National Centre for Social Research

NEET Risk Index: Methods Report

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Research funded by the Youth Futures Foundation

APRIL 2026

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This project was carried out in compliance with ISO20252

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Acknowledgements

The authors would like to thank Dr Andrea Barry and the staff at the Youth Futures Foundation for generously funding this research and supporting the research team through the process.

This research would also not have been possible without the support of Julie Parkinson and staff at Blackpool Council, who helped facilitate in the scoping interviews that informed this research.

We would also like to thank the many contributors who provided a wealth of insight and knowledge into the experiences and barriers that young, NEET people are facing across England, helping to ensure that the tool accurately captured these experiences. They include Rita Pilkington from Right to Succeed, Viv Counsell-Thomas and Kay Vaughaun from the Lancashire Careers Hub, and Caroline Waring, Blackpool and Fylde College, and Selina Hayes, Blackpool FC Community Trust.

Finally, we would like to extend our gratitude to Prof George Leckie, University of Bristol, and Dr Andrew Bell, University of Sheffield, whose methodological guidance and expertise helped refine the methodological approach.

The funders, advisors and contributors listed above provided constructive contributions, comments and suggestions. However, they were not asked to endorse the content or conclusions of this report. The authors alone are responsible for the final content.

This work was undertaken in the Office for National Statistics Secure Research Service using data from ONS and other owners and does not imply the endorsement of the ONS or other data owners.

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1. Introduction

This report describes the development of a practical early warning model of labour market risk for young people using routinely collected administrative data.

In recent years, the number of young people spending time not in employment, education or training (NEET) has risen and now remains consistently high. This report summarises the development of an improved model for the early identification of NEET risk, designed to be applied earlier in the school journey and implemented using only routinely collected administrative data. This makes the approach feasible to roll out at scale across England.

Building on previous research by the National Centre for Social Research into NEET risk factors, and on Blackpool Council's practical experience of implementing a similar tool, the project aims to produce a more accurate, earlier-warning measure of NEET risk that local authorities and schools can use without additional data collection. The introduction below sets out the wider context of NEET policy.

The following chapters describe the qualitative research that shaped the index design, the data and modelling approach used to produce the index, and key groups that were identified as at heightened risk of becoming NEET. The report discusses the index's strengths and limitations, and provides guidance around how it can be implemented in practice.

1.1 Not in Education, Employment, or Training (NEET)

Young adults aged between 16 and 24 years are defined as being NEET if they are not in employment and are outside any form of education or training, including apprenticeships, government programmes, or job-related training undertaken in the last four weeks (ONS, 2025). NEET rates have risen in recent years. An estimated 12.7% of all people aged 16 to 24 were not in education, employment or training in July to September 2025. This equates to 946,000 young people (ONS, 2025b).

This is a significant policy challenge and one that is disproportionately likely to affect those from marginalised groups, who are more likely to face barriers to entering education, training and employment. These factors often overlap, which compounds risk, particularly where SEND status and low qualifications are combined with other characteristics (Youth Employment Outlook, 2025). Evidence shows that experience of being NEET carries 'scarring effects' which negatively impact a young person's future health, earnings, and employment outcomes (Youth Employment Outlook, 2025).

Indeed, young adults who are categorised as NEET often face limited opportunities for personal and professional development. Without access to education, employment, or training, they may struggle to acquire the skills and qualifications necessary for rewarding employment (Bynner and Parsons, 2002;

MacDonald, 2011). This can lead to a cycle of poverty and social exclusion, as they may find it increasingly difficult to enter or re-enter the labour market (Scarpetta et al., 2010).

These challenges have been seen as increasing the risk of experiencing mental health issues among young people who are NEET, such as depression and anxiety, due to a lack of purpose and social engagement (Gariepy et al., 2022). However, the causal relationship in this context is less clear, as poor mental health may be pushing young adults to be out of work and education, or could be explained by factors linked to both depression or anxiety and being NEET (see Fergusson et al., 2001).

The NEET challenge also has wide economic implications at a societal level (Bell and Blanchflower, 2011). A high NEET rate can indicate a loss of potential productivity and economic contribution. This strains public resources, as governments may need to allocate more funds to social welfare programmes, unemployment benefits, and other support services. Additionally, the lack of a skilled workforce can impede economic growth and innovation (Scarpetta et al., 2010).

1.2 NEET policy interventions

Policy actions to reduce NEET rates primarily focus on improving access to education and training or creating job opportunities for young adults. Initiatives such as the launch of vocational training programmes, creation of apprenticeships and mentorship schemes, or specific support services have been developed as part of the solution to the problem. Examples include the government commitment of offering a guaranteed work placement for 18-21 year olds on Universal Credit and looking for work for 18 months or longer (Morton, 2025), the launch of Young Futures Hubs which bring together local support services and enrichment activities (Prime Minister’s Office, 2025), or the implementation of new employment programmes such as the Summer Jobs Programme (Forsyth et al., 2025).

Many policy initiatives primarily target individuals who have completed – or are about to finish – formal compulsory education and are 16 years old or older. Nevertheless, evidence seems to indicate that the risk of an individual of experiencing NEET often emerges earlier in life (see Crowley et al., 2023), either as an effect of inadequate education or nonlinear education trajectories (Belfield and Levin, 2007), or as a consequence of experiencing disadvantaged familial and social backgrounds early in life and throughout adolescence (Heckman, 2006). Therefore, seeking to prevent young people from becoming NEET before they turn 16 should be seen as equally important to reducing NEET rates as post-16 education and employment opportunities.

The Department for Education (2025) has recently taken steps to address data access limitations by integrating a risk assessment into the National Client Caseload Information System (NCCIS). The NCCIS holds information for local authorities on young people, aged 16 to 19, who are absent from other administrative sources, aiming to record their main activity, such as being NEET. This risk assessment was estimated by aggregating a set of indicators, some drawn from the DfE’s National Pupil Database and others already collected as part of the NCCIS, following an approach known as “Risk of NEET Indicators” (RONI). This solution is based on data already collected by government, reducing the need to collect additional data in a local setting and freeing up resources that can be spent to support young adults with at-risk profiles.

While this represents an important move in the right direction, the earliest data available in this tool (drawn from the NPD) will be about children's situation in school years 10 and 11, meaning that this solution does not fully solve the first limitation discussed here: it does not facilitate preventive risk mitigation actions in earlier education years. Additionally, the RONI approach applies equal weighting to all risk factors; this may lead to inaccurate estimations of NEET risks that prioritise young people with an increased number of risk factors, rather than having the most impactful risk factors.

