Department for Education

Key Stage 2 attainment and early labour market outcomes

Research report

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All statistical analyses were performed using R Statistical Software (v4.1.2, R Core Team, 2021).

Executive summary

The main contribution of this report is to provide estimates of the changes in labour market outcomes associated with small improvements in KS2 test scores. Every pupil takes these tests in their final year of primary school and so these test scores represent the best available measure of primary school attainment. The data and methods used uncover key differences in the magnitude of estimates by subject and pupil subgroups.

Estimates are derived using the Longitudinal Educational Outcomes (LEO) data. LEO is an administrative dataset that links education records with income and employment records, for every child in the state school system in England. Although LEO provides detailed histories of education, employment, and earnings, it has its limitations. Linked records only exist for the 1985/86 birth cohort onwards, so, individuals' annual earnings can only be observed up until their early thirties. This report therefore focuses on labour market outcomes (both employment and earnings) between the ages of 25 and 33.

This report adds to a growing literature that uses LEO to estimate the labour market returns to attainment at various stages of a pupil's educational journey.[1] Previous estimates of the labour market returns associated with primary school attainment are limited to tests taken by individuals as part of the 1970 British Cohort Study. The findings from this report therefore help improve our broader understanding of the link between labour market outcomes and primary school attainment.

Key findings

The findings indicate that:

- The labour market return to increased overall KS2 attainment is positive. A one standard deviation improvement in KS2 test scores is estimated to be associated with a boost to earnings of around 24% in the early thirties. This is equivalent to almost £7,000 at age 33. It is also associated with a 2-percentage point increase in the likelihood of being employed at age 33.
- The equivalent improvement in KS2 maths attainment has a three-times larger effect on earnings and two-times larger effect on employment prospects at age 33, compared to KS2 English and science.
- Including controls for highest level of qualification, reduces the estimated increases in earnings. For improved attainment in KS2 English, the returns become insignificant, suggesting returns are generated through facilitating further higher-

[1] Existing studies at other stages include; Britton et al. (2020) on Higher Education, Espinoza and Speckesser (2019) on Further Education, and Hodge, Little and Weldon (2021a) on GCSEs.

level study. Whilst in maths, estimates remain significant, suggesting the skills acquired hold intrinsic value in the labour market.

- The labour market returns to KS2 attainment are larger for women than men. Between the ages of 25 and 33, in both percentage and absolute monetary terms, the equivalent improvement in attainment increases earnings more for women than it does for men. It also increases the probability of employment by 5-percentage point more.
- FSM eligible pupils have a 5-percentage point larger boost to their likelihood of employment through their late twenties and early thirties, compared to their more well-off peers, from the same improvement in KS2 attainment. They also experience remarkably similar percentage terms earnings increases, but the absolute monetary returns are smaller.
- Across the whole earnings distribution individuals have positive returns to KS2 attainment. In fact, the lowest earners have the largest returns, implying a universal raising of standards would reduce future income inequality.

Introduction

Key Stage 2 (KS2) encompasses the school years 3 to 6 in primary school. Since 1995[2], pupils have sat national assessments at the end of KS2 when they are typically 10 or 11 years old.

The government recently set out its ambitions to improve school-age outcomes. One of the missions stated in the Levelling Up White Paper (DLUHC, 2022) and reiterated in the Schools White Paper (Department for Education, 2022a) is that

> "by 2030, 90% of children will leave primary school having achieved the expected standard in reading, writing and maths" (Department for Education, 2022a)

The expected standard is defined as a pupil scoring a scaled score of at least 100.[3] The potential economic benefits of achieving this ambition have already been measured in billions of pounds (Department for Education, 2022b). However, these estimates rely on associations between GCSE attainment and lifetime earnings and do not link potential benefits directly to primary age attainment.

Existing evidence on the associations between primary age attainment and labour market outcomes is sparse. Specifically, there is no existing evidence that explores variation between KS2 test performance and labour market outcomes.[4] The measurement of the associations between primary age attainment and earnings has been limited to several analyses of the 1970 British Cohort Study[5], where participants had left primary school by the time KS2 tests were introduced.

This report estimates the effects on 'early career' (between the ages of 25 and 33) labour market outcomes, associated with marginal improvements in KS2 test scores. Effects on two key outcomes are examined; earnings given employment, and the probability of employment. The Longitudinal Educational Outcomes (LEO) dataset makes this possible. The administrative dataset allows individual level KS2 test scores and pupil characteristics, to be linked with data on earnings and employment. This is a level of detail that has, until relatively recently, been unavailable to researchers using other existing UK data.

The remainder of this report discusses the existing literature, methodology, outlines the results and provides further discussion.

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[2] The coronavirus pandemic meant assessments were cancelled in 2020 and 2021.
[3] Raw KS2 marks are converted into scaled scores, which allow comparisons over time. Scaled scores are between 80 and 120, pupils scoring at least 100 are said to have met the expected standard. More detail is available at: https://www.gov.uk/guidance/understanding-scaled-scores-at-key-stage-2.
[4] To the author's knowledge.
[5] Three of these studies are briefly reviewed in the next section.

Literature

There are no studies that attempt to examine the labour market returns to KS2 attainment.[6] The closest comparative studies use the 1970 British Cohort Study[7] (BCS) to examine the labour market returns to performance on tests[8] conducted at age 10. Here three such studies are briefly reviewed; Machin and McNally (2008), Crawford and Cribb (2013), and Gregg, Macmillan and Vittori (2019).

Machin and McNally (2008) assess the impact of the introduction of the National Literacy Project (NLP), a pilot programme run in 1996. As an extension, they use the 1970 BCS to quantify the size of the economic benefits generated through the positive attainment impact of the programme. They estimate Mincerian type models[9] to establish the association between age 10 reading scores and earnings at age 30. A one standard deviation improvement in reading scores is found to be worth between £830–£2,160 per annum. Assuming constant returns by age and a 3% discount rate, they then extrapolate the present discounted value between the ages 20 to 65.

Crawford and Cribb (2013) build on Machin and McNally (2008) by extending the analysis to both reading and maths, and consider variation over additional ages. They estimate earnings returns separately at ages 30, 34 and 38. Returns are found to be larger for equivalent improvements in maths scores, compared to reading scores. They report a 2%–7% return to a one standard deviation increase in reading scores compared to a 7%–15% return to a one standard deviation increase in maths scores. Returns are shown to be relatively constant across different ages and are also relatively robust to switching between weekly and hourly earnings.

Gregg, Macmillan and Vittori (2019) estimate a version of 'lifetime earnings' returns. They estimate the returns, including workless spells between the ages of 26 and 42 for males. The percentage returns are smaller than reported in previous papers, likely because this now includes periods of zeros earnings. They estimate a 2.3% return to a one standard deviation increase in reading scores and 6.3% return to a one standard deviation increase in maths scores. Additionally, they employ Quantile Regression to assess how the returns vary across the distribution of future earnings. They find a 'U' shaped relationship for Maths scores and a positive relationship for English scores, with insignificant returns at the lower end of the earnings distribution.

The improved availability of linked administrative data, LEO, has led to an expansion of studies exploring the returns to education in the UK. Whilst this report seeks to be the

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[6] That the author is aware of.
[7] The 1970 British Cohort Study follows a cohort of people born in a single week in April 1970. See https://cls.ucl.ac.uk/cls-studies/1970-british-cohort-study/ for full details of the study.
[8] The Edinburgh Reading Test and Friendly Maths Test are used, details of these tests can be found in Parsons (2014).
[9] Mincer (1974)

first to estimate the earnings returns associated with KS2 attainment, earnings returns have already been examined using LEO, at other educational stages.

The Institute for Fiscal Studies (IFS) have undertaken considerable analysis of the returns to higher education qualifications. As a headline, they estimate that obtaining an undergraduate degree is associated with a 20% increase in average net lifetime earnings (Britton, Dearden, et al., 2020). The detailed provided by LEO has enabled the exploration of the variation in returns by subject and institution (Britton, Dearden, et al., 2020), socio-economic group and ethnicity (Britton, Dearden and Waltmann, 2021), degree classification (Britton et al., 2022) and postgraduate study (Britton, Buscha, et al., 2020).

The Centre for Vocational Education Research (CVER) have explored the returns to vocational education. They find positive returns across a range of different qualification levels (Patrignani, Conlon and Hedges, 2017) and have uncovered variation by subject (Battiston et al., 2019). Previous DfE work has explored the lifetime returns to improved GCSE attainment, again providing detailed estimates by subject and pupil subgroups (Hodge, Little and Weldon, 2021). They find a one standard deviation improvement in overall GCSE performance is associated with £96,000 of discounted earnings over a lifetime.

Data

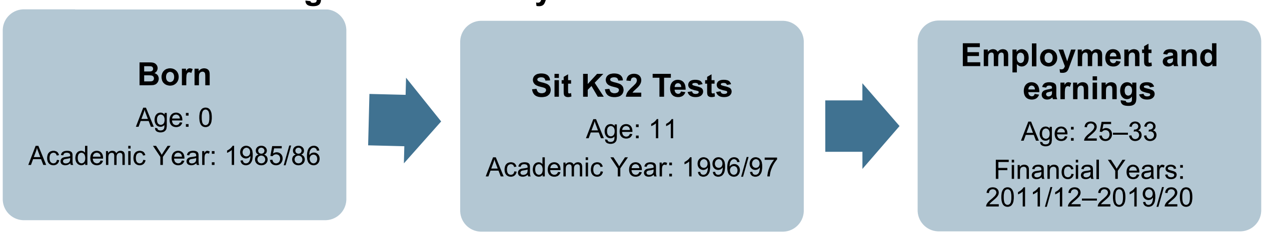
Longitudinal Educational Outcomes (LEO)

Longitudinal Educational Outcomes (LEO) is an administrative dataset that links the Department for Education's National Pupil Database (NPD), containing pupils school records, with various HMRC and DWP datasets containing detailed information on employment, earnings, and benefit claims. The 1985/86 birth cohort[10] is the earliest cohort for which this data link is possible.

Data is currently available on declared earnings and employment up to and including the 2020/21 tax year, when the individuals in the earliest cohort were approximately 34 years old. Unfortunately, the introduction of the furlough scheme during the Coronavirus pandemic has made earnings data collected in the 2020/21 tax year incomparable to previous years and so it is excluded from the analysis. An additional consideration is that information on earnings for self-employed persons is only available between the 2013/14 and 2019/20 tax years. This is particularly relevant when conducting analysis of the associations between KS2 attainment and the probability of being in employment. Using data outside of this range may lead to self-employed persons being mistakenly identified as not employed.

The NPD contains full school records of pupils in state funded schools.[11] This includes attainment scores, such as KS2 test results, and pupils' characteristics. It identifies which primary school a pupil attended, their gender and ethnicity, whether they were eligible for Free School Meals (FSM), had Special Educational Needs (SEN) and/or if English was their first language are all identifiable in the data. Unfortunately, the data does not capture some of the potential wider contributions, such as parental income and occupation, pupils' home learning environment or measures of pupils' non-cognitive skills.

Figure 1: 'Journey' for the 1985/86 birth cohort



[10] Individuals born between the 1st of September 1985 and the 31st of August 1986.
[11] Pupils that attended non-state-funded schools are excluded from all analysis in this report.

The analysis presented in this report focuses on the earliest available cohort of pupils in LEO, those born between September 1985 and August 1986. Using the earliest possible cohort of pupils maximises the period in the labour market that individuals can be observed. Figure 1 illustrates the 'journey' this cohort of pupils has taken over time. These pupils sat their KS2 tests in summer 1997, at the end of primary school. By the financial year 2019/20, the latest year of usable data, they were 33 years old.[12] Sensitivity analysis is performed using the three subsequent cohorts to check that the selection of one particular year group does not inadvertently bias results.

Key Stage 2 assessments

Statutory assessments at the end of KS2 were first introduced in 1995. These tests have evolved since, but their primary objective has remained the same, to test pupils' basic skills at the end of primary school. A timeline of key changes is provided in Appendix A. Tests are taken at the end of year 6 when pupils are typically 10 or 11 years old, in English, maths and science.[13] Importantly, the tests are externally set and marked. The results of KS2 tests are 'high stakes' for primary schools, as they are published in national school performance tables (since 1996). However, results are relatively 'low stakes' for pupils themselves, for instance, they have no bearing on the secondary school a pupil attends.

