# Higher Horizons Tracking Report 2026 (October Update):

## statistical analysis of progression rates of Higher Horizons participants and non-participants

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Please note: the HESA Standard Rounding Methodology has been applied to all descriptive numbers provided in this report:

1. Counts of people are rounded to the nearest multiple of 5.
2. Percentages are not published if they are fractions of a small group of people (fewer than 22.5).
3. Averages are not published if they are averages of a small group of people (7 or fewer).

Rounding and suppression are applied only to published descriptive counts and percentages. Statistical models were fitted on the underlying dataset without rounding.

I'm also grateful for the advice and discussions about methodology with Dr Nick Garnett, Liverpool John Moores University. The idea to add Bayesian analysis was his and is the biggest update to the analysis since last year.

# Executive Summary

This report estimates the association between taking part in Higher Horizons outreach and progressing to higher education by age 19. It uses a sample of 33,680 students recorded in HEAT by Higher Horizons, with expected entry years between 2019 and 2023. Three statistical approaches, producing six estimates, compare participants with non-participants from similar backgrounds, taking account of cohort year, sex, ethnicity, disability and two area-based measures of disadvantage (TUNDRA and IMD). Together they provide strong and consistent evidence of a positive association between participation and progression. This is not a causal evaluation, and the methods used cannot confirm that participation caused increases in progression.

## Key findings

1. **Participants were more likely to progress to higher education.** Across all six estimates, participants progressed at a rate 7.2 to 8.0 percentage points higher than similar non-participants. In odds terms, participants had 44% higher odds of progressing to higher education than similar non-participants.

2. **The association has become smaller in recent cohorts.** The difference was around 11 percentage points for the 2019 and 2021 cohorts, but fell to around 5 points for the 2023 cohort. It remained positive in every year. This analysis does not test why the gap has narrowed, and future reports should track whether the trend continues.

3. **More contact hours were associated with higher progression.** Compared with non-participants, the odds of progressing were 13% higher for students with fewer than 3 contact hours, 47% higher for those with at least 3 and fewer than 16 hours, and 81% higher for those with 16 or more hours. The low-dose effect was too small to detect reliably within most single years.

4. **Among participants, a high dose was associated with a progression rate about 10 percentage points higher than a low dose.** Participants with 16 or more contact hours progressed at a rate 10.2 to 10.7 percentage points higher than similar participants with fewer than 3 hours. This suggests that sustained engagement is more valuable than one-off or ad hoc engagement. An exploratory analysis of the full range of contact hours suggests progression rises over the first 3 hours and again beyond 16 hours, with little change in between.

5. **Some activity types were more strongly associated with progression than others, although these findings are exploratory.** Campus Visits showed the strongest and most consistent positive association, and Summer Schools, Mentoring and IAG were also positively associated with progression. Subject Specific activity showed no clear association. Attainment Raising showed no

statistically significant association in the regression analysis, and a small negative association in the Bayesian analysis. This most likely reflects the fact that these activities are targeted at students with lower prior attainment, rather than any effect of the activity itself.

6. **The estimates are slightly lower than in the May 2026 report.** The participation odds ratio is 1.44, compared with 1.52 in May, and the matched difference is 7.2 to 8.0 percentage points, compared with 8.7 to 8.9. This mainly reflects the addition of the 2023 cohort, in which participants and non-participants progressed at more similar rates. The direction and significance of the findings are unchanged.

## Limitations

All of the results are associations. The analysis does not control for prior attainment, which is strongly linked to progression; attainment data was not available for this analysis. The analysis also does not control for other unmeasured factors such as motivation and family support.

Checks suggest an unmeasured factor would need to be moderately strong to explain the participation result away. Prior attainment could plausibly be such a factor, although Higher Horizons does not target students for activity based on their attainment so there is no reason to believe all students who take part in Higher Horizons activities are high attaining. Students attending the same school or college share influences that the models do not capture, so the intervals reported are likely to be narrower than they should be. Four of the five cohorts had their education significantly disrupted during the Covid-19 pandemic, which the models can only partly account for.

## Recommendations

The findings support ensuring every participant receives at least 3 hours of contact, increasing the proportion who receive sustained contact of 16 hours or more, and tracking contact hours as an operational measure. The recommendation on 16 or more hours rests partly on exploratory analysis.

The findings also support ensuring that campus visits remain a key part of the Higher Horizons offer.

Further research should prioritise access to prior attainment data, investigate why the association has narrowed in recent cohorts, and develop the activity-type analysis. Full recommendations are set out at the end of this report.

# Introduction

Higher Horizons is a partnership of universities and colleges working together to deliver widening access activities across Staffordshire, Shropshire and Cheshire. Led by Keele University since 2015, the partnership has delivered this work through successive government-funded programmes: Aimhigher (2004 to 2011), the National Networks for Collaborative Outreach (2015 to 2016), and the National Collaborative Outreach Programme, now called Uni Connect (2017 to present). Since 2017, Higher Horizons has delivered nearly 8,700 activities and engaged with 73,100 individual young people across its region.

Higher Horizons uses the Higher Education Access Tracker (HEAT) to record participant activity and track progression to higher education. All participants are logged in HEAT alongside a record of the activities they have taken part in, and their data is submitted to the Higher Education Statistics Agency (HESA) for matching into the HESA Student record. This report is an update on the first major analysis of participant outcomes since Higher Horizons joined HEAT in summer 2025, following the closure of its previous tracking service, EMWPREP. This report develops the methodology used in the previous analysis and adds a further cohort of students to the tracked dataset.

