effects during the freeze in the youth rates are statistically significant for individuals aged between 16 and 20 (compared to 21 and 22 year olds). The study found evidence of a positive employment effect resulting from the freeze. Neumark and Wascher (2004) analysed the responsiveness of youth employment to minimum wages across 17 OECD countries over the period 1975-2000. The authors found that minimum wages are associated with job losses for young people and that the effects are stronger in countries with restrictive labour standards and high unionisation of the workforce.

On the other hand, some studies have found that wage rates do not significantly affect the education or employment choices of young people. Crawford et al. (2011) looked at the education and employment outcomes of a cohort of young people entering the labour market in the aftermath of the 2008/09 recession comparing low wage and high wage geographical areas. The study found that the minimum wage had neither drawn young people away from education and into work nor adversely affected their employment prospects.

Beyond employment outcomes, apprentice pay may also be associated with other outcomes, such as completion rates. Gallacher et al. (2004) for example found that low wages are a factor contributing to high staff turnover. Studies looking at other jurisdictions have found similar results. Bessey and Backes-Gellner (2008) examine the factors which affect the probability of dropping out of an apprenticeship in Germany. They find that higher relative apprenticeship wages (compared with unskilled wages in the same sector) are associated with lower probability of dropping out. In Australia, Karmel and Mlotkowski (2011) find that the level of the training wage has a positive effect on completion rates in ‘non-trades’ while expected wage upon completion positively affects completion rates in ‘trades’.

2 ANALYTICAL APPROACH

This section discusses the data sources and the empirical strategy that we have used to estimate the impact of the increase in the AR on the number and quality of apprenticeships. We organise it in three parts:

- **Data sources:** this describes the advantages and disadvantages of the data sources:
  - Apprentice Pay Survey (APS) and the Annual Survey of Hours and Earnings (ASHE) for pay
  - Independent Learner Record (ILR) for the number of apprenticeships
  - National Apprentices Survey for vacancies
  - Data on quality of apprenticeships
- **Empirical methods:** this discusses the Difference-in-Difference econometric strategy we designed to evaluate the impact of the increase in the AR.
- **Descriptive statistics:** this presents some high-level statistics on pay, number of apprenticeships and vacancies from the main data sources.

2.1 Data Sources

2.1.1 APS and ASHE

There are two main sources to measure variation in apprentice pay:

- **APS:** a survey of approximately 9,400 apprentices in GB (of which roughly 5,000 in England), carried out every two years (typically between July and September).
- **ASHE:** a survey of workers employed in the UK, based on a 1% sample of Pay-As-You-Earn (PAYE) employee jobs, containing data on hourly earnings and several demographic characteristics (applicable to a reference week after the end of the financial year in April of each year). We accessed ASHE data in the Office for National Statistics' Virtual Microdata Laboratory (VML). Standard ASHE data available in the VML do not include information on workers in Northern Ireland, so we have focused our analysis on Great Britain.

We have relied on the APS to analyse variation in apprentice pay, for the following reasons:

- **Sample size**: the sample size of apprentices available in APS, though not very large in absolute terms, is larger than available in the ASHE data, which only includes 2,000 apprentices or fewer in each year.
- **Coverage across sectors:** ASHE has limited coverage of some key apprenticeship frameworks (e.g. Health and Social Care). This would not enable us to confidently estimate the proportion of apprentices who were affected by the AR increase and the variation in pay across frameworks.

- **Availability of information on worker characteristics:** ASHE does not have variables to identify the ethnicity or disability status of workers, making it impossible to verify the impact of the AR increase across these two dimensions.

These considerations made APS the best dataset available for our purposes. However APS also presents the following limitations:

- **Timing:** we would like to measure pay in 2015 (prior to the announcement of the AR increase), but the APS is only available in 2014 and 2016.
- **Limited sample size:** the sample size is appropriate to analyse variation in pay across breakdowns (framework, age bands, gender) nationally, but it makes it challenging to conduct analysis at any lower geographical level.
- **Measurement:** information on pay is not always accurate, because it is self-reported by apprentices, rather than by employers (as in ASHE).

Given the limited sample size available in APS, we have used the NUTS 2 classification to split apprentices across geographical areas. We experimented with other geographical units such as Government Office Region (GOR) and Upper Tier Local Authorities (UTLA) but concluded that these are less suited for the purposes of our work. A GOR-level analysis would hide a considerable degree of intra-region variation in pay. On the other hand, the sample size available from the APS would not be sufficient to measure apprentice pay at UTLA level with sufficient precision.

2.1.2 ILR

The ILR is an administrative dataset including information on all learners in Further Education using providers receiving public funding. The ILR is restricted to England, and contains information on learner characteristics, route onto the course and outcomes, including:

- Age, ethnicity and disability;
- Subject area and level of the course;
- Attributes of the course (such as start date and guided learning hours); and
- Outcome of the course (completion status and grade).

We can use the ILR to identify the number of apprenticeships across all the breakdowns of interest (age, level, gender, and apprenticeship framework), partitioning learners across geographical areas through the postcode of their training provider. As we have information on the start date and the end date of learning aims, we can both compute the *starts (*the number of individuals starting an apprenticeship) and the *stock* (the total number of individuals undertaking an apprenticeship) within a given period of interest.

Crucially, the ILR is missing information on apprentice pay. In theory, this limitation can be overcome by accessing the ILR-WPLS dataset, in which information on learners is linked to P45 and P14 records from the Work and Pensions Longitudinal Study (WPLS) . The tax records could potentially allow computing more reliable estimates of hourly apprentice pay, provided that a sufficient number of apprentices are covered. Accessing this dataset was not feasible within the current project, but it clearly constitutes a potential area of further research.

2.1.3 Vacancies

The Education and Skills Funding Agency (SFA) gathers data on the number of apprenticeship vacancies and the number of candidates. In principle, these data could be valuable to understand whether the increase in the AR had helped attract an increasing number of individuals to enrol for an apprenticeship.

We have been unable to use these data in the econometric analysis, because they were only available at the regional level, whereas our baseline specification was estimated at the more granular NUTS2 level.

We have also faced some difficulties in using these data for comparisons across frameworks. The data covered subject areas (e.g. Maths and Science, Humanities) rather than apprenticeship frameworks (e.g. Hairdressing, Customer Service). This made it difficult to meaningfully identify vacancies in some of the sectors that have been particularly affected by the AR increase. For instance, the vacancies in Hairdressing are subsumed within the “Retail and Commercial Enterprises” subject area, which also includes other pathways.

2.1.4 Data on quality

In principle, three databases contain some information on the *quality* of apprenticeships:

- **ILR:** data on Guided Learning Hours (GLH), completion status and prior attainment.
- **APS:** information on training hours both in 2014 and 2016.
- **Education and Skills Funding Agency (SFA):** self-reported levels of learner satisfaction, within the Learner Satisfaction Survey.

In practice, we focused on drop-out rates from the ILR (i.e. the proportion of individuals who do not complete their apprenticeship) to evaluate the impact of the AR increase on the *quality* dimension (See section 2.2.2 for more detail). Below we explain why we have not used the other potential quality measures.

Guided Learning Hours

The increase in the AR could potentially cause apprentices to receive fewer hours of learning. Employers could request them to work beyond the “standard hours” to compensate for the higher hourly wage, making it more challenging for them to attend their classes. However, guided learning hours are a poor measure of the amount of learning effectively undertaken by the apprentice, as they are only meant to provide an indication of the ideal amount of learning hours for each course.

Prior Attainment

In principle, the AR increase might have also encouraged *higher quality* individuals to apply to apprenticeships (i.e. applicants with higher prior attainment). However, the ILR only has good data coverage on the International Standard Classification of Education (ISCED) level of past qualifications, whereas it has very limited information (for fewer than 5% of apprentices) on past GCSE grades. This makes it difficult to assess the effective *quality* of individuals undertaking apprenticeships.

Training hours

As well as learning hours, the AR increase could negatively affect the hours of training that apprentices receive from employers. However, the APS questionnaire does not aim to measure accurately training hours separately from hours spent working. Training hours recorded in APS are gathered to ensure the total number of hours spent by an apprentice in the workplace is recorded accurately. As a result, training hours were not recorded for approximately two thirds of apprentices in both APS 2014 and 2016.

Learner Satisfaction

The AR increase could either increase or decrease learner satisfaction. The learners affected by the AR increase could feel that they are being more fairly rewarded through higher hourly wages. Alternatively, if employers demand them to work longer or with greater intensity to compensate for higher hourly labour costs, their level of satisfaction might decrease. Unfortunately, the Learner Satisfaction Survey from the SFA may not be the best metric to assess these competing hypotheses, because it focuses on the satisfaction with the learning and counselling offered by the provider, rather than on the overall satisfaction with the apprenticeship.

2.2 Empirical methods

2.2.1 Baseline econometric methodology

The main objective of our project is to evaluate whether the increase of the AR in October 2015 has affected the number of apprenticeships. In principle, the increase in the AR could have two competing effects on the number of apprenticeships:

- Firms might be less willing to hire apprentices, due to an increase in their labour costs (the *labour demand* effect)
- Individuals might be more inclined to apply for or complete an apprenticeship, as this is now more financially attractive than alternative options, such as other forms employment, education or inactivity (the *labour supply* effect)

In an ideal world, we would like to test these two effects separately, by comparing the actions of a treated group of individuals (or firms) to a control group who has not been affected by the increase in the AR. However, the lack of granular data on vacancies posted by firms and applications made by prospective apprentices

– described in Section 2.1.3 – implies that we can only analyse the aggregate effect. Even with respect to this aggregate effect, the data available and the nature of the AR increase pose several challenges:

- The change in the Apprentice Rate was universal (across the UK), so it is not straightforward to identify a control group of apprenticeships that were not affected by the policy.
- Apprenticeships differ substantially from other forms of employment (BIS, 2015). This implies that it is difficult to identify a reliable control group among non-apprentices.
- The AR applies not only to apprentices under 19, but to all apprentices in the first year of their apprenticeship. Therefore, using older apprentices as a control group for younger apprentices (who may be more likely to be affected) may not be appropriate.
- The evolution of apprenticeships over time can vary substantially between different course frameworks. Differences in the growth of apprenticeships between frameworks *moderately* affected by the AR and *heavily* affected framework may be influenced by several factors other than the AR increase.
- Apprenticeships exhibit strong seasonality, making it undesirable to compare the impact of the AR increase across different time periods in the same year.