Figure 2 illustrates the raw mark distribution for the 1996/97 KS2 cohort. English tests were marked out of 100, science and maths tests out of 80. The mark distributions are relatively symmetric, although the distribution of maths and English marks have a slightly longer left tail. A measure of total KS2 attainment is created by evenly weighting the three subject marks.[14] Prior to estimating the econometric models described below, the total attainment scores and the individual subject marks are standardised.[15]

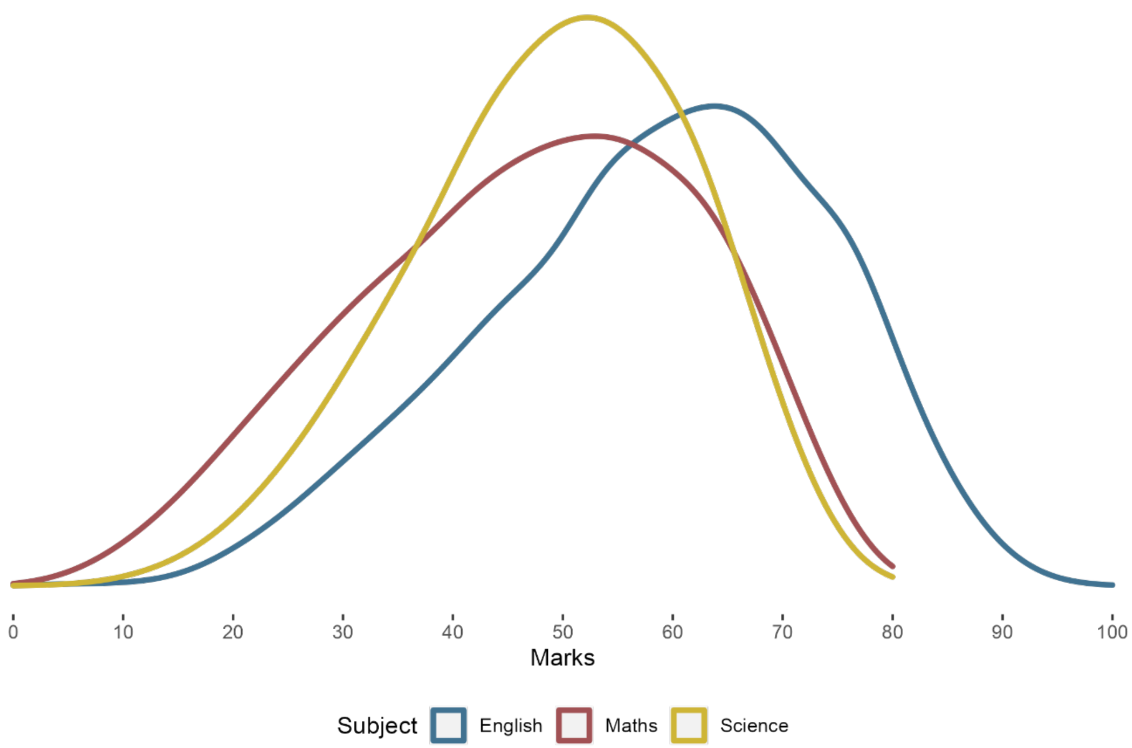
[12] All individuals born in the 1985/86 birth cohort were 33 years old for at least 5 months in the financial year 2019/20.

[13] Externally assessed science assessments were only taken until 2009. They have since been replaced by teacher assessments.

[14] The total attainment score is out of 300, $total_i = 100 * \sum_{s=1}^{3} \frac{mark_{i,s}}{\max(mark_s)}$

[15] The distributions of marks are standardised using the formula $z_i = \frac{x_i - \mu}{\sigma}$, where μ and σ are the mean and standard deviation respectively.

Figure 2: 1996/97 KS2 mark distribution, by subject



Notes: These are smoothed density estimates.

Methodology

This report estimates the associations between marginal changes in KS2 attainment and two key labour market outcomes;

- Earnings (*given employed*), and
- Probability of employment.

Earnings returns

To estimate the earnings returns associated with marginal improvements in KS2 performance a simple wage equation is used. At each age, Ordinary Least Squares (OLS) regression is used to estimate the linear equation:

$$\ln(w_i) = \alpha + \beta \boldsymbol{X}_i + \gamma \boldsymbol{Z}_i + \varepsilon_i \qquad (1)$$

where w_i are individuals' gross annual earnings, $\boldsymbol{X}_i$ is a vector of KS2 scores and $\boldsymbol{Z}_i$ is a vector of control variables. Coefficients are estimated on a sample that includes only employed persons at each age. The resulting estimated coefficients, $\hat{\beta}$, can be approximately interpreted as the percentage increase in gross annual earnings associated with a one standard deviation increase in KS2 test scores.[16] Several variations of the linear equation are estimated, with increasing numbers of controls in the $\boldsymbol{Z}_i$ vector. Despite accounting for a range of potential confounders, the results can still only be interpreted as strong associations rather than causal effects. For these to be estimates of the true causal effects of marginal changes in KS2 attainment on future earnings, it would have to be assumed there were no other unobserved factors which also affect individuals' earnings.

Six different specifications are estimated, varying both the $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$ vectors. $\boldsymbol{X}_i$ is either a vector of the three separate standardised subject scores (English, maths, and science) or the standardised total points score (a weighted summation across the three subjects). $\boldsymbol{Z}_i$ includes either:

1. Gender, region
2. [*Preferred specification*] Primary school attended, gender, Free School Meal (FSM) status, ethnicity, Special Educational Needs (SEN), English as Additional Language (EAL), IDACI.
3. As (2), with the addition of highest qualification level achieved

[16] The coefficients are in log points, so the transformation $(e^{\beta} - 1) * 100$ needs to be performed to derive a precise percentage increase. However, $\beta \approx (e^{\beta} - 1)$ for small values of β.

See Appendix E for a full breakdown of how these control variables are used in each of the models. Specification 1 is included as it is analogous to some of those reported in Machin and McNally (2008), and Crawford and Cribb (2013). Specification 2 adds additional controls to enhance this simple model, importantly capturing primary school attended and proxies for individual and geographical disadvantage (FSM status and IDACI). This is the preferred specification.

Specification 3 includes additional post-treatment controls for the highest level of qualification achieved. Whilst previous specifications estimate the total effect of improved KS2 attainment on earnings, this attempts to strip out the *indirect* effects generated through altered educational pathways and therefore identify the inherent value of higher KS2 skills in the labour market (the *direct* effect). However, it has been argued that the inclusion of post-treatment[17] controls can create a version of traditional selection bias (Angrist and Pischke, 2009). Machin and McNally (2008) argue estimates of earnings returns that control for future education should be viewed as a "lower bound estimate (or even an under-estimate)". Results from such a specification are included to give some insight into the decomposition of effects but should be treated with caution. The *total effect* though, as estimated using specification 2, is most pertinent given the economic value of any policy that improves KS2 attainment should include any benefits derived from the educational pathways opened to individuals as a result.

It is plausible that the earnings returns may differ for individuals depending on where they place in the earnings distribution. A given marginal improvement in KS2 attainment, may provide greater returns to individuals with high future earnings than someone in a low paying job, or vice versa. The linear regression model described above, allows for the estimation of the conditional mean of the outcome variable (logarithmic wages). To provide greater insight into the possible variations over the earnings distribution, quantile regression (Koenker and Bassett, 1978) is used to estimate a series of conditional quantiles of the outcome variable:

$$Q_\tau(\ln(w_i)) = \alpha(\tau) + \beta(\tau)\boldsymbol{X}_i + \gamma(\tau)\boldsymbol{Z}_i,\ \ \tau = 0.1, \dots, 0.9 \qquad (2)$$

where τ indicates the quantile of interest and Q is the conditional quantile function. This method allows the returns at a given percentile to vary, independently of any other percentile. The resulting estimates can provide useful insights into the extent to which improved attainment exacerbates or reduces future wage inequality.

There is precedent for using quantile regression to explore heterogeneities in the returns to education. Existing work has largely focused, as with the rest of the returns to education literature, on the return to an additional year of schooling (see Harmon, Oosterbeek and Walker (2003); Harmon, Walker and Westergaard-Nielsen (2001);

[17] In this case the 'treatment' is pupil attainment on KS2 tests.

Martins and Pereira (2004); Walker and Zhu (2001)). Other work has explored the heterogeneity in returns to attending HE (Walker and Zhu, 2013). Gregg et al. (2019) use quantile regression techniques to identify heterogeneities in the impact of age 10 test scores on earnings across the distribution. Maths scores exhibit a 'U' shaped relationship over the 'lifetime' earnings distribution, with bottom and top earners benefiting from the highest returns. English test scores though exhibit a positive slope over the distribution of earnings, with insignificant returns for those at the lower end of the earnings distribution.

Employment probability

The earnings return estimates provide insight at the 'intensive' margin. To what extent individual wages vary with attainment in KS2 tests, provided they are employed. The effects at the 'extensive' margin are also of interest, how the likelihood that individuals will be employed varies with attainment.[18] Employment is known to be an important determinant of life-satisfaction, regardless of the wage offered (Grün et al., 2010; Layard et al., 2012).

It is important that self-employed persons are identifiable and included in any analysis of the probability of employment, else they will be mistakenly treated as not employed. This limits the useable sample to the tax years 2013/14–2019/20, when the 1996/97 KS2 cohort were between the ages of 27 and 33. Linear models of the same formulation as those used to estimate the earnings returns are estimated. Emp_i, a binary employment indicator, is modelled as a linear combination of the vectors $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$, containing standardised KS2 scores and control variables respectively:

$$Emp_i = \alpha + \beta X_i + \gamma Z_i + \varepsilon_i \tag{3}$$

This type of model is commonly known as a Linear Probability Model (LPM). The estimated coefficients, $\hat{\beta}$, can be approximately interpreted as the percentage point increase in the probability of employment associated with a one standard deviation increase in KS2 test scores.

As before, the identification strategy relies entirely on selection on observables. For the results to be causal estimates of KS2 attainment on the probability of employment, it would have to be assumed that there are no other factors apart from those included in the vector of control variables ($\boldsymbol{Z}_i$) that contribute to an individuals' likelihood to be employed. Therefore, these findings should again be viewed as strong associations, rather than causal estimates.

An alternative to estimating the LPM described in equation 3 would be to use a nonlinear binary response model, such as a probit or logit. The main advantage of using the linear

[18] An individual is treated as employed if they have non-zero earnings in a given financial year.

model is that it would be computationally challenging to estimate the equivalent nonlinear binary response model (Greene, 2004). The raw coefficients from a nonlinear model are also harder to interpret directly and calculating average marginal effects across many parameters in a large dataset is infeasible. This is pertinent for the preferred specification which requires the estimation of a large number of fixed effects (16,194 primary schools).[19]

There are three potential issues with using LPMs to estimate binary outcome models, however, these can be allayed:

1. **Estimates obtained using a LPM are not constrained to the unit interval which can generate bias and inconsistent estimates.** However, Horrace and Oaxaca (2006) show that the introduced bias is proportionate to the fraction of predicted probabilities outside of [0,1]. So, provided the LPM model predicts few probabilities outside the unit interval the estimates can be expected to be broadly unbiased.

2. **OLS estimation imposes heteroskedasticity in the case of a binary response variable.** However, any introduced heteroskedasticity can be counteracted using heteroskedasticity-consistent standard error estimators.[20]

3. **A linear model will not produce true marginal effects.** This is also true for the 'wrong' nonlinear model. Given the true underlying model is unknown, any given nonlinear model will likely still not estimate the true marginal effects.

Appendix D compares the use of the LPM with an alternative probit model, to validate the suitability of the chosen model.[21]

[19] Individual school-level fixed effects do not need to be estimated directly in the LPM, but instead can be implemented using the within transformation. This is not possible when using a non-linear model.
[20] This report uses the HC1 estimator, see MacKinnon and White (1985) for details.
[21] Both models are estimated using specification 1, which includes controls for region and gender only. Estimating probit models with more sophisticated specifications is too computationally expensive, due to the inclusion of school level fixed effects.

Results

Earnings returns by age

This section estimates the earnings returns at each age between 25 and 33. Further investigating variation in the return by:

- KS2 subject,
- gender and Free School Meal (FSM) status, and
- the future income distribution.

Throughout this section the estimates shown in the figures, and described in the text, have been adjusted so they can be precisely interpreted as the percentage increase in earnings.[22] 95% confidence intervals are constructed for each estimate by first calculating heteroskedasticity-consistent standard errors using the HC1 estimator[23], and then also subsequently adjusting. Tables containing all the results can be found in the accompanying supplementary tables.

Total KS2 marks

First, the linear model described in equation 1, where $\boldsymbol{X}_i$ is a vector of overall standardised KS2 scores[24] is estimated. The results are shown in Figure 3. Using the preferred specification, the estimated annual earning returns increase through the late twenties before levelling off in the early thirties. Estimates suggest earnings returns are around 15% at age 25, rising through the late twenties, before reaching around 24% in the early 30's.

Estimates of the earnings returns obtained using specification 3, which includes post-treatment controls for the highest level of qualification achieved, are much more consistent across all ages. A relatively constant 12% return is estimated across the full range of ages. These estimates attempt to capture the inherent value of higher KS2 skills in the labour market, regardless of future educational pathways. Taken together with the estimates using specification 2, this would indicate that the variation over the late twenties in the earnings returns is predominantly due to improved KS2 attainment altering educational pathways. A simple decomposition would suggest that in the early thirties, 50% of the earning return is attributable to higher educational pathways and 50% is attributable to the inherent value of skills measured at the end of KS2. This

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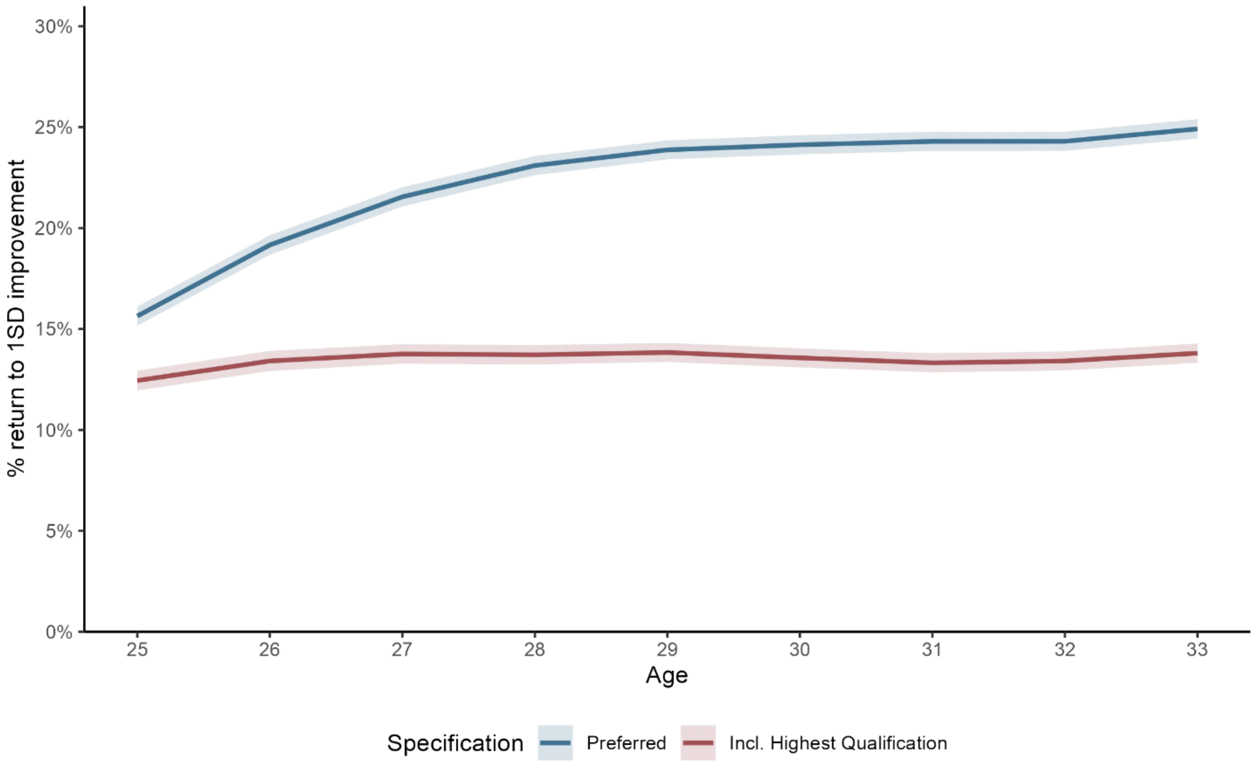
22 $\hat{\beta}_{adj} = (e^{\hat{\beta}} - 1) * 100$ where $\hat{\beta}$ are the estimated coefficients of interest.

