What impact did the maths interventions in the Opportunity Areas programme have on KS2 maths attainment in the North Yorkshire Coast Opportunity Area?

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1. Abstract

This report looks at the impact the Opportunity Areas (OA) programme had on Key Stage two (KS2) maths attainment in North Yorkshire Coast[1] OA. This report uses a quasi-experimental approach using a two-stage propensity score matching (PSM) combined with a difference-in-difference approach to measure the average treatment effect of the programme on KS2 maths attainment in the North Yorkshire coast, from academic year 2016/17 to 2018/19. This research shows that the North Yorkshire Coast OA experiences a positive increase in KS2 maths attainment; there is a statistically significant +1.15 effect on pupil maths scores. However, whether this increase can be attributed to the OA programme is less clear. The propensity score matching approach is useful, yet inherent flaws in the approach means that there is a limit to how much causal inference can be placed on the OA programme. The main reason for this is the likelihood of omitted variable bias. The overall findings of this report do conclude that there has been an improvement in KS2 maths attainment for North Yorkshire Coast. Further analysis of the OA programme, applying alternative impact analysis models that build upon the findings from this report would strengthen the evidence base of place-based programmes and the relative improvements in social mobility. This analysis can better develop policy design and decision making. Following this argument, the UK Government has recently announced a new place-based programme Priority Education Investment Areas, which builds on the OA programme.

[1] North Yorkshire Coast refers to Scarborough Local Authority District.

2. Introduction

2.1. Background and context

The Opportunity Areas (OAs) programme was launched in academic year 2016/17 by the Department for Education (DfE) (GOV.UK, 2017). The underlying purpose of the programme was to increase social mobility for selected areas in England using education as the driving tool/proxy (DfE, 2017). There were 12 OAs selected across England. North Yorkshire Coast was one of the selected OAs and the focus of this report. The North Yorkshire Coast encompasses the Scarborough Local Authority District (LAD) (DfE, 2016/17). The programme provided funding to each OA to spend on education projects on the key priority areas for that OA. One of North Yorkshire Coasts priority areas was to improve KS2 maths attainment.

The selection methodology of these 12 OAs was based on two indexes – the Social Mobility Index (SMI) and Achieving Excellence Areas (AEA) index (DfE, 2017). The SMI index identified the best and weakest LADs in England where young people from poorer backgrounds have the chance to succeed. The AEA index gives an overall indicator for schools in LADs based on their current performance and capacity to improve. Using these two indicators 32 LADs were chosen as a 'long-list'. These 32 LADs[2] were then reduced to 12. The final areas chosen, creating the Opportunity Areas, were:

- Blackpool
- Bradford
- Derby
- Doncaster
- Fenland and East Cambridgeshire
- Hastings
- Ipswich
- North Yorkshire Coast
- Norwich
- Oldham
- Stoke on Trent
- West Somerset

This programme was of national scale and the Department for Education provided £90 million worth of funding into the programme.

2.2. Rationale of focus

North Yorkshire Coast produced a delivery plan (DfE, 2016/17) to successfully take part in the OA programme. This plan outlined four priority areas:

1. Early years - Children get a head start in life through a high-quality early years education.
2. Maths - The North Yorkshire Coast becomes an area where children excel in maths, specifically in KS2.

[2] LADs - OA Selection Methodology file Gov.uk.

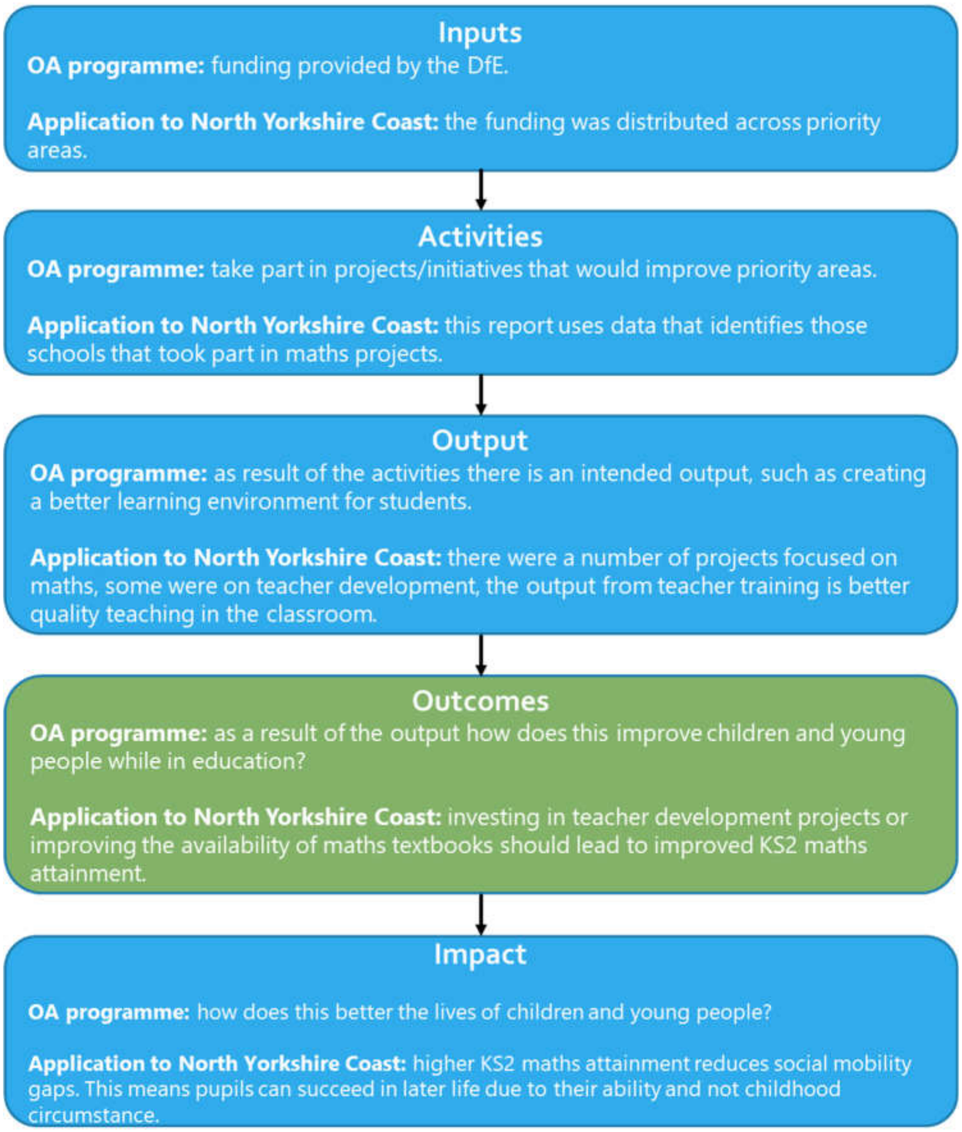
3. Literacy - A generation of readers who use the power of literacy skills and a love of reading to unlock future opportunities.
4. More ‘good’[3] secondary school places

North Yorkshire Coast was chosen for this report because of the ability to measure impact and the availability of data. This quasi-experimental impact analysis report measures KS2 maths attainment in North Yorkshire Coast and the treatment effect of the OA programme. Literacy, Early years and Secondary school places are broader aims that holistically improve social mobility but are more difficult to measure, these are longer term goals for North Yorkshire Coast OA.

2.3. Theory of change

The illustration below is a comprehensive view of the OA programme, looking at the key stages in the OA programme and highlighting the area of focus for this report – measuring outcomes, which translates to KS2 maths attainment in North Yorkshire Coast for this report.

Flowchart 1. OA theory of change



[3] ‘Good’ – is an Ofsted rating, which is a rating of overall school performance.

3. Literature review

3.1. Theory

To first understand why increasing maths attainment for North Yorkshire is important, the concept of social mobility must be explained. Drawing on two definitions of social mobility underpin this report and the true measure of increasing social mobility in the Opportunity Areas programme. Francis and Wong (2013) determine social mobility as the ability for individuals to move up the social ladder based on merit and ability (Wong, 2013). The Sutton Trust defines social mobility as 'how someone's adult outcomes relate to their circumstances as a child' (Helen Jenkins, 2017). Combining the two better encapsulates the social mobility context for the Opportunity Areas programme – the life prospects of an individual are determined by their childhood circumstance and ability. Social mobility is intrinsically linked also to equality of opportunity – individuals should have the same chances in life regardless of their socio-economic background, gender, age, race, birthplace, or other circumstances beyond their control (OECD, 2019). This highlights the importance of levelling up social mobility across England and thus the Opportunity Areas programme. Inequalities in education, due to place or family circumstance, reduces equal opportunity and weakens social mobility (Christine Farquharson, 2022). Children and young people from poorer socio-economic families and disadvantaged backgrounds are especially unfairly impacted, which should not limit individuals from achieving their full potential (Rachel Classick, 2021). Looking internationally, the UK socio-economic educational attainment gaps are extremely wide (OECD, 2018), meaning a large attainment difference for children and young people from lower-income and disadvantaged backgrounds compared to those that are not.