In light of these challenges, we decided to use geographic variation in the "fraction of apprentices affected" (i.e. the proportion of apprentices paid below £3.30 in APS 2014) to identify the effect of the AR increase. The basic intuition is that the impact of the AR change should be stronger as the "fraction of apprentices affected" increases. Areas where 20% of apprentices in APS 2014 (such as Yorkshire) were paid below £3.30 should be more affected than areas in which only 12% of apprentices (such as Greater London) were paid below £3.30. This is a relatively common approach in the minimum wage literature – see for example Stewart (2002). To isolate the impact of the AR increase from other policy shocks and reflect our concerns about seasonality, we compared the stock of apprenticeships for a given month *before* the introduction of the Apprentice Rate (in the 2014/15 academic year) to the stock of apprenticeships for the same month *after* the introduction of the AR (in the 2015/16 academic year).[4] Following this approach, we estimated the following difference-in-differences baseline model:

$$\log(app)_{at} = \alpha + \gamma_a + \beta d_t + \delta(d_t\theta_a)) + \varepsilon_{at} \qquad (1)$$

where d_t is a time trend for the academic year, γ_a is an area-specific effect, app_{at} identifies the apprenticeships undertaken in a month across areas a and year t for a group of apprenticeships and $\theta_a$is the proportion of people paid below £3.30 in APS 2014 for the same group (expressed in a scale from 0 to 100). Due to the

[4] We use the stock rather than the starts because it is a less volatile measureand more comparable to employment. However, we have also included apprenticeship starts among the robustness checks.

sample size limitations in APS, we have relied on the NUTS2 classification to identify 30 geographical areas.[5]

Within this baseline specification, the δ coefficient picks up the effect of the increase in the Apprentice Rate on the number of apprenticeships in a given month. A positive (negative) coefficient would be an indication that the supply (demand) channel is leading to an increase (decrease) in the number of apprenticeships.

We have experimented with different variations of this basic specification:

- We have run the model on different samples (all apprenticeships, those aged 16-18, those doing Level 2 only, those doing Level 3 only, all eligible apprenticeships, and by males and females) to see whether there were any differences in the impact of the AR between different groups of apprentices.
- Given uncertainty on the exact timing of the impact of the AR increase, we have run the specification on 3 different months (October, January, April). This also allows us to check whether the AR impact appears to vary over time. However, effects estimated from later specifications (January and April) present a risk of contamination from impacts of other policy changes, including among others the introduction of the National Living Wage in April 2016.
- To verify whether the impact was different across frameworks, we have run the model on two groups of apprenticeships separately: those in relatively higher-paying frameworks (i.e. frameworks with a "low fraction of apprentices affected") and those in lower-paying frameworks (i.e. frameworks with a "high fraction of apprentices affected").
- To further investigate the impact of the AR on the "framework-mix", we have run a model with the apprenticeships in a framework as the dependent variable and the overall "fractions of apprentices affected" as the independent variable.

We have also conducted a number of checks to test the robustness of our findings, described in detail in section 3.2.

2.2.2 Methodology for further econometric results

As well as the effect on the number of apprenticeships, we were also interested in testing if the increase in the Apprentice Rate had an impact on the *quality* of apprenticeships being undertaken. As discussed in section 2.1.4, we have relied on drop-out rates as a rough proxy for quality. To estimate the impact of the AR increase on drop-out rates, we use the following variation of our baseline Difference-in-Difference specification:

$$\left(\frac{Apprenticeships\ dropped}{Total\ apprenticeships\ starts}\right)_{at} = \alpha + \gamma_a + \beta d_t + \delta(d_t\theta_a) + \varepsilon_{at} \qquad (2)$$

[5] There are 33 NUTS2 in England, but we combine the five London areas ("Inner London – East", "Inner London – West", "Outer London – East and North East", "Outer London – South", and "Outer London – West and North West") into two wider areas: "Inner London" and "Outer London". This is because of the low sample size in the APS data in the "Inner-London – West" area (less than 30 apprentices in 2014) and to a lower extent in the Outer London South area (less than 60 under-25 apprentices in 2014.

where $(Apprenticeships\ dropped / Total\ apprenticeships\ starts)$ is a ratio of the apprenticeships started but later interrupted before the end of the academic year[6] to the total apprenticeship starts in a month (on a scale from 0 to 100) for a particular group and the other variables are defined as above. Unlike in our baseline specification, we use apprenticeship starts rather than the stock of apprenticeships, because they offer a more intuitive explanation. By focussing on starts, we are effectively analysing the impact of the AR increase on the drop-out rate in a single "cohort" of apprenticeships, rather than taking a blended average across cohorts.

In line with the baseline specification, the δ coefficient picks up the effect of the increase in the AR. In this case, a positive and statistically significant coefficient would suggest that the increase in the AR has negatively affected completion. This could be due to employers trying to compensate for higher wage costs by reducing other benefits or introducing tougher working conditions. A negative and statistically significant coefficient might instead indicate that the increase in the AR has contributed to attract more talented candidates or that apprentices are less likely to drop out to pursue other routes (such as inactivity or employment).

Beside the number and the quality of apprenticeships, we also investigated whether the increase in the AR had any effect on the composition of the apprentice population in terms of ethnicity and of the prevalence of disabilities:

- In the general population, ethnic minorities are more likely to be paid close to the National Minimum Wage/National Living Wage than individuals of white ethnicity.[7] However, ethnic minority apprentices are typically paid more than white apprentices.[8] Therefore, ethnic minorities may have been affected by the AR increase less than individuals of white ethnic background.
- The prevalence of low pay among individuals with disabilities has been reported to be higher than among others.[9] As a consequence, the AR increase may have affected disabled individuals more than the non-disabled.

To test these hypotheses, we adopt a similar specification to the one we have employed for drop-out rates. Our dependent variable is the ratio of apprenticeship starts from a group of interest (either from a non-white background or with self-reported disability) to the total apprenticeship starts. In this case, a negative and statistically significant treatment effect might suggest that the AR increase has had a particularly strong negative impact on the

[6] Ideally, one would also test whether longer-term drop-out rates (e.g. drop-outs within eighteen months or two years from the apprenticeship start date) were affected. However, this would have required us to access data on the 2016/17 academic year, which will not be available until 2018.

[7] The Low Pay Commission (2016) estimates that the proportion of individuals paid within 5 pence of the NMW/NLW (the 'coverage' of the NMW/NLW) in 2016 was higher among ethnic minorities than among workers of white ethnicity.

[8] According to the APS 2014 data, the median hourly pay for Level 2 and 3 apprentices in Great Britain was £6.30 among White apprentices, lower than other ethnic groups reported (£6.63 among Asian/Asian British; £6.60 among Black/Black British; £6.81 among Mixed/Other).

[9] For example, the Low Pay Commission (2016) has estimated that nearly 20% of disabled individuals were paid within 5 pence of the National Minimum Wage/National Living Wage in 2016, compared to around 10% of non-disabled; the Office for National Statistics reported the median hourly pay in 2016 for disabled individuals at £10, compared to £11.2 among non-disabled (https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/adhocs/006740averageusualandpaidhoursbegenderandaveragehourlypaybyethnicityanddisablity).

employment of individuals with disabilities, or of individuals from a white ethnic background.

2.3 Descriptive Statistics

2.3.1 Apprentice pay before the October 2015 increase

The empirical strategy described in Section 2.2 above requires geographical variation in the extent to which the AR increase was binding for local apprentice pay. APS 2014 includes information on 9,367 apprentices in Great Britain, of which there were 7,978 whose pay could be calculated accurately based on the apprentice's responses to the questionnaire.

Table 1 below reports median pay and proportion of apprentices paid below £3.30 per hour (the "fraction of workers affected", as defined above) in England, Scotland and Wales as measured in the APS 2014 data. The figures are likely to represent a lower bound for median pay and an upper bound for the fraction of workers affected, if apprentice pay has grown between 2014 and 2015.[10]

Table 1 Basic hourly apprentice pay by country in Great Britain, 2014

Country	Median hourly pay	Fraction of workers affected	Unweighted sample size
England	£6.31	16.2%	4,633
Scotland	£6.16	12.9%	1,866
Wales	£6.77	9.1%	1,479
Great Britain	£6.31	15.8%	7,978

Source: *Frontier analysis of APS 2014 data*

Note: *Figures only including apprentices for whom pay could be computed accurately*

Across Great Britain, nearly 16% of apprentices were paid under £3.30 per hour in 2014. Workers on higher apprenticeships (Level 4 and higher) are largely unaffected by the AR: only 1% of higher apprentices were paid less than £3.30 per hour. As a result, the remainder of this section focuses on Level 2 and 3 apprenticeships, which in 2015/16 accounted for around 95% of all apprenticeship starts in in England.

Variation in apprentice pay by geography

Within England, levels of apprentice pay vary across regions, as show in Table 2 overleaf: the fraction of workers paid below £3.30 per hour was lowest in London (12%), and highest in Yorkshire and the Humber (21%).

[10] Trends in pay among full-time employees (as detailed for example in https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/2015provisionalresults#distribution-of-earnings) and our own estimates using Labour Force Survey data suggest that apprentice pay may have grown between 2014 and 2015.