1.3 Assessing Future Risk of NEET Before Age Sixteen

In 2022, the National Centre for Social Research (NatCen) and Youth Futures Foundation (YFF) collaborated on a project exploring to what extent and how different individual factors combined and interacted in increasing the risk of experiencing NEET among young adults. Our previous research (Crowley et al., 2023) revealed that:

- Most young adults experience multiple factors that are linked to an increased risk of being NEET in early adulthood (on average, each young adult aged 13 to 25 in England experiences four risk factors),

- Some risk factors were more likely to co-occur alongside other risk factors (for example, having a limiting physical disability and having poor mental health were often experienced together), and

- The overall risk of NEET can be assessed by aggregating the risk associated with each individual risk factor a young person displays. The risk emerging from the interaction of different factors did not make a person's risk of NEET notably higher or lower than what would be found by simply adding up the risks from each factor.

The different components and related risk factors of NEET indicated that a risk index – a measure obtained by summing the risk associated with different factors experienced by the young adult – would be an appropriate way of capturing the risk in a single number. Such a risk score could easily be used in policy action, by enabling stakeholders to prioritise those young people who are most at risk and intervene earlier.

While the index presented in our previous research can show the variation of risk across young adults, it has two limitations for empirical use in a real policy setting, where it might be used, for example, by applying the model to data on current students to generate forward-looking estimates of their NEET risk using information collected about them. The first limitation is that it does not show how the risk is accrued over time but only presents a static measure of risk for those who are already young adults, making it difficult to use the index for preventive risk mitigation policy actions. Secondly, the NEET risk index includes factors that are not directly observable or measured in an empirical policy context. For example, schools and local authorities do not hold data for pupils in compulsory education on their familial socio-economic status or their parents' attitudes towards formal education. These types of information are typically collected only through dedicated social surveys, and gathering them at scale through administrative systems would pose major logistical and operational challenges. This limitation hampers the usability of the index in a real data context, such as by a local authority.

Following the publication of this work, it was subsequently learned that one local authority, Blackpool Council, was already utilising an independently developed index for NEET risk. This index, called "Risk of NEET Indicators" (RONI), was developed and operationalised in partnership with Right to Succeed, a non-governmental organisation invested in improving the life chances of disadvantaged adults in England through place-centred approaches (Right to Succeed, 2024). Blackpool's practical experience with RONI provided an opportunity to understand the operational realities of implementing a risk index and embedding it in local authority practice.

1.4 Research Aims and Report Structure

This research extends a previous collaboration between the Youth Futures Foundation and the National Centre for Social Research by further developing earlier work on risk factors for becoming NEET (Crowley et al., 2023) and Blackpool Council's experience implementing a local RONI tool. The aim is to adapt and strengthen that approach so it can be applied more widely using routinely collected administrative data.

The report sets out the methodology used to construct the revised NEET risk index, the guiding principles behind the analytical choices made, and the considerations needed for applying the index in practice. It is intended to support both replication of the modelling and operational adoption by local authorities or schools.

The remainder of the report is structured as follows. Chapter 2 summarises insights from focus groups and interviews with practitioners and stakeholders in Blackpool, which informed the design of the index. Chapter 3 describes the data sources and modelling approach. Chapter 4 presents the technical results, robustness checks, and assessments of predictive performance. Chapter 5 provides practical guidance for local authorities and schools on how the index could be implemented in operational settings.

2. Understanding the context for the index use in Blackpool

2.1 Introduction

This chapter presents qualitative research conducted with Blackpool Council as a case study partner to inform the development of a quantitative NEET risk index. The Youth Futures Foundation are to publish other outputs from the Connected Futures work in Blackpool, and additional information on this work is given later in this chapter. To ensure our methodology and risk factor selection reflected not only academic literature but also operational needs and lived experiences, we conducted interviews and focus groups with staff across charities, educational institutions, and the Council. Blackpool's existing Risk of NEET indicators (RONI) system provided valuable insights into the practical application of risk monitoring tools. The findings from this qualitative work – covering determinants of NEET risk, operational requirements, and implementation challenges – formed the foundation for our design of the NEET risk index we propose in this report.

2.2 Stakeholder Interviews and Focus Groups

The first step of the research project was to assess whether it was feasible to produce a NEET risk index that could be implemented in local authorities, and how to do it.

To cover these operational and practical aims, we needed to understand how local authorities are currently engaging with solutions designed to monitor and understand the risk of NEET in their area. We conducted several focus groups and stakeholder conversations in the Blackpool area. Blackpool was selected as a local partner for this project because the Council was engaging in understanding and monitoring the risk of NEET using a locally developed index, known as RONI (Risk of NEET Indicators). The use of RONI in Blackpool started in 2022-2023 and predates the launch of RONI in the NCCIS database in 2025, which used a different set of indicators from Blackpool's original implementation (Department for Education, 2025).

We conducted seven interviews and five focus groups, primarily talking to relevant stakeholders from organisations involved in designing, using, and managing RONI. We gathered information from a broad range of stakeholders, from frontline staff to policy experts, including but not limited to:

- Blackpool Council Teams.
- Right to Succeed.
- Youth Futures Foundation.

- Education Diversity.
- Senior leadership of post-16 schools and colleges.
- Blackpool Football Club Community Trust.

While the content was tailored to each stakeholder group – discussing technical aspects, data, or policy needs as relevant – the interviews and focus groups primarily covered the following points:

- What are the determinants of NEET status in young adults?
- What are the operational needs that RONI was set to cover?
- How is RONI data collected, analysed, and disseminated?
- How is RONI used by different stakeholders?
- Where can RONI be improved?

This chapter includes a summary of different themes relevant to the project that were discussed or emerged over the course of the interviews and focus groups. The first section will focus on the determinants of NEET, while the second will outline findings on the use of RONI.

2.3 Identified Determinants of NEET Risk

The RONI measures in use in Blackpool encompassed 15 different indicators, summarised in five themes (Table 1). While most of these were known to the research team and have been used or considered in the earlier version of the index (Crowley et al., 2023), during the focus groups and interviews, the stakeholders discussed and expanded upon some of these risk factors. Their reflections highlighted some aspects particularly relevant for the understanding of NEET experiences. Many of the factors raised in the focus groups, such as educational experiences and aspects of deprivation, overlapped with those risk factors identified in our earlier research and could be captured in administrative data. These are discussed, in turn, in this section.