23 See MacKinnon and White (1985) for details of the HC1 estimator. Estimation uses the 'estimatr' package (Blair et al., 2022).

24 The weighted summation of KS2 test scores in English, maths, and science. This new aggregated quantity is then standardised.

interpretation should be viewed with caution. Machin and McNally (2008) argue estimates of earnings returns that control for future education should simply be viewed as a “lower bound estimate (or even an under-estimate)”.

Figure 3: Estimated returns to overall KS2 attainment



Notes: The preferred specification (blue) includes controls for Gender, Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. The other specification (red) adds controls for the highest qualification level achieved. Standard errors are calculated using the HC1 estimator. The raw log points estimates have been translated into percentages.

The linear model imposes that earnings returns are constant across the distribution of attainment. In other words, the linear model presumes that a top performing pupil who increases their KS2 score by one mark, will see the same earnings increase as a lower performing pupil also achieving one extra mark. Appendix C compares the linear approach with an alternative non-parametric approach which relaxes this assumption of linearity. The resulting non-parametric estimates are approximately linear, suggesting returns are indeed constant across the distribution of attainment. This helps verify that the linear model does not impose problematic constraints.

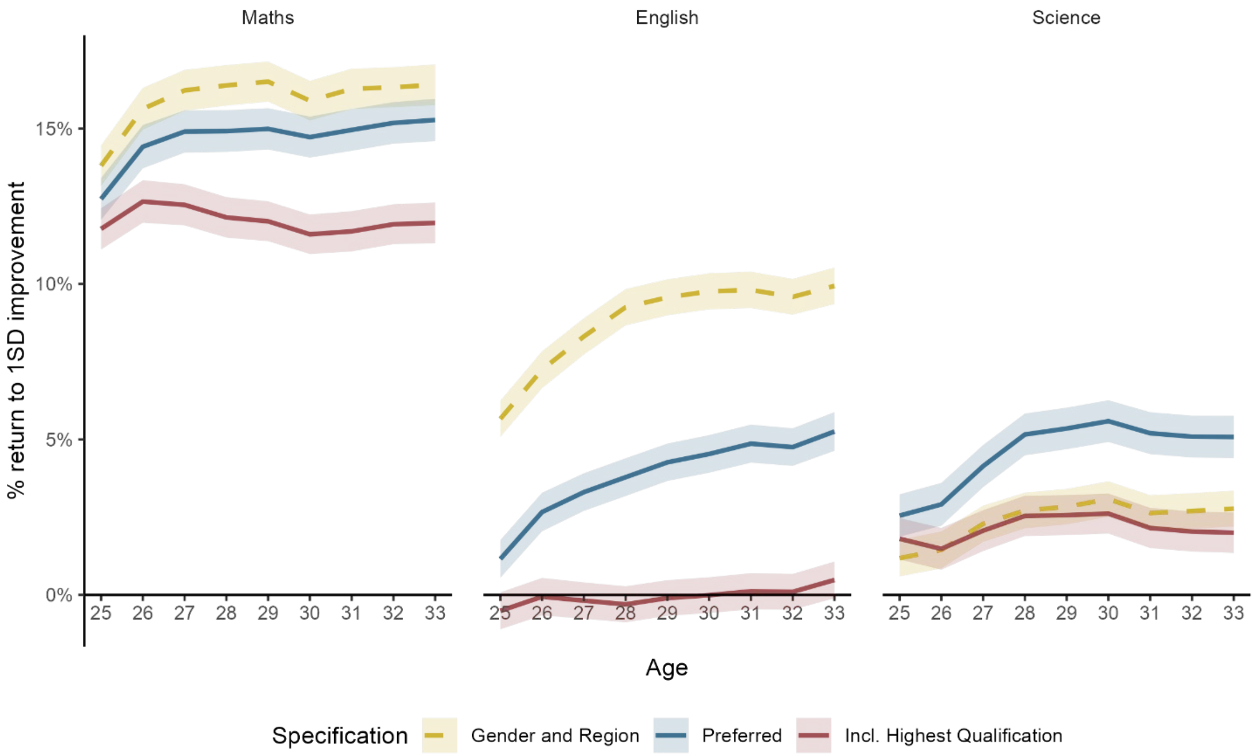
Differences by KS2 subject

Earning returns are found to be largest to increased attainment in KS2 mathematics vis-à-vis English and science. This holds true across all the specifications. The preferred specification implies that returns to English increase over age, with returns rising from 1% at age 25 to 5% by age 33. Earnings returns to science follow a similar pattern, also reaching around 5% by age 33. The earnings return to maths are more constant across age, a one standard deviation change in test scores is estimated to be associated with around a 15% increase in earnings between the ages of 26 and 33.

The specification that also controls for highest education level obtained (3), finds null earnings returns for improved attainment in KS2 English. This suggests that the skills assessed in KS2 English may not hold much direct value to employers in the labour market by employers. However, given the positive returns estimated in specification 2, improved attainment in KS2 English appears to instead acts as a facilitator. Opening downstream educational opportunities to individuals, that in themselves are likely to increase future earnings.

Improvements in KS2 maths attainment also in part do likely increase earnings through facilitating further study. Shown by the lower estimates when highest education level is included in the model. However, these skills appear to be valued by employers directly. In fact, the inherent value of basic numeracy seems to be the dominant effect in the labour market, with the inclusion of highest qualification in the specification only reducing the estimated returns slightly.

Figure 4: Estimated earnings returns by KS2 subject



Notes: Earnings returns to all three subjects are estimated simultaneously in the same equation. The first specification (yellow) includes controls for gender and region. The preferred specification (blue) adds Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. The final specification (red) adds controls for the highest qualification level achieved. Standard errors are calculated using the HC1 estimator. The raw log points estimates have been translated into percentages.

The estimates obtained by subject can be compared to those reported in Crawford and Cribb (2013). The specification shown in dashed yellow in Figure 4, only controls for gender and region are included, mirroring one of their specifications. At age 30, Crawford and Cribb (2013) find earnings returns of 6.1% and 14.4% for one standard deviation improvements on age 10 reading and maths tests, respectively. Similarly, larger returns are estimated for marginal improvements in KS2 maths test scores (15.5%) than for an equivalent improvement in KS2 English scores (9.5%). Whilst this pattern is consistent with that observed by Crawford and Cribb (2013), the magnitude of effect is larger for both subjects. This is more acute for improvements in reading/English. There are several possible explanations for these discrepancies, including the tests used, the time difference between cohorts, the sample sizes and the measure of earnings used.

Monetary returns

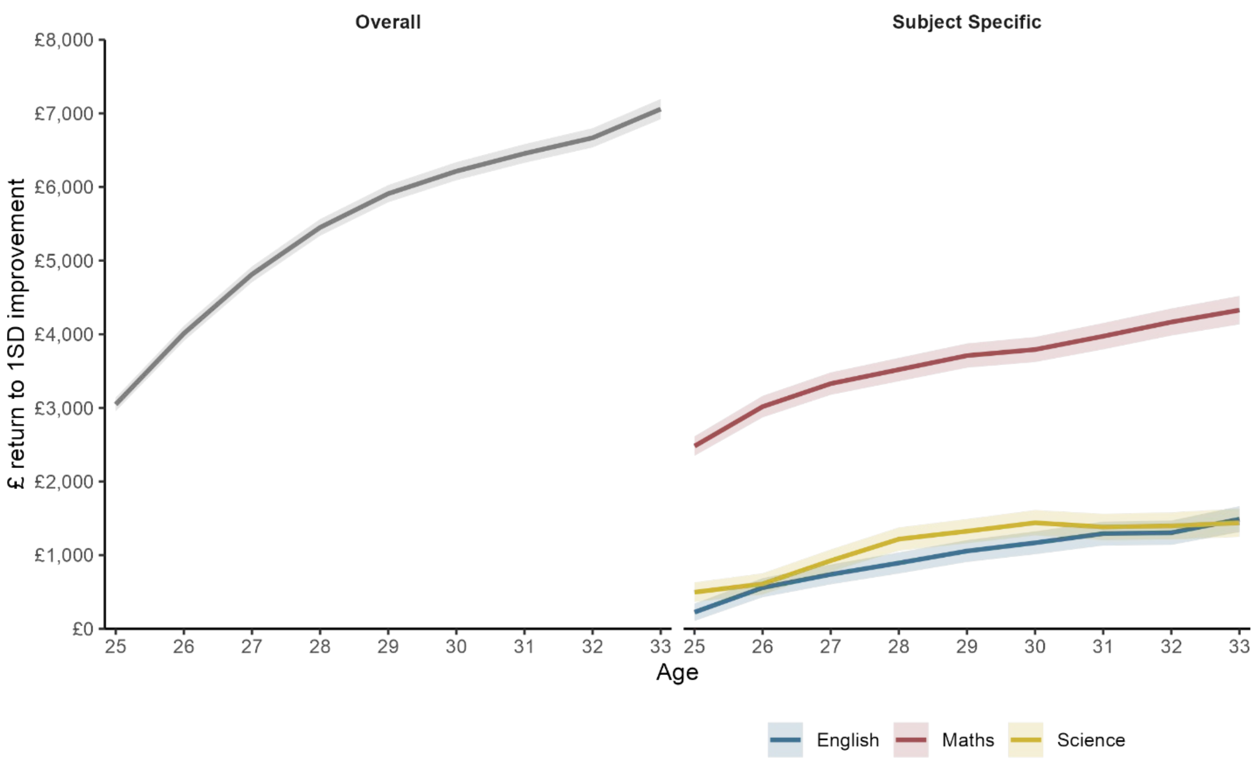
The preceding results estimate the percentage earnings return to improvements in both overall and subject specific KS2 attainment. This is in part for ease, the logarithm of annual earnings is used in the regression models, so the raw coefficients are in log points, easily translatable to a percentage. This is the well-used approach to estimating earnings equations since Mincer (1974) and allows for the comparisons with previous studies. Additionally, a percentage uplift is potentially more informative for inferring long-term patterns, something explored further in the discussion section below.

However, for individuals, a more meaningful measure of the earnings returns is the monetary value of a given improvement in attainment. Focusing on the results estimated under the preferred specification, the annual percentage returns at each age (shown in Figures 3 and 4) are multiplied by the mean average earnings at each age (in 2020/21 prices, undiscounted). Figure 5 shows the resulting undiscounted monetary returns to overall KS2 attainment are strictly increasing over the period. Despite the flattening of percentage terms returns in the early thirties, given the profile of wages is increasing throughout the period (see Figure 15), the monetary earnings returns continue to rise in the early thirties.

A one standard deviation improvement in overall KS2 attainment is worth £3,000 at age 25, £6,000 at age 30, rising to £7,000 by 33. Interpreting these numbers should be done with some care, they are in constant prices (2020/21) but are not discounted. Patterns by subject mirror those in Figure 4, given the same multiplier (average earnings) is applied. A one standard deviation improvement in KS2 maths performance has a considerably larger return (£4,000 at age 33) than the same improvement in either English or science (£1,500 at age 33).

Machin and McNally (2008) estimate monetary valuations of age 10 tests in the 1970 BCS. Controlling for gender and region, they find a one standard deviation improvement in reading scores to be worth £2,160 at age 30, in 2001 prices. This is equivalent to £3,275, in 2021 prices.[25] This helps verify the magnitude of the findings estimated in this report. An almost identical model (specification 1) suggests the same improvement in KS2 English scores is associated with an earnings boost of £2,515.[26]

Figure 5: Estimated monetary returns to improved KS2 attainment



Notes: Estimates using preferred specification which includes Gender, Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. Standard errors are calculated using the HC1 estimator. The raw log points estimates have been translated into percentages and then multiplied by the mean average earnings at each age. All figures are in 2020/21 prices but are undiscounted.