Increasing social mobility aligns also to underlying economic theory of human capital. Human capital theory views education as an investment, this investment yields a productive and efficient labour market which stimulates the economy (Weisbrod, 1962). Education can be seen as both a consumer and capital good, it provides utility to individuals and serves as an input for developing human resource for economic and social transformation (Almendarez, 2011). Theodore Schultz (1961) and Gary Becker (1964) were two of the most prominent contributors to human capital theory. Additional works from Howard Gardener Nelson-Phelps, Bowles-Gintis and Spence expand human capital theory and have developed further theoretical understanding (Chattopadhyay, 2023). The view of many labour economists is that human capital is a combination of the Becker, Schultz and Gardener view – human capital is valued in the market because it increases firms' profits (LSE, 2009). Expanding this in relation to education specifically in the OA programme, higher levels of attainment are valued more in the labour market, individuals can receive higher wages and gain access to more opportunities due to their improved human capital. Improved human capital can provide greater social mobility. Achieving greater social mobility not only benefits individuals but improves firms and the overall economy. Microeconomic theory supports this, stating that higher Marginal Revenue Product of Labour (due to increased ability) results in higher wages (individual benefit); leaning on efficiency wage theory, high wages can produce higher productivity and output for firms resulting in supernormal profits (firm benefits), as stated by Schultz, Becker and Gardener (LSE, 2009). These profits then stimulate the economy or correct government failure through government taxation. Empirical literature finds that better social mobility results in higher productivity, better employment and access to higher education and lifelong learning (Helen Jenkins, 2017; Woodfield S, 2013). Evidence suggests that this would result in a 2% increase in GDP equivalent to £39bn (Oxera, 2017). Improving levels of social mobility for future generations in the UK would boost the economy up to £140 million a year by 2050 (Helen Jenkins, 2017).

3.2. Existing educational analysis

There is vast educational research on pupil attainment and research focuses on the disparities in achievement of pupils from different backgrounds. To understand the intended impact of the OA programme (improved pupil outcomes), this review looks at the existing evidence and research of low social mobility through education. Education drives social mobility, yet inequalities exist in education. Differences in educational attainment are influenced by social class, family, pupil and place-based characteristics (Strand, 2021). Talent, ability and merit can all be interpreted in an educational landscape as attainment level, children and young people who score *the same attainment results should have equal opportunity.* Empirical evidence, looking at each phase of education, shows how attainment and life-chances are dependent on schooling and upbringing. Washbrook and Waldfogel (2010) found a significant gap in literacy ability for pre-school children from low-income and high-income families. Children in lower income families had a difference in literacy ability of 11.1 months *(Washbrook, 2010)*. In some areas of deprivation over half of children that start school have speech, language and communication needs *(England, 2021)*. When children begin primary school, education differences amplify. At the age of 11, KS2 children who have poor language skills are more likely to struggle with English, and 11 times more likely to struggle with maths *(James Law, 2009)*. Research shows that children who struggle with maths and english in KS2 are three times more likely to experience mental health problems and twice as likely to be unemployed by age 34 *(James Law, 2009)*. This supports literature on growing socio-economic attainment gaps and the rationale for social mobility intervention. Attainment differences persist into KS4. The Social Mobility Commission *(Commission, 2017)* found that 51% of Children who are eligible for Free School Meals in London achieve A*-C in english and maths GCSE. Whereas only 36% of children who are eligible for FSM in other regions in England achieve A*-C *(Commission, 2017)*. Evidence of educational variance in attainment due to place, not just income and family characteristics. In addition, a greater number of Children and learners in receipt of Free School Meals (FSM) attend poorer performing schools in LADs that perform badly, as opposed to similar FSM pupils that live in LADs that perform relatively better ***(Commission, 2017)***. Furthermore, the same report found that disadvantaged young people are nearly twice as likely to not be in education, employment or training one year after their GCSEs compared to young people not from a disadvantaged background.

3.3. Quasi-experimental methodology

Place-based programmes such as the OA programme are likely to exhibit selection bias; this bias is a form of systematic error (Miri Yemini, 2023). In the OA programme it is likely there are systematic differences between those pupils that partake in the programme (treatment group) and those who do not (control group). Failing to account for selection bias does not yield rigorous results and any conclusions made based on bias results will not stand against scrutiny (Shenyang Guo, 2020). The ideal solution is to use randomization, which is not possible for this programme as participants in the programme are selected. Quasi-experimental analysis accounts for this bias and evaluates the association between intervention and an outcome when the treatment group is not random (Marin L. Schweizer, 2016). This research employs a propensity score matching technique, combined with a difference-in-difference regression analysis. There is significant literature in measuring the impact of education intervention programmes using this approach. Difference-in-difference research is most known from the works by Card and Kreuger (1993) who researched the average treatment effect of a rise in minimum wages in New Jersey against Pennsylvania (where wages did not rise) (Krueger, 1993). This research and many that followed, proved the validity of the difference-in-difference method when evaluating a treatment change. Propensity score matching and difference-in-difference are common techniques used to assess impact of government intervention policies (Treasury, 2020). Belfi et al (2016) used propensity score matching to show primary school students in higher income areas achieved higher grades (Barbara Belfi, 2016) . Powell et al (2019) explored the impact on attainment when pupils are taught by teachers with higher credentials, findings proved that small positive impacts were found on pupil attainment. However, this report highlighted the limitations of this analysis, unobservable differences cannot be accounted for in propensity score matching (Marvin G. Powell, 2017). The Troubled Families programme, which is an intervention programme to support disadvantaged children in families with complex needs, matches those children in receipt of the programme to those who are not and compares outcomes. This paper found a positive outcome, less children were classed as 'Children in Need', (MHCLG, 2018). The analysis in this research report adopts a similar approach by the DfE on Sponsored Academies (Adam Hatton, 2019).This research employs a multivariate linear regression to select the matching variables for propensity score matching. The research is extensive and evaluates the performance of sponsored academies across England, highlighting that performance for certain treated academies increased while identifying the inherent difficulties of quasi-experimental analysis. This paper serves as a proof of concept, using similar data the propensity score method works, to ensure quality and assure rigour in results comparisons to this report are made. Through analysis of the literature, it is clear this is a viable approach, yet there is also evidence of reporting bias from this analysis. The number of quasi-experimental studies that report positive findings is far greater than reports of negative results (David L. Streiner, 2012). While evidencing findings throughout this report, it is important to refer to the caveats of this approach. Streiner (2012) also highlights the limitations of this methodology, emphasising the importance of matching for as much observable variables as possible, if this is not possible accept results are bias. In real world applications this is the case for most analysis - ensuring the propensity scores are balanced and similar between groups, if not the average treatment effect is unclear. Matching for as many observables is important, but if these observables do not aid matching or are irrelevant to the treatment or selection they are not needed.

3.4. Summary

Summarising this review there is supportive economic theory as to why the OA programme is important. Educational analysis currently supports the rationale for intervention by the UK government of developing a social mobility programme. The methodology outlined for this report is suitable for educational intervention programmes, yet there are limitations outlined in the literature.

4. Data

4.1. Source and variables

The literature on the propensity score matching methodology highlights the importance of obtaining relevant variables on North Yorkshire Coast project interventions and specifically the schools that took part in which projects, without this information a control and treatment group cannot be determined. Therefore, a data collection was conducted to gain all relevant data on the OA projects that were undertaken in the North Yorkshire Coast. This data collection involved meeting with the DfE OA leads to discuss project information and bridge any gaps of missing information. Collecting data on all 12 OAs was a task analysts completed within DfE and resulted in a central database of all OA projects across all 12 areas, in total there were over 300 projects that took place. See Table 1 below of projects filtered by subject (maths) for North Yorkshire Coast.

Table 1. Maths projects in North Yorkshire Coast and project length

Project	Subject	2016/17	2017/18	2018/19	Can schools be identified?
Maths Month	Maths			Y	No
Targeted Maths	Maths			Y	No
Mastery specialist / TRG	Maths	Y	Y	Y	Yes
Summer CPD through maths hub	Maths		Y	Y	Yes
Mastery Readiness	Maths		Y	Y	Yes
Mastery Specialists	Maths	Y	Y	Y	Yes
Maths guidance report training	Maths		Y	Y	Yes
Intervention in a mastery context	Maths	Y	Y	Y	Yes
1st Class@number	Maths		Y	Y	Yes
1st Class@number (2)	Maths	Y	Y	Y	Yes
Mastery in mixed age	Maths		Y		Yes
Mastery in mixed age (2)	Maths		Y	Y	Yes
Success @ artithmetic	Maths	Y	Y	Y	Yes
Maths no problem text book training	Maths	Y	Y	Y	Yes
EEF Guidance	Maths		Y	Y	Yes
EY Maths CPD	Maths	Y	Y		Yes
EY maths	Maths		Y	Y	Yes
Maths Transition	Maths		Y	Y	Yes
SSIF 1 Meta Cognition	Maths		Y	Y	Yes

A key component of the data collection is to understand the length of each project, this it to ascertain whether the impact of the project can be measured. The project data shows that all projects ran in 2017/18, a small number in 2016/17 therefore, it is fair to assume the treatment year of 2017/18 onwards. The second important step using this project data is to identify the schools that took part in these projects. The OA policy team shared a tracker of schools that took part in each project, from there a treatment group can be identified – any school that took part in a project in 2017/18 is considered treated (full list in Annex A).