Table 2 Basic hourly pay by Government Office Region in England, Level 2 and 3 apprentices, 2014

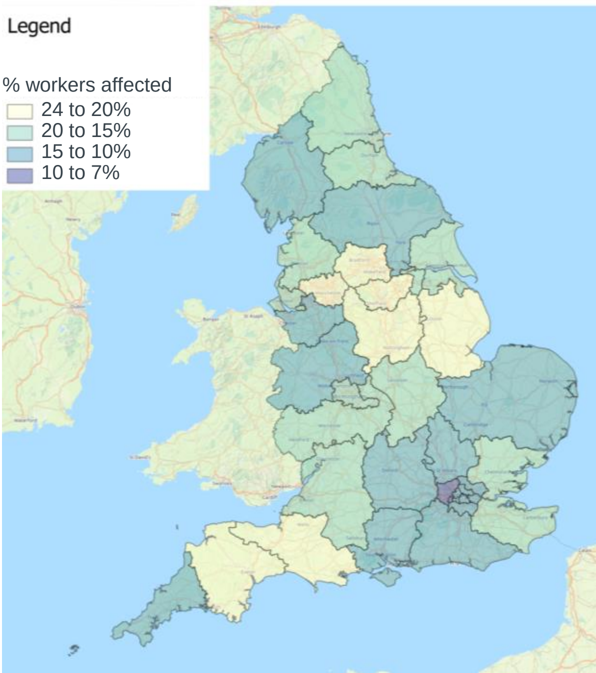
Region	Median hourly pay	Fraction of workers affected	Unweighted sample size
North East	£6.39	17.9%	296
North West	£6.33	16.6%	674
Yorkshire and the Humber	£5.83	21.1%	451
East Midlands	£6.00	18.8%	414
West Midlands	£6.35	14.8%	502
East of England	£6.25	13.8%	414
South East	£6.61	14.1%	546
London	£6.47	12.0%	382
South West	£6.09	20.0%	536

Source: Frontier analysis of APS 2014 data

Note: Figures only including apprentices for whom pay could be computed accurately

Moreover, regional statistics hide a significant amount of intra-regional variation. We explore variation by Nomenclature of Territorial Units for Statistics (NUTS) areas at level 2 – a standard developed and maintained by the European Union. There are 33 NUTS2 areas in England, and this is the highest level of geographical detail at which we can compute pay statistics, given the sample size available from the APS data. Figure 3 below shows the fraction of workers affected in 2014 across NUTS2 areas in England, where lighter areas (yellow) indicate higher fractions than darker areas (blue).

Figure 3 Fraction of workers affected by NUTS2 areas in England, level 2 and 3 apprentices, 2014



Source: Frontier analysis of APS 2014 data

Note: Figures only including apprentices for whom pay could be computed accurately

Intra-regional variation is particularly significant in the South West, where the fraction of workers affected was 24% in Dorset and Somerset, compared to 19% in the Gloucestershire, Wiltshire and Bath/Bristol areas.

Variation in apprentice pay by framework

Table 4 below shows median pay and the fraction of workers affected by course framework. The Hairdressing and Management frameworks are strikingly different to the others, with considerably lower and higher pay respectively. In principle, this would make it interesting to examine the effect of the AR increase on the Hairdressing framework specifically. We provide indicative estimates in Section 3.3 of this report, but the sample size available makes it challenging to apply our empirical strategy to specific frameworks.

Table 4 Basic hourly pay by course framework in England, Level 2 and 3 apprentices, 2014

Course framework	Median hourly pay	Fraction of workers affected	Unweighted sample size
Business and related	£5.75	24.0%	502
Children's Learning and Development and Well Being	£5.02	30.0%	308
Construction and related	£5.03	20.0%	315
Customer Service	£6.73	17.6%	259
Electrotechnical	£5.68	12.9%	394
Engineering, Manufacturing Technologies and related	£5.83	15.1%	651
Hairdressing	£2.86	61.5%	316
Health, Social Care and Sport	£6.52	8.1%	487
Hospitality	£6.31	9.6%	282
Management	£8.38	1.0%	217
Retail	£6.64	13.1%	295
Other level 2 and 3 frameworks	£5.94	21.7%	213

Source: Frontier analysis of APS 2014 data

Note: Figures only including apprentices for whom pay could be computed accurately

However, with the exception of the Management framework, other frameworks also included apprentices paid below £3.30, even in relatively high-paying cases. For example, median pay in Retail was £6.64, higher than the national average of £6.31, but 13% of apprentices in this framework were paid below £3.30. Overall, Business and related, Engineering, Manufacturing technologies and related, Hairdressing, and Health, Social Care and Sport accounted for nearly 60% of all affected apprentices.

Variation in apprentice pay by age

As expected, younger workers tend to receive lower pay than older workers. Around half of apprentices aged 16 to 18 in 2014 were paid less than £3.30, as shown Figure 5 below, and would therefore be directly affected by the increase in the AR (if still eligible as of October 2015).

Table 5 Basic hourly pay by age in England, Level 2 and 3 apprentices, 2014

Age group	Median hourly pay	Fraction of workers affected
16 to 18	£3.33	49.4%
19 to 20	£5.03	23.0%
21 to 24	£6.44	12.2%
25 or older	£7.26	2.3%

Source: Frontier analysis of APS 2014 data

Note: Figures only including apprentices for whom pay could be computed accurately

Variation in apprentice pay by gender

The APS 2014 data shows that the apprentice pay structure is slightly unusual in that there is relatively little variation by gender compared to all full-time employees.[11] The median pay in 2014 was slightly higher for female apprentices, while the fraction of workers affected was virtually the same across gender, as shown in Table 6 below.

Table 6 Basic hourly pay by gender in England, Level 2 and 3 apprentices, 2014

Gender	Median hourly pay	Fraction of workers affected
Female apprentices	£6.38	83.2%
Male apprentices	£6.16	83.6%

Source: Frontier analysis of APS 2014 data

Note: Figures only including apprentices for whom pay could be computed accurately

However, it is worth noting that a number of course frameworks are mainly attended either by female or male apprentices, as reported in Table 7 overleaf. The Children's Learning and Development and Well Being, Hairdressing, and Health, Social Care and Sport frameworks have a very high incidence of female apprentices. Conversely, males account for most apprenticeships in the Construction, Electrotechnical, and Engineering, Manufacturing Technologies and related frameworks.

[11] ASHE data suggests that across the UK, median hourly earnings of full-time employees has been around 10% higher among men than among women from 2014 to 2016. Source: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/earningsandworkinghours/bulletins/annualsurveyofhoursandearnings/2016provisionalresults#gender-pay-differences.

Table 7 Distribution of apprentices across frameworks, by gender

Course framework	Male apprentices	Female apprentice	Overall
Business and related	9.0%	15.6%	12.2%
Children's Learning and Development and Well Being	0.7%	10.1%	5.2%
Construction and related	9.6%	0.2%	5.1%
Customer Service	5.3%	6.9%	6.1%
Electrotechnical	4.2%	0.1%	2.2%
Engineering, Manufacturing Technologies and related	32.2%	1.1%	17.2%
Hairdressing	0.9	7.0%	3.8%
Health, Social Care and Sport	10.4%	31.4%	20.5%
Hospitality	5.7%	7.6%	6.6%
Management	6.2%	7.7%	6.9%
Retail	8.4%	6.7%	7.6%
Other Level 2 and 3 frameworks	7.4%	5.6%	6.5%

Source: Frontier analysis of APS 2014 data

Note: Figures only including apprentices for whom pay could be computed accurately

Compliance with the Apprentice Rate

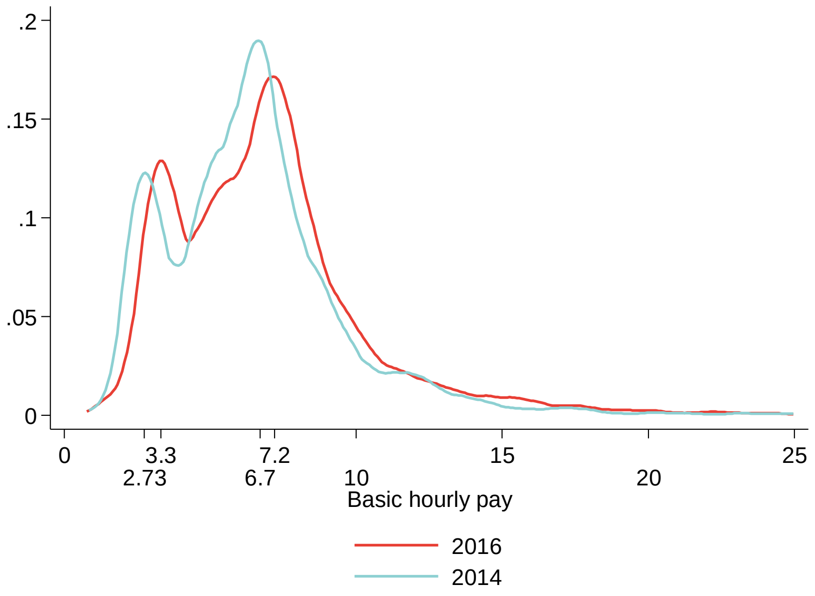
It is important to note that compliance of apprentice pay with the appropriate minimum wage rates (including the AR) has been reported to be relatively low. According to the Apprenticeship Pay Survey 2014 report, 15% of Level 2 and 3 apprentices were paid below the appropriate minimum wage in 2014.[12] The level of non-compliance was found to be considerably higher in lower-paying frameworks, including Hairdressing and Children's Care. Drew et al. (2016) suggest that these are upper bound estimates of non-compliance. More conservative estimates based on ASHE data or on APS records documented by payslip information suggest substantially lower non-compliance rates. The following section shows that the increase in the AR taking place in October 2015 was binding, as it was above existing rates for many apprentices. However, the issue of non-compliance should be taken into account when interpreting our results reported in Section 3.