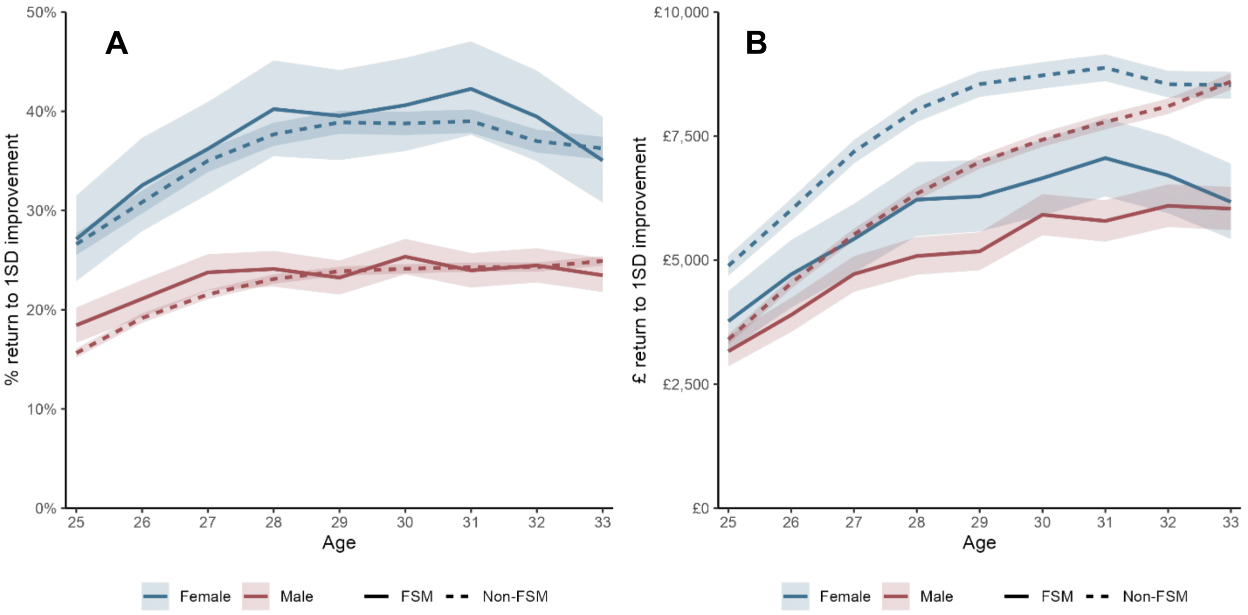
Differences by gender and FSM status

Gender and Free School Meal (FSM) status are included as interaction terms in the preferred model (specification 2). This allows for additional insight into how earnings

[25] Earnings inflated using the ONS CPI Index (Series ID: D7BT, Dataset: MM23).
[26] Estimate is not shown in figure, see supplementary tables.

returns vary for different sub-groups of the population. Panel A of Figure 6 shows the percentage earnings returns to a one standard deviation improvement in KS2 performance. Variation in returns is predominately driven by gender. Females experience a 9–18 percentage points higher return to the equivalent improvement in attainment than males do, across all ages. In contrast, FSM status has very little impact on the magnitude of percentage terms returns.

Figure 6: Earnings returns, by gender and FSM status



Notes: Estimates using the preferred specification which includes Gender, Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. Gender and FSM status are interacted with overall standardised KS2 attainment. Standard errors are calculated using the HC1 estimator. The raw log points estimates have been translated into percentages in panel A and subsequently multiplied by the sub-group mean average earnings in panel B. All figures are in 2020/21 prices but are undiscounted.

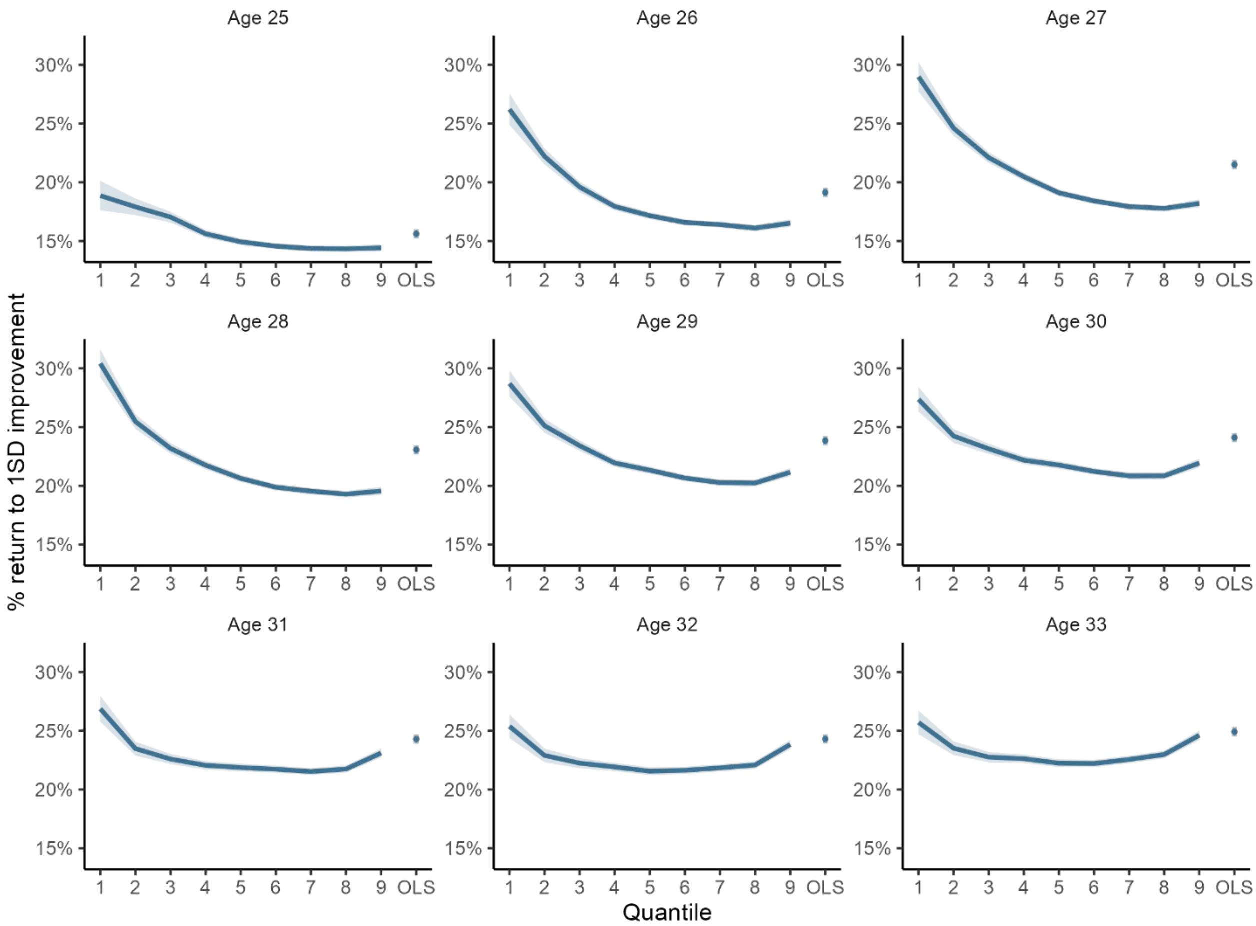
As above, whilst a comparison of the percentage terms earnings returns is useful, the absolute monetary returns are also of interest. Panel B multiplies the estimated percentage returns from the model, by the subgroup (mean) average annual wages. This allows us to measure the expected returns to a one standard deviation improvement in KS2 attainment in monetary terms. Given different subgroups have differing average age-earnings trajectories (see Figure 15) the pattern of estimated returns changes.

FSM status drives more of the variation in monetary returns between individuals than gender does. Whilst in percentage terms the returns are similar regardless of FSM status, in monetary terms non-FSM pupils have higher returns across all ages. This is likely driven by existing intergenerational income immobility, meaning those eligible for FSMs at school go on to earn, on average, less in the labour market, regardless of attainment.[27] As with the percentage returns estimates, females have broadly higher returns than males in monetary terms. By age 33 though, the 'gap' closes with gender making virtually no difference to the earning return.

Heterogeneity in the returns over the distribution of earnings

Next, the extent to which heterogeneities in the earnings returns exist across the future wage distribution are investigated. Figure 7 shows the results of estimating the earnings return at each decile of the wage distribution, at each age, using the Quantile Regression (QR) model described in Equation 2.[28]

Figure 7: Earnings returns, by decile of the earnings distribution



Note: Estimates using specification 2 which includes gender, Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. The raw log points estimates have been translated into percentages.

[27] Carneiro et al. (2022) show human capital can explain some but not all the observed variation in intergenerational income mobility.

[28] Implemented using the 'quantreg' package (Koenker, 2022).

Across the entire wage distribution[29] individuals see positive returns to improved KS2 attainment. However, these returns are not constant across the wage distribution. Across all ages, those at the bottom of the earnings distribution have larger estimated percentage returns to the equivalent improvement in attainment than those at the top. This pattern of effects does though appear to become less pronounced as individuals get older. A 'U' shape develops, where the returns are higher at the top and bottom of the wage distribution than in the middle.

Table 1: 10/90 and 10/50 ratios of earnings returns

Age	10/90 ratio	10/50 ratio
25	1.30	1.25
26	1.58	1.52
27	1.58	1.51
28	1.55	1.47
29	1.36	1.34
30	1.25	1.25
31	1.16	1.23
32	1.06	1.17
33	1.04	1.15

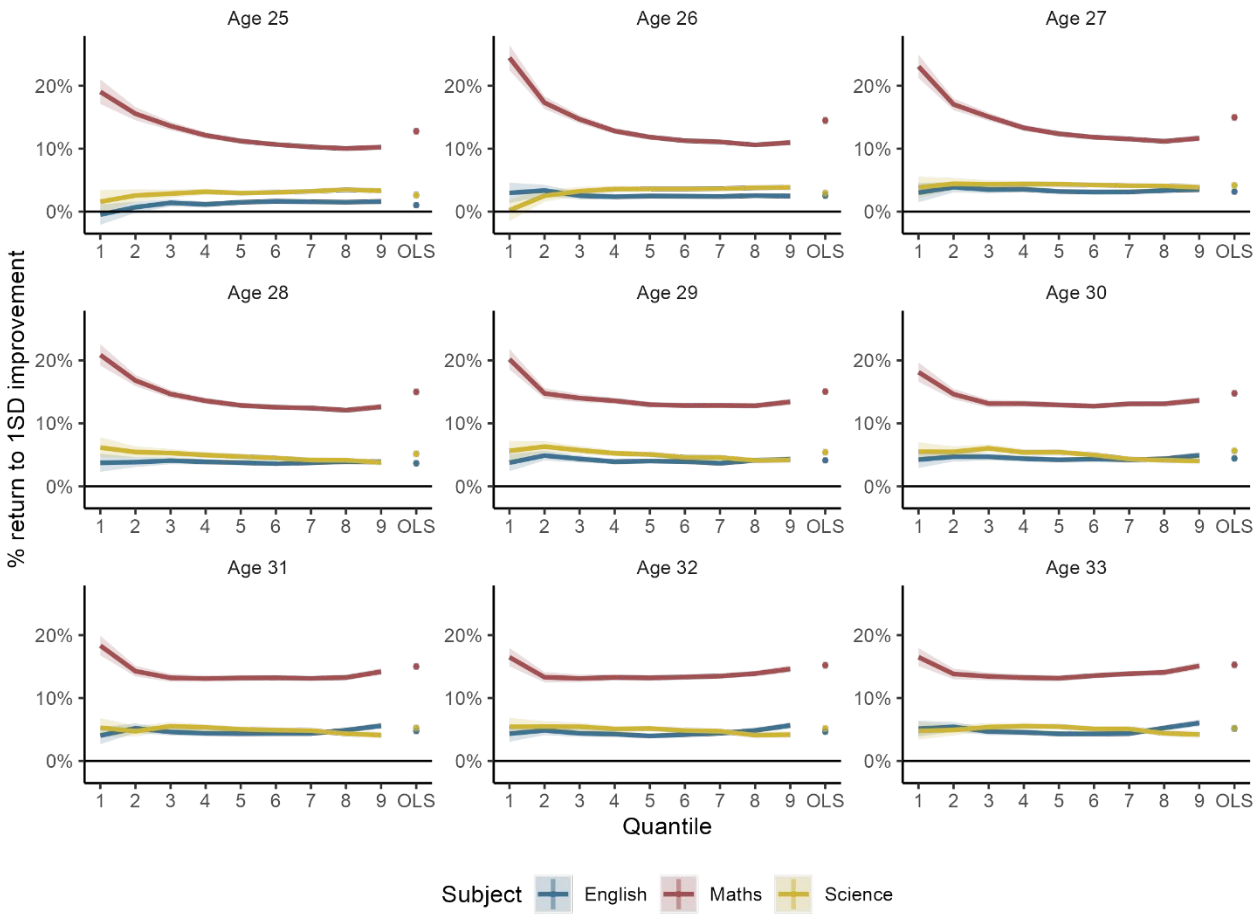
The 90/10 ratio, how much larger the earnings return at the 10^{th} percentile is compared to the 90^{th} percentile, for the same marginal change in attainment, gives a numeric quantity to compare.[30] This ratio never falls below one (see Table 1). Similarly, the 10/50 ratio is 1.15 at its lowest point. In other words, the earnings return for an earner at the 10^{th} percentile are always at least 15% larger, given an equivalent marginal attainment improvement, than for a median earner. This would suggest that a universal improvement in KS2 attainment, across all pupils, would likely reduce future wage inequality. Additionally, assuming there is some correlation between the earnings and ability distributions, this would imply that maximising the returns to education may require increasing educational investment for less able individuals.