The complete tracking dataset now contains 61,295 students who were eligible to take part in Higher Horizons activities between 2015 and 2024. The dataset contains both those who participated and those who did not. Students have been tracked into HE entry years up to 2024/2025, providing a longitudinal view of each student's journey from outreach engagement through to HE entry. This analysis focuses on a subset of these data: the five cohorts with expected entry years between 2019 and 2023. These cohorts were chosen because they had all been tracked for at least two years, allowing us to determine if they had progressed to higher education by age 19.

This report updates the Higher Horizons Tracking Report 2026 (May 2026), which analysed the four cohorts with expected entry years between 2019 and 2022. HESA tracking data for the 2024/25 academic year has since become available, completing the by-19 window for the 2023 cohort, which is added here. This report is accompanied by a technical annex which includes details on how the dataset was constructed, exploratory data analysis tables, and full results of the logistic regression models, propensity score matching, and Bayesian analysis.

# Methodology

## Research Question

This analysis investigates whether students who participate in Higher Horizons outreach activities progress to higher education at higher rates than students from similar demographic backgrounds who did not participate. Specifically, the analysis addresses three questions:

1. Do participants progress to higher education at a higher rate than non-participants from similar demographic backgrounds?
2. Does dose matter: do participants with a higher amount of outreach engagement progress at higher rates?
3. Does activity type matter: do participants in certain types of outreach activity progress at higher rates?

The methods used cannot confirm that participation caused any observed differences in progression. They can instead demonstrate statistically significant associations between participation and progression. The analysis also cannot account for unobserved factors such as motivation, personal circumstance, or parental support, nor does it control for prior attainment, as this data is not available to Higher Horizons. Attainment is strongly correlated with progression to HE and its absence is the most significant limitation of this study.

## How the analysis works

This report uses three statistical approaches to compare the progression rate of Higher Horizons participants with that of similar students who did not take part: logistic regression, propensity score methods and Bayesian analysis. The propensity score approach is applied in four different ways, so together the three approaches produce six estimates of the participation effect. Each approach adjusts for the same characteristics: cohort year, sex, ethnicity, disability, and TUNDRA and IMD quintile. Because they make different assumptions and handle the data in different ways, agreement between the methods gives confidence that the results do not depend on one particular method.

The outcome examined through these statistical methods is progression to higher education by age 19. This measures whether students were found in higher education in either of the two years following the typical period of level 3 study.

## Logistic regression

Logistic regression estimates how the chance of progressing to higher education differs between participants and non-participants once the other characteristics are taken into account. Its main output is an odds ratio. An odds ratio of 1 means no difference between the two groups. An odds ratio of 1.5 means participants had 50% higher odds of progressing than otherwise similar non-participants. Odds are not the same as probability: 50% higher odds does not mean 50% more students progressed.

To make the results easier to interpret, the regression results are also converted into percentage points. This is done by g-computation: the model predicts each participant's chance of progressing twice, once as a participant and once as if they had not taken part, and averages the difference. The result is the difference in progression rate that participation is associated with among the students who took part. This is the main figure reported throughout.

## Propensity score methods

Propensity score methods take a different route. They first estimate each student's likelihood of taking part in outreach activities, given their characteristics. This is known as their propensity score. They then use this score to build a fair comparison group of non-participants who look like the participants. All comparisons are made within the same cohort year.

Four versions are used. Propensity score matching pairs each participant with the non-participant whose score is closest. A pair is only made if the two scores are close enough, and each non-participant can be used only once. Participants without a close enough match are left out, which in early cohorts with few non-participants means many are dropped. Coarsened exact matching groups students who share exactly the same combination of characteristics and compares participants and non-participants within each group. Inverse probability weighting keeps every student and gives more weight to non-participants who resemble participants, so the weighted comparison group has the same make-up as the participants. Propensity score stratification divides students into five bands by their score and compares participants and non-participants within each band. It is used only as a check, because it did not fully balance the groups.

## Bayesian analysis

The Bayesian analysis fits a model similar to the logistic regression but works in a different statistical framework. It starts from prior assumptions about some of the relationships in the data, and then updates them using the Higher Horizons data. For sex and ethnicity, these starting assumptions are based on published Department for Education progression rates for the six local authorities Higher Horizons serves. For participation itself, the starting assumption is deliberately neutral, so the estimate

comes from the Higher Horizons data alone. Checks confirmed that the results do not depend on these assumptions.

The Bayesian analysis produces credible intervals rather than confidence intervals. A 95% credible interval of +6.5 to +8.5 percentage points means that, given the model and the data, there is a 95% probability that the true effect lies in that range. The analysis can also make direct statements about probability, such as the chance that an effect is larger than a given size. For activity types, it uses partial pooling: results for activity types with few students are treated more cautiously, so a small group cannot produce an extreme result by chance.

## Checking the results against unmeasured factors

None of these methods can account for characteristics that are not in the data, of which prior attainment is the most important. Three checks are used to judge how strong such a factor would need to be to explain the results away. An E-value gives the minimum strength of association, on the risk ratio scale, that an unmeasured factor would need with both taking part and progressing. Larger values mean a stronger factor would be needed. A Rosenbaum bounds analysis asks how much an unmeasured factor would need to change a student's chance of taking part before the matched result stopped being statistically significant. A tipping-point analysis tests specific scenarios, such as a factor that doubles the chance of progressing and is much more common among participants, to see at what point the result would disappear. None of these checks shows that such a factor does not exist. They show how strong it would need to be.

Finally, all of the methods estimate associations. They show whether participants progress at higher rates than similar students who did not take part, but they cannot confirm that participation caused the difference.