Table 1. RONI Indicators

Theme	Indicator
Education	Pupils who have attended a Pupil Referral Unit / been educated off-site / been in alternative provision
	Permanent Exclusion
	Fixed Term Exclusion
	Missed Education between schools
	Attendance below 85%
Educational Needs	Education and Health Care Plan (EHCP)
	Special Educational Needs (SEN) support, no EHCP
Child Protection	Looked after Children
	Child Protection Plan
	Home instability (Child in Need, Families in Need, Carer/parent in the system, split families)

Health	Substance Abuse
	Mental Health and/or Wellbeing Concerns
	Involved with Children and Adolescent Mental Health Services
	Physical Health
Crime	Pupils known to Youth Offending Team

Prevention and Early Risk

We learned that the RONI captures the risk among young people during Key Stage 4, at age 16. All the frontline staff we spoke with believed this was too late for effective intervention. They highlighted that by this age, pupils are about to leave their educational setting, which makes it highly difficult to mitigate the risk or shift the tide; both because the window for intervention is narrow, and because the school environment itself provides the primary means of identifying and reaching individuals who need support. In their opinion, risk needs to be assessed as it emerges in the earlier stages of the education journey.

Frontline staff suggested that most of the risk factors emerge at younger ages, such as the pupils' reading level at the transition from primary to secondary education. A pupil who is unable to read to expected standard by the end of Key Stage 2 is likely to struggle throughout their educational journey and face much greater NEET risk than pupils by the end of Key Stage 2 who are reading at or above expected standard.

Stakeholders also recommended considering the timing of a risk factor experience. For example, the recency of an exclusion significantly impacts how strongly it is a predictor of NEET, as an individual may have experienced an exclusion many years ago but has since been successfully integrated back into mainstream education.

SEN and Alternative Provision

Pupils in alternative education across the Blackpool area, including those in pupil referral units, mental and physical health support settings, and respite provision, are considered at high risk of becoming NEET due to their educational needs.

Having special educational needs or being in alternative provision can affect how a pupil's attainment is understood. Different groups of pupils progress at different rates, so the same qualification can reflect very different levels of achievement. For example, a result that represents strong progress for a pupil with complex needs may not appear as a high grade when compared to their peers. This means that measures of attainment need to be interpreted in the context of each pupil's educational needs.

Many pupils in Blackpool do not sit standard GCSE assessments, so a wider set of qualifications is needed to capture positive attainment. Staff explained that some pupils follow alternative education routes, such as NVQs or apprenticeships, and therefore work towards different awards that better reflect their abilities and progression. To ensure the index recognised this, we included a broader range of equivalent qualifications in the modelling. We then combined these different measures into a single comparable indicator of attainment.

Elective Home Education

A group of young people who are particularly vulnerable to becoming NEET are those who are Electively Home Educated (EHE) and do not attend an educational setting. The frontline staff informed us that there are two main categories of EHE children in the local area. The first group includes children whose parents decide to remove them from formal education and provide effective and high-quality education within the home themselves or with tutors. The second group includes children who have records of expulsions from school or absences for a variety of reasons – ranging from mental to physical health conditions, behavioural problems, or family and community attitudes towards formal education. Parents remove their children from schools in order to avoid fines and sanctions due to their children missing school, avoid follow-ups with caseworkers, or because they do not value formal education. We learned that this second group includes those with a historically higher level of NEET risk indicators. Additionally, the risk factors pushing children to become EHE overlap strongly with risk factors for becoming NEET later in life, such as prolonged absence or poor mental health.

We learned that being able to identify EHE children in our index could provide strong predictive power for determining the risk of NEET in later life. However, accurately identifying EHE children in large administrative datasets may prove challenging due to their being disconnected from a public education system.

Area Risk Factors

Stakeholders also stressed the importance of area factors, responsible for creating an additional layer of risk for pupils in the local authority. In Blackpool, these area factors are particularly important, as they reflect multiple dimensions of the economic transformation that many areas of the North of England have witnessed since the 1980s. Firstly, there is the decline of manufacturing that, in Blackpool, translated into a shift towards a service economy dominated by hospitality. Secondly, we have the decline of hospitality itself, which started to wither with the wider commercialisation of low-cost flights, leading to international holiday destinations becoming more appealing. Finally, we have the transformation of hospitality, which – according to the interviewed stakeholders – saw Blackpool being transformed from a holiday destination to a gambling and stag-party hub.

In the labour market, this primarily meant that a large part of the employment offering became seasonal, with many relying on hospitality work in the summer. The employment seasonality is causing an overall job insecurity, with young adults being pushed in and out of work.

The job insecurity is pushing people – including young adults – out of the area, decreasing the demand for housing. At the same time, the hospitality heritage and the decline of this economic sector mean that there is a large availability of accommodations, such as hotel rooms. According to many stakeholders we consulted, affordable housing is making Blackpool the perfect destination for economically disadvantaged social groups, while the high availability of hotel rooms is increasing the volume of refugees, children looked after, and children in care in the area. Caseworkers and frontline staff identified these groups as likely to become NEET. The significant population turnover also contributes to increasing local NEET rates by causing disruptions in pupils' education.

2.4 Existing RONI use in Blackpool

There are two core reasons for the use of RONI. The first reason is directly linked to the need to offer support and optimise the allocation of the Council's resources. Within the schools in Blackpool, many of the students experience some form of risk of being NEET. When there are a lot of pupils that may need support, and the number of frontline staff personnel and caseworkers is insufficient for helping everyone, it becomes necessary to proceed with some form of prioritisation.

The second reason is linked to the need to understand why NEET rates are particularly high in Blackpool – how is the risk distributed? What policy actions are helping to promote its reduction? Other than supporting individual students, are there actions that can be taken to support social groups of specific schools?

These two groups of problems – allocating resources and a lack of understanding around the distribution of NEET risk – can be addressed by quantifying the risk of NEET that each pupil experiences. In this section, we discuss in turn the data processing and analysis method for RONI.

Data Processing

RONI is formed by 15 different indicators. Schools are asked to record and report how many indicators each pupil experiences. School staff and caseworkers supporting RONI data collection stressed in interviews and focus groups how important it is to remove this reporting responsibility from the schools, which are often struggling to allocate time for this task and need to be constantly reminded, leading to a further increase in workload for all the agents involved in this process.