[12] Department for Business, Innovation and Skills, "Apprenticeship pay survey 2014", BIS Research Paper No.207, available at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/387319/bis-14-1281-apprenticeship-pay-survey-2014.pdf.

2.3.2 Impact of the October 2015 increase on apprentice pay

Figure 8 below shows the distribution of basic hourly pay for Level 2 and 3 apprentices in England according to APS 2014 and 2016. The 2016 density is shifted to the right compared to the 2014 density, suggesting an increase in apprentice pay along the entire distribution.

Figure 8 Distribution of basic hourly pay in England, Level 2 and 3 apprentices, 2014 and 2016



Source: Frontier analysis of 2014 and 2016 APS data

Note: Figures only including apprentices for whom pay could be computed accurately

The distribution in both years presents spikes corresponding to the AR and to the National Minimum Wage/National Living Wage. The leftmost spike in the 2016 distribution is around £3.30 hourly pay, suggesting that the October 2015 increase has indeed affected apprentice pay. However, a left tail of the distribution below £3.30 remains. As noted in the Low Pay Commission's Autumn 2016 report[13], there may be legitimate reasons why some workers are paid below the AR, for example where their accommodation is provided by the employer. However, estimates of non-compliance suggest that in 2016, 5 to 18% of apprentices were paid below the relevant minimum wage (compared to 6 to 16% in 2014).[14] Therefore, there is a significant degree of non-compliance, which may have grown from 2014 to 2016. This should be taken into account when reading our results on the impact of the AR increase on the employment and composition of apprentices.).

Median pay for Level 2 and 3 apprentices in England increased from £6.30 per hour in 2014 to £6.70 in 2016. The proportion of workers paid below £3.30 per

[13] Available at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/575634/10583-LPC-National_Living_Wage_WEB.pdf

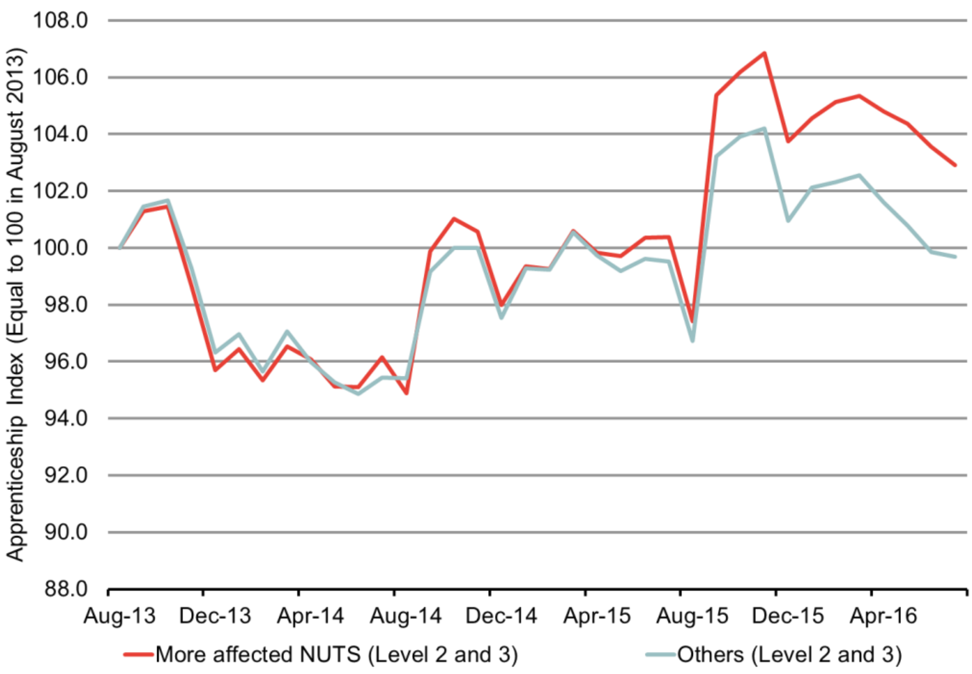
[14] Using ASHE data, APS data, or APS information from payslips leads to different estimates, as discussed in Drew et al. (2016).

hour decreased from 16.2% in 2014 to 10.3%. This proportion is somewhat higher for female apprentices in 2016: 10.8% compared to 9.7% among males. However, this is likely to be driven, at least in part, by the different impact of the AR across frameworks, given the substantial differences across frameworks in gender composition documented above.

2.3.3 Variation in apprenticeship numbers

Figure 9 below shows trends in the apprenticeship stock across more affected and less affected NUTS2 areas in England from the 2013/14 academic year to 2015/16.[15] For the purpose of this comparison, we define 'more affected' NUTS2 as those above the 75th percentile in the distribution of the fraction of workers affected by the AR. The number of apprenticeship in both groups of NUTS2 areas have been indexed they are equal to 100 at the start of the 2013/14 academic year.

Figure 9 Trends in overall Level 2/3 apprenticeships stock



Source: Frontier Economics using data from the ILR

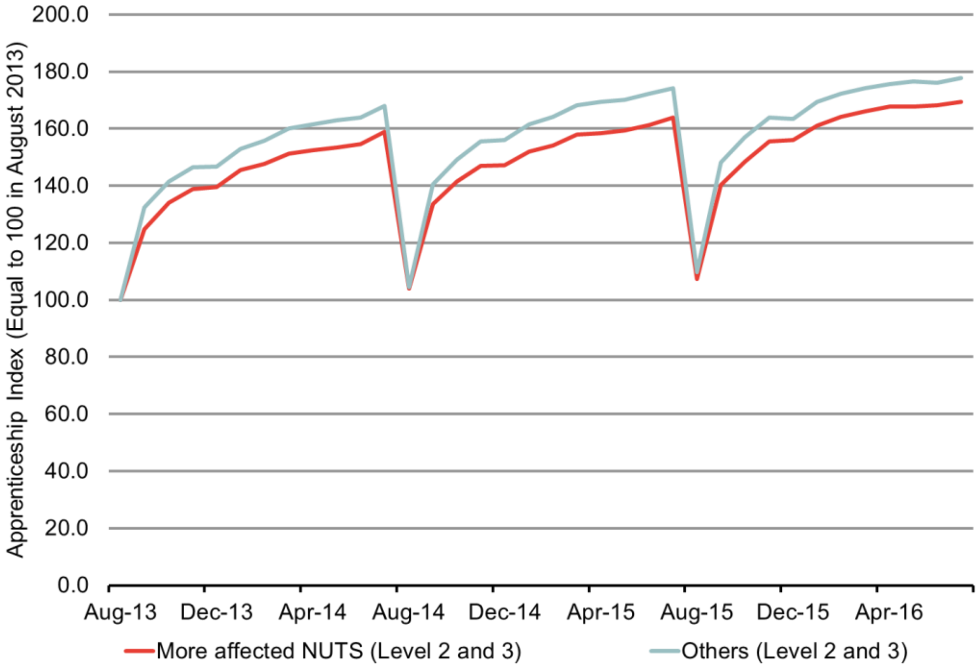
Note: More affected NUTS include Derbyshire and Nottinghamshire, Devon, Dorset and Somerset, Essex, Greater Manchester, Gloucestershire, Wiltshire and Bath/Bristol area, Lincolnshire, South Yorkshire, Tees Valley and Durham, West Yorkshire. These are the 10 areas above the 66th percentile.

Both groups display highly seasonal patterns, reaching a peak around September (in line with the start of the academic year). Interestingly, both groups feature an increase in the Apprenticeships Index from September 2015, over and above pre-existing seasonal patterns. More affected areas exhibit a larger increase in apprentice numbers.

[15] In line with the econometric analysis, we aggregate the London NUTS 2 areas into two areas, "Inner London" and "Outer London".

In contrast, no such effect is found when looking at apprentices aged 16 to 18 (in Figure 10 below). In this case, differences in apprenticeship numbers between more and less affected areas appear stable across the period in consideration (with the exception of the pronounced seasonal drop in August, in line with the end of the academic year).

Figure 10 Trends in overall Level 2/3 apprenticeships stock for individuals aged 16 to 18



Source: Frontier Economics using data from the ILR

Note: More affected NUTS include Cornwall and Isles of Scilly, Derbyshire and Nottinghamshire, Gloucestershire Wiltshire and Bath/Bristol area, Greater Manchester, Inner London, Lancashire, Lincolnshire, South Yorkshire, West Midlands, West Yorkshire. These are the 10 areas above the 66th percentile.

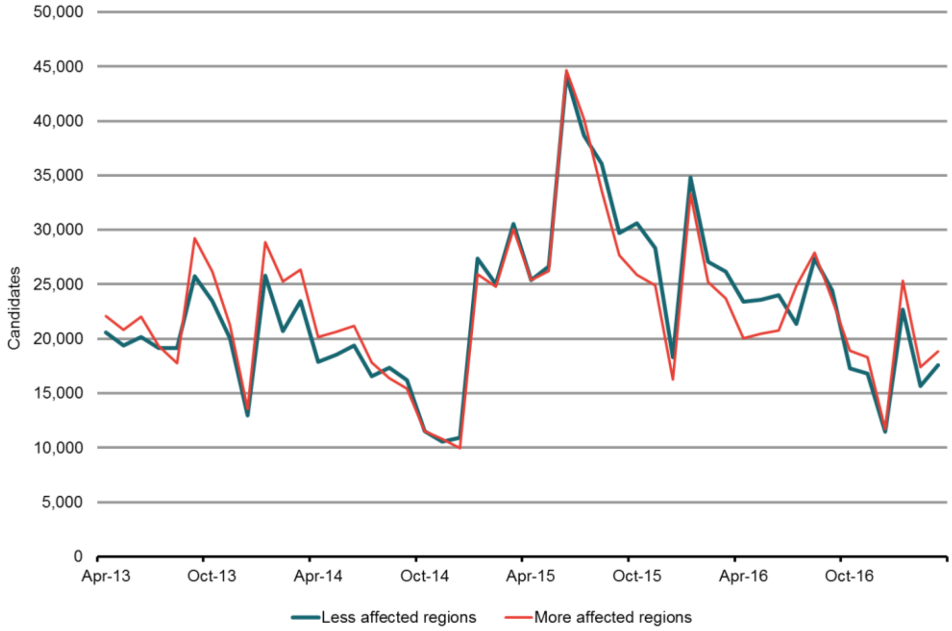
2.3.4 Variation in candidates and vacancies

Figure 11 shows the trend in the number of candidates across more affected and less affected Government Office Regions in England.[16] for the last four financial years (from April 2013 to March 2017).