The same QR model is used to explore whether heterogeneities in the earnings returns across the future wage distribution also exist for attainment in different subjects. Again, across the wage distribution individuals see positive returns to improved KS2 attainment in all subjects. Earnings returns to English and science attainment are relatively constant across the distribution at all ages. In contrast, the estimated earnings return to improvements in KS2 maths attainment vary, with low earners receiving higher returns. It therefore appears that maths attainment drives most of the patterns observed in overall returns. This is in line with the findings of Gregg, Macmillan and Vittori (2019), who find

[29] More precisely, the modelled percentiles of the distribution.
[30] Similar measures are typically used to look at income inequality.

that 'lifetime earnings' returns are 'U'-shaped for maths scores across the earnings distribution.[31]

Figure 8: Earnings returns, by decile of the earnings distribution, by KS2 subject



Note: Estimates using specification 2 which includes gender, Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. The raw log points estimates have been translated into percentages.

Sensitivity analysis

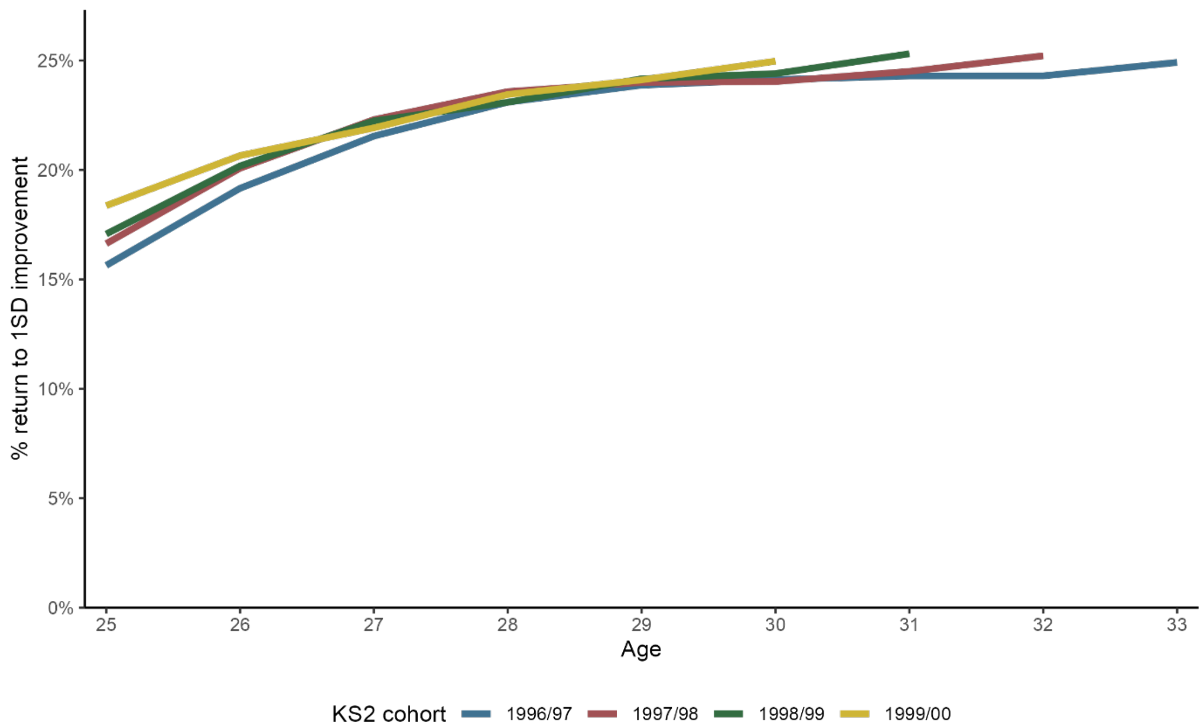
The sample of individuals used in the estimation of earnings returns has been limited to one cohort of pupils, who sat their KS2 tests in the 1996/97 academic year and have subsequently been employed through PAYE. This section describes two sensitivity analyses to help verify the restrictions placed on the estimation sample have not biased the resulting estimates.

[31] They find a positive relationship for English scores though, with insignificant returns at the lower end of the earnings distribution.

Year groups

First, models are re-estimated using the three subsequent cohorts of pupils, who sat their KS2 tests in the academic years 1997/98–1999/00. Figure 9 compares estimates across the four different cohorts of the earnings returns to a one standard deviation improvement in overall KS2 performance using the preferred specification. For the later cohorts there is less available earnings data as they were younger in the latest tax year (2019/20). There are some differences in the estimated returns at younger ages, but by age 28 the returns across different cohorts converge.

Figure 9: Earnings returns by age, comparing cohorts

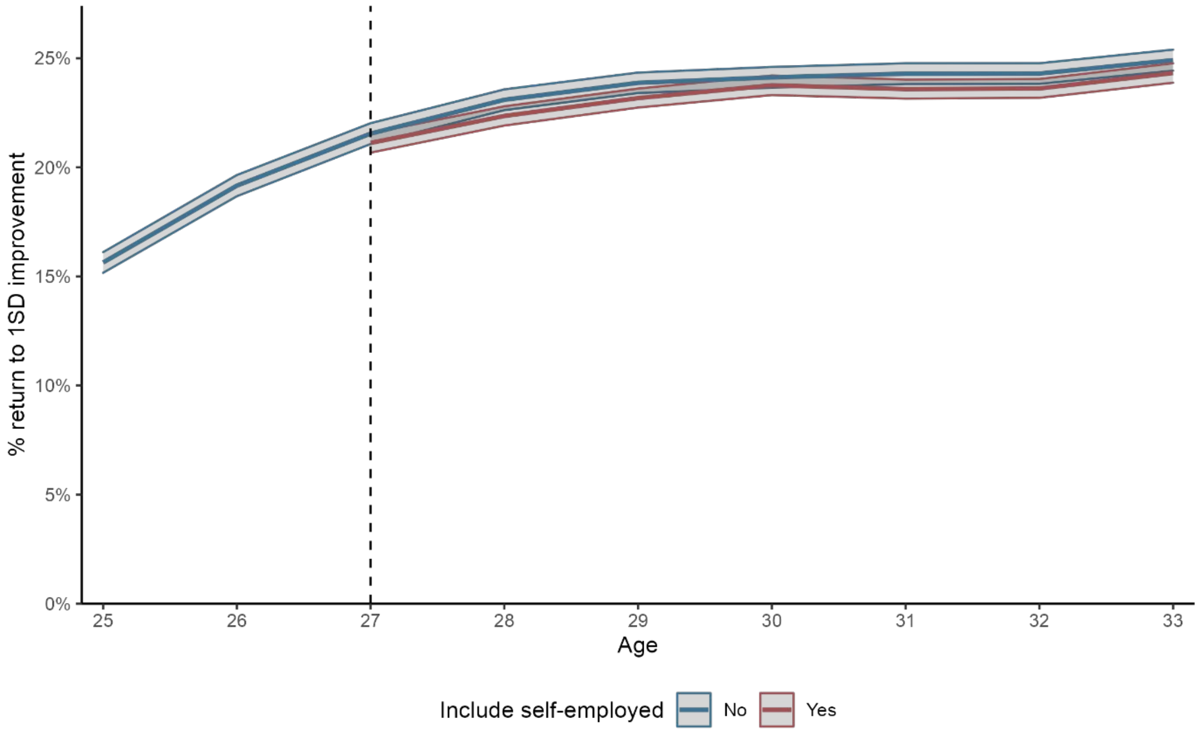


Notes: Estimates using specification 2 which includes gender, Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. The raw log points estimates have been translated into percentages. Confidence intervals are not plotted in the figure for readability purposes. All point estimates and the corresponding 95% confidence intervals are available in the supplementary tables.

Self-employed

Second, models are re-estimated with the inclusion of self-employed earners in the sample. The analysis so far has focused only on a sample of individuals employed and paid through HMRC's PAYE system. Data on the self-employed, collected through self-assessment tax returns, is only available for the tax years 2013/14–2019/20. For the 1985/86 birth cohort, between 4.3% and 5.8% of individuals are self-employed at each age and have not been included in the main analysis. It should also be noted that both the PAYE and self-assessment data likely underestimate earnings for some individuals as they do not include some alternative forms of income e.g., dividend payments.

Figure 10: Earnings returns by age, the inclusion of self-employment



Notes: Estimates using specification 2 which includes gender, Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. Standard errors are calculated using the HC1 estimator. The raw log points estimates have been translated into percentages

Excluding self-employed individuals could be problematic if they have very different patterns of earnings returns then other employed persons. However, given data constraints, dropping them allows for comparable analyses over a wider range of ages. Figure 9 compares the earnings returns estimates when self-employed individuals are excluded from the estimation sample (the main model), and when they are included. Below age 27 (to the left of the dashed line) self-employment data is unavailable for this cohort. From age 27 to 33, including self-employed persons in the sample reduces the annual earnings return by no more than 1 percentage point at each age.

Employment probabilities by age

This section estimates the employment returns at each age between 25 and 33. Further investigating variation in the return by:

- KS2 subject, and
- gender and Free School Meal (FSM) status.

Throughout this section estimation results from Linear Probability Models (LPMs), as outlined in Equation 3, are presented. The estimates can be interpreted as the percentage point increase in the probability of employment from a one standard deviation improvement in KS2 test scores. 95% confidence intervals are constructed using heteroskedasticity-consistent standard errors using the HC1 estimator.[32] Tables containing all the results can be found in the accompanying supplementary tables. Appendix D compares the headline results obtained using the LPM with an alternative probit model.[33]

Total KS2 marks

First, a model where $\boldsymbol{X}_i$ is a vector of overall standardised KS2 scores[34] is estimated. The results are shown in Figure 11. The estimated annual employment returns decrease steadily throughout the late twenties and early thirties. Estimates using the preferred specification suggest earnings returns are around 3.2pp at age 25, falling to 2pp by age 33.

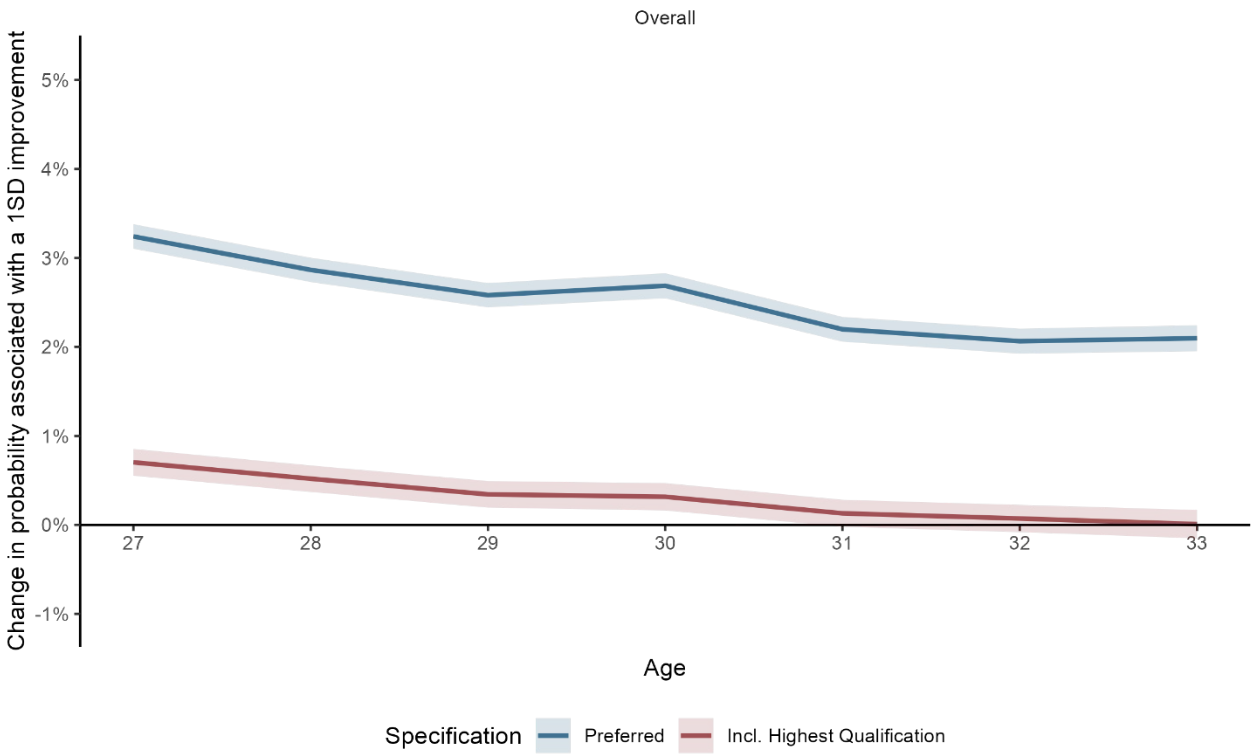
A one standard deviation increase in KS2 attainment is estimated to be considerably lower when post-treatment controls for the highest level of qualification achieved are included (specification 3). The associated increase in probability of employment is less than 1 percentage point across all ages and null effects are found in the early thirties. These estimates capture whether the innate value of KS2 skills can affect the probability of employment in the labour market, regardless of future educational pathways.