KS2 data is obtained from the DfE's Pupil Data Repository[4]. The data used for this impact analysis is pupil level and anonymised. The dataset is of pupil level attainment and characteristics, such as maths and reading scores as well as ethnicity, Free School Meal (FSM) status, Special Educational Needs (SEN) and Children in Need (CIN). The data also includes school identifiers, such as the school Unique Reference Number and Local Authority Code. A full list of the variables used in this analysis can be found in Annex B. The importance of propensity score matching is the ability to match pupils in the treatment group (receipt of OA intervention) to pupils in a control group (no OA intervention). To match these pupils and generate propensity scores all pupil characteristics must be controlled for. Furthermore, in this two-staged propensity score matching approach school level characteristics must be created. This is done by aggregating the pupil level characteristics. For example, when aggregating FSM pupils, a school rate can be determined based on the count of free school meal pupils and total number of pupils in that school. Aggregated variables are used in the first propensity score matching. Explained in the methodology chapter, a two-stage propensity score matching approach accounts for school level characteristics and pupil level. At school level there are several other variables that are included in the data, for better matching. Literature proves that there is a level of differentiation in attainment in relation to Ofsted. To obtain historic Ofsted data and match this into the data set, data was sourced from Get Information About Schools (GIAS)[5].

4.2. Limitations

The project data does have its limitations. One of the biggest is that there is no measure of project intensity. For instance, one project may have focused solely on teacher training that would transfer to higher pupil attainment, whereas another project might improve maths literacy. There is no way to differentiate, which project was more or less intensive and therefore had a greater impact. The assumption therefore is that all projects provide a similar level of impact. There are limitations with the DfE data also, attainment data is only available up to 2018/19, data collection was halted for 2019/20 and 2020/21, then collected again in 2021/22. This was due to Covid-19. Table 2 below shows this:

Table 2. Available data in the OA time period

OA Programme Year	-1	0	1	2	3	4	5
Corresponding academic year	2015/16	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22
Attainment data available?	Y	Y	Y	Y	N	N	tbc

Some projects continued past 2018/19, which is not shown in Table 1. If there was a longer time series of data available more robust analysis could be conducted. OA leads indicated that attainment impacts did occur but are sceptical if this will be seen in the analysis due to the short period of measurement. The OA programme began in 2016/17, meaning 2017/18 is a reasonable treatment year for this analysis as all projects were underway (see Table 1). This research then measures the impact of the OA programme in North Yorkshire Coast up to

[4] Accessed publicly via the ONS SRS.
[5] Downloads - GOV.UK (get-information-schools.service.gov.uk)

academic year 2018/19. The project and pupil data used highlights the complexities and limitations of analysis.

5. Methodology

5.1. Hypothesis

Hypothesis: interventions from the OA programme in North Yorkshire Coast impacted KS2 maths attainment. If pupils within North Yorkshire Coast took part in the OA programme, then their maths attainment from academic year 2017/18 to 2018/2019 will improve, compared to a similar school and pupil, without the programme. The dependent variable is KS2 maths attainment, measured at school level as a rate and a as a maths score at pupil level. The KS2 maths attainment variable at school level is the percentage of pupils that reached the expected standard in maths. The pupil level variable gives a raw score from 0-120[6]. The hypothesis will be proven true if a statistically significant effect is found on KS2 maths attainment for North Yorkshire Coast.

5.2. Research design

This is a two staged propensity score matching approach combined with difference-in-difference estimation. To achieve this the research design is illustrated below.

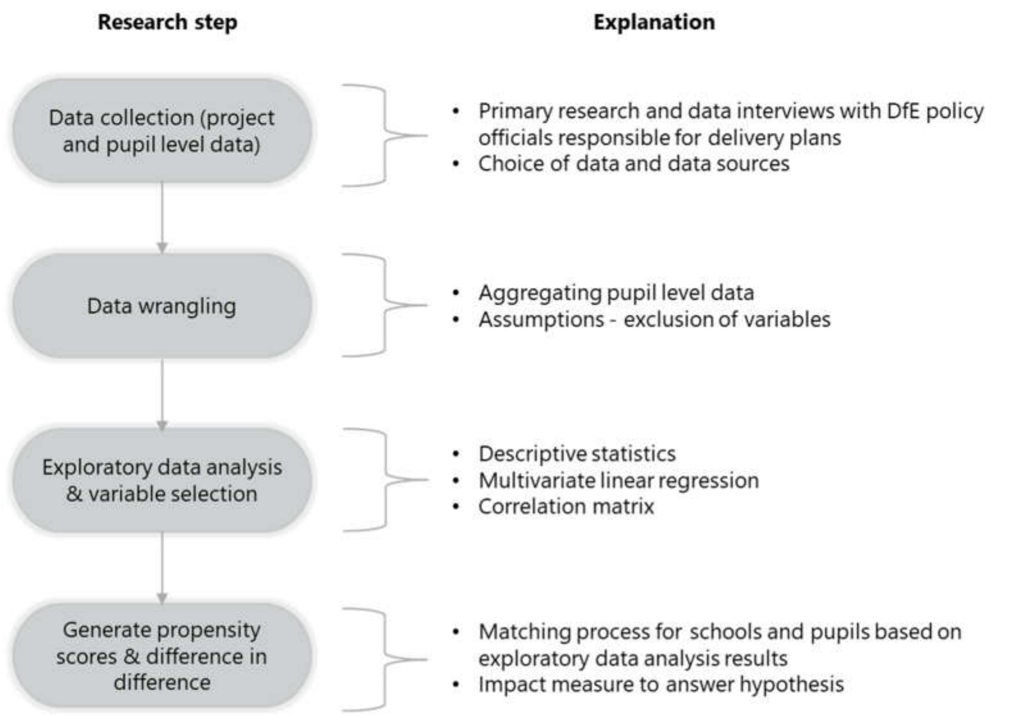


Figure 1. Research design

[6] Key stage 2 tests - GOV.UK (www.gov.uk)

5.2.1. Data collection

Project data collection was achieved through conversations with OA leads in the DfE. Section 3.1 discusses the data collected. Examples of questions asked are as follows:

- Please can you confirm this list of projects (self-constructed data, see table 1 section 4.1)?
- Do you have information about which schools and pupils have been affected by each project?
- Do you know project start and end dates?
- Do you have any sense of an expected time when impacts can be measured?

Answers to these questions formed the project data collection for North Yorkshire Coast OA. This project data is used in conjunction with the KS2 data in section 4.1 to conduct the impact analysis.

5.2.2. Data wrangling

Data wrangling refers to transforming, reorganising and mapping raw data into a usable form for analysis. Part of this research step is to exclude schools and pupils that can bias and yield inaccurate results. Empirical evidence shows that there is a 'London effect' in educational attainment, where pupils from London achieve higher attainment scores, especially those pupils from disadvantaged backgrounds (Andy Ross, 2020). As the OA programme and this analysis is focused on improving KS2 maths attainment, with a specific focus on areas of low social mobility and high disadvantage, including London schools and pupils as comparators would yield unfair and inconclusive results. London schools and pupils were removed from any analysis. A further data obstacle was to ensure that school identifiers (URNs) matched across the years of data. This is a panel data set, observing school and pupil characteristics over time. The challenge posed is that schools and pupils change, school Unique Reference Numbers (URNs) can change, due to academisation, closures, amalgamation etc; and pupils can move between schools. This increased the complexity of producing a dataset for analytical use. School level Links data from GIAS allowed all URN and pupil changes to be accounted for. This strengthens the quality of the dataset and ensures greater robustness of findings.

5.2.3. Exploratory data analysis

This research step is key in variable selection for the matching process and to understand the data. Initial high level descriptive analysis will assess maths attainment for North Yorkshire Coast, looking at North Yorkshire Coast historic attainment. Following this, conducting a multivariate linear regression and step-wise regression begins the investigative process of variable selection for the model exploring the relative significance variables may or may not have on regression and matching models. The ability to control for all potential confounding variables is crucial for matching to be successful. Running a multivariate linear regression of all potential control variables on the KS2 maths attainment metric will determine which control variables to include in the PSM analysis. The purpose of the multivariate linear regression in this study is to: 1) understand the data and interactions of control/explanatory variables with the dependent variable; and 2) to support decisions of the relevant control variables to include in the matching that can stand up to education theory and analytical scrutiny.

5.2.4. Propensity score matching & difference-in-difference

Propensity score matching is a quasi-experimental analysis technique that compares outcomes between treated and non-treated subjects that are matched on their probability of receiving treatment (calculated as a propensity score) based on shared observable characteristics. Propensity score matching has become a common research technique, especially in educational analysis (Marvin G. Powell, 2017). This is because drawing causal inferences in educational settings is hindered by the lack of randomisation, interventions are either selected or self-selected by participants. Controlling for variables related to self-selection enables researchers to obtain more precise estimates (Horst, 2016). This impact analysis adopts the propensity score matching structure outlined below.