In line with the descriptive statistics for the apprenticeships stock, there does not seem to be a difference in trend between more affected and less affected areas. It is also unclear whether the trends in the number of candidates overall have been particularly affected by the increase in the AR. The number of apprentice candidates starts to increase from January 2015 (before the announcement of the AR increase) and then peaks in June 2015 (around the time of the announcement of the Government’s target to reach 3 million apprenticeships starts by 2020). It has since tailed off – returning to its levels of 2013 and 2014.

[16] This was the most detailed geographic unit available for these data.

Figure 11 Trends in candidates across more affected and less affected regions

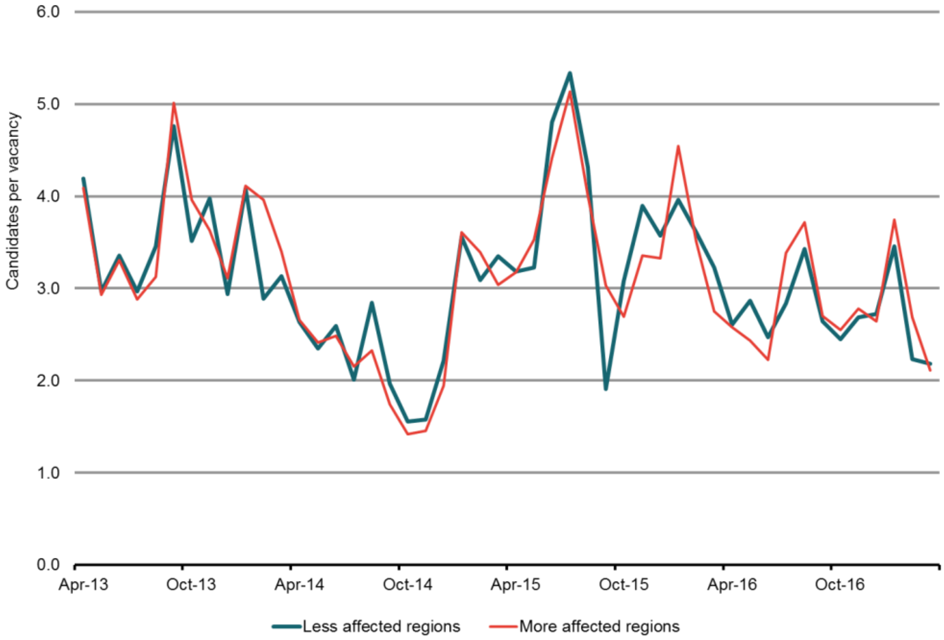


Source: Frontier Economics using data from the SFA

Note: Less affected regions include London, South East, East of England, West Midlands

The conclusions do not change substantially when focusing on candidates per vacancy (in Figure 11 below). The trends are similar across less affected and more affected regions, both before and after the increase in the AR.

Figure 12 Trends in candidates per vacancy across more affected and less affected regions



Source: Frontier Economics using data from the SFA

Note: Less affected regions include London, South East, East of England, West Midlands

3 ECONOMETRIC ANALYSIS OF THE IMPACT OF THE APPRENTICE RATE INCREASE

We discuss our econometric estimates of the impact of the AR increase in three distinct sections:

- **Baseline econometric results:** estimated impact on the number of apprenticeships;
- **Robustness checks:** further discussion of the baseline econometric results and their sensitivity;
- **Further econometric results:** results on our proxies of apprenticeship quality, on the composition of the apprentice population, and results specific to the Hairdressing framework.

3.1 Baseline econometric results

Table 13 overleaf reports estimated effects of the AR increase on year-on-year changes in the apprenticeship stock, measured at three different points in time: end of October 2015, January 2016 and April 2016. The impact of the AR increase is picked up by the coefficient on the $d_t\theta_a$variable. Multiplying the coefficient by 100 yields the percentage change in apprenticeships resulting from a 1 percentage point increase in θ_a, the proportion of apprentices paid below £3.30 as of July to September 2014.

The October 2015 model implies that a 1 percentage point increase in θ_a leads to a statistically insignificant (at the 10% level) increase of 0.14% in the apprenticeships stock. Estimated effects become larger in January and April and statistically significant at the 5% level. In principle, these effects could be driven by the *labour supply* channel. The increase in the AR could have made apprenticeships more attractive with respect to education, employment or inactivity. However, the limited data on vacancies we have described section 2.1.3 do not show that the number of candidates for apprenticeships has increased in areas more affected by the AR hike. Moreover, APS 2016 data suggests that awareness of the AR among Level 2 and 3 apprentices in 2016 remained broadly in line with 2014 estimates: according to 2016 APS data, 66% of Level 2 and 3 apprentices in Great Britain were aware of the AR, and 28% of its hourly rate, compared to 62% and 26% in 2014 respectively.[17]

The fact that the coefficients progressively increase as we move towards April 2016 might instead suggest that the results could be driven by the introduction of the National Living Wage (NLW) in April 2016. The fraction of workers affected by the introduction of the NLW and the fraction of apprentices affected by the increase in the AR are likely to be positively correlated across areas. If an area has a higher proportion of low-paid workers, it is likely that it will also have a

[17] Source: APS 2014 and APS 2016.

higher proportion of low-paid apprentices. Hence, in order to save on labour costs in the short-term, employers in lower paying areas (more affected by the NLW and the AR increase) might have started offering apprenticeship contracts rather than full-time or part-time employment contracts. This would lead to an increase in the stock of apprenticeships regardless of the impact of the AR increase.

Table 13 Baseline econometric results for the all apprenticeships in levels 2/3

$\log(app)_{at}$ for different months			
VARIABLES	October 2015	January 2016	April 2016
d_t	0.0177	-0.0114	-0.0294
	(0.0196)	(0.0223)	(0.0296)
$d_t\theta_a$	**0.00139**	**0.00291****	**0.00350****
	(0.00100)	(0.00112)	(0.00157)
Constant	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
R-squared	0.695	0.650	0.408
Number of NUTS	30	30	30

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. Results in Bold pass the placebo test at the 10% level (i.e. there is no statistically significant effect in the periods before the introduction of the AR).*

Looking at the effects estimated on specific breakdowns of apprentices (in Table 14 below) offers some evidence to confirm this hypothesis and provides some further insight on the underlying drivers.

The estimated effect of the AR increase is not statistically significant among younger apprentices (aged 16 to 18) and apprentices in lower-paying frameworks, who we would expect to be most affected by the change. This suggests that the positive effect could be driven by older apprentices and those in higher-paying frameworks – those who were more likely to be affected by the introduction of the NLW.[18] When we look at higher-paying frameworks specifically, we find some evidence of differences in trends between more and less affected areas pre-existing the AR increase. This suggests that findings on higher-paying frameworks should be considered with caution. However, what we find is not that apprenticeships in higher-paying frameworks had been growing at a faster rate in more affected areas already in the year before the increase of the AR. On the contrary, year-on-year changes between 2013/14 and 2014/15 as of October and April show slower growth of apprentice numbers in more affected areas.

[18] The NLW only applied to individuals aged 25 or over. To test more formally the hypothesis that the positive results are driven by the introintroduction of the NLW, we therefore estimate the model for individuals aged 16 to 24 only. In line with our interpretation, we obtain statistically insignificant coefficients at the 10% level.

The treatment effects are positive at the 5% level for Level 2 apprenticeships and for apprenticeships undertaken by males, but they are statistically insignificant (at the 10% level) for apprenticeships undertaken by females and for Level 3 apprenticeships. This indicates that the increase in apprenticeships has been mostly driven by males doing Level 2 apprenticeships.

Table 14 Baseline econometric results for different groups

$d_t \theta_a$ for different months

GROUPS	October	January	April
All Level 2/3	**0.00139**	**0.00291****	**0.00350****
	(0.00100)	(0.00112)	(0.00157)
Level 2	**0.00171**	**0.00356****	**0.00475****
	(0.00104)	(0.00141)	(0.00199)
Level 3	**0.00005**	**-0.00101**	**-0.000485**
	(0.00157)	(0.00174)	(0.00174)
Level 2/3 for 16-18 age group	**-0.000462**	**0.00002**	**0.000269**
	(0.000775)	(0.000857)	(0.000971)
Level 2/3 eligible for AR	**0.00107**	**0.00290****	**0.00388****
	(0.00106)	(0.00114)	(0.000654)
Level 2/3, eligible males	**0.000131**	**0.00926*****	**0.0129*****
	(0.00319)	(0.00311)	(0.00444)
Level 2/3, eligible females	**0.000824**	**0.00162**	**0.000895**
	(0.00159)	(0.00228)	(0.00250)
Sectors with low proportion of workers affected	0.00327**	**0.00631*****	0.00780***
	(0.00145)	(0.00203)	(0.00203)
Sectors with high proportion of workers affected	**-0.000663**	**-0.000158**	**-0.000460**
	(0.000770)	(0.000621)	(0.000725)

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. Results in* ***Bold*** *pass the placebo test at the 10% level (i.e. there is no statistically significant effect in the periods before the introduction of the AR). All models are estimated with Fixed Effects, two time periods and the fraction of workers affected for the group, in line with the baseline specification.*

Isolating the apprentices eligible for the AR (those aged 16 to 18 or those in the first year of their apprenticeship) does not substantially affect the results.