This problem – lack of time and resources to support data collection and preparation – is also behind data quality concerns. During focus groups, we learned that school staff often record some risk factors based on memory, with pastoral teams attempting to remember information and the circumstances of all pupils attending the school. Also, in some cases, schools do not engage with this task (either due to data not being available or not having workload capacity), meaning that RONI data is available for 70-90% of the students enrolled in the Council's schools.

Once the information is collected and compiled by teachers and support staff into a spreadsheet, it is transferred for data processing. The resulting risk measure, RONI, is computed for each pupil, and the information is fed back to caseworkers across schools and the local authority, who can use it to organise their work and outreach activities towards the students at higher risk of NEET. Different stakeholders confirmed that in the future, RONI estimates would be communicated with the Council, potentially fed back to the schools in the area, and integrated into the Council's systems for regular monitoring. However, the further dissemination of the RONI estimates was not in place when we engaged in the focus groups.

Method

RONI can be defined as an additive index. The 15 risk factors are added together, resulting in a score that ranges from zero (the pupil does not experience any risk factors) to 14[1] (the pupil experiences all the risk factors). The resulting score is divided into four risk bands, as defined in Table 2[i], with caseworkers offering support starting from pupils in the high-risk tier.

Table 2. RONI Risk Bands[2]

No. indicators	Risk band	
0	No risk	
1-3	Low risk	
4-6	Medium risk	
7-14	High risk	

The most important limitation with this method is the difficulty in linking RONI and its risk bands to the NEET outcome, because it is unknown whether the student experiencing these risk factors eventually experienced NEET status, or not. Not being able to establish this connection causes three additional limitations.

The first limitation is related to construct validation (DeVellis and Thorpe, 2021; Diamantopoulos and Winklhofer, 2001): Is RONI a good indication of NEET risk? During the focus groups, we discussed any attempts to establish construct validation, such as linking post-16 EET (employment, education or training) to RONI data. However, these attempts were hindered by the inability to identify a post-16 outcome for most of the cases, as local authorities do not have the statutory authority to fully monitor and record the different activities and outcomes of many young people after the age of 16. This means that construct validation can only be based on external evidence of studies (including Crowley et al., 2023), which have identified the association between those risk factors and NEET status. The reviews of these studies show that those indicators are indeed a good indication of NEET risk, suggesting that the construct is probably valid (it is probably a good indication of NEET risk), and linking it to an outcome may not be the key priority.

The other two limitations pose bigger methodological problems. The inability to link the indicators to an outcome means that it is not possible to weight or calibrate the indicators based on their impact on NEET. For instance, being known to the youth offending team, experiencing poor physical health, or living in an unstable home are considered to have the same impact on NEET. However, our earlier research (Crowley et al., 2023) into risk factors that increased young people's likelihood of spending time NEET between ages 18 and 25 suggests, for instance, that poor physical health (especially in the form of a physical disability) is twice as influential in determining NEET as being known by the youth

[1] The maximum is 14, not 15, because two indicators are mutually exclusive. A pupil can have an Education and Health Care Plan (EHCP) or other forms of non-EHCP SEN support, but not both.
[2] Detail on the process of defining the risk bands was not available; however, the implications of these risk bands are discussed at the end of this chapter.

offending team. In turn, the relationship between being NEET and involvement in crime and anti-social behaviours can be largely explained by home instability factors – including poverty.

In practical terms, the existing RONI is able to identify risk but may not accurately rank pupils by the level of risk they experience, as in some cases it may misrepresent the risk experienced by the different pupils.

The last limitation is linked to the four RONI tiers – from no risk to high risk. In the absence of an outcome, the tiers may be deemed arbitrary. Is 7 a good threshold for high risk? Are pupils with three or fewer indicators at low risk? Our previous research (Crowley et al., 2023:21) indicated that the relationship between the number of risk factors and the prevalence of NEET is linear, so it is difficult to place a clear threshold. However, we identified some clear thresholds when comparing the numeric values of a calibrated index, scaled to have a range between 0 and 100, with the prevalence of NEET (2023:34). In particular, the risk started to increase linearly from score 10 until score 60, reached a plateau until score 80, before experiencing a further linear increase. This seems to indicate that a calibrated numeric score may provide a better indication of risk tiers than a sum of the number of indicators.

3. Index design and Data analysis method

3.1 Introduction

Drawing on the insights from stakeholders in Blackpool, we translated these findings into concrete design decisions for our own risk index. This section outlines how we moved from qualitative findings to defining the project's objectives, determining suitable data sources, and establishing our analytical approach.

3.2 Refining the aims of the project

We established five priorities for the project, assessed the availability and suitability of different data sources, and designed a research methodology that would improve on limitations identified in Blackpool's RONI system while ensuring the resulting index remained feasible for local authorities to implement.

The five priorities were:

- **Enable earlier NEET risk assessments**. Design an approach that can be applied throughout secondary school. Being aware of earlier accumulation of risk gives caseworkers the possibility to start mitigating the risk while the child is still in school.
- **Include new determinants of NEET risk**. In particular, information such as moving into Elective Home Education (EHE), specific forms of Special Education Needs, and KS2 and KS4 detailed attainment, as they were identified in qualitative fieldwork as responsible for strong variations in the likelihood of experiencing NEET.
- **Remove the need for fresh data collection**. The key aims were to both reduce the workload for the different stakeholders involved – starting from schools and caseworkers – but also to increase the quality of the data (fewer missing data and more consistent information across schools).
- **Ensure that local authorities can use the results in NEET risk assessments**. Councils should be able to access and review the data required and generate local, evidence-based individual-level NEET risk assessments, which should also enable aggregated risk assessments by school and by small areas.
- **Robust statistical methodology**. In line with the method used in our previous research (Crowley et al., 2023), we wanted to ensure that the risk assessment is directly linked to the NEET outcomes it seeks to measure. This will help ensure that the index measures NEET risk more accurately, is calibrated to the most and least impactful risk factors and uses the right thresholds for a high level of NEET risk.

This chapter is dedicated to a discussion of the scoping and feasibility of different solutions for the fulfilment of these priorities, and to the outline of the final research design.