## Key terms

| Term | Meaning |
|---|---|
| **Percentage point (pp)** | The difference between two percentages. A rise from 30% to 37% is 7 percentage points. |
| **Odds ratio** | How much higher or lower the odds of progressing are for one group than another. 1 means no difference. |
| **Average effect on participants (ATT)** | The difference in progression rate between participants and what their rate is estimated to have been had they not taken part. |
| **Confidence interval** | A range of plausible values for an estimate. Narrower intervals mean more precise estimates. |

| | |
|---|---|
| **Credible interval** | The Bayesian equivalent: the range within which the true effect lies with 95% probability, given the model and data. |
| **Statistically significant** | Unlikely to have arisen by chance if there were no real difference ($p < 0.05$). |
| **Propensity score** | A student's estimated likelihood of taking part, based on their characteristics. |
| **E-value** | How strongly an unmeasured factor would need to be linked to both taking part and progressing to explain a result away. |

## Changes to the Methodology Since the Previous Report

A small number of changes have been made to the methodology since the May 2026 report. Each is a refinement intended to improve the analysis, but this means the results are not a like-for-like comparison with the earlier report. The changes are:

1. Disability has been added as a covariate to all analyses.
2. Early progressors are now only excluded from the dataset if they are not an exact match to the HESA Student Record.
3. Contact hours banding has been revised because later cohorts have, on average, substantially more contact hours than earlier ones because they have had longer to participate in the Higher Horizons programme (which began in this iteration in 2017). The "High" band is now defined as 16 or more contact hours. This threshold was chosen from the distribution of contact hours in the 2021 to 2023 cohorts, where it sits close to the 75th percentile of participants' hours.
4. The dose-response propensity score matching now compares low dose to high dose students, rather than low dose and no dose students.

## Data Collection

Data was collected by Higher Horizons staff. Before 2020, data was collected individually from participants, with parents or carers providing data for pre-16 students. From 2020, Higher Horizons moved to bulk data collection, receiving data directly from schools for their entire student population. This is why the dataset contains both participants and non-participants and why there are larger cohorts of non-participants in later entry years.

Participants and non-participants are drawn from around 100 schools and colleges within the Higher Horizons region, selected because more than 40% of their students come from areas with the lowest participation in higher education.

Tracking fields (name, date of birth and postcode) were mandatory; contextual information (sex, ethnicity, free school meal eligibility and disability status) was optional, so some of this data is missing. Postcode has been used to calculate area-

based measures of disadvantage, with TUNDRA and IMD quintiles provided by HEAT. Free School Meal eligibility was not used as a control because it had the largest proportion of missing data and it required dropping too many students from the analysis.

It is also important to note that the region Higher Horizons covers has a lower rate of progression to HE by age 19 than the national progression rate in 4 of the 6 local authority areas it serves, with the biggest gap of -9.0 percentage points in Stoke-on-Trent where much of the sample is drawn from. Of the remaining two local authorities, one's progression rate by 19 is the same as the national rate, while the last one is just 0.9 percentage points above the national rate. Traditionally, this is not a region with high rates of participation in higher education[1].

## Constructing the Analysis Dataset

The raw dataset contains 61,295 unique student records with expected HE entry years spanning 2015 to 2024. Several filtering steps were applied to produce a final dataset suitable for analysis, summarised below and described in full in the technical annex.

For this analysis, the cohort was restricted to those with expected entry years of 2019 to 2023. Participants who engaged in outreach after their expected entry year were removed, as were non-participants whose data was collected after their expected entry year. These individuals had effectively passed the outcome window and represent a different route through education. Students who had progressed to higher education before their expected entry year were removed as described above. Finally, students with missing demographic data were dropped from the sample, as the statistical methods used in the analysis required full demographic data to be available.

All data is sent to HESA year-on-year and earlier cohorts of students are matched into the HESA Student Record again. This means there may be slightly different numbers of students in the earlier cohort years than there were in the last report. Partly this is because of dropping the students with missing data on disability, but it may also be because there have been slight adjustments in earlier cohort data due to data cleaning taking place within HEAT or in how HESA conducted the matching. This is standard practice with HEAT and HESA's yearly tracking.

The final analysis dataset contains 33,680 students.

***Table 1: Participants and Non-participants per Expected HE Entry Year***

| Expected HE Entry Year | Non-participants | Participants | Total |
|---|---|---|---|
| **2019** | 670 | 2,080 | 2,750 |
| **2020** | 915 | 2,360 | 3,280 |

[1] Statistics taken from the Department for Education, *Widening Participation in Higher Education* for the 2024 cohort.

| | | | |
|---|---|---|---|
| **2021** | 2,200 | 3,695 | 5,895 |
| **2022** | 4,565 | 4,450 | 9,020 |
| **2023** | 7,660 | 5,080 | 12,740 |
| **Total** | **16,010** | **17,670** | **33,680** |

There are also some demographic differences between the two groups (see Table 2). Participants are more concentrated in the lower TUNDRA and IMD quintiles, reflecting the place-based targeting of outreach activities towards students who are least likely to progress to HE. Demographics are broadly comparable to the demographic composition of last year's dataset.

***Table 2: Demographic Characteristics of Participants and Non-participants***

| Demographic Variable | Participants | Non-participants |
|---|---|---|
| **Female** | 53% | 49% |
| **Male** | 47% | 51% |
| **TUNDRA Q1 and Q2** | 68% | 45% |
| **IMD Q1 and Q2** | 57% | 37% |
| **Ethnicity: White** | 85% | 91% |
| **Ethnicity: Asian** | 7% | 3% |
| **Ethnicity: Black** | 2% | 1% |
| **Ethnicity: Mixed** | 4% | 4% |
| **Free School Meals eligible (all students, including unknown)** | 17% | 9% |
| **Declared disability** | 17% | 27% |

The participant group had also become more disadvantaged over time, particularly on the place-based measures. The proportion of participants from TUNDRA quintile 1 (areas with the lowest rates of HE participation) rose from 32% in 2019 to 45% in 2023, while the proportion from quintile 5 fell from 8% to 5%. A similar pattern is visible in the IMD quintile distribution: the proportion of participants from quintile 1 grew from 29% in 2019 to 38% in 2023. By contrast, the non-participant group remained broadly stable in its TUNDRA and IMD composition across all five years.