To further characterise how the AR increase has affected the mix in apprenticeships across frameworks, we also present the results of the models with apprenticeships in a framework as the dependent variable and the overall "fractions of apprentices affected" as the independent variable (in Table 15 below). To facilitate the interpretation of the results, we have ordered the frameworks from the one with the highest fraction of apprentices affected by the AR increase (Hairdressing) to the one with lowest fraction of apprentices affected (Management).

Table 15 Baseline econometric results for different apprenticeship frameworks

GROUPS	October	January	April
Hairdressing	**-0.00166**	**-0.00177**	**0.000462**
	(0.00321)	(0.00319)	(0.00323)
Children Development	**0.00109**	**0.00171**	**0.00182**
	(0.00322)	(0.00331)	(0.00341)
Business & Related	**-0.00142**	**-0.00048**	**0.00152**
	(0.00335)	(0.00338)	(0.00309)
Construction	0.000685	**0.00194**	**0.00277**
	(0.00371)	(0.00409)	(0.00413)
Customer Service	**-0.0109**	**-0.0104****	**-0.0133****
	(0.00655)	(0.00462)	(0.00524)
Retail	**0.00787**	**0.0178*****	**0.0153*****
	(0.00587)	(0.00539)	(0.00443)
Engineering	**0.00648***	**0.00657**	**0.00862***
	(0.00319)	(0.00408)	(0.00491)
Electrotechnical	**0.00246**	**0.000176**	**-0.000749**
	(0.00222)	(0.00262)	(0.00315)
Hospitality and Catering	0.00481*	**0.00446**	**0.00505**
	(0.00276)	(0.00308)	(0.00312)
Health, Social Care and Sport	**-0.00301**	**-0.000226**	**0.00136**
	(0.00319)	(0.00417)	(0.00419)
Management	**0.00610****	**0.00704****	**0.00273**
	(0.00262)	(0.00291)	(0.00525)

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Red are statistically significant and negative. Results in Yellow are statistically insignificant. Results in **Bold** pass the placebo test at the 10% level (i.e. there is no statistically significant effect in the periods before the introduction of the AR). All models are estimated with Fixed Effects, two time periods and the fraction of workers affected for all Level 2/3 apprentices, due to the APS sample size limitations.*

The results do not point to a definite conclusion about the impact of the AR increase. There does not seem to be a particularly strong relationship between the sign and magnitude of the treatment coefficients and the fraction of workers affected within the framework. For instance, the effect on Hairdressing is negative in October and January, but not statistically significant at the 10% level. Conversely, Management (a framework in which approximately 1% of apprentices in 2014 were paid below the AR) exhibits a positive and statistically significant coefficient at the 5% level in October and January. It is possible that a mixture of sector-specific dynamics, re-categorisations of existing apprenticeships and the bite of the NLW across sectors might be driving these effects.

However, these models are helpful in explaining the results by gender. Frameworks with a large proportion of female apprentices (such as Hairdressing and Health and Social Care) exhibit small treatment effects. Likewise, Engineering (which accounts for about one third of male apprentices, but approximately 1% of female apprenticeships) displays a positive and sizeable coefficient (when compared to other frameworks). This suggests that the results by gender are likely to reflect differences in the distribution of male and female apprentices across frameworks, rather than intrinsic characteristics of male and female apprentices.

3.2 Robustness checks

To verify the robustness of our results, we have experimented with several alternative specifications:

- **Apprenticeship starts:** Estimating the model on apprenticeships starts rather than the apprenticeships stock
- **Binary treatment effect:** Estimating the model using a binary treatment effect for “High Fraction of apprentices affected” and “Low Fraction of apprentices affected” NUTS2
- **Control variables:** including control variables (population growth and the lag of employment) in the baseline specification.
- **Triple-Difference approach:** using a pseudo-Triple Differences approach to control for differences in employment trends across geography and time

These specifications have not led to substantially different results with respect to our baseline specification. We discuss them below, and we include the underlying regression outputs in Annexe A.

Apprenticeship Starts

We have estimated the model with apprenticeship starts as the outcome variable, rather than the apprenticeships stock, for the following groups:

- All Level 2/3 apprentices
- Level 2 and Level 3 only
- Apprentices aged 16-18

- Frameworks with a lower (or higher) proportion of apprentices affected

Generally, the standard errors on the treatment effect are larger and the estimates less precise, reflecting the higher volatility of apprenticeship starts. However, in line with the baseline specification, the effects are greater in January and April than in October. Moreover, the coefficients on younger apprentices tend to be smaller than the coefficients on the entire sample.

Binary treatment effect

We have estimated all the models from the baseline specification (with stock as an outcome variable) using a binary treatment variable instead of the fraction of workers affected. The binary treatment effect acquires a value equal to one for the fifteen NUTS2 with the highest fraction of apprentices affected and zero otherwise. In line with the baseline specification, we obtain the following results:

- The treatment effects in January and April are larger than the treatment effects in October
- The treatment effects on younger age groups are smaller than those for all apprentices
- The treatment effects are substantially larger for male apprentices than for females
- The same sectors (Retail, Engineering, Hospitality & Catering, Management) exhibit positive and statistically significant coefficients

The key difference is that the coefficient on all Level 2/3 apprenticeships is positive and statistically significant (at the 5% level) in October as well as in January and April. However, this is not robust to changes in the definition of the treatment variable. When we change the definition of the binary indicator to include the ten NUTS2 with the highest fraction of apprentices affected (rather than fifteen), the coefficient halves in size and it becomes statistically insignificant at the 10% level.

Control variables

We were concerned that our treatment effects could be picking up the impact of past trends in the local labour market. For instance, the NUTS with a larger proportion of apprentices affected could have experienced weaker job growth before the increase in the AR. This could cause some positive re-adjustment in the following periods, which could be absorbed by our treatment effects.

To account for this possibility, we have included the following control variables in our baseline specification:

- The log of Full Time Employment in the two time periods before the increase in the AR (for all Level 2/3 apprentices and for the eligible apprentices)
- The log of the yearly Youth Employment Rate in the two time periods before the increase in the AR (for apprentices aged 16 to 18)

The inclusion of these control variables does not substantially change the significance or magnitude of the treatment coefficients.

Triple Difference approach

As well as past trends, we thought that the treatment effect might be affected by contemporaneous changes to economic performance. For instance, NUTS with a larger fraction of apprentices affected could have experienced faster growth in economic activity. If this was the case, our treatment effect might be picking up the impact of an improvement in the local labour market, rather than the genuine impact of the increase in the AR. In order to control for this possibility, we have estimated a triple difference specification:

$$growth\_app_{at} - growth\_empl\_control_{at} = \beta + \delta\theta_a + \varepsilon_{at} \quad (3)$$

where $growth\_app$ identifies the growth in average apprenticeships undertaken in a quarter (October-December or January-March) across areas a and year t, $growth\_emp\_control$ stands for the growth in employment for a suitable control group from the Labour Force Survey in the same quarter, and the other variables are defined as in the baseline specification.

We adopt an age-discontinuity approach to identify a suitable control group. We consider a group of workers slightly older than the group of relevant apprentices. These workers should not be directly affected by the AR increase, but their growth rate could be a good proxy for the level of growth that the group of apprentices would have experienced, had the increase in the AR not taken place. Along these lines, we estimate the model for three separate samples:

- Apprenticeships undertaken by individuals aged 16-18 (using employment for individuals aged 19-21 as the control group)
- Apprenticeships undertaken by eligible individuals aged 16-20 (using employment for individuals aged 22-25 as the control group)
- Apprenticeships undertaken by eligible individual aged 16-24 (using employment for individuals aged 26-30 as the control group)

The treatment coefficients are not statistically significant at the 10% level: the standard errors are very large. Interestingly, the treatment effects on the model for individuals aged 16-18 become more negative, when compared to the baseline specification, for both quarters (October-December or January-March). This suggests that taking into account local labour market dynamics could affect our estimates. However, given the existing data limitations, we cannot explore this hypothesis any further.

3.3 Further Econometric results

3.3.1 Quality

The results for our *quality* specification on drop-out rates are reported in Table 16. Specifically, we estimate the impact of the AR increase on the proportion of apprentices who drop out within the first year of their apprenticeship. As we only have access to ILR data for academic years 2013/14 to 2015/16, we cannot use drop-out rates over a longer period (e.g. drop-outs within the first two apprenticeship years). Moreover, we cannot follow apprentices after September 2016. Therefore, for starts in January and April 2016, we could only compute drop-outs within seven and four months from the start date respectively. These short-term drop-out rates are likely to be less informative than the one-year rate based on October starts.

Given that both our treatment and outcome variables are rates expressed on a scale from 0 to 100, the interpretation of the treatment effect is different from that of the baseline specification. In this case, the treatment effect reports the percentage point change in the drop-out rate resulting from a one percentage point increase in θ_a. For instance, the model for all Level 2/3 apprentices implies that an increase in θ_a by one percentage point leads to a statistically insignificant (at the 10% level) 0.02% increase in the drop-out rate.

Table 16 Baseline econometric results on drop-out rates for the October cohort

$\left(\frac{Apprenticeships\ dropped\ for\ group}{Total\ apprenticeships\ starts}\right)_{at}$ VARIABLES	All Level 2/3	Level 2/3 for 16-18 age group	Level 2/3 for 16-24 age group
d_t	0.226	-1.830	-1.451
	(2.432)	(4.825)	(2.058)
$d_t \theta_a$ for group	0.0208	0.0453	0.0604
	(0.138)	(0.0977)	(0.0708)
Constant	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
R-squared	0.040	0.010	0.012
Number of NUTS	30	30	30

Source: *Frontier Economics analysis, using data from the ILR and APS*

Note: *Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant.*

The results from these models suggest that the increase in the AR has not had a significant impact on drop-out rates. The treatment effect is statistically insignificant at the 10% level across the three groups we have considered. For the 16-18 age group, we have also run the model on the drop-out rate for the September cohort, in line with the beginning of the school year. The results were in line with those presented in Table 16 above.