3.3 Data Scoping and Feasibility

Our review of the requirements started from the data. To ensure that local authorities and schools could implement the new index in their processes without additional data collection processes, further workload, or increased data risks, we needed to be sure that the data for the index met these criteria

- Already available to local authorities and schools, and to the research team in this project for the computation of the index.
- Consistently structured, and therefore unlikely to change in future data collection rounds.
- Include risk factors measured when undertaking formal education, as well as employment, education, and training outcomes up to the age of 25.

At the time of this project, the only education dataset that was accessible to local authorities and schools, and can be accessed by researchers for analysis, is the National Pupil Database (NPD). This is generated starting from the School Census, which consists of pupil-level data combined by schools once a term (Jay et al. 2019). The data – including attainment, absence, exclusions, special educational needs, ethnicity and school enrolment information – is collected by local authorities that transmit it to the Department for Education as part of their statutory data duties.

Effectively, the NPD also satisfied the second requirement of the list above: by being part of the national statistics and Department for Education monitoring, the NPD was also highly resistant to significant changes over time in how the data was collected, recorded, and made available.

This left us with the third requirement: being able to link the school data to post-16 outcomes. This means that our data needed to be longitudinal (including observations over time for the same individual). We considered two options:

- **Survey data linked to administrative data.** Longitudinal surveys such as Understanding Society (Department for Education and ISER, 2020) or birth-cohort studies such as Next Steps or the Millennium Cohort Study (Centre for Longitudinal Studies, 2019), are linked to NPD data and include information about the life-long trajectories of their sample members, including post-16 education, employment, and training outcomes.

- **Combined administrative data.** The Longitudinal Education Outcomes (LEO, see Department for Education, 2024) is a dataset that links data from the National Pupil Database (NPD), Individualised Learner Records (ILR), Higher Education Statistics Agency (HESA), University College Admission System (UCAS), and employment, earnings and benefits data provided by His Majesty Revenue and Customs (HMRC), the Department for Work and Pensions (DWP), and the Office for National Statistics (ONS).

We investigated both solutions and concluded that we would have incurred problems with sample sizes if we opted for survey data. We identified at least three reasons why these problems would have occurred with survey but not with administrative data. Firstly, survey data would not have covered with sufficient confidence many of the risk factors identified in the data. For instance, in a survey dataset, we would have expected no more than a handful of sample members to have been classified as Children in Need when growing up (not sufficient for analysis), while we expected to have a few thousand cases falling in this category in the administrative data. Secondly, we were particularly interested in local authority estimates, but we did not have the certainty that survey data could cover all the local authorities of England and, if it did, that they were covered with a sufficient sample size for analysis. The main reason for this is that studies based on random probability samples are usually operationalised through forms of geographical multi-stage sampling (Ruel et al., 2016), meaning that not all the local authorities are selected, and the areas selected within local authorities are not necessarily representative of the local authority as a whole. Thirdly, not all sample members in a survey agree to data linkage with administrative data sources, with the proportion of linked cases varying by study and by type of linkage. In Understanding Society, consent for linkage to NPD in the 7th wave of the study was just above 80% (Jäckle et al., 2021).

Given these considerations, we proceeded with administrative data from the LEO dataset. However, using administrative data also involves compromises. Administrative datasets are created for operational purposes rather than research, and even when well-maintained, they often contain gaps, inconsistencies, or incomplete information, with no documentation explaining why values are missing or why individuals appear or disappear between records. These limitations meant that, in some cases, we were unable to determine why individuals entered or exited the dataset or why specific fields were missing. This makes it harder for analysts to identify potential sources of bias or decide on appropriate corrective steps when preparing the data for modelling.

This contrasts with survey data, where the final analytic dataset typically contains only completed responses and can be weighted to be representative of a wider population, and where variable derivation is usually more clearly documented. However, survey data also have limitations: it relies heavily on self-report and recall, which can introduce their own inaccuracies, and it is typically far more costly to collect – making it less practical as a basis for an index intended for routine operational use.

3.4 Analysis Predictors

The second aspect we assessed at the scoping and feasibility phase was the availability of predictors necessary for the analysis. These were primarily risk factors for NEET status. We started from the list of indicators covered in RONI and continued with the elements that emerged during focus groups and interviews with stakeholders, and used in our previous research (Crowley et al., 2023).

The key consideration before covering the predictors available in the analysis is that we were restricted to data available for all pupils in a local authority setting. This means that information ranging from home instability to socio-economic status, or from substance abuse to parental attitudes, could not be included. Indeed, even if we switched from administrative data sources to survey data sources for the calibration of the index, we could not be sure that the local authorities were able to consistently access the information for all the pupils in their schools, without reaching out to other administrative sources or to the school pastoral teams. Given that one of our objectives was to minimise workload and fresh data collection, we preferred to limit the selection of analysis predictors to what educational administrative data could offer.

After scoping the LEO technical documentation, we isolated some risk factors for NEET status that could be captured in the data. However, some of them were later removed, either because not available for the cohorts of interest, or due to limitations with the data identified during the initial exploratory analysis. These aspects are summarised in Table 3.

The absence of several risk factors is a limitation to the index's ability to fully capture the range of difficulties and barriers that children experience. Future iterations of this work should continue to update the index as new administrative data become available, allowing additional risk factors to be incorporated. One example of these limitations, shown in Table 3, is the exclusion of mental health as a risk indicator, due to insufficiently reliable data. This is a significant limitation, as poor mental health has become an increasingly common reason why people aged 16 to 24 are NEET. Although some aspects of poor mental health may be indirectly reflected through the SEN indicator, its omission is still likely to reduce the effectiveness of the index in identifying young people's NEET risk.

It should also be noted that this table does not include fixed characteristics such as gender or ethnicity, as the index focuses on characteristics of young people that can be acted upon through policy or service interventions. We also considered including gender and ethnicity as factors in the model to improve its predictive accuracy; however, after controlling for the role of other risk factors, neither provided a further improvement in predictive quality (see Section 4.3).

Table 3. Summary of Identified Risk Factors

Risk factor	Operationalisation	Decision
Reading and maths levels at the end of KS2.[3]	The information was available in the KS2 exam results. Pupils with no KS2 record (e.g., recent migrants or those moving between the independent and state sectors) are included in a separate missing category.	Kept in the analysis
School move (disruption of learning)	This could be obtained from the comparison of school identifiers within and between years.	Dropped during initial exploratory analysis: Small volume of school moves Too many assumptions made when deriving the variable
Elective home education (EHE) (including moving in and out of EHE)	The NCCIS tables capture information about EHE, but the	EHE was dropped from the analysis because there were too many missing values in the NCCIS

[3] KS2 attainment is measured using the former national curriculum level system, which applied to the cohorts analysed in this report. These levels were discontinued for later cohorts and replaced with scaled scores, so future applications of the model would require an appropriate mapping between the two systems.