As well as becoming more socio-economically disadvantaged over time, participants in later cohorts engaged with the programme more intensively, at least until the most recent cohort. Mean contact hours rose from 6.8 hours in 2019 to 13.6 hours in 2022, before falling back slightly to 12.7 hours in 2023, consistent with the funding reductions that affected the programme from 2021 onwards and saw an overall reduction in activity. This overall increase also reflects the fact that students in later cohorts were

younger when the current programme began and therefore had more years in which to accumulate engagement.

The mix of activity types delivered to participants also changed substantially over the cohort years. IAG remained the most common activity type throughout, with the proportion of participants receiving at least one IAG session rising from 53% in 2019 to 82% in 2023. Campus Visit reach was relatively stable across all years at around 40% to 44%. Attainment Raising and Subject Specific activity both grew over the earlier cohorts before easing back in 2023. Summer Schools and Mentoring remained low in reach throughout. Participants in later cohorts also engaged with a broader range of activity types. Data tables showing some of these changes are available in the technical annex.

## Does participation matter?

The analysis covers 33,680 students with expected entry years from 2019 to 2023: 17,670 participants and 16,010 non-participants. Before any adjustment, 38.2% of participants progressed to higher education by age 19, compared with 30.5% of non-participants, a gap of 7.7 percentage points. However, participants are more likely to come from the areas with the lowest rates of higher education participation. A fair comparison therefore needs to set them against non-participants with similar characteristics. Six methods were used to make this comparison, each matching or adjusting on cohort year, sex, ethnicity, disability, and TUNDRA and IMD quintile.

After making these demographic adjustments, the methods showed that participants progressed to higher education by age 19 at a rate about **7 to 8 percentage points higher** than similar non-participants. The gap was positive in every cohort year, but it has narrowed in the most recent cohorts. The unadjusted gap of 7.7 points is similar to the adjusted estimates only by coincidence. Within each cohort year, adjustment generally widens the gap.

The effect size (in percentage points), interval and students within the analysis are given in Table 3 and visualised in Figure 1.

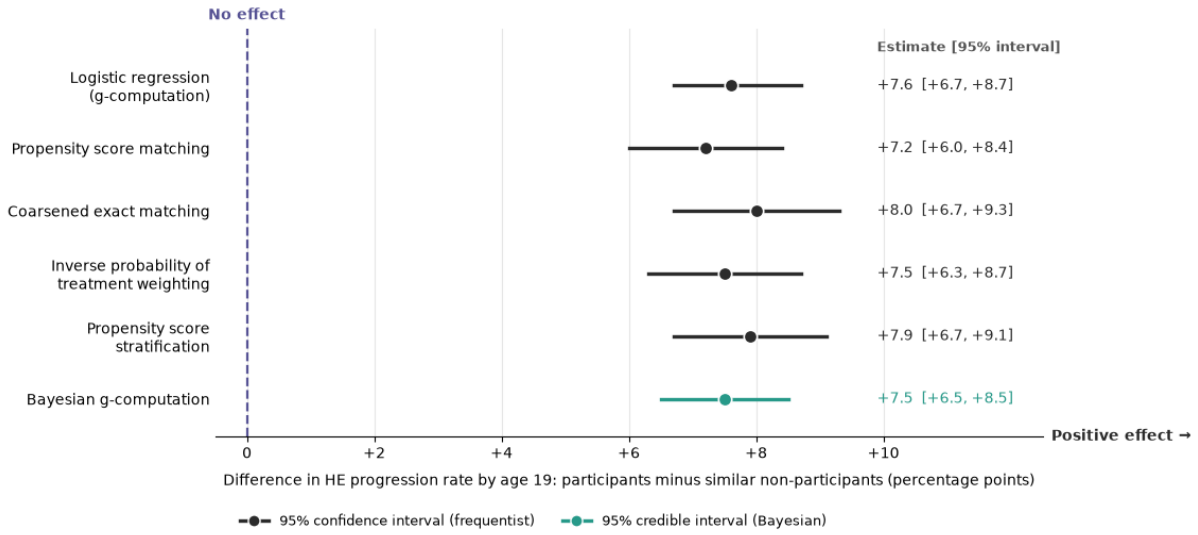
***Table 3: Participation Effect by Method***

| Method | Effect (pp) | 95% interval | Students analysed |
|---|---|---|---|
| **Logistic regression (g-computation)** | +7.6 | +6.7 to +8.7 | 33,680 |
| **Propensity score matching** | +7.2 | +6.0 to +8.4 | 11,170 matched pairs |
| **Coarsened exact matching** | +8.0 | +6.7 to +9.3 | 17,125 participants |
| **Inverse probability of treatment weighting** | +7.5 | +6.3 to +8.7 | 33,680 |
| **Propensity score stratification** | +7.9 | +6.7 to +9.1 | 33,680 |

| | | | |
|---|---|---|---|
| **Bayesian g-computation** | +7.5 | +6.5 to +8.5* | 33,680 |

*A credible interval; the other rows give confidence intervals.