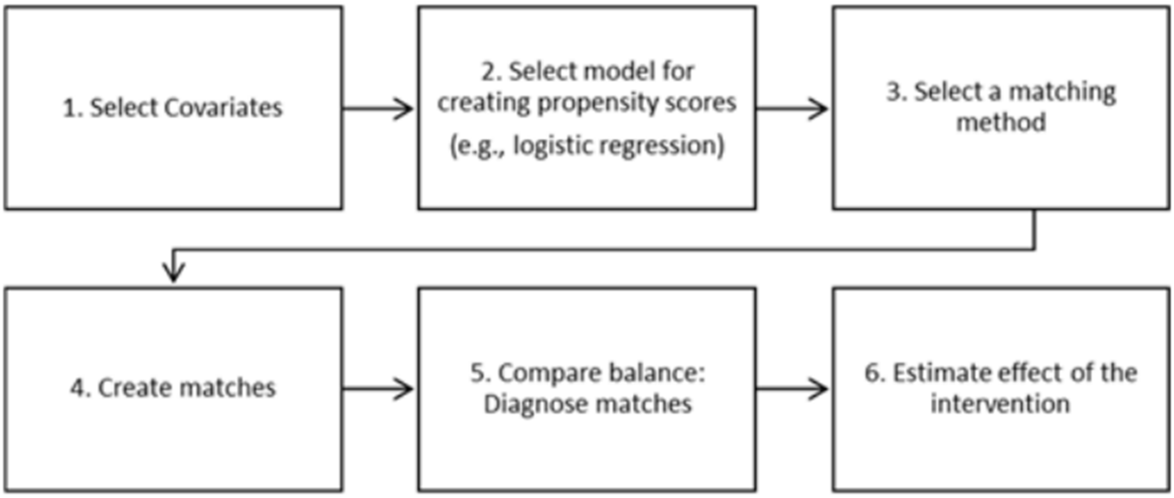


Figure 2. Visualising the methodology (Horst, 2016)

The selection of covariates is based on literature and the results of the exploratory data analysis. For the validity of the analysis it is important to identify key variables that have impact on attainment and OA selection; then decide the variables to include in the matching process (Stuart, 2010). The exclusion or inclusion of certain covariates impacts the inferences to be made on the analysis and therefore the OA programme (Steiner, 2010). This report takes a two-stage propensity score matching approach as literature shows that it is a viable solution to include the school level propensity score as a variable when performing the pupil level matches. This is a technique used by the Department for Education and has been applied to published studies (Adam Hatton, 2019).

A common model used to generate propensity scores is logistic regression. The regression is used to match schools with similar distribution of confounders so differences in the outcome measure (KS2 maths attainment) can be measured as the treatment effect (Austin, 2010; Stuart, 2010). Other model specifications may use discriminant analysis or mahalanobis distance (Rosenbaum, 1983; Stuart, 2010). For this analysis logistic regression is best suited as it is the default regression model in the R package used, the R package used is Matchit[7].

The following step is to determine the matching process. The Matchit package uses the 'ratio' argument to determine the number of matches and the 'method' argument to determine the type of match. For this analysis, it is sensible to use a nearest neighbour matching method with a ratio of 1:1, for every treatment school in North Yorkshire Coast it is matched to one non-OA

[7] Matchit function - RDocumentation

non-London school in England, that has the closest propensity score. The matching method also does not include replacement. Without replacement means that one OA school is matched to its nearest neighbouring school and that school is then unable to be matched to another. This ensures that the comparator schools are equal to the number of North Yorkshire Coast schools that received the intervention.

When a dataset of matched schools is created, the balance needs to be assessed. A good balance would indicate that the propensity scores for the North Yorkshire Coast schools and the corresponding matched non-OA school are similar and similarly distributed. If the balance is acceptable and holds up to analytical challenge, then inferences can be made from the matching.

The final step to measure the effect of the treatment (OA programme) adopts a difference-in-difference method. Where the coefficient of the interaction variable will indicate the impact of the OA programme. Difference-in-difference regressions are common in estimating treatment effects. The β_3 regression coefficient below will measure the average treatment effect in a difference-in-difference approach.

$$MATSCORE_i = a + \beta 1 * Treatment\_yr_i + \beta 2 * OA_i + \beta 3 * (Treatment\_yr_i * OA_i)$$

In the OA programme, the first difference corresponds to the change in maths scores for each group between 2016/17 and 2018/19. The second difference is the difference between the calculated differences for each group. The method measures the causal effect of an intervention by comparing outcomes. This method assumes that in the absence of the OA programme the difference between the treatment and control group would be constant over time (Guido Schwerdt, 2020).

5.3. Advantages and disadvantages

Table 3. Evaluating research methods

Method	Advantages	Disadvantages
Multivariate and stepwise linear regression	This is a widely used method in research and easy to implement. Can identify variables associated with the outcome variable and help identify important confounding variables. Stepwise is especially helpful for large datasets.	Assumes errors are normally distributed and independent, which may not be the case for propensity score matching. OLS may select variables that are not actually confounding variables and stepwise regression can lead to overfitting of the model.
Propensity score matching	Balances confounding variables between treatment and control groups, making it easier to estimate causal effects. It helps reduce selection bias. A viable approach when a randomised controlled trial is not feasible.	Relies on the assumption that all relevant confounding variables are being measured, if not this results in omitted variable bias. The method can be sensitive to the choice of matching specification.
Difference-in-difference	Used to control for time-invariant confounding variables such as gender and SEN. A good method to calculate the average treatment effect of an intervention.	Relies on the assumption that without the treatment the trajectory of the treatment group would be the same as the control group. This method is sensitive to the choice of treatment year.

6. Results

6.1. Exploratory analysis

Before running any econometric tests or matching, the PDR data is analysed in its raw form. This will indicate, at very high level, whether KS2 maths attainment has increased during the period in question. Figure 3 below outlines KS2 maths attainment increases for pupils in North Yorkshire Coast.

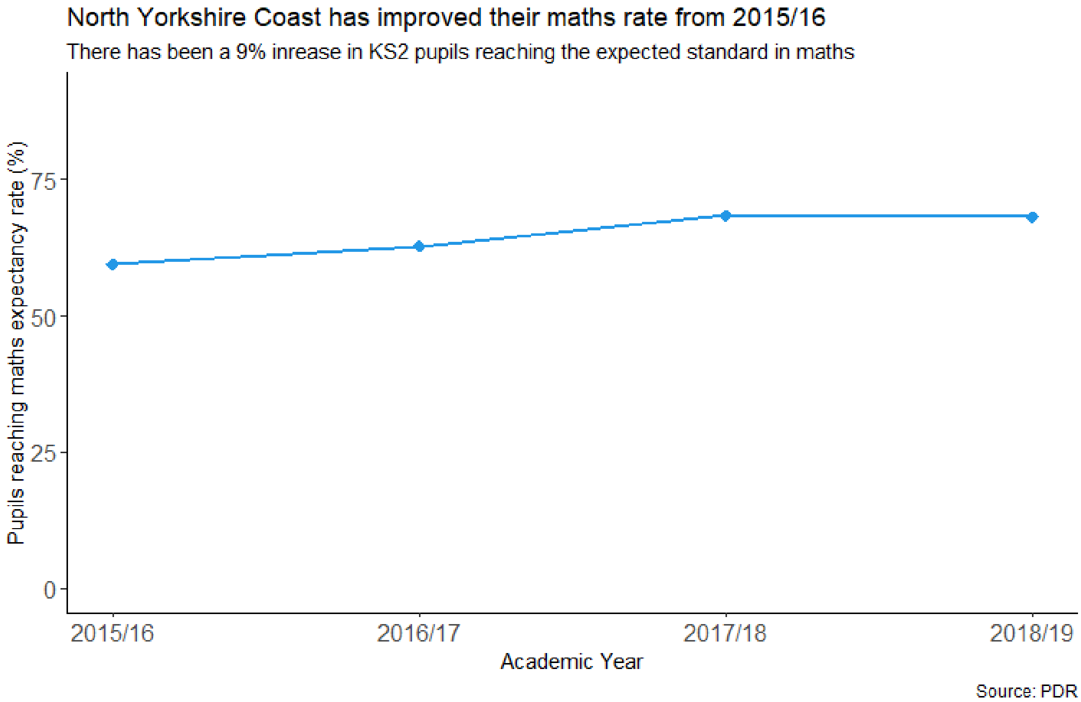


Figure 3. Maths expectancy rate in North Yorkshire Coast from 2015/16

In 2018/19, 790 out of 1160 pupils were achieving the expected standard in KS2 maths. The years 2016/17 to 2017/18 saw the largest increase in pupils' attainment, right at the inception of the OA programme. Additionally, figure 3 shows rising maths attainment before OA intervention. This could be due to influencing factors at school or pupil level; for example, if Ofsted ratings were low or there were more free school meal pupils. Alternatively, economic theory would suggest that signalling is also a potential contributor to the rising attainment in this period (Tatum, 2023). It is an unobservable effect, but one that may have influenced North Yorkshire Coast; if schools know they are to be receiving DfE funding and project interventions then they may begin planning or performing better in anticipation of the programme. Furthermore, when looking at the outcome measure KS2 maths attainment, there is variation at school and pupil level. Some schools and pupils will have done better than others. To observe this, figure 4 shows a density plot at school level. Comparing the KS2 maths expectancy school rate for 2015/16 to 2018/19 for North Yorkshire Coast, all OAs and all schools in England (excluding OAs).