Previously, the observed increase in earnings associated with higher KS2 attainment was found to be explained by both the inherent value of skills measured at the end of KS2 and the ability to access higher level educational pathways, in approximately equal measure. The probability of employment, however, appears to be explained almost

[32] See MacKinnon and White (1985) for details of the HC1 estimator. Estimation uses the ‘estimatr’ package (Blair et al., 2022).
[33] Under specification 1, which includes controls for region and gender only. Estimating probit versions of the more sophisticated specifications is too computationally expensive, due to the inclusion of school level fixed effects.
[34] KS2 test scores in English, maths and science are added together for each pupil. This new aggregated quantity is then standardised.

entirely by KS2 attainment facilitating higher level study. As in the context of earnings returns above, this decomposition should be interpreted with caution.

Figure 11: Employment returns to improved KS2 attainment

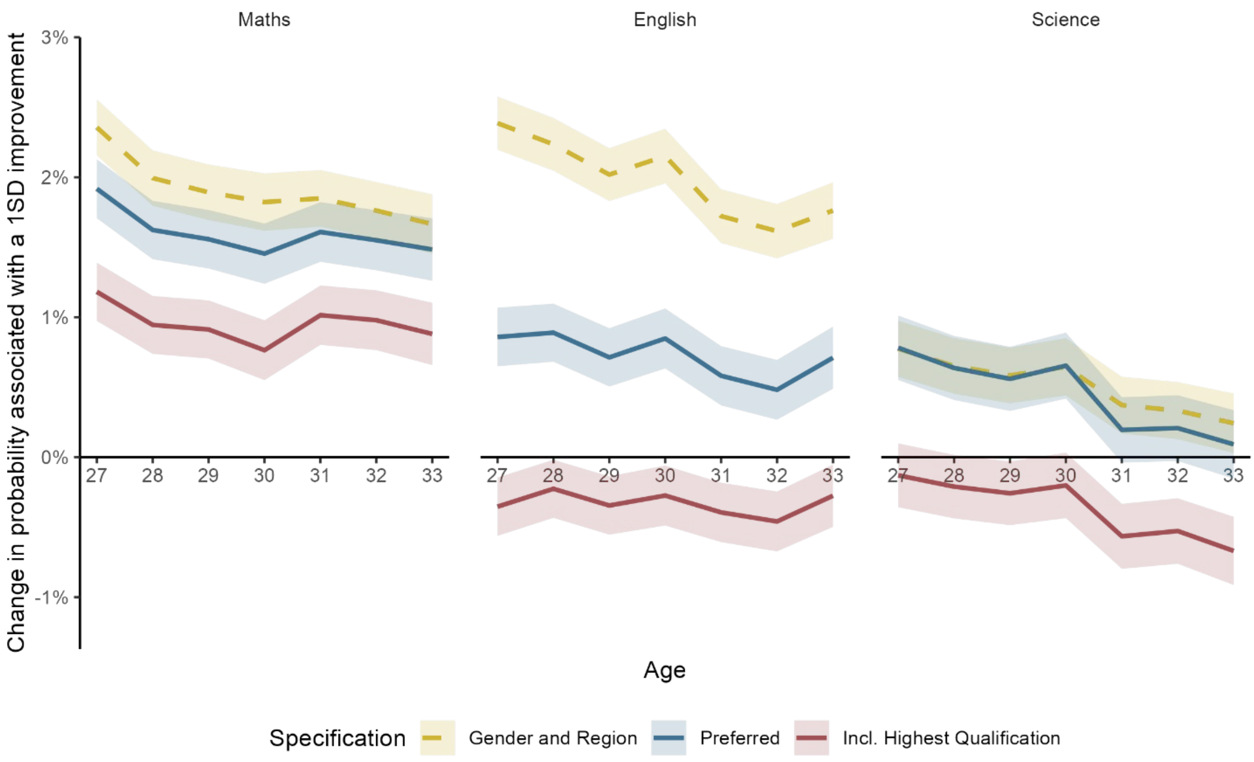


Notes: Specification 1 includes controls for gender and region. Specification 2 [preferred] adds Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. Specification 3 adds controls for the highest qualification level achieved. Standard errors are calculated using the HC1 estimator.

Differences by KS2 subject

As in the case of the earnings returns estimated above, employment returns are found to be largest to increased attainment in KS2 mathematics vis-à-vis English and science. The preferred specification indicates that returns to a one standard deviation improvement in English scores are consistently below 1 percentage point. Similarly returns to science are small and exhibit a decline over age, such that by the early thirties, estimated returns are not significantly different from zero. Returns to maths are much larger across all ages, although still decline over age. The employment return to a one standard deviation improvement in KS2 maths test scores is estimated to be around 2-percentage points at age 25, falling to 1.5-percentage points at age 33.

Figure 12: Employment returns to improved KS2 attainment, by subject



Notes: Employment returns to all three subjects are estimated simultaneously in the same equation. Specification 1 includes controls for gender and region. Specification 2 adds Free School Meal (FSM) status, Ethnicity, Special Educational Needs, English as Additional Language (EAL), IDACI and primary school attended. Specification 3 adds controls for the highest qualification level achieved. Standard errors are calculated using the HC1 estimator.

Using specification 3, a model that additionally controls for highest education level obtained, finds null (or even negative) earnings returns for attainment in KS2 English and science. This would appear to suggest these skills have little direct impact on the probability of employment in the labour market. The employment returns estimate for Maths on the other hand, remain positive at around 1 percentage point. As was the case for earnings returns, improved basic numeracy skills seem to have direct impacts on labour market outcomes, with the inclusion of controls for future educational journey's not eliminating the estimated employment returns.

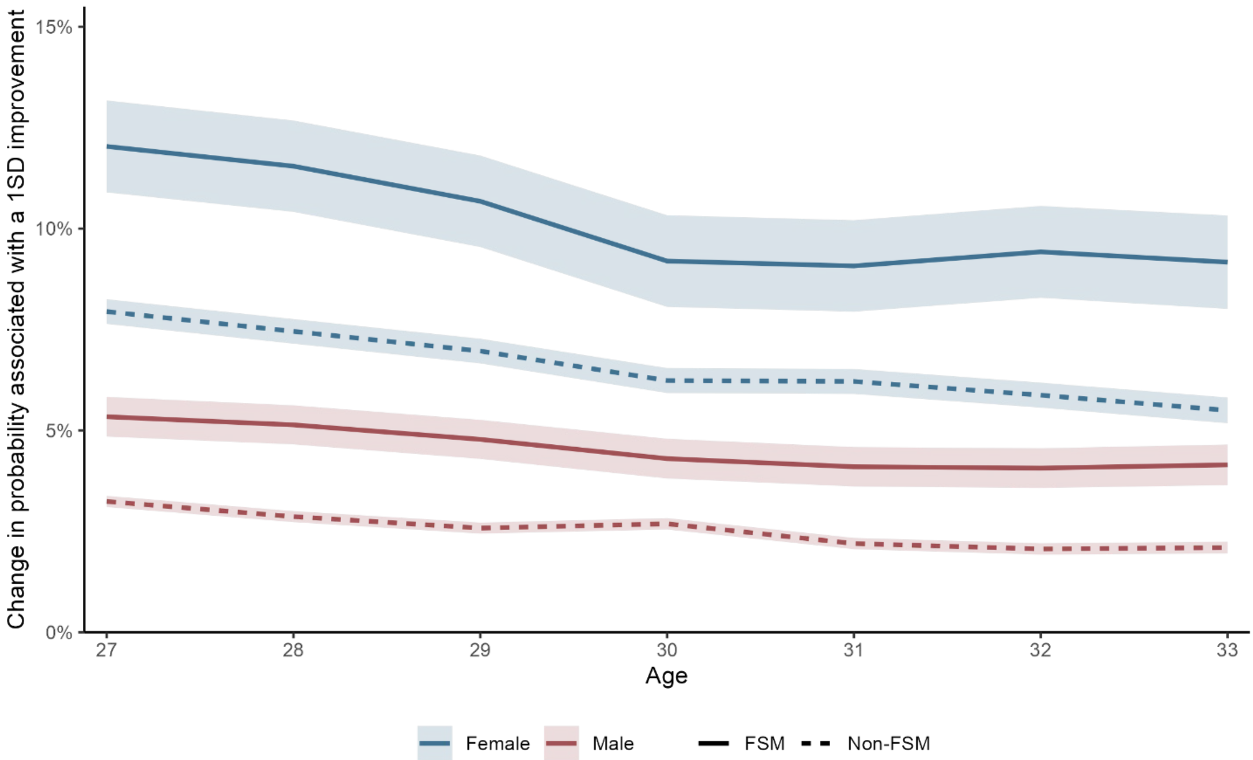
Differences by gender and FSM status

Gender and Free School Meal (FSM) status are included as interaction terms in the preferred model (specification 2). This again allows for additional insight into how earnings returns vary for different sub-groups of the population. Figure 13 shows the increase in the probability of being employed associated with a one standard deviation improvement in KS2 performance.

Women have a 5-percentage point greater boost to their employment likelihood than their male peers. This is true regardless of a pupils' FSM eligibility. This mirrors the findings above that females also experience higher earnings given they are employed, and suggests overall females experience greater labour market returns to improved KS2 performance. It should though be noted there are some difficulties with modelling participation decisions of females in adulthood that we cannot control for in this model, for example childbirth.

FSM eligible pupils though have higher employment returns than their more well-off peers. The boost to the probability of employment is up to 5-percentage points greater for the same improvement in KS2 test scores. This contrasts with the patterns observed in earnings returns, where percentage returns were found to be similar, but FSM eligible pupils were found to gain less in monetary terms.

Figure 13: Employment returns to improved KS2 attainment, by gender and FSM status



Discussion

This report has provided the first published labour market returns estimates to KS2 test scores. This is achieved using the LEO data and variation has been explored by subject, and by pupil characteristics. However, the available data cannot capture every variable that could plausibly affect both KS2 attainment and earnings. If there are important unseen characteristics that are correlated with both test scores and earnings, the estimates above will contain some bias. This section briefly describes some other key considerations surrounding these figures.

Implications for recent and future pupil cohorts

Forecasting the impact of educational attainment on labour market outcomes is inherently difficult. The sample of pupils used in this analysis sat their KS2 test twenty-five years ago. Using old data on test scores is unavoidable if the aim is to measure long-run outcomes. The implications of this time-lag though should be considered when using these and similar findings to make predictions in current policy contexts.

The premium that employers attach to different types and levels of skill changes, often unpredictably. The type and scarcity of foundational skills acquired during KS2 also changes over time. Syllabuses change, as does the reporting of results. For example, until 2014 pupils were awarded levels[35], but currently raw marks are converted to a scaled score, with 100 signifying the expected standard. For this reason, this report has focused on the distribution of raw marks and reported standard deviation impacts, with the aim of the findings being more generalisable.

Other challenges have been brought into focus by the Coronavirus pandemic, both through its disruption to KS2 exams[36] and its negative effects on the labour market. In addition, there are potential longer-term structural shifts in employment caused, for instance, by automation. These forms of uncertainty are not discussed in this report. However, when interpreting or using these estimates, it ought to be acknowledged that an observed relationship between KS2 attainment and earnings is a highly imperfect guide to the future.

Using figures in economic appraisal

Wages are commonly used to value the economic benefits of investments in education. There is a need for cautious interpretation and application of these estimates in economic appraisal. The Department for Education's 'Schools Policy Appraisal Handbook' (Hodge,

[35] Levels between 1 and 5 were awarded.
[36] KS2 assessments were cancelled in 2020 and 2021 due to the pandemic.

Little and Weldon, 2021b) provides detailed guidance on how to use returns estimates appropriately, in the appraisal and evaluation of school-based policy interventions.

Job market signalling, as outlined in the seminal work of Spence (1973), is often a key concern of any estimation of the returns to education. Test scores may signal a learner's innate motivation and abilities, irrespective of whether schooling augments productivity. Signalling effects are not thought to dominate the human capital enhancing impacts of improved attainment (Card, 2001, Wyness et al., 2021). They are also typically a larger concern when estimating the returns to higher level qualifications where attainment will likely be 'signalled' to employers, for example holding an undergraduate degree. KS2 test scores on the other hand are unlikely to be observed by employers in the labour market. However, as this report reveals, a certain fraction of the returns to higher KS2 attainment are likely generated through progression to higher educational pathways.

Another consideration is that earnings and employment outcomes predominately represent the private return to education, alongside the benefit to the exchequer (although these are not disaggregated in this report). These estimates do not capture potentially valuable improvements in productivity, welfare, and wellbeing. Neither do they capture the spill-over effects of increased human capital on other citizens or on the overall size of the economy.

Lifetime earnings

One plausibly use of the findings in this report would be to extrapolate earnings returns at older ages (beyond age 33). Some applied research has previously assumed there is a 1:1 relationship between current and lifetime earnings. Findings from this report indicate variation in the earnings return over age, which would suggest this does not hold true, at least for all ages. However, returns to overall KS2 attainment are found to level out and become constant in the early thirties. Between the ages of 30 to 33 consistent returns of around 24% are estimated.