***Figure 1: Participation Effect Estimated by Every Method***




The six methods take different approaches and include different groups of students. Propensity score matching could not find a close match for 37% of participants, most of them from the most disadvantaged groups, and leaves them out. Coarsened exact matching leaves out only 3%, mostly participants from ethnic minority groups. Inverse probability weighting and the Bayesian analysis include every student. Despite these differences, all six estimates fall within one percentage point of each other. This agreement shows that the result does not depend on how the comparison is made. It cannot, however, rule out factors that none of the methods measure, of which prior attainment is the most important. Expressed as an odds ratio, the regression estimate means that participants had 44% higher odds of progressing than similar non-participants (odds ratio 1.44, 95% CI 1.37 to 1.52).

## Differences across cohort years

The pooled estimate of about 7.5 percentage points is an average across five cohorts whose experience of the programme differed considerably. As Table 4 shows, the difference was around 9 to 12 percentage points for the 2019 to 2021 cohorts. It fell to around 6 to 7.5 points for 2022 and around 5 points for 2023. The regression analysis shows the same pattern: the participation odds ratio was 1.80 (1.59 to 2.05) for the 2021 cohort and 1.27 (1.17 to 1.38) for 2023, and the two intervals do not overlap. In the Bayesian analysis, a model that allowed the effect to vary by year also fitted the data better than one that assumed a single effect.

*Table 4: Difference in progression rate by cohort year (percentage points)*

| Cohort | Propensity score matching | Coarsened exact matching | Inverse probability weighting | Bayesian (95% credible interval) |
|---|---|---|---|---|
| **2019** | +10.6 | +11.4 | +10.5 | +11.4 (+7.6 to +15.1) |
| **2020** | +9.3 | +8.6 | +8.8 | +8.5 (+4.9 to +12.0) |
| **2021** | +11.6 | +11.1 | +10.6 | +11.5 (+9.1 to +13.8) |
| **2022** | +6.8 | +6.5 | +6.0 | +7.5 (+5.7 to +9.4) |
| **2023** | +4.7 | +5.4 | +4.7 | +4.5 (+2.9 to +6.1) |

This analysis does not test why the difference has narrowed. Possible explanations include the changing make-up of the participant group and changes to how the programme was delivered during and after the Covid-19 pandemic. The highest difference in 2021 may also be partly attributable to the awarding of level 3 exam results by teacher assessed grades due to the Covid-19 pandemic, which saw higher results than usual awarded to students. This meant that more students than might be typical met their university entry requirements. Future reports should track whether the trend continues as further cohorts are added.

## Robustness of the result

Several checks suggest the result is not an artefact of any single cohort or modelling choice. Repeating the Bayesian analysis five times, leaving out one cohort year each time, gave estimates between 6.6 and 9.1 percentage points. Changing the Bayesian model's starting assumptions moved the estimate by at most 0.06 points, and replacing them with neutral assumptions gave 7.48 rather than 7.49.

Because this is an observational study, the result could still be affected by characteristics that were not measured. Four checks, taken from three of the methods, show how strong such a factor would need to be.

The first two are E-values, which show how strongly an unmeasured factor would need to be linked to both participation and progression to explain the estimate away. For the logistic regression estimate of 7.6 percentage points, the E-value is 1.85 (1.76 at the confidence-interval limit). For the Bayesian estimate of 7.5 percentage points, it is 1.84 (95% credible interval 1.74 to 1.94). An unmeasured factor would need a risk ratio of at least about 1.85 with both participation and progression, over and above the measured characteristics. The two E-values are calculated the same way and agree closely.

The third check is a tipping-point analysis on the Bayesian model. It found that the credible interval would only include zero in two cases. The first is a single factor that

doubled the odds of progression and was present in 80% of participants but only 20% of non-participants. The second is a factor that multiplied the odds of progression by 2.5 with a 70/30 split.

The fourth check, a Rosenbaum bounds analysis, applies to the propensity score matching estimate of 7.2 percentage points. It found that an unmeasured factor would need to raise a student's odds of participating by about 1.35 times, compared with an otherwise identical matched non-participant, before that estimate stopped being statistically significant. Prior attainment is the most plausible such factor, and it is not available in this dataset.

Taken together, these results show a consistent positive association between participation and progression to higher education by age 19. They cannot confirm that participation caused the difference.

## Does dose matter?

Students who received more contact with Higher Horizons were more likely to progress to higher education by age 19. Participants who received 16 or more hours of contact progressed at a rate about 10 to 11 percentage points higher than similar participants who received fewer than 3 hours, and this was consistent across five methods. The gain is not spread evenly across the range of hours. Progression rises over the first 3 hours and again beyond 16 hours, with little change in between, although this finding about the shape of the curve is exploratory.

Each participant's total contact hours were grouped into three bands: Low (fewer than 3 hours), Medium (at least 3 and fewer than 16 hours) and High (16 or more hours). Across all five cohorts, 23.6% of participants fell in the Low band, 54.0% in the Medium band and 22.4% in the High band. Before any adjustment, progression rates rose from the Low to the Medium to the High band in every cohort year. Taking all years together, however, the unadjusted progression rates for the Medium and High bands were identical, at 39.3%. This is because the students who build up the most hours also tend to be the most disadvantaged, and so are less likely to progress to begin with. The analyses below compare students with similar backgrounds to account for this.

### Compared with non-participants

The logistic regression replaced the single participation measure with the three contact-hours bands, comparing each with non-participants. After controlling for cohort year and demographics, students in the Low band had 13% higher odds of progression than non-participants (odds ratio 1.13, 95% CI 1.04 to 1.22). The Medium band had 47% higher odds (odds ratio 1.47, 95% CI  1.39 to 1.56), and the High band had 81% higher odds (odds ratio 1.81, 95% CI 1.68 to 1.96). All three were statistically significant.