Risk factor	Operationalisation	Decision
	information is not available for earlier years (before age 15).	tables due to the difficulty with collecting data for individuals not engaging with other systems. This meant it was not possible to differentiate cases who were EHE from those who moved in/out of the system more generally.
Attendance	The absence tables in NPD included indicators of permanent absence during the academic year and the number of absences for different reasons.	Kept in the analysis as a dichotomous indicator for permanent absence in the academic year.
Involvement in crime	The NCCIS tables capture information about custodial and offending sentences, but the information is not available for earlier years (before age 15).	Dropped in the analysis due to many missing values in the NCCIS tables.
Fixed exclusions	The information was available in the exclusion tables.	Kept in the analysis
Eligibility for Free School Meals	FSM eligibility was taken from the annual school census, with the variable indicating whether the pupil was eligible for FSM on the date of the census.	Kept in the analysis
Residence in a deprived area (IDACI)	IDACI scores were taken from the school census and based on the postcode of the pupil's place of residence.	Kept in the analysis
SEN provision	A categorical variable taken from the school census that outlines what level of support a child with SEN receives.	Kept in the analysis
Part time schedule	A binary indicator taken from the school census that shows whether the pupil is attending school full-time or not.	Part time schedule from the analysis was dropped as the historic measure applied to a very small number of cases.
Alternative provision	A categorical indicator that shows if the pupil receives any alternative provision, that is education offered by a non-mainstream school	Alternative provision was dropped from the analysis as the historic measure applied to a very small number of cases.
Child looked after	A measure was taken from the NPD that indicated whether the pupil had been looked after for at least one day during the year.	Kept in the analysis

Risk factor	Operationalisation	Decision
Child in need	A measure was taken from the NPD that indicated whether the pupil was classed as a child in need on the date of the school census. It indicates that a child has been assessed by social services as needing help or protection due to risks to their development, health, or because they are disabled.	This variable was not included in the analysis as the data was not sufficiently available for the period of the analysis.[4]
KS4 exam results	Taken from the Key Stage 4 data of the NPD, a binary indicator was derived to show it the pupil had achieved 5 A* - C GSCEs including Maths and English.	Kept in the analysis
English first language	The record of the pupil's first language was taken from the school census and used to show whether the pupil's first language was English.	Kept in the analysis
Primary SEN type	A categorical measure taken from the school census that shows the nature of the pupil's primary special educational need.	Kept in the analysis
School type	The type of establishment the pupil attended was taken from each academic Key Stage	Dropped from the analysis due to limited data on non-mainstream schools, leading to a derived variable that lacked granularity.
Mental health	Information is available only when mental health is classified as disability or when it is a reason for absences.	Dropped due to the measure being unreliable and due to the volume of missing values.
Physical health	Information is available only when physical health is classified as disability or when it is a reason for absences.	Dropped due to the measure being unreliable and due to the volume of missing values.
Having own children	Pregnancy or having children are registered in the NCCIS tables	Not included due to the volume of missing values in the NCCIS tables.

[4] It is important to be mindful of what the risk index does and does not measure. The index provides one source of evidence that can support practitioners in assessing whether a child may be at increased risk of becoming NEET. However, it should be considered alongside other information about the child and their circumstances, because the index cannot capture every aspect of a young person's situation.

Analysis Cohorts

The last element for the initial assessment focused on the pupils' cohorts that could be used in the analysis. Being a longitudinal dataset for the study of education and its outcomes, LEO's cases can be primarily classified by the year they entered education, the academic year within which they turned five years of age.

We focused on four cohorts, as indicated in Table 4

Table 4. LEO Data Cohorts

	Age 10 to 11 (Yr6)	Age 15 to 16 (Yr11)	Age 23 to 24	Status
Cohort 1	2003/04	2008/09	2016/17	Dropped
Cohort 2	2004/05	2009/10	2017/18	Dropped
Cohort 3	2005/06	2010/11	2018/19	Retained
Cohort 4	2006/07	2011/12	2019/20	Retained

The decision on the cohorts to include in the analysis was primarily driven by two considerations. The first one is that NEET is an outcome that is measured in a specific age band: in young adults up to the age of 24. After that, their NEET classification mutates to economic inactivity or unemployment. The second consideration is that the educational and employment experiences of people during the outbreak of COVID-19, like the furlough scheme and deferred university placements, mean that administrative data during this time is non-representative outside of the COVID-19 period, 2020 to 2022. These two elements meant that we needed to focus on the latest cohorts to turn 24 before 2020, when the pandemic started.

Upon starting the analysis, the earliest cohorts (Cohorts 1 and 2) were dropped from the analysis dataset. This is motivated by three elements:

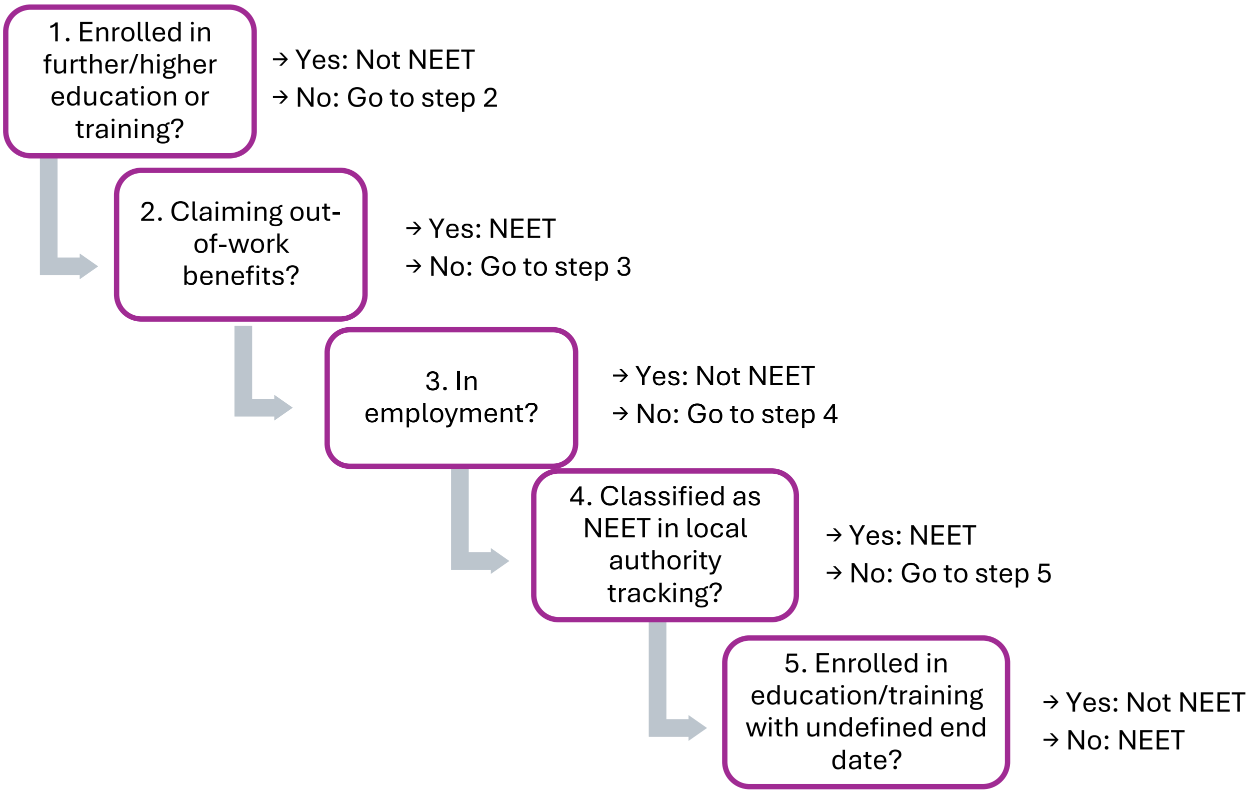
- The overall data quality (including inconsistencies and degree of missingness) was much greater in the most recent cohorts (Cohorts 3 and 4). This was due to the infancy of the recording process of several factors, such as being classed as a child in need, during the period of the earlier cohorts.
- Some variables measuring NEET risk factors were not available in the earlier cohorts (Cohorts 1 and 2).
- Many variables measuring NEET risk factors were available, but their collection had recently started, so they were not available in previous years. We also found many inconsistencies and missing values in this earlier data, potentially due to lags or delays in full implementation.

3.5 Research Design

Outcome

The outcome of the analysis was whether a young person experienced being in a period of continuous NEET for at least 12 months. Our derivation of NEET was conceptualised following the methodology applied by the Department for Education for the study of NEET on LEO data (2018). This followed a hierarchical process (Figure 1). For each month, the first condition to apply was to determine whether the individual was classified as NEET for a given month.

Figure 1. NEET Derivation Process



The hierarchical process started from HESA (Higher Education Statistics Agency) and the Individualised Learner Records (ILR) data, checking whether the young adult was enrolled in further or higher education or training after Year 11. The second and third steps relied respectively on DWP and HMRC data, assessing whether the young adult was in receipt of out-of-work benefits[5] or was receiving employment income. The remaining steps were based on the National Client Caseload Information System (NCCIS), which could hold additional information on NEET status or forms of education or training that the young adult was attending.

[5] Out of work benefits included Jobseekers Support Allowance, Jobseekers Training Allowance, Employment Support Allowances, Incapacity Benefit, Income Support, Passported Incapacity benefit, Severe Disablement Allowance, Pension Credit, and UC-out-of-work conditionality groups.

In this hierarchical derivation of NEET status, we found that less than approximately 1% of participants in higher and further education did not have a defined end date of their course, making it difficult to assess accurately whether they were NEET at a certain month. Therefore, these cases had an assumed end date of 12 months after the start of the most recent year of their course.

Once the derivation of the NEET outcome for the single months after the end of Year 11 was completed, the analysis outcome was derived by identifying the young adults in the data who were classified as NEET for 12 consecutive months. This was decided to avoid counting as NEET contingent events that may take an individual out of employment, education, or training for a short period of time (e.g., up to six or eight months). For instance, medical circumstances, volunteering and unpaid activities, sabbatical breaks and travelling, pregnancies, and short-term caring responsibilities are expected not to result in a NEET classification exceeding a 12-month threshold. Being NEET for 12 consecutive months or longer is likely to reflect long-term and lasting personal circumstances, structural impediments, or decisions, likely to leave a long-lasting mark on the future earning trajectories and on the socio-economic positioning of the individual.

Analysis Sample

The analysis was based exclusively on pupils in England who attended state-funded schools and enrolled to Year 6 in the academic years 2005/06 or 2006/07. It excluded pupils in England who went to private schools or were educated at home. The analysis sample included 1,090,555 cases. 12% of them had a continuous experience of NEET lasting at least 12 months from the age of 16 to 24 (134,147 cases), while 88% (956,408 cases) did not. Table 5 outlines the age, sex, and ethnicity composition of the cohorts; a breakdown of the cohorts by all risk factors is given in Table 7.

Table 5. Demographic Summary of Analysis Sample

Variable	Category	Count	Percentage	Percentage NEET
Total	-	1,090,555	-	12
Cohort	Cohort 3 (Yr11: 2010/11)	548,297	50	12
	Cohort 4 (Yr11: 2011/12)	542,258	50	13
Sex	Male	556,380	51	12
	Female	534,175	49	13
Ethnic background	White - British	852,393	78	13
	White - Irish	3,767	<1	11
	Any other White background	34,570	3	8
	Bangladeshi	13,321	1	12
	Pakistani	31,913	3	12
	Indian	25,274	2	5
	Chinese	4,352	<1	3
	Any other Asian background	13,610	1	7
	Black African	28,122	3	10
	Black Caribbean	15,193	1	18
	Any other Black background	5,379	<1	15

	White and Asian	7,656	1	11
	White and Black African	3,674	<1	13
	Any other Mixed background	13,128	1	13
	Mixed or Multiple ethnic groups	12,901	1	20
	Travellers, Gypsy/Roma or Irish Heritage	1,495	<1	38
	Other ethnic groups	12,937	1	10
	Unknown	10,870	1	13

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2.