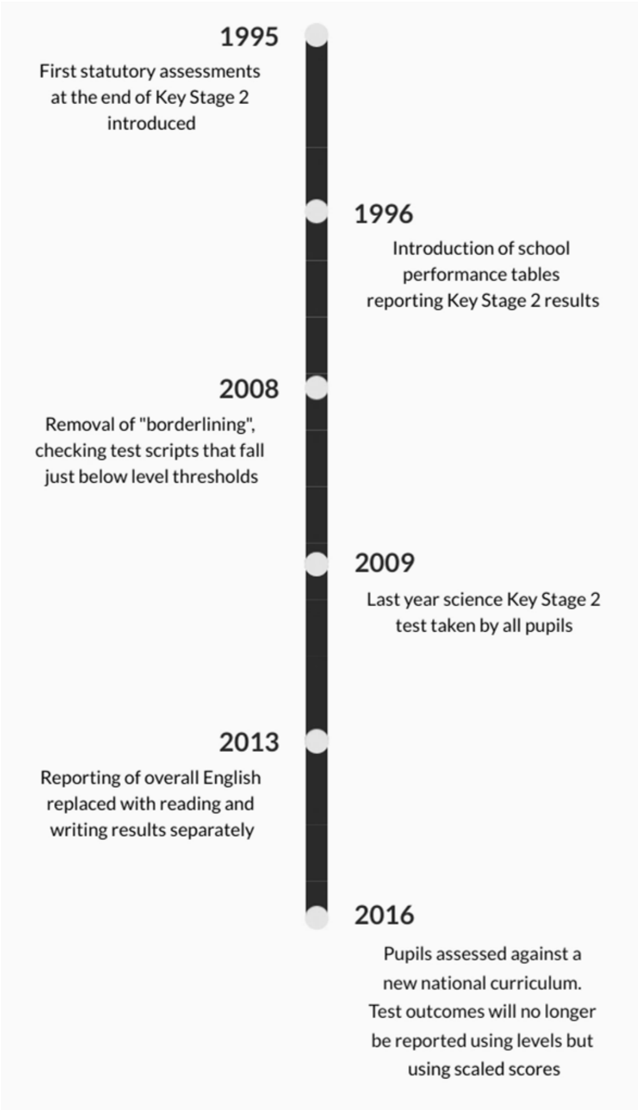
Haider and Solon (2006) find that current earnings are an adequate proxy for lifetime earnings between the early thirties and the mid-forties. This would suggest that that this level of annual return may be expected for lifetime earnings. Böhlmark and Lindquist (2006) find corroborating evidence that current earnings in the thirties and forties are an adequate proxy for lifetime earnings for men. However, they find significantly different patterns for women. Women display more variety in their life-cycle labour supply and income trajectories, and so the 1:1 relationship between the earnings return at any given age and lifetime earnings returns does not hold.

Therefore, extrapolating returns at older ages or for whole lifetime earnings should only be done with caution. Further direct exploration of the lifetime earnings returns to KS2 attainment akin to that of Britton et al. (2020) for undergraduate degrees and Hodge et al. (2021a) for KS4 attainment, would enable more robust conclusions to be drawn.

Appendices

A. Changes to KS2 assessments

Figure 14: Timeline of key changes to KS2 tests



Author's graphic. See p.43 of Bew (2011) and Annex F in Department for Education (2016) for a more detailed history of statutory assessment since the 1988 Education Reform Act and the introduction of the National Curriculum.

B. Summary statistics

Table 2: NPD Summary Statistics - 1996/97 cohort

Characteristic	N = 436,093
KS2 English Marks	58 (15) [Max:100]
KS2 Maths Marks	47 (15) [Max:80]
KS2 Science Marks	49 (13) [Max:80]
Total KS2 Marks	154 (40) [Max:256]
Gender	
Female	212,417 (49%)
Male	223,676 (51%)
English as an Additional Language (EAL)	31,163 (7.1%)
Ethnic Group	
Any Other Ethnic Group	6,846 (1.6%)
Asian	23,708 (5.4%)
Black	11,945 (2.7%)
Chinese	1,424 (0.3%)
Mixed	333 (<0.1%)
Unclassified	9,345 (2.1%)
White	382,492 (88%)
IDACI	0.20 (0.17)
Region	
East Midlands	37,895 (8.7%)
East of England	47,537 (11%)
London	52,061 (12%)
North East	25,489 (5.8%)
North West	67,969 (16%)
South East	65,636 (15%)
South West	41,789 (9.6%)
West Midlands	50,609 (12%)
Yorkshire and The Humber	47,108 (11%)
Highest Qualification Level	
Level 0	8,293 (1.9%)
Level 1	68,325 (16%)
Level 2	80,556 (18%)
Level 3	122,473 (28%)
Level 4	6,317 (1.4%)
Level 5	10,884 (2.5%)
Level 6	103,252 (24%)
Level 7	32,410 (7.4%)
Level 8	3,583 (0.8%)
FSM eligible	51,446 (12%)
SEN provision	
No SEN	373,840 (86%)
SEN	55,756 (13%)
SEN with statement	6,497 (1.5%)

Note: Mean (SD) [Max: Maximum]; n (%); Mean (SD).

Figure 15: Annual earnings by demographics

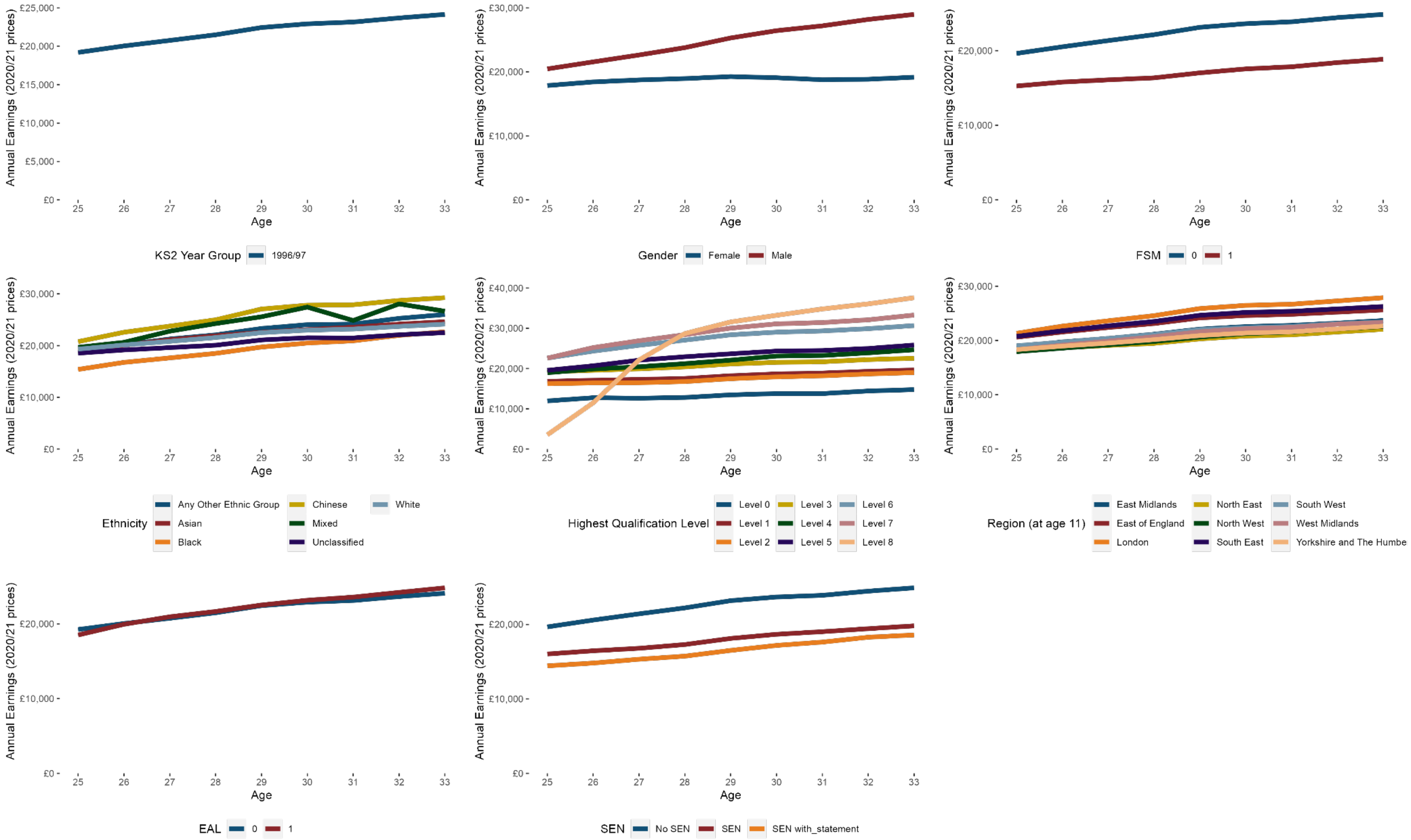
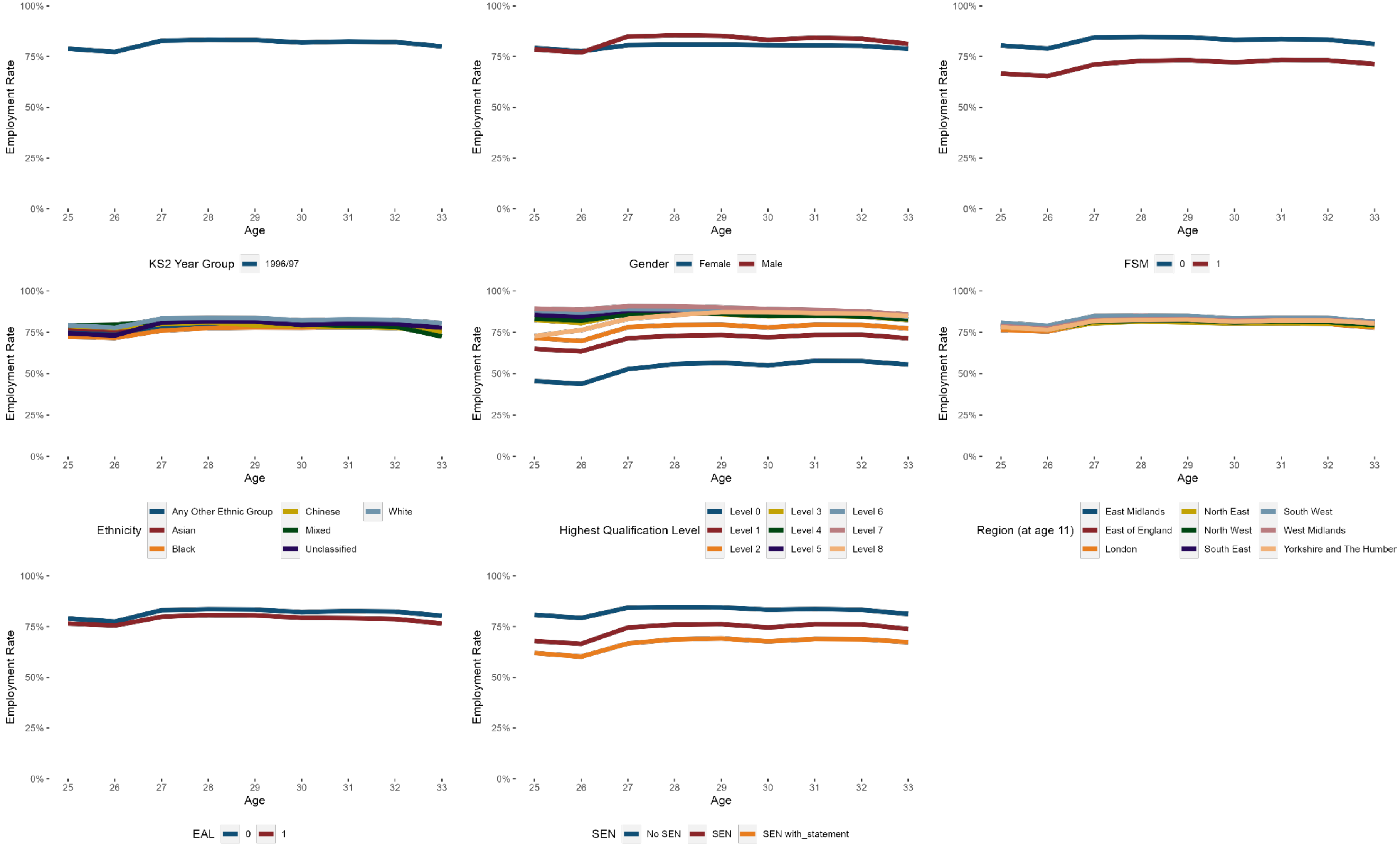


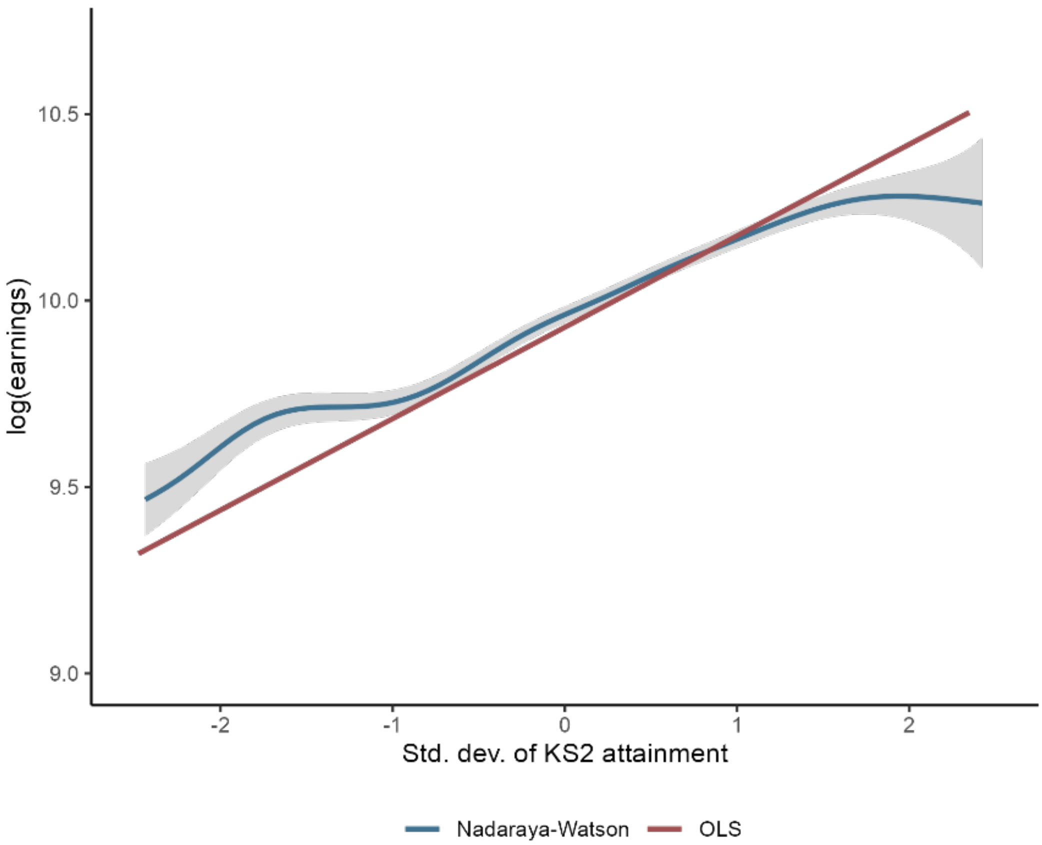
Figure 16: Employment rate by demographics



C. Non-parametric methods

The linear models outlined in Equation 1, whose estimation underpins the findings of this report, impose that the earnings returns are constant across the distribution of attainment. However, it is plausible that a marginal improvement in marks for an individual that is towards the bottom of the KS2 attainment distribution has a different return to an individual who experiences the same improvement but is towards the top of performers. To test the assumption of linearity, an alternative model is also estimated. Non-parametric methods allow much more flexibility as they do not prescribe a functional form and so can reveal structural features in the data that might be missed by classical linear OLS methods.