When the model was fitted separately for each cohort year, the Low < Medium < High ordering held in all five years. The Medium and High bands were statistically significant in every year. The Low band was significant only in 2021 and 2022, which suggests that the effect of a low dose is real but too small to detect reliably within most single years.

## High dose compared with low dose among participants

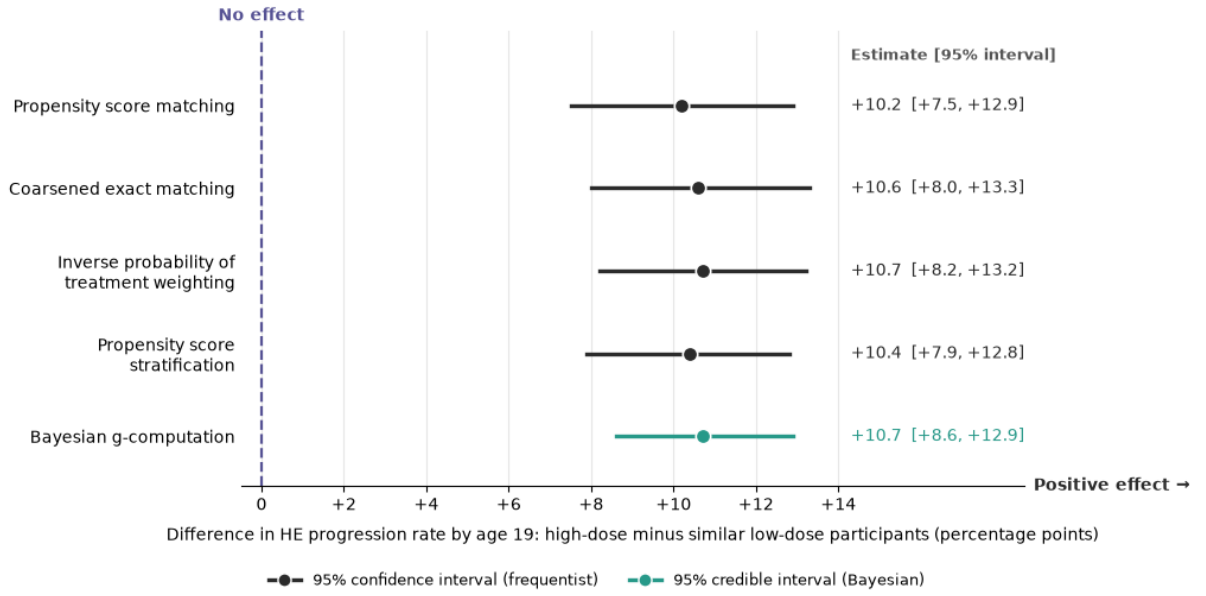
The propensity score and Bayesian analyses asked a more tightly defined question: among students already taking part, is more contact associated with higher progression? They compared the 3,960 participants in the High band with the 4,170 in the Low band, leaving out the Medium band so that the comparison is between the two ends of the range. Each method balanced the two groups on cohort year, sex, ethnicity, disability, and TUNDRA and IMD quintile. Table 5 shows the results.

***Table 5: Dose-Response Analysis Results by Method***

| Method | Effect (pp) | 95% interval | Students analysed |
|---|---|---|---|
| **Propensity score matching** | +10.2 | +7.5 to +12.9 | 2,460 matched pairs |
| **Coarsened exact matching** | +10.6 | +8.0 to +13.3 | 3,840 high-dose participants |
| **Inverse probability of treatment weighting** | +10.7 | +8.2 to +13.2 | 8,130 |
| **Propensity score stratification (check only)** | +10.4 | +7.9 to +12.8 | 8,130 |
| **Bayesian analysis** | +10.7 | +8.6 to +12.9* | 8,130 |

*A credible interval; the other rows give confidence intervals.

***Figure 2: High-Dose Effect Estimated by Every Method***



All five estimates fall within 0.5 percentage points of each other. Propensity score matching matched 62% of high-dose participants. Among the matched pairs, 40.9% of high-dose students progressed, compared with 30.7% of low-dose students. Because the matched result can depend on the order in which students are matched, the matching was repeated 200 times in different orders. This gave an average of 10.6 percentage points; every run fell between 9.2 and 12.2 points and was statistically significant. Coarsened exact matching kept 96.9% of high-dose participants, and inverse probability weighting kept everyone, with the same result when the weights were capped. Stratification did not fully balance the groups, so it is treated as a check on the direction of the effect; the difference was positive in 22 of its 25 year-by-band groups.

The difference was positive in every cohort year for propensity score matching, coarsened exact matching and inverse probability weighting (Table 6). It was largest in 2019 and 2020, but each of those years had fewer than 200 high-dose students, so those estimates are less precise. From 2021 onwards the difference was more stable, at between about 7 and 12 percentage points.

***Table 6: High-dose vs low-dose difference by cohort year (percentage points)***

| Cohort | Propensity score matching | Coarsened exact matching | Inverse probability weighting |
|---|---|---|---|
| **2019** | +21.3 | +21.2 | +22.5 |
| **2020** | +11.5 | +18.2 | +15.9 |
| **2021** | +6.8 | +10.7 | +12.0 |
| **2022** | +10.9 | +10.2 | +10.3 |
| **2023** | +9.4 | +8.6 | +7.8 |

The Bayesian model passed every convergence check. Overlap between the two groups was weaker than in the participation analysis. Restricting the estimate to the 3,840 high-dose participants with at least one comparable low-dose student gave the same result, +10.7 percentage points (+8.6 to +12.8). Replacing the model's starting assumptions with neutral ones did not change the estimate.