3.3.2 Ethnicity and disability

The econometric results on the ethnicity and disability mix for the October cohort are presented in Table 17. The treatment effect has a similar interpretation as in the drop-out rate models. The table shows the estimated percentage point change in the proportion of individuals who reported a disability (leftmost column) and in the proportion of individuals who reported their ethnicity as other than white (rightmost column), resulting from a one percentage point increase in θ_a.

Table 17 Baseline econometric results on ethnicity and disability mix for October

$\left(\frac{\text{Apprenticeships started within group}}{\text{Total apprenticeships starts}}\right)_{at}$ VARIABLES	Individuals with disability (Level 2/3)	Individuals from non-white ethnic group (Level 2/3)
d_t	1.932	0.390
	(1.447)	(1.642)
$d_t\theta_a$for group	-0.0378	-0.0192
	(0.0875)	(0.0884)
Constant	Yes	Yes
Fixed Effects	Yes	Yes
R-squared	0.378	0.004
Number of NUTS	30	30

Source: *Frontier Economics analysis, using data from the ILR and APS*

Note: *Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant.*

For both groups, we observe a negative but statistically insignificant coefficient (at the 10% level). Therefore, we do not find evidence that the AR increase has had a different effect by ethnicity or by reported disability. The results for January and April (reported in Annex A) are also consistent with this conclusion.

3.3.3 Focus on Hairdressing

As reported in Section 2.3, Hairdressing displays lower levels of average pay when compared to other frameworks, with the proportion of apprentices paid below £3.30 in APS 2014 also particularly high. Therefore, we aimed to test whether the Hairdressing framework has been especially affected by the AR increase.

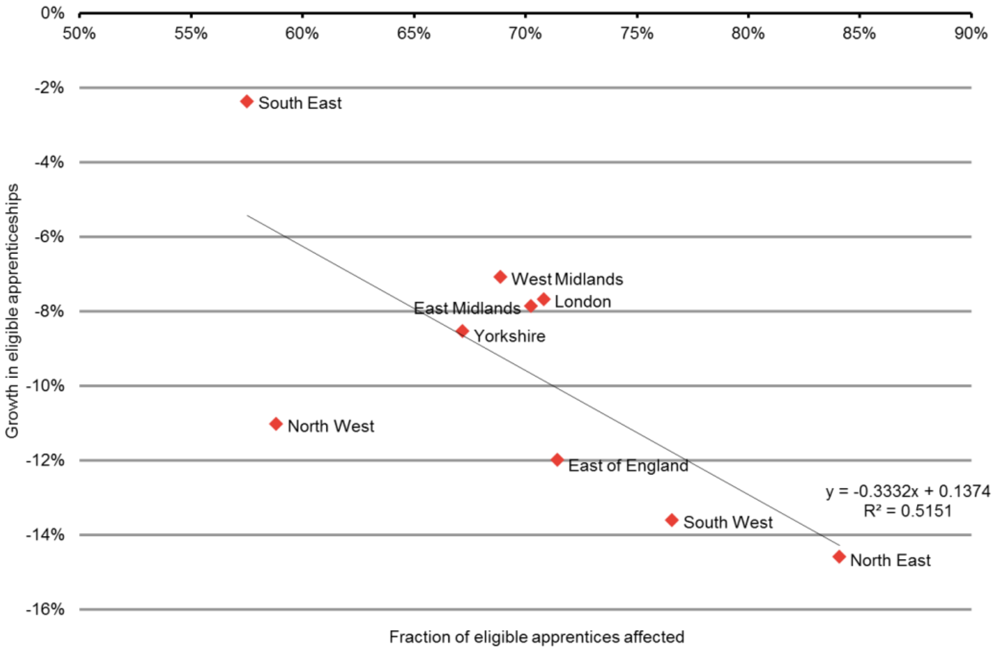
As a result of the peculiar pay structure of the framework, it is likely that the overall fraction of workers affected (as employed used in section 3.1) does not reflect geographical differences in pay for Hairdressing. This means that it would be useful to compare the growth in Hairdressing apprenticeships to the fraction of workers affected *within* the Hairdressing framework.

However, we only have 316 Hairdressing apprentices in England from APS in 2014. Given this low sample size, we have produced some tentative analysis using regions, as opposed to NUTS, as the main geographical unit.

Table 18 below reports a scatter plot of the growth rate in Hairdressing apprenticeships eligible to the AR from October 2014 to October 2015 and the fractions of eligible Hairdressing apprentices affected by the AR increase. We observe a negative and statistically significant relationship (at the 5% level) between the fraction affected and the growth rate. This could potentially be the result of the *labour demand* effect. Employers might be less willing to hire apprentices because of an increase in labour costs.

The implied size of the effect is not negligible. Hairdressing apprentices eligible to the AR decreased between October 2014 and October 2015 by 9% across England and 13.6% in the South West, where the fraction of eligible Hairdressing apprentices affected by the AR is relatively high (approximately 77% compared to 68% across England). The relation illustrated in Figure 18 would imply that 2.9 of the 4.6 percentage point difference between South West and England are explained by the AR increase having a greater negative effect in the South West.

Table 18 Relationship between growth rate and fraction of AR-eligible apprentices affected in Hairdressing, October 2014 to October 2015



Source: Frontier Economics analysis, using data from the ILR and APS

Nevertheless, these results ought to be treated with caution, because they are based on very small sample sizes. They only provide some evidence that the Hairdressing sector could have been particularly affected by the AR increase. Further research is required to better understand the extent of this effect.

4 CONCLUSION

We have used the best available secondary data and a well-established econometric framework to study the effect of the October 2015 increase in the AR on apprentice numbers. Our main econometric specification finds no statistically significant evidence of a negative impact of the large AR increase in October 2015 on apprentice numbers or on completion rates. The lack of a negative effect is consistent across specifications and the robustness checks we have carried out. We find some tentative evidence of a possible negative effect in specific low-paying frameworks notably Hairdressing. However, we cannot be confident of the robustness of this finding as it is based on few observations.

We find some mixed evidence that the effect may be positive, in increasing the volume of apprenticeships, but we cannot be certain that the findings are not driven by other important policy initiatives introduced around the same time, such as the introduction of the National Living Wage and various initiatives to promote apprenticeships. This positive effect is larger for male apprentices, most likely because they account for the majority of apprentices in frameworks which were positively affected by the increase in the AR.

We do not find strong evidence that the quality of apprentices has changed following the introduction of the AR, albeit we acknowledge that our ability to measure quality is very limited.

We find no evidence that the composition of the apprentice population in terms of ethnicity or the prevalence of disability has changed as a result of the increase in the AR.

Our efforts have highlighted that the data on apprentices could be improved. The APS which we have used to measure apprentice pay and hence calculate how binding the increase of the Apprentice Rate is has relatively small samples which makes granular analysis challenging. Similarly, the data on the quality of apprentices (such as prior attainment) in the ILR is very patchy limiting our ability to measure this particular outcome. Future research could build on and improve this work by:

- exploring whether more granular analysis based on matched administrative data (e.g. ILR/WPLS) may improve the precision of the estimates and/or allow to investigation of sector-by-sector dynamics;
- exploring whether other data sets such as the National Pupil Database (NPD) matched to the ILR can allow researchers to study whether the higher AR has attracted apprentices with better prior attainment; and
- investigating the relationship between the number of apprenticeships and the introduction of the National Living Wage. This might enable us to better understand the interdependences between the Apprentice Rate and other minimum wage thresholds.

5 REFERENCES

Bessey, D. and Backes-Gellner, U. (2008), *Dropping out and revising educational decisions: Evidence from vocational education*. University of Zurich Working Paper 40. Available at: https://edudoc.ch/record/32263/files/zu09036.pdf

Crawford, C., Greaves, E., Jin, W., Swaffield, J., Vignoles, A. (2011), *The impact of the minimum wage regime on the education and labour market choices of young people.* Report to the Low Pay Commission. Available at: http://webarchive.nationalarchives.gov.uk/20121204172414/http://www.lowpay.gov.uk/lowpay/research/pdf/IFS_LPC_report_copy-edited_final.pdf

Department for Business, Innovation and Skills (2015), Amendment to the National Minimum Wage regulations 2015 – increase in NMW rates, Impact Assessment Numner LM002, available at https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/448555/BIS-15-309-IA-amendment-to-the-national-minimum-wage-regulations-2015-increase-in-NMW-rates.pdf

Drew, H., Ritchie, F., Veliziotis, M. (2016), *Understanding Apprentice Pay*, report prepared for the Low Pay Commission, available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/573431/Understanding_apprentice_pay_Drew_Ritchie_Veliziotis.pdf

Gallacher J., Whittaker S., Crossan B., Mills, V. (2004), *Modern Apprenticeships: Improving Completion Rates,* Edinburgh: Scottish Executive Social Research. Available at: http://www.gov.scot/Publications/2004/03/19059/34269

Higton J., Hirst A., Klahr R., Lefaucheux M., Salmon C. (2012), *An Assessment of the Introduction of the Apprentice Rate*, Report for the Low Pay Commission. Available at: http://webarchive.nationalarchives.gov.uk/20130708093021/http://www.lowpay.gov.uk/lowpay/research/pdf/LPC-IpsosMORICambridgePolicyConsultantsIntroduction_of_the_Apprentice_RateFINAL.pdf