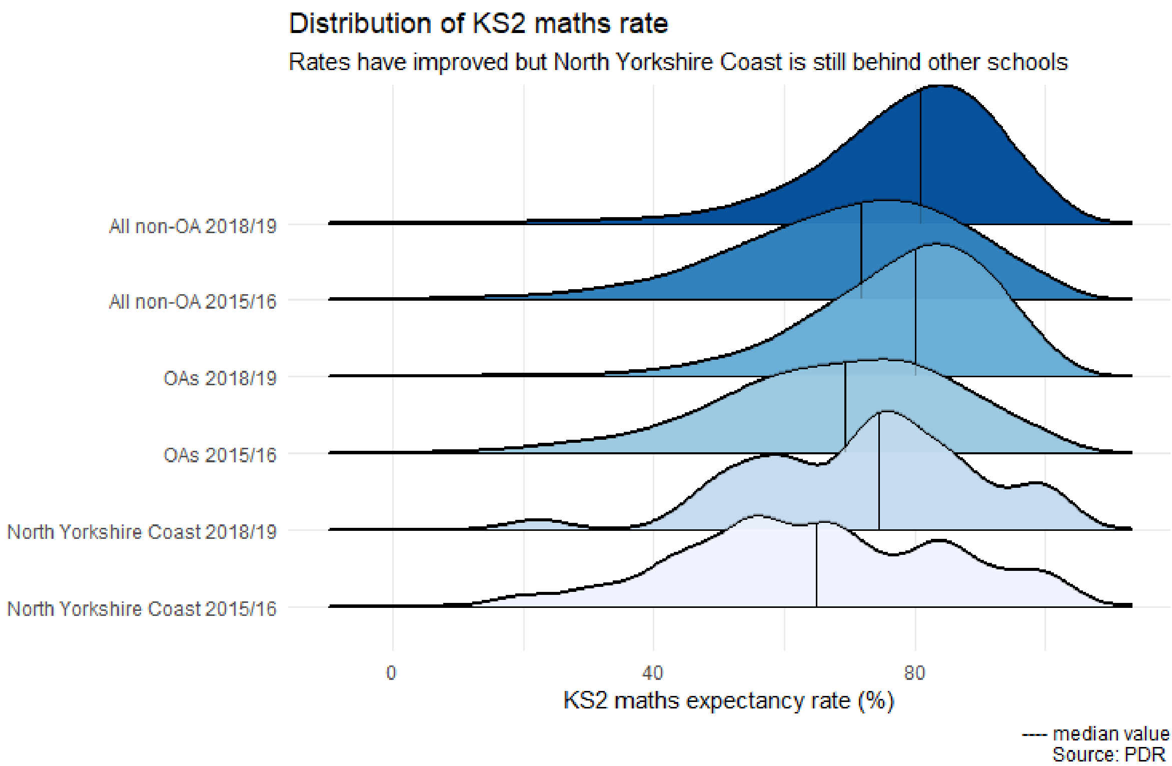


Figure 4. Comparing the distribution of maths expectancy rates

The distribution shows that there has been improvement in KS2 maths expectancy rates from 2015/16 to 2018/19, supporting the findings from figure 3. There have been improvements for all groups, North Yorkshire Coast, all OA schools and all non-OA schools. Observing these increases, it shows that North Yorkshire Coast is still behind the non-OA and OA school distributions, shown by a lower median measure for KS2 maths expectancy. The exploration of the raw data highlights that there have been improvements in KS2 maths attainment for North Yorkshire Coast, as well as for other schools. Whether this increase in North Yorkshire Coast can be attributed to the OA programme will be determined by the difference-in-difference results.

Investigating the data further through multivariate and step-wise OLS regression of the school level characteristics determines variables selection for school level matching. Propensity score matching should not only match on the determinants of selection (the SMI and AEA index) but also the variables that influence the outcome measure. Therefore, it is important to run a school level OLS understanding the relationship of the dependent variable MATH_EXP_S and independent variables in the dataset. Looking at the regression output in table 4, it shows two school level regression models, using the school level maths expectancy rate against key school level covariates.

Table 4. Regression output

	Dependent variable:	
	MATH_EXP_S	
	OLS	OLS step-wise
	(1)	(2)
EAL_PERC_S	-0.002	
	(0.013)	
DISA_PERC_S	-0.041^{***}	-0.041^{***}
	(0.008)	(0.007)
MATHSCH_16	0.229^{***}	0.230^{***}
	(0.007)	(0.007)
MATHSCH_15	0.039^{***}	0.045^{***}
	(0.010)	(0.008)
MATHSCH_14	0.009	
	(0.008)	
SENPROV_S	-0.275^{***}	-0.276^{***}
	(0.011)	(0.011)
NWBRI_S	0.011	0.010^{**}
	(0.010)	(0.005)
CONSEC_LOW_OFSTED_S	-0.021^{***}	-0.021^{***}
	(0.002)	(0.002)
CIN_S	-0.053^{**}	-0.052^{**}
	(0.021)	(0.021)
ABS_OVERALL_RATE_S	-2.523^{***}	-2.528^{***}
	(0.124)	(0.124)
NUMB_ELIG_S	0.00003	
	(0.00005)	
Constant	0.723^{***}	0.726^{***}
	(0.009)	(0.009)
Observations	13,285	13,285
R^2	0.284	0.283
Adjusted R^2	0.283	0.283
Residual Std. Error	0.130 (df = 13273)	0.130 (df = 13276)
F Statistic	477.545^{***} (df = 11; 13273)	656.516^{***} (df = 8; 13276)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Step-wise regression is an iterative method that assesses the statistical significance of each variable in a linear regression model. Variables such as EAL_PERC_S, MATHSCH_14 and NUMB_ELIG_S in model 1 are excluded in model 2, meaning these predictors do not aid the model fit and are not statistically significant, highlighted by corresponding p-values; all other variables are statistically significant. It is surprising that EAL_PERC_S is not statistically significant as this was a variable used in the sponsored academies research (Adam Hatton, 2019). Focusing on model 2, the adjusted R^2 value 0.28 indicates the independent variables are weak at explaining the variation in the dependent variable. This R^2 is not of significant concern because this is common with datasets that have high levels of variability within variables, such as school level characteristics. Additionally, the lack of explanation of the school variables on maths attainment is expected, Choi and Kim (2008) found that 19% of the variance in maths attainment (MATH_EXP_S) can be explained by school level characteristics, which supports the low R^2 values (Choi, 2008). Investigating model 2 further, the coefficients coincide with theory; variables that setback attainment all have negative coefficients. For instance, the percentage of disadvantage, absence rate, Ofsted rating, Children in Need rate and Special Educational Needs rate, are all factors that influence maths attainment. Schools with a greater percentage of their pupils identifying with these variables will, according to the model, have lower maths attainment. Heteroskedasticity exists within the model however, shown in figure 5.

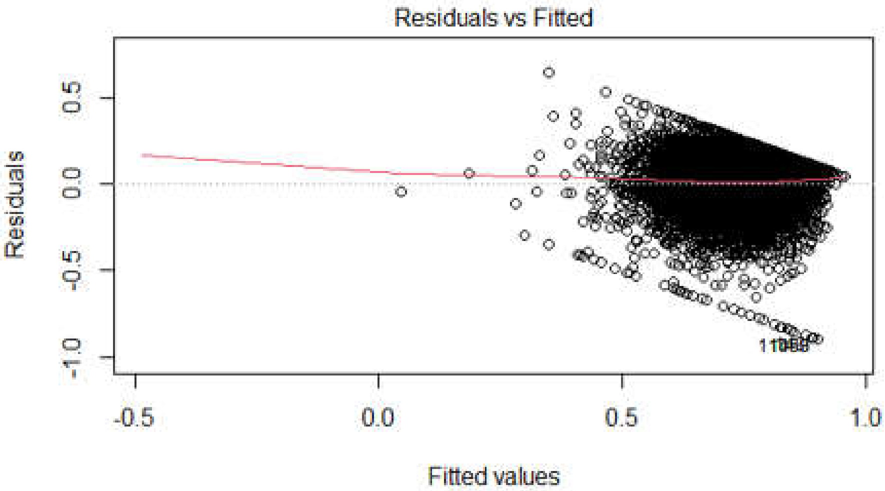


Figure 5. Residuals vs fitted values plot

If homoskedasticity exists, then there would be random and equal distribution of plots in figure 5 and a flat red line. Figure 5 shows that the red line is slightly curved, and residuals seem to decrease when fitted y values increase, indicating a pattern. To confirm the presence of heteroskedasticity in the data, a Breusch pagan test rejects the null hypothesis of homoskedasticity with a p-value of 2e-16. To rectify this, HAC standard errors are used in the model, which did not provide a solution. Additionally, model 2 results in a Ramsey Reset test value of 2e-16, indicating that the model is mis-specified. This suggests that the data could be in the wrong form, improperly pooled or omitting key variables. Due to the inherent nature of school level analysis, it can be assumed the rejection of the Ramsey Reset Test null hypothesis of correct specification is due to missing variables, which are unable to be observed. A model using log form did not alter the Reset test results. Calculating the variance inflation factor, yields results no greater than 4 for all variables signifying there is no problematic multicollinearity in model 2. Lastly, the calculation of the Durbin Watson value of 1.92 and p-value of 4e-05, indicates no presence of autocorrelation in the model. See Annex C for all tests in exploratory data analysis.