## Across the full range of contact hours

The comparison of high-dose and low-dose students leaves out everyone in the Medium band. It also cannot show how progression changes as contact hours build up. A further Bayesian analysis therefore used all 17,670 participants to look at progression across the whole range of contact hours, taking account of the same background characteristics as before. Three ways of describing the pattern were tested. The first gave each band its own progression rate. The second assumed that each doubling of

contact hours makes the same difference. The third was more flexible and allowed the pattern to change at 3 hours and at 16 hours.

The first approach gives the simplest summary. Once differences in background are taken into account, the progression rate was 32.6% in the Low band, 38.5% in the Medium band and 43.8% in the High band. Moving from Low to Medium was associated with a rise of about 6 percentage points, and moving from Medium to High with a further rise of about 5 points. This shows that the identical unadjusted progression rates for the Medium and High bands reflect the different backgrounds of the students in each band, not a lack of benefit from further contact.

The flexible approach described the data best. It suggests that progression rises steadily over the first 3 hours of contact, changes very little between 3 and 16 hours, and then rises again beyond 16 hours. The model was set up to be sceptical of any change in pattern, so the changes it found come from the data. However, the points at which the pattern could change were fixed at 3 and 16 hours rather than tested. The exact shape of the curve, and in particular the flat section between 3 and 16 hours, should therefore be treated as exploratory.

### Robustness of the result

The dose results are larger than the participation results, but that does not make them more certain. Participants are not given their contact hours at random. They build them up partly through their school's engagement, and that engagement may itself make them more likely to progress. Checks suggest any unmeasured factor would need to be fairly strong before it influences the results. For the high-versus-low result, it would need to roughly double both a student's likelihood of receiving a high dose and their likelihood of progressing, over and above the characteristics already taken into account. Put another way, it would need to multiply the odds of progressing by two and a half and be found in 80% of high-dose students but only 20% of low-dose students. Fuller details of these checks are in the technical annex.

Taken together, these results show a consistent link between more contact hours and higher progression. The high-dose difference of about 10 percentage points compares participants with other participants, so it should not be added to the participation effect. Because contact hours were not assigned at random, these results cannot confirm that additional hours cause higher progression.

## Does activity type matter?

Some types of Higher Horizons activity are more strongly associated with progression to higher education than others. Campus Visits show the strongest and most consistent positive association across methods. Summer Schools, Mentoring and IAG are also

positively associated with progression, while Subject Specific and Attainment Raising activity show no clear positive association. These findings are exploratory.

Activities were grouped into seven broad types: Campus Visits, IAG (information, advice and guidance), Attainment Raising, Subject Specific, Summer Schools, Mentoring and Other. IAG reached the most participants, rising from 53% of participants in 2019 to 82% in 2023. Campus Visits reached a stable 40% to 44% of participants each year. Summer Schools, Mentoring and Other each reached fewer than 4% of participants across the period. Many students took part in more than one type: 7,590 of the 17,670 participants attended two or more. Each type was therefore analysed as a separate yes-or-no measure rather than as a single category, so that each result holds attendance at the other types constant.

## Results across methods

Two main methods were used, and they answer slightly different questions. The logistic regression compares students who attended each type with non-participants, holding cohort year, demographics and attendance at the other types constant. The Bayesian analysis uses participants only, comparing students who attended each type with other participants who did not. It also uses a method called partial pooling, which treats results based on few students more cautiously. Because the comparison groups differ, the sizes of the effects are not directly comparable between the two methods, but their order and direction can be compared. Table 7 sets out both.

***Table 7: Association between activity type and progression (exploratory)***

| Activity type | Participants | Regression odds ratio vs non-participants (95% CI) | Bayesian difference vs other participants, percentage points (95% credible interval) | Chance the association is positive | Chance it is the most effective type |
|---|---|---|---|---|---|
| **Campus Visit** | 7,390 | 1.54 (1.45 to 1.63) | +8.3 (+6.9 to +9.7) | >99.9% | 49% |
| **Summer School** | 595 | 1.38 (1.16 to 1.64) | +5.8 (+2.1 to +9.6) | >99% | 6% |
| **Mentoring** | 425 | 1.26 (1.03 to 1.55) | +4.1 (−0.1 to +8.3) | 97% | 2% |
| **IAG** | 12,825 | 1.20 (1.14 to 1.26) | +2.0 (+0.4 to +3.6) | 99% | 0% |

| | | | | | |
|---|---|---|---|---|---|
| **Subject Specific** | 3,845 | 0.98 (0.90 to 1.06) | −0.5 (−2.1 to +1.2) | 30% | 0% |
| **Attainment Raising** | 4,110 | 0.94 (0.87 to 1.02) | −1.9 (−3.6 to −0.3) | 1% | 0% |
| **Other*** | 145 | 1.71 (1.21 to 2.43) | +7.9 (+0.7 to +15.1) | 99% | 44% |

*Based on very few students and a mix of activities, so this result is highly uncertain.

In the regression, Campus Visits, Summer Schools, Mentoring and IAG were all positively associated with progression and statistically significant. Neither Subject Specific activity ($p = 0.549$) nor Attainment Raising ($p = 0.118$) was statistically significant. The Bayesian analysis gives the same order and direction for every type except Other. Other has the highest odds ratio in the regression, but it falls to second place in the Bayesian analysis once its small size is taken into account. Even so, the ranking is far from certain. Campus Visits have the highest probability of being the most effective type, but at 49% this is well short of certainty. The 145-student Other category still holds a 44% chance, which reflects how little is known about it rather than evidence that it works well. The Mentoring interval includes zero, so that result is less certain than the others.