Karmel, T. and Mlotkowski, P. (2011), *The impact of wages and the likelihood of employment on the probability of completing an apprenticeship or traineeship*. NCVER Research report. Available at: https://www.ncver.edu.au/publications/publications/all-publications/the-impact-of-wages-and-the-likelihood-of-employment-on-the-probability-of-completing-an-apprenticeship-or-traineeship

London Economics (2015), *The Impact of the minimum wage on young people*. Final report to the Low Pay Commission. Available at:

https://londoneconomics.co.uk/wp-content/uploads/2015/03/Final-Report-Impact-of-the-minimum-wage-on-young-people-Low-Pay-Commission-12-01-2015.pdf

Low Pay Commission (2016), *National Minimum Wage*, Low Pay Commission Report Autumn 2016. Available at:

https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/575634/10583-LPC-National_Living_Wage_WEB.pdf

Neumark, D. and Wascher, W. (2004), *Minimum Wages, Labor Market Institutions, And Youth Employment: A Cross-National Analysis.* Industrial and Labor Relations Review, 2004, 57(2), pp. 223-48. Available at: http://www.nber.org/papers/w7299

Speckesser, S. and Behling, F. (2013), *An impact analysis of the introduction of the Apprentice Rate of the National Minimum Wage,* research paper to the Low Pay Commission for the preparation of its 2013 report. Available at: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/226951/National_minimum_wage_apprentice_rate_impact_anaylsis.pdf

ANNEX A ROBUSTNESS CHECKS

Apprenticeship Starts

Table 19 Baseline econometric results for different groups for Apprenticeships Starts

$d_t\theta_a$ for different months GROUPS	October 2015	January 2016	April 2016
All level 2/3	-0.00103	0.00882	0.00312
	(0.00494)	(0.00598)	(0.00756)
Level 2	-0.00198	0.00463	0.00210
	(0.00305)	(0.00481)	(0.00589)
Level 3	-0.00882	-0.0112	0.0135
	(0.00733)	(0.00774)	(0.0128)
Level 2/3 for 16-18 age group	-0.00229	0.000786	0.00304
	(0.00275)	(0.00355)	(0.00388)
Sectors with Low proportion of workers affected	0.00759*	0.0176**	0.0149
	(0.00373)	(0.00794)	(0.0118)
Sectors with High proportion of workers affected	0.000348	0.00463	-0.00187

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. All models are estimated with Fixed Effects, two time periods and the fraction of workers affected for the group, in line with the baseline specification, but with the log of apprenticeships starts as the outcome variable.*

Binary treatment effect

Table 20 Baseline econometric using a Binary Treatment Effect (for NUTS above the median)

$d_t\theta_a$ for different months GROUPS	October 2015	January 2016	April 2016
All level 2/3	0.0206**	0.0261**	0.0372***
	(0.00967)	(0.0103)	(0.0135)
Level 2	0.0120	0.0259	0.0436**
	(0.0161)	(0.0166)	(0.0199)
Level 3	-0.00253	-0.00325	0.00901
	(0.0137)	(0.0142)	(0.0155)
Level 2/3 for 16-18 age group	-0.0159	-0.00944	-0.00708
	(0.0123)	(0.0148)	(0.0154)
Level 2/3 eligible for AR	0.0124	0.0302*	0.0447**
	(0.0128)	(0.0150)	(0.0170)
Level 2/3, eligible males	-0.00791	0.0678	0.135*
	(0.0463)	(0.0553)	(0.0675)
Level 2/3, eligible females	0.0141	0.0158	0.0142
	(0.0271)	(0.0341)	(0.0348)
Sectors with Low proportion of workers affected	0.0208	0.0496***	0.0587***
	(0.0129)	(0.0131)	(0.0169)
Sectors with High proportion of workers affected	-0.0107	-0.00963	-0.0163

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. All models are estimated with Fixed Effects, two time periods and the fraction of workers affected for the group, in line with the baseline specification, but with a binary treatment indicator as the treatment variable (equal to 1 if the proportion of apprentices affected is above the median)*

Table 21 Baseline econometric using a Binary Treatment Effect (for NUTS above the 66th percentile)

$d_t\theta_a$ for different months GROUPS	October 2015	January 2016	April 2016
All level 2/3	0.0103	0.0228**	0.0279**
	(0.00872)	(0.00975)	(0.0129)
Level 2	0.0103	0.0317**	0.0422**
	(0.0132)	(0.0144)	(0.0178)
Level 3	0.00856	-0.00162	0.00773
	(0.0123)	(0.0146)	(0.0154)
Level 2/3 for 16-18 age group	-0.00888	0.000722	0.000926
	(0.0123)	(0.0151)	(0.0163)
Level 2/3 eligible for AR	0.0169	0.0301**	0.0317*
	(0.0124)	(0.0140)	(0.0158)
Level 2/3, eligible males	-0.000200	0.0694	0.121
	(0.0506)	(0.0551)	(0.0769)
Level 2/3, eligible females	0.00176	-0.00919	-0.0224
	(0.0260)	(0.0346)	(0.0365)
Sectors with Low proportion of workers affected	0.0237**	0.0459***	0.0573***
	(0.0108)	(0.0127)	(0.0152)
Sectors with High proportion of workers affected	-0.00391	0.00347	-0.00542

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. All models are estimated with Fixed Effects, two time periods and the fraction of workers affected for the group, in line with the baseline specification, but with a binary treatment indicator as the treatment variable (equal to 1 if the proportion of apprentices affected is above the 66th percentile)*

Control variables

Table 22 Baseline econometric results with lagged employment as a control variable for the October 2014 to October 2015 specification

$\log(app)_{at}$ for different groups VARIABLES	All level 2/3	Level 2/3 eligible for AR
d_t	0.0214	-0.0269
	(0.0184)	(0.0206)
$d_t\theta_a$ for group	0.00131	0.000967
	(0.000978)	(0.00101)
$log(Employment)_{t-1}$	-0.103	-0.275
	(0.156)	(0.308)
Constant	Yes	Yes
Fixed Effects	Yes	Yes
R-squared	0.698	0.181
Number of NUTS	30	30

Source: *Frontier Economics analysis, using data from the ILR and APS*

Note: *Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. The data on employment cover full time employees in the October to September period from the Labour Force Survey.*

Table 23 Baseline econometric results with lagged employment as a control variable for the January 2015 to January 2016 specification

$\log(app)_{at}$ for different groups VARIABLES	All level 2/3	Level 2/3 eligible for AR
d_t	0.000357	-0.104***
	(0.0207)	(0.0281)
$d_t\theta_a$ for group	0.00255**	0.00291**
	(0.00103)	(0.00115)

$log(Employment)_{t-1}$	-0.328	0.0148
	(0.218)	(0.329)
Constant	Yes	Yes
Fixed Effects	Yes	Yes
R-squared	0.671	0.584
Number of NUTS	30	30

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. The data on employment cover full time employees in the January to December period from the Labour Force Survey.*

Table 24 Baseline econometric results with lagged employment as a control variable for the April 2015 to April 2016 specification

$\log(app)_{at}$ for different groups		
VARIABLES	All level 2/3	Level 2/3 eligible for AR
d_t	-0.0242	-0.105***
	(0.0287)	(0.0343)
$d_t\theta_a$ for group	0.00344**	0.00389***
	(0.00155)	(0.00139)
$log(Employment)_{t-1}$	-0.176	-0.472
	(0.253)	(0.362)
Constant	Yes	Yes
Fixed Effects	Yes	Yes
R-squared	0.415	0.491
Number of NUTS	30	30

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. The data on employment cover full time employees in the April to March period from the Labour Force Survey.*

Table 25 Baseline econometric results with the lagged youth employment rate as a control variable for the January 2015 to January 2016 specification

$\log(app)_{at}$ for different groups		
VARIABLES	All level 2/3	Level 2/3 for 16-18 age group
d_t	-0.00375	0.0283
	(0.0238)	(0.0432)
$d_t\theta_a$for group	0.00217*	0.000625
	(0.00114)	(0.000868)
$log(Youth\ Employment\ Rate)_{t-1}$	0.201	-0.345**
	(0.130)	(0.163)
Constant	Yes	Yes
Fixed Effects	Yes	Yes
R-squared	0.710	0.645
Number of NUTS	28	28

Source: Frontier Economics analysis, using data from the ILR and APS

*Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant. The youth employment rate applies to individuals aged 15 to 29 only. As the rate was only available at the calendar year level, we focus on the January specification. The two London areas are excluded from the analysis, because Eurostat only reports the rates by NUTS2 area (rather than the total number of people in employment and the total population separately).*

Triple Differences approach

Table 26 Results for the Triple Difference specification from October-December 2014 to October-December 2015

$growth\_app_{at} - growth\_emp\_control_{at}$			
VARIABLES	Level 2/3 for 16-18 age group	Level 2/3 eligible for AR and younger than 20	Level 2/3 eligible for AR and younger than 24
$d_t\theta_a$ for group	-0.112	0.342	-0.323
	(0.413)	(0.396)	(0.495)
Constant	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
R-squared	0.001	0.019	0.017
Number of NUTS	30	30	30

Source: *Frontier Economics analysis, using data from the ILR and APS*

Note: *Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant.*

Table 27 Results for the Triple Difference specification from January-March 2015 to January-March 2016

$growth\_app_{at} - growth\_emp\_control_{at}$			
VARIABLES	Level 2/3 for 16-18 age group	Level 2/3 eligible for AR and younger than 20	Level 2/3 eligible for AR and younger than 24
$d_t\theta_a$ for group	-0.470	0.290	0.0532
	(0.472)	(0.581)	(0.419)
Constant	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
R-squared	0.013	0.011	0.001
Number of NUTS	30	30	30

Source: *Frontier Economics analysis, using data from the ILR and APS*

Note: *Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Results in Green are statistically significant and positive. Results in Yellow are statistically insignificant.*

www.frontier-economics.com