Despite model 2 and the school level data failing tests of robustness, the method still stands. The purpose in this step-wise regression is to identify variables that are important to maths attainment, which can be used to match treated and non-treated schools. These school level variables are identified in model 2. Tests on the school level data and model highlight the inherent difficulties within the data, as well as support the approach of a matching method. School level variables alone are difficult to model, so combining school and pupil level characteristics is a viable approach. Furthermore, the Matchit function (see section 5.2.4) uses a logistic regression, as part of the exploratory analysis, a logistic regression was calculated (see Annex C). The results and tests were like those outlined above – a model that provided some understanding of school variables that impact maths attainment but is not robust as a single model. This exploratory analysis informs variable selection for the matching process. The propensity score matching process employs regression to create propensity scores not to infer impact on the dependent variable; therefore, the causal inferences from these exploratory models simply support variable selection in the matching process; the lack of robustness in the OLS models do not have significant impact on propensity score matching. The fact that this OLS analysis fails to meet the specifications of the Gauss Markov Theorem further supports the need for an alternative model, such as propensity score matching. Exploring further school level regression analysis is therefore counterintuitive to the propensity score matching approach. A regression analysis of the pupil level data can be found in Annex D, which informs variable selection for the pupil matching process. There is little need to explore these results in detail as they were similar to the school level regression. However, the pupil level OLS model fit was much stronger than the school level OLS model. There are several statistically significant pupil variables like those identified in the school level OLS analysis, with the exception of pupils who have English as an Additional Language (EAL) becoming statistically significant. Ultimately, the OLS results inform variable selection. Significant investigation is not required of these models as this analysis focuses on propensity score matching and difference-in-difference regression. Although, it is important to acknowledge that these models are likely to fail the criteria for the Gauss Markov theorem (Dodge, 2008). These models are unlikely to be the best linear unbiased estimators, which is a limitation in the variable selection process.

6.2. Propensity score matching

6.2.1. School level matching

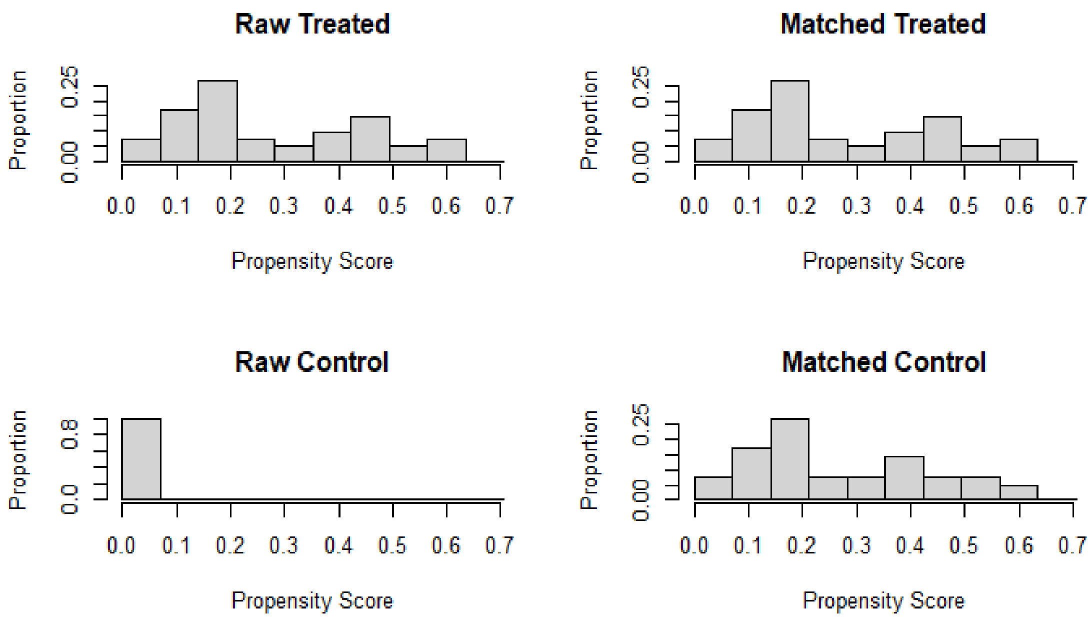
A fair assumption is to include all statistically significant variables in the exploratory analysis, as well as the SMI and AEA variables in the matching process. This is because both the variables related to OA selection need to be included in the matching (Stuart, 2010). The balance of matches is also important. It is desirable to compute propensity scores that are high, indicating the school is likely to have received the OA intervention, but also the balance between the control and treatment group is crucial. If the matched control group has propensity scores that are different to the treatment group, then the matching between the two is weak. Therefore, both balance and propensity score values are important for matching; visual and numerical inspection of results confirms the strength of matching. To ensure the best matches and highest propensity scores multiple matching iterations took place. The final matching formula is outlined below.

Figure 6. Matchit function formula at school level

```
matchit(OA ~  DISA_PERC_S + READSCH_16 + WRITSCH_16 +
        MATHSCH_16+ READSCH_15 + WRITSCH_15 + MATHSCH_15 +
        KS1AVG_S + SENPROV_S + CONSEC_LOW_OFSTED_S + CIN_S +
        SMC_I + AEA_I + NUMB_ELIG_S,
        data = School_Data,
        method = "nearest",
        replace = FALSE,
        ratio = 1)
```

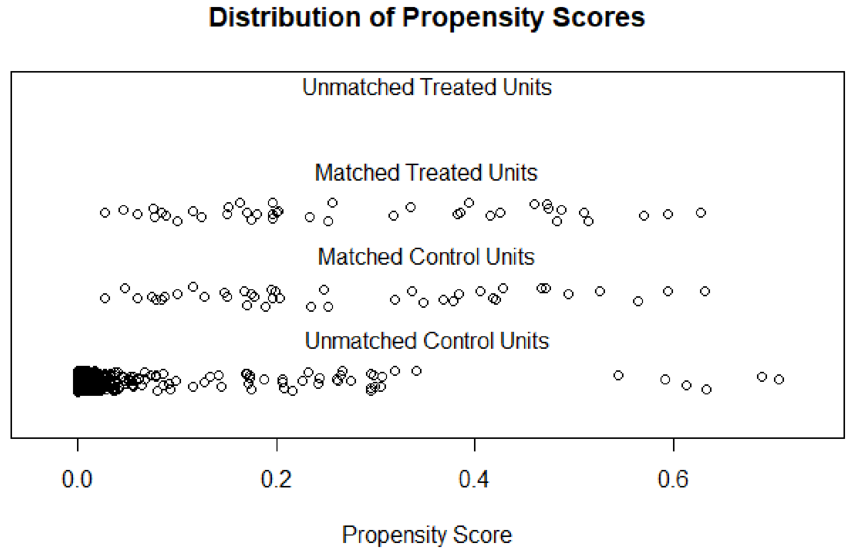
The matching formula reflects most of the findings from the exploratory regression analysis. These variables were included for two key reasons: these variables are key to education analysis theory; these variables provide the best propensity scores and balance of the treated and control group. Variables such as NWBRI_S and ABS_OVERALL_RATE_S have been dropped, despite significance in exploratory analysis; these variables are very variable at school level, including them did not benefit the matching process. Both absences and being a non-white British pupil influence maths attainment, subsequently these variables are included in the pupil matching, where the matching is better. The variables NUMB_ELIG_S is included, acting as a proxy for school size. Two new variables are added to the model READSCH and WRITSCH, both are attainment variables for reading and writing respectively. These variables are included because OAs selection was based on areas with low social mobility and performance; academic scores are an indicator of performance, therefore, matching should include all attainment measures not solely maths, to encompass all performance. These variables are also lagged by two academic years; OA selection was based on historic Reading, Writing and Maths attainment. Figure 7 checks the robustness of the matching.

Figure 7. Comparing the treated and control groups after matching



The histograms show the balance is relatively equal; there are slight proportional differences when propensity scores are greater than 0.4, however, these differences are not significant; the distribution of propensity scores for North Yorkshire Coast schools are similar to the matched control group. This means, after matching, the schools in the control and treated group are similar in terms of their propensity to receive a certain treatment (the OA programme). Therefore, meaningful comparisons can be made as North Yorkshire Coast schools are now being compared to similar schools. Additionally, the variance ratio of propensity scores for the intervention group and control group is 1.07, a ratio near to 1 implies good balance (Rubin, 2001). Further inspection of a jitter plot highlights that all 41 North Yorkshire Coast schools are matched to 41 non-OA schools in figure 8.

Figure 8. Comparing the distribution of propensity scores at school level



6.2.2. Pupil level matching

Once the control schools have been identified, the two-stage propensity score matching process can be conducted. The matching process is the same as at school level but now includes pupil level variables (determined by pupil regression analysis and theory) and includes the propensity score for North Yorkshire Coast schools and control schools. This is what makes this analysis two-stage, as the analysis from the school level matching is inputted into the pupil level matching calculations. The matching function is shown below as well as the balance of propensity scores, where pscore_sch equals the school level propensity score. Note that pupils' maths attainment (MATSCORE) is not included at pupil level, this is because unlike school level attainment, for a pupil their historic attainment is the KS1AVERAGE.

```
matchit(OA ~ FSM6 +  CIN + GENDER + SENF + KS1AVERAGE +
          Absences_range + pscore_sch,
        data = Pupil_Data_2019_PSM2,
        method = "nearest",
        replace = FALSE,
        ratio = 1)
```

Figure 9. Matchit function formula at pupil level

The Matchit function significantly improves the balance of treated pupils with control pupils. Following the charts in figure 10 from left to right explains the pupil matching process and how balance improves. The two-stage approach, accounting for school level characteristics within the pupil matching, yields the best and most robust results.