## Attainment Raising

The Attainment Raising result needs careful interpretation. In the May 2026 report it showed a statistically significant negative association (odds ratio 0.85). This year the regression odds ratio is 0.94 and no longer statistically significant. When the model was fitted separately for each cohort year, the odds ratio rose from around 0.67 for 2019 to around 1.12 for 2023, and a formal test confirmed that the activity-type associations vary by year ($p < 0.001$). This suggests the change in the pooled result is at least partly due to the changing make-up of later cohorts. The Bayesian analysis, which compares only participants, finds a small negative association of -1.9 percentage points. Attainment Raising activities are typically aimed at students with lower prior attainment, who are less likely to progress whatever support they receive. Because prior attainment is not available in this dataset, the models cannot fully account for this selection process. The negative association is therefore most likely to reflect who takes part in these activities. It should not be read as evidence that the activity reduces progression.

## Robustness and validation

The regression model was well calibrated, and its predicted progression rates were within 1.1 percentage points of observed rates in every risk group.

The Bayesian analysis was run in two versions. In one, each activity type was estimated on its own. In the other, the pooled version, results for types with few students are treated more cautiously and drawn towards zero. The two versions predicted the data equally well. The pooled version is reported because it stops very small groups, such as the 145 students in the Other category, from producing extreme results, while still keeping every type in the analysis. Pooling changed the smallest types the most and the largest types very little. Both versions passed all convergence checks. Full diagnostics for all models are given in the technical annex.

No E-value or tipping-point analysis was carried out for the activity types. Each result compares students who did a given type with those who did not. The results should therefore not be added to each other, to the dose effects or to the participation effect.

Taken together, the results point to Campus Visits as the activity type most consistently associated with higher progression. Summer Schools, Mentoring and IAG show smaller positive associations. Because these comparisons are exploratory and cannot account for how students come to take part in each activity, they are best used to guide further investigation rather than to decide which activities to deliver.

## Limitations

This study does not include a control for attainment because this data was not available to Higher Horizons. Higher attainment is strongly correlated with an increased likelihood of progression to higher education. Future work in this area could be strengthened if this data was made available.

Due to some issues with data collection, the clustering effect of schools is also not controlled for within this study. Though there are some broad similarities between the schools targeted for outreach, the analysis cannot fully account for school-level differences such as institutional culture or school-level careers advice and support. The intervals reported here do not allow for this, so they are likely to be narrower than they should be.

This study covers years in which education was significantly disrupted by the Covid-19 pandemic. Four of the five cohorts included in this analysis had their pre-university education disrupted by the Covid-19 pandemic. The 2020 and 2021 cohorts did not sit level 3 examinations, while the 2022 and 2023 cohorts did not sit GCSE exams. Higher Horizons activity also moved largely online during this period. Assessment arrangements were changed in 2019/2020 (Centre Assessed Grades) and 2020/2021 (Teacher Assessed Grades). In both years, concerns were raised about grade inflation, with more students than usual receiving their expected grades and securing university places. It is therefore possible that progression rates for the 2020 and 2021 cohorts in this analysis are higher than they would have been under normal assessment

conditions. The statistical methods used throughout include Expected HE Entry Year as a covariate to attempt to absorb some of this variation, but it is impossible to totally control for it within this study. While Expected HE Entry Year absorbs average cohort-level differences, it cannot disentangle pandemic assessment effects, outreach delivery mode, university admissions changes, and changes in participant composition.

The statistical analysis also cannot control for unobserved variables such as motivation, parental support, or individual circumstance which influence progression to higher education.

The addition of a disability control this year required dropping students with missing disability data, which removes around 3,120 students from the sample created using last year's methodology. As with any exclusion, this carries a risk of introducing bias if the dropped students differ systematically from those retained; this is discussed in the technical annex.

# Recommendations

This final section sets out a series of recommendations. These are split into recommendations for outreach practitioners and recommendations for further research.

## Recommendations for practice

These recommendations assume that the associations observed in this study are at least partly causal.

1. Practitioners should focus first on ensuring every participant receives at least 3 hours of contact, where the evidence is strongest, and aim to increase the proportion of participants receiving 16 or more hours.
2. Practitioners should ensure that Campus Visits, complemented by IAG remain the core part of the Higher Horizons offer, and that the majority of students are able to engage with these activity types.
3. Track contact hours per participant as an operational target, including this measure in internal reporting dashboards. This measure should use the contact hour bands used in this report.

## Recommendations for further research

This study could be improved by including controls for attainment. This data is not currently available to Higher Horizons, but whether it could be accessed to improve the statistical modelling used throughout this study should be investigated.

Future work should investigate why the positive association between participation in Higher Horizons activities and progression to higher education has become smaller in recent cohorts.

The activity-type analysis should be developed further. This year's finding that the association for Attainment Raising activity is weaker than last year, and no longer statistically significant in the regression, appears to be at least partly driven by the changing composition of cohorts. This would also further develop the dosage findings in this report, asking if type of activity (or combinations of types of activity) matters within the dose. This year's report has further developed the exploratory analysis of activity types by using Bayesian methods to analyse participation in different types of activity, and this should continue to be developed. Further analysis of dose might also examine if timing matters, and whether activities delivered in specific year groups seem to be associated with higher rates of progression than others.

As additional years of HESA data become available, students should continue to be added to these models to see if these effects persist across cohorts. This is particularly relevant as we move further away from the pandemic. HEAT estimates that HESA tracking data for the 2025/2026 academic year should be available in Summer 2027, which would complete the by-19 window for the 2024 cohort. This would add a further 12,330 students to the analysis.