Figure 17: OLS vs. Nadaraya-Watson regression



A Nadaraya-Watson estimator is used.[37] Intuitively, this can be seen as estimating a series of local average effects. Figure 17 compares the resulting estimates from the Nadaraya-Watson regression with those from the classical OLS model. The resulting non-parametric estimates are approximately linear, suggesting the assumption that the

[37] Estimation is done using the 'np' package (Hayfield and Racine, 2008). Least-squares cross-validation is used to select bandwidths.

earnings return to KS2 scores are constant across the distribution of attainment is sensible. It is less clear the linearity assumption still holds in the extreme tails of the distribution (beyond two standard deviations from the mean). However, few (~5%) individuals sit at these extremities.

Machin and McNally (2008) also find that earnings returns are approximately constant across the distribution of attainment. They use both parametric models, where they allow separate effects on earnings for the top and bottom half of the reading score distribution, as well as non-parametric models.

D. Comparing the Linear Probability Model (LPM) with a probit model

The preferred approach to estimate employment returns, as described in the main text, is to model employment as a linear production function. Here the findings from the Linear Probability Model (LPM) are compared with an alternative probit model of the form:

$$P(Emp_i = 1|X_i, Z_i) = \Phi(\alpha + \beta X_i + \gamma Z_i), \quad i = 1, \dots, N \tag{4}$$

where Emp_i is a binary employment indicator $\boldsymbol{X}_i$ is a vector of standardised KS2 scores, $\boldsymbol{Z}_i$ is a vector of control variables and $\Phi(\cdot)$ is the cumulative standard normal distribution function. The estimated $\hat{\beta}$ coefficients from the probit model can be difficult to interpret directly and are not comparable with the coefficients produced by the LPM. However, the average partial effect (APE) can be calculated:

$$\widehat{APE}_{\beta} = \hat{\beta}\left[\frac{1}{N}\sum_{i=1}^{N}\phi\left(\alpha + \hat{\beta}X_i + \hat{\gamma}Z_i\right)\right] \tag{5}$$

This is obtained by calculating the partial effect for each individual (i)[38], and averaging.

This $\widehat{APE}_{\beta}$ is directly comparable to the estimated $\hat{\beta}$ coefficient from the LPM.[39] Both correspond approximately to the percentage point increase in probability of being employed, associated with a one standard deviation increase in KS2 test scores. Figure 18 plots the resulting estimates under specification 1.[40] The average partial effects from

[38] $\frac{\partial}{\partial X_i} = \beta\phi(\alpha + \beta X_i + \gamma Z_i)$

[39] See page 592 in Wooldridge (2012)

[40] Controlling for gender and region only. The more complex specifications are not estimated using the probit formulation as it would be computationally too expensive to estimate the quantity of school level fixed effects required.

both models are very similar. The LPM estimates are consistently higher, although never by more than 0.2 percentage points.

The predicted probability vectors from both the LPM and probit models are also compared. This helps verify that at the individual level, like at the population level (Figure 18), the choice of model does not alter results considerably. The (Pearson) correlation coefficients between the two predicted probability vectors are shown in Table 3. These show very high correlation across all 21 models, with all coefficients exceeding 0.99.

Figure 18: Estimated Average Partial Effects (APEs)

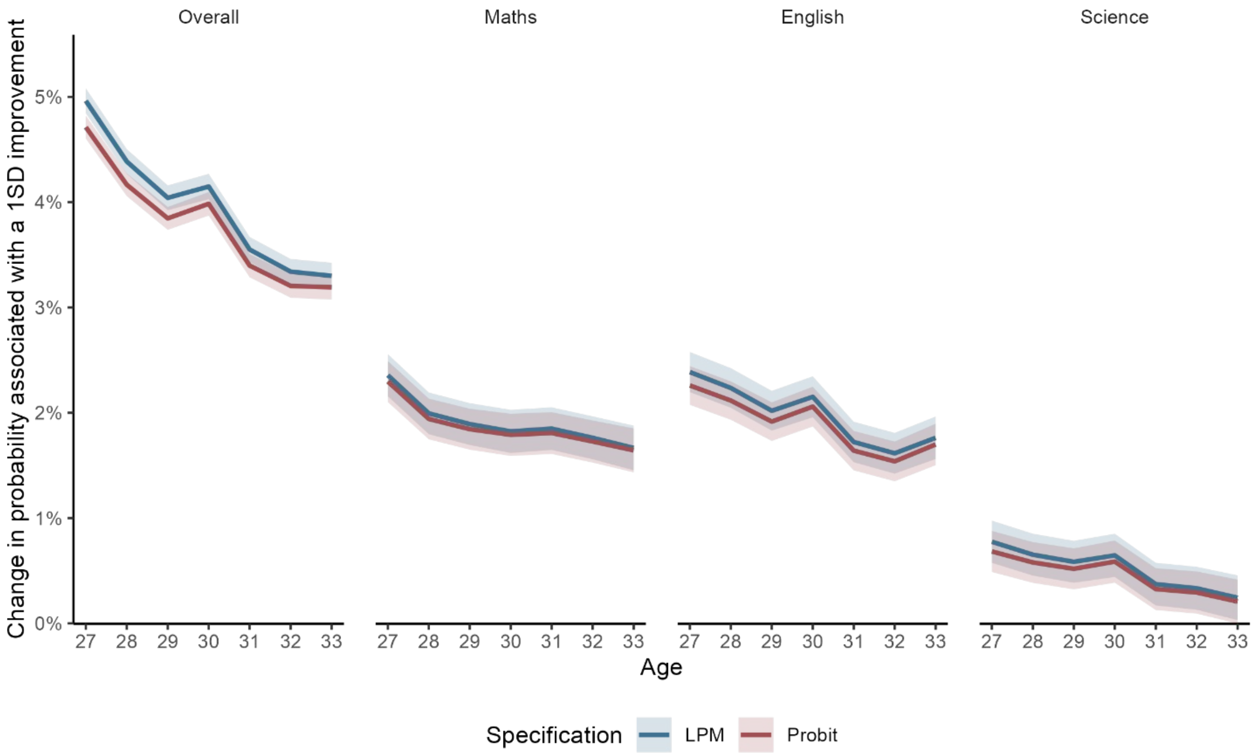


Table 3: Correlation between the predicted probability vectors

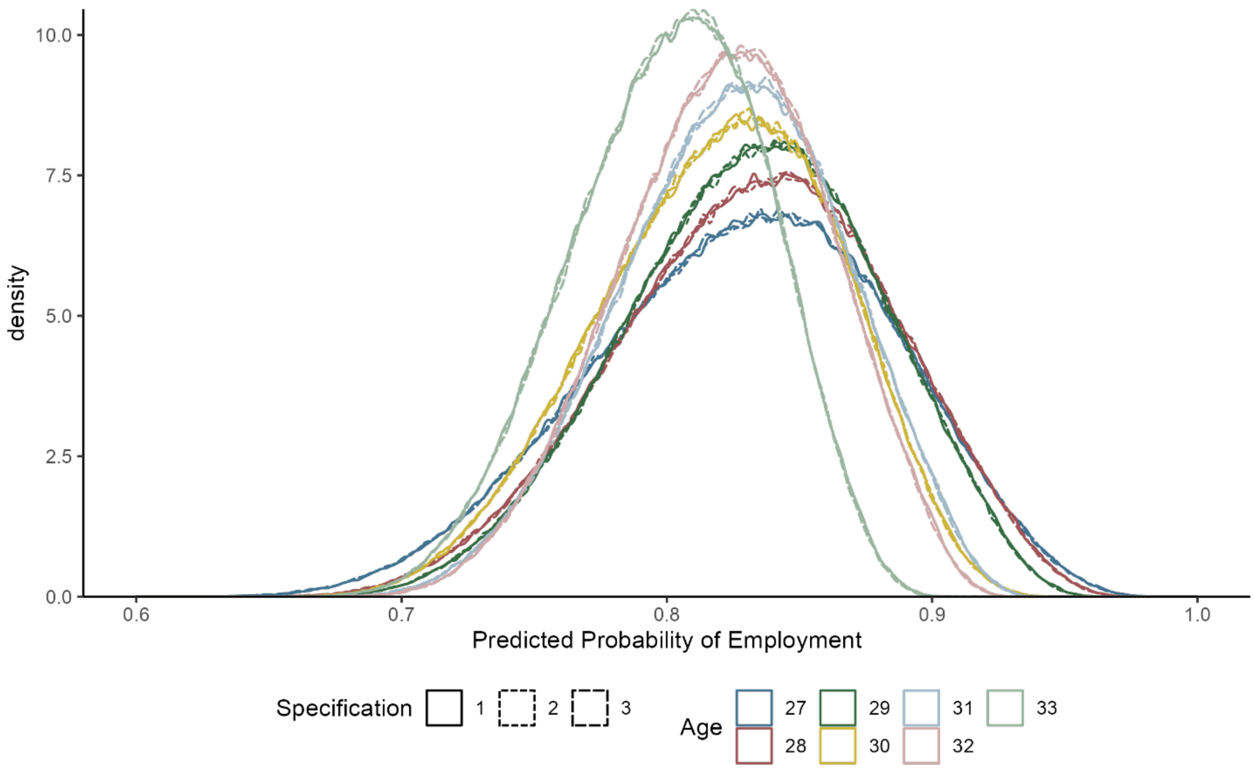
	Age 27	Age 28	Age 29	Age 30	Age 31	Age 32	Age 33
English, Maths	0.99240	0.99305	0.99406	0.99582	0.99585	0.99648	0.99770
English, Maths, Science	0.99246	0.99311	0.99412	0.99584	0.99589	0.99652	0.99774

Total KS2 marks	0.99248	0.99316	0.99415	0.99587	0.99591	0.99654	0.99777

Note: Figures are the Pearson correlation coefficients[41] between the two predicted probability vectors.

The predicted probabilities estimated using a LPM are not constrained to the unit interval, [0,1]. Given these predicted probabilities cannot plausibly fall outside of this interval, using a LPM can generate bias and inconsistent estimates. Horrace and Oaxaca (2006) show the proportion of predicted probabilities outside of the unit interval increases the bias of LPM estimates. Figure 19 illustrates the distributions of predicted probabilities for the 21 models estimated.[42] These LPM generate no probabilities outside the unit interval, so little or no bias is introduced. Note also that the distribution of predicted probabilities changes as individuals get older, both the spread and the average probability of being employed increases slightly over time before seemingly stabilising at around 85%.

Figure 19: Distribution of predicted probabilities



[41] $\rho_{\{X,Y\}} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}$, where cov is the covariance and σ is the standard deviation

[42] 3 different specifications are estimated at each of 7 different ages (27–33)

E. Model controls

Table 4: Details of controls included in the models under different specifications

	Possible values	**C&C (2013)**	**Preferred**	**Incl. highest qualification**	***Additional notes***
Gender	Male, Female	✓	✓ (interaction)	✓ (interaction)	
Free School Meal (FSM) Status	Eligible, Not Eligible		✓ (interaction)	✓ (interaction)	
Government Office Region (GOR)	East Midlands, East of England, London, North East, North West, South East, South West, West Midlands, Yorkshire and The Humber	✓			*Region at the time pupil sat KS2 tests*
Primary school attended	16,194 schools		✓ (fixed effect)	✓ (fixed effect)	
Ethnicity	Asian, Black, Chinese, Mixed, White, Any Other Ethnic Group, Unclassified		✓	✓	
Special Educational Needs (SEN)	SEN, SEN with statement, No SEN		✓	✓	*SEN status at age 16*

English as Additional Language (EAL)	Yes, No		✓	✓	
IDACI	Fraction of children living in income deprived families (0–1)		✓	✓	*In the LSOA the pupils home address is located*
Highest qualification level[43]	Level 0–8			✓	

Note: Interaction variables are interacted with the vector of KS2 test scores. To implement fixed effects, the within transformation is used to de-mean variables by group (school).

[43] For a mapping of different qualification types to levels see https://www.gov.uk/what-different-qualification-levels-mean/list-of-qualification-levels

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