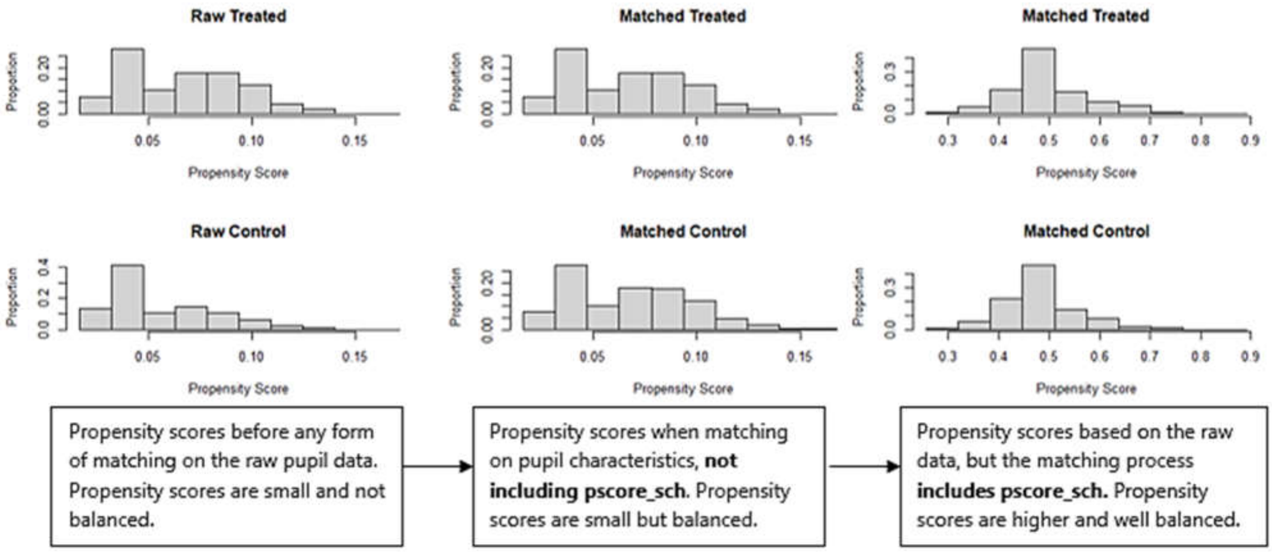
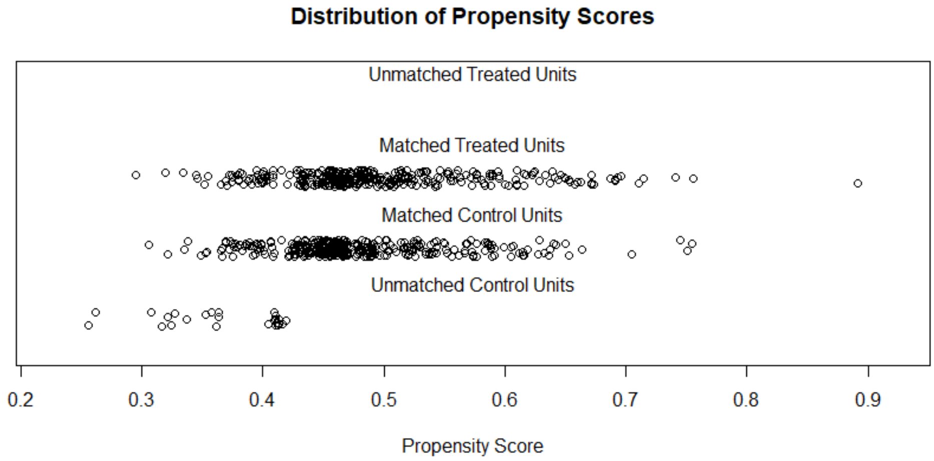


Figure 10. Comparing the matched groups, with and without the school level propensity score

Checking the robustness of matching using jitter plots confirms that the matching process is successful and pupils in North Yorkshire Coast have been correctly matched to similar pupils in non-OA schools. Figure 10 demonstrates the pupil matches. Additionally, the variance ratio is 1.14, which is close to the desired target of 1, further evidence of strong matching for the two-stage method.

Figure 11. Comparing the distribution of propensity scores at pupil level



6.3. Intervention results

The final step in the research is to determine the average treatment effect, this determines whether the OA programme did influence KS2 maths attainment. The difference-in-difference results can be seen in table 5.

Table 5. Difference-in-difference results

	Dependent variable:
	MATSCORE
Treatment_yr	0.560
	(0.389)
OA	0.994^{**}
	(0.410)
Treatment_yr:OA	1.153^{**}
	(0.567)
Constant	100.792^{***}
	(0.283)
Observations	2,974
R^2	0.017
Adjusted R^2	0.016
Residual Std. Error	7.707 (df = 2970)
F Statistic	16.949^{***} (df = 3; 2970)
Note:	*p<0.1; **p<0.05; ***p<0.01

The difference-in-difference estimate is analysing whether the OA programme intervention resulted in a statistically significant change in pupil level maths scores for North Yorkshire Coast pupils compared to similarly matched schools. The equation of the fitted model is represented below:

$$MATSCORE_i = 100.79 + 0.56 * Treatment\_yr_i + 0.99 * OA_i + 1.15 * (Treatment\_yr_i * OA_i)$$

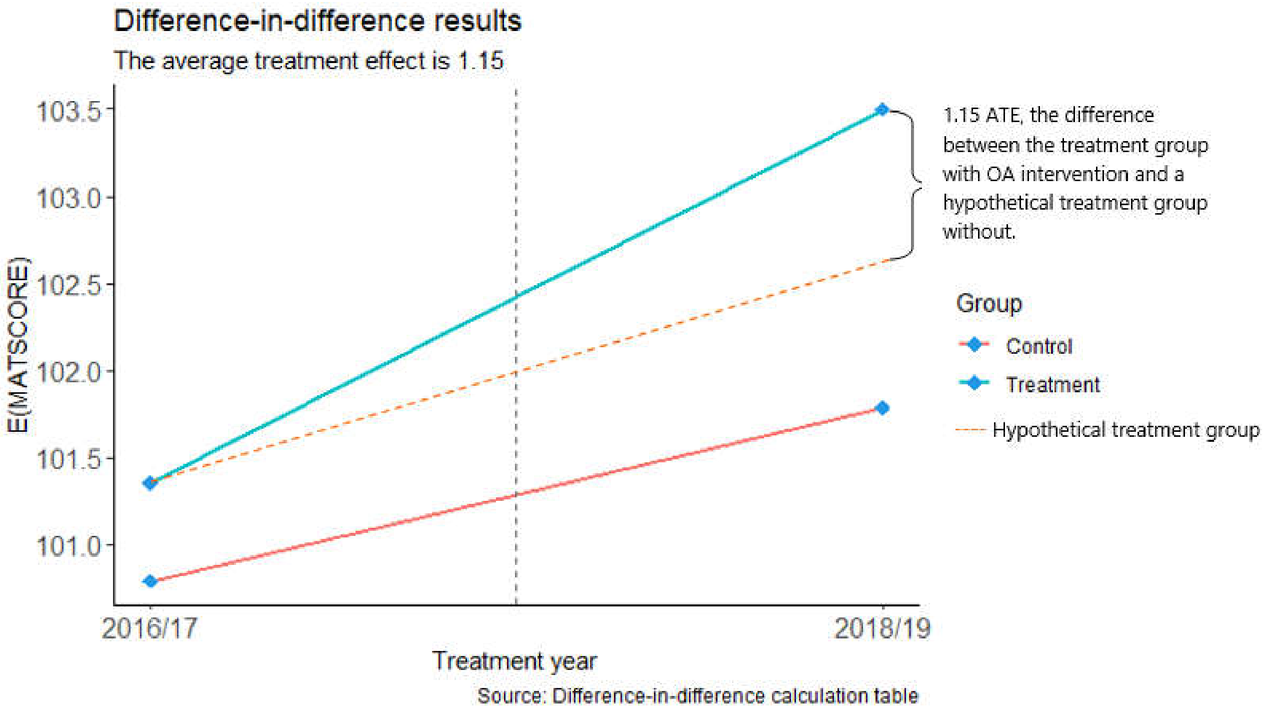
The average treatment effect is shown by the $Treatment\_yr_i * OA_i$ coefficient. Therefore, the average treatment effect of the OA programme on North Yorkshire Coast maths attainment is +1.15, which is statistically significant. This result is determined by the difference-in-the-differences, shown in table 6.

Table 6. Understanding difference-in-difference

	Before OA (OA = 0)	**After OA (OA = 1)**	**After - Before**
Control group	100.792	101.786	0.994
Treatment group	101.352	103.499	2.147
Treatment - Control	0.560	1.713	**1.153**

Furthermore, the average treatment effect (ATE) can be observed visually in figure 12.

Figure 12. Visualising the difference-in-difference results and OA impact



Inspecting the results by each term, it is observed the intercept variable (constant) is statistically significant. The constant variable estimates the mean MATSCORE in the control group preceding the OA intervention. The value of the estimated mean MATSCORE is the intercept of the difference-in-difference regression: 100.79. The Treatment_yr term is 0.56 and not statistically significant, therefore, does not aid model fit or explanation of the pupil maths score variable. The OA term is statistically significant, and shows that being an OA impacts the maths score variable. Finally, the key term of interest, is the difference-in-difference estimator of 1.15, which is significant, indicating that there has been a positive effect of the OA programme on North Yorkshire Coast pupil maths scores.

Evaluating the model outputs shows that the adjusted R^2 value is very low. The model has only been able to explain 0.02% of the variance in the response variable MATSCORE. This is a weak result which questions the inference of the model. However, the F-statistic is 16.95 and statistically significant at 0.01%. This confirms that the model's variables are jointly significant, and the variables together are better at explaining the variance of MATSCORE than a simple mean model. Furthermore, all variables are positive (+) meaning their effect increases MATSCOREs. Overall, there are negative and positive aspects to the model interpretation.

7. Conclusion

In response to the research question, the OA programme had a positive impact on KS2 maths attainment for pupils in North Yorkshire Coast, using a treatment period of 2017/18 and measuring outcomes from academic year 2016/17 to 2018/19. Of those schools that took part in maths intervention programmes, their pupils, compared to similar pupils at similar schools, saw improved maths scores. However, this research is not perfect. While the matching and difference-in-difference estimator yielded positive results it is important to acknowledge that this is still a quasi-experimental approach. A suggested next step is sensitivity analysis on these findings. The research design is sufficient for quasi-experimental impact analysis, but if research was to go beyond this report, there are many different approaches (such as synthetic controls) to model the OA intervention effect that could produce different results. The biggest limitation in this research is omitted variable bias; all control variables should be included in modelling. This is simply not possible in educational research; there are so many unobservable effects that influence attainment, this research uses the best publicly available data to reduce omitted variable bias, but important variables such as teacher quality and home life of pupils cannot be accounted for fully. The DfE who have access to granular pupil sensitive data *may* be able to complete impact analysis at specific pupil level, identifying specific cohorts/groups of pupils that received the OA intervention, not just all KS2 pupils in a school as well as controlling for more school, pupil, area and familial variables. Furthermore, it would be interesting to observe the later life outcomes of pupils that received OA intervention. The aim of this intervention is to improve social mobility by developing human capital through equal opportunity. Using data such as the Longitudinal Education Outcomes database would begin to show the longer term impact of this programme. The findings from this report warrant further investigation, this would be of specific interest to policy makers in the DfE. The results from this report show that this policy likely had positive impact, therefore, in further policy making, this report (and any further analysis) can be used to make evidence-based decisions.

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Annex A

URN	School name
144679	Airy Hill Community Primary School
121314	Barrowcliff School
146312	Braeburn Primary and Nursery School
121373	Brompton and Sawdon Community Primary School
144680	Castleton Community Primary School
121358	Cayton Community Primary School
121486	Danby Church of England Voluntary Controlled School
121377	East Ayton Community Primary School
143290	East Whitby Primary Academy
121610	Egton Church of England Voluntary Aided Primary School
121459	Filey Junior School
147448	Friarage Community Primary School
121528	Fylingdales Church of England Voluntary Controlled Primary School
121319	Gladstone Road Primary School
144678	Glaisdale Primary School
121296	Goathland Primary School
121497	Hackness Church of England Voluntary Controlled Primary School
121498	Hawsker Cum Stainsacre Church of England Voluntary Controlled Primary School
121451	Hunmanby Primary School
144682	Lealholm Primary School
121362	Lindhead School
121507	Lythe Church of England Voluntary Controlled Primary School
145633	Newby and Scalby Primary School
121321	Northstead Community Primary School
121300	Oakridge Community Primary School
121336	Overdale Community Primary School
121525	Ruswarp Church of England Voluntary Controlled Primary School
121357	Seamer and Irton Community Primary School
121301	Seton Community Primary School
121491	Sleights Church of England Voluntary Controlled Primary School
121515	Snainton Church of England Voluntary Controlled Primary School
147211	St George's Roman Catholic Primary School
148022	St Hedda's Roman Catholic Primary School
121658	St Hilda's Roman Catholic Primary School
121615	St Martin's Church of England Voluntary Aided Primary School, Scarborough
147278	St Peter's Roman Catholic Primary School
146112	Stakesby Community Primary School
140018	Thomas Hinderwell Primary Academy
144681	West Cliff Primary School
121349	Wheatcroft Community Primary School
121526	Wykeham Church of England Voluntary Controlled Primary School

Annex B

Variable ID	Data level	Interpretation
ABS_OVERALL_RATE_S	School	The number of days pupils are absent from school / total school days
AEA_I	Area	Achieving Excellence Areas Index used for OA selection
Absences_range	Pupil	Number of missing days for that pupil, then grouped into ranges
CIN	Pupil	Pupil level identifier for a Child in Need
CIN_S	School	The percentage of CIN pupils
CONSEC_LOW_OFSTED_S	School	Ofsted rating if Ofsted reports a school as requires improvement or inadequate in two consecutive inspections. Proxy for school performance
DISA_PERC_S	School	The percentage of FSM pupils in the school (Disadvantaged pupils)
EAL_PERC_S	School	The percentage of pupils who have English as an Additional Language
FSM6	Pupil	Pupil level identifier for disadvantage
GENDER	Pupil	Male or Female - 1 for male, 0 for female
KS1AVERAGE	Pupil	Previous pupil level attainment at KS1
KS1AVG_S	School	KS1 average scores, a proxy for early years performance/prior attainment
LAD_CODE	School and pupil	Local Authority District identifier
MATHSCH_14	School	The percentage of pupils reaching expected standards in maths for 2014
MATHSCH_15	School	The percentage of pupils reaching expected standards in maths for 2015
MATHSCH_16	School	The percentage of pupils reaching expected standards in maths for 2016
NUMB_ELIG_S	School	Number of eligible students for KS2 exams, a proxy for class size
NWBRI_S	School	The percentage of Non-White British Pupils
OA	Area	Flag of whether that school or pupil is in an OA
pscore_sch	Pupil	The school level propensity score used in pupil matching
SENF	Pupil	Pupil level identifier for Special Educational Needs child
SENPROV_S	School	The percentage of pupils with Special Educational Needs
SMC_I	Area	Social Mobility Index used for OA selection
URN	School and pupil	School identifier - Unique Reference Number

Annex C

```
bptest(OLS) # heteroskedasticity

       studentized Breusch-Pagan test

data:  OLS
BP = 975.22, df = 11, p-value < 2.2e-16

> dwtest(OLS) # autocorrelation

       Durbin-Watson test

data:  OLS
DW = 1.9227, p-value = 6.002e-06
alternative hypothesis: true autocorrelation is greater than 0

> resettest(OLS, type = "regressor", power = 2) # RESET test
misspecification

       RESET test

data:  OLS
RESET = 50.581, df1 = 11, df2 = 12719, p-value < 2.2e-16

> resettest(OLS, type = "regressor", power = 2) # RESET test
misspecification using logs

       RESET test

data:  OLS
RESET = 37.374, df1 = 11, df2 = 12719, p-value < 2.2e-16


> vif(OLS)
         EAL_PERC_S          DISA_PERC_S           MATHSCH_16
MATHSCH_15          MATHSCH_14           SENPROV_S
           4.498603             1.814024             1.518277
2.011778            1.817691             1.181922
            NWBRI_S CONSEC_LOW_OFSTED_S                CIN_S
ABS_OVERALL_RATE_S          NUMB_ELIG_S
           4.439034             1.028062             1.342222
1.416033            1.103852
```

Annex D

	Dependent variable:
	MATH_EXP_S
	Logistic regression
DISA_PERC_S	-0.176
	(0.126)
MATHSCH_16	1.263***
	(0.113)
SENPROV_S	-1.225***
	(0.204)
CONSEC_LOW_OFSTED_S	-0.093***
	(0.030)
ABS_OVERALL_RATE_S	-14.181***
	(2.398)
NUMB_ELIG_S	0.002*
	(0.001)
Constant	1.069***
	(0.141)
Observations	13,285
Log Likelihood	-4,345.593
Akaike Inf. Crit.	8,705.186
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
	MATSCORE
FSM6	-0.893***
	(0.017)
EALGRP	1.815***
	(0.021)
CIN	-0.439***
	(0.037)
GENDER	0.686***
	(0.015)
SENF	-2.763***
	(0.022)
Absences_range	-0.996***
	(0.016)
KS1MATPS	1.384***
	(0.002)
Constant	80.863***
	(0.056)
Observations	485,717
R^2	0.521
Adjusted R^2	0.521
Residual Std. Error	5.017 (df = 485709)
F Statistic	75,377.020*** (df = 7; 485709)
Note:	*p<0.1; **p<0.05; ***p<0.01