It is important to note that some individuals are not included in the data. According to the Office for National Statistics (2020), there were 1,227,425 live births in England in 1995 and 1996, which provides a baseline for the expected number of pupils entering education. Our analysis sample of 1,090,555, together with 35,154 individuals excluded due to missing data, accounts for approximately 92% of these births. The remaining gap is largely explained by pupils who attended private schools (7-9% of UK pupils, Henseke et al., 2021: Kynaston & Green., 2019), equivalent to between 85,000 and 110,000 pupils in these birth cohorts. Migration was also expected to affect this discrepancy, with immigration increasing and emigration decreasing the overall size of the cohort of young people.

Department for Education data also exclude children who are home educated (Elective Home Education). While historical data are limited, in 2022, there were 80,900 pupils living in England who were educated at home and did not attend formal schooling (Long and Danechi, 2023). These figures likely account for the majority of the 35,154 cases excluded due to missing information, primarily because of the absence of a school identifier or local authority details. Although home education was identified during the interviews and focus groups as a potential driver of NEET outcomes, its impact could not be assessed in this analysis due to the reliance on school-based administrative data.

Analysis Method

The analysis was carried out using a multilevel regression model, also known as a hierarchical or mixed-effects model. There were two main reasons for choosing this method. The first reason is that the observations in the data – pupils – were not independent. Pupils in the Longitudinal Educational Outcomes can be clustered in groups based on two key features: the school they attend and the area where they live. This means that some students, especially those attending the same school and living in the same area, are likely to be more similar to each other, compared to pupils from other areas and schools. These commonalities break the assumption of observation independence in regression analysis, influencing the prevalence of the outcome in certain groups and the relationship between risk factors and the outcome across the sample. In practical terms, multilevel models avoid the mis-estimation of standard errors in the analysis.

The second reason for using multilevel models relates to the insights they offer about how variation in outcomes is structured. Multilevel models partition the unexplained variance in an outcome across different levels of the data hierarchy. In practice, this means identifying how much of the residual variation sits at the local-authority level, how much at the school level (where included), and how much remains at the individual level, although this does not imply that the variance at any level is caused solely by that level. It may just simply reflect the concentration of pupils with similar (individual level) characteristics in those areas. Even so, this partitioning can provide policy-relevant context by showing whether unexplained differences in NEET outcomes tend to cluster geographically or whether most of the remaining variation lies between individuals.

A separate model was fitted to the data for each school year between Year 6 (defined as Yr6 in this report) and Year 11 (Yr11), resulting in six models. The decision to fit six different models was based on the necessity to compute a different index for the different stages of the pupils' journey in the education system. For instance, before Year 11 – when the GCSE exam results become the key predictor for NEET status – the index assigned a greater importance to other variables, such as the scores when transitioning from primary to secondary education. In other words, NEET predictors vary and assume different importance across different school years.

Initially, each model included two groups of random intercepts: the school attended by the student in the year and the local authority where the student lived when aged 16 (school year 11). However, the school identifier was removed from the models in the course of the analysis for three reasons:

1. The school ID is pseudonymised in the LEO data, meaning that it is impossible to understand which coefficients apply to each school, and, therefore, the school's contribution to the pupil's NEET risk cannot be accounted for in the index in an operational real setting.

2. The disclosure rules of the Trusted Research Environment used in the analysis (the SRS) did not allow the extraction of school-level information. Therefore, even if the school identity was known, it would not have been possible to apply the school weight to the index formula.

3. The index would be applied to cohorts of students who entered education at least one decade after the cohorts used for the analysis. There is evidence indicating that school effects could quickly lose their predictive power over time (see Leckie and Goldstein, 2009). This suggests that, even in the event that the school identifiers were not pseudonymised and their coefficients exportable from the trusted research environment, they could have a negative contribution to the accuracy of the index.

The random effect by local authority was retained in the analysis, resulting in 150 different clusters. Two local authorities, the "Isle of Scilly" and the "City of London," were removed from the analysis. The decision was justified by the small number of pupils in the analysis sample from those areas.

All models were based on the same number of observations, namely 1,090,524 pupils.

Predictors

For each school-year model, the predictors were coded to reflect risk factors that had emerged by then. For instance, a pupil diagnosed with a special educational need in year 8 would not have the diagnosis included in the models for the years 6 and 7. Additional information on these predictors can be found in Appendix E.

Table 6. Risk Factors by Academic Year

Predictor	Description	Models					
		Yr6	Yr7	Yr8	Yr9	Yr10	Yr11
Persistent absence (Yr6)	Binary annual indicator (yes or no) for persistent absence, a pupil who has missed 10% or greater of their sessions in school for that year.	X	X	X	X	X	X
Persistent absence (Yr7)			X	X	X	X	X
Persistent absence (Yr8)				X	X	X	X
Persistent absence (Yr9)					X	X	X
Persistent absence (Yr10)						X	X
Persistent absence (Yr11)							X
Exclusion (Yr6)	Binary annual indicator (yes or no) for exclusions from school (either temporary or permanent).[6]	X	X	X	X	X	X
Exclusion (Yr7)			X	X	X	X	X
Exclusion (Yr8)				X	X	X	X
Exclusion (Yr9)					X	X	X
Exclusion (Yr10)						X	X
Exclusion (Yr11)							X
Type of SEN (Yr6)	Type of SEN diagnosis. "No SEN" if the student was never diagnosed with SEN up to that year. If there is a diagnosis, we considered the latest type of SEN diagnosed up to that year.	X					
Type of SEN (Up to Yr7)			X				
Type of SEN (Up to Yr8)				X			
Type of SEN (Up to Yr9)					X		
Type of SEN (Up to Yr10)						X	
Type of SEN (Up to Yr11)							X
SEN provision (Yr6)	Type of provision offered in the year to the pupil with SEN.	X					
SEN provision (Yr7)			X				
SEN provision (Yr8)				X			
SEN provision (Yr9)					X		
SEN provision (Yr10)						X	
SEN provision (Yr11)							X
Whether FSM (Yr6)	Number of years[7] when a pupil was classified as Free School Meal up to the year in the model. The first measure (Yr6) is a binary measure (whether the pupil was FSM in YR6)	X					
No. years as FSM (Up to Yr7)			X				
No. years as FSM (Up to Yr8)				X			
No. years as FSM (Up to Yr9)					X		
No. years as FSM (Up to Yr10)						X	
No. years as FSM (Up to Yr11)							X

[6] A temporary exclusion is the removal of a pupil from a school for a fixed period of time, typically a few days. A permanent exclusion leads to the permanent removal of a pupil from a school.
[7] Using separate annual indicators estimates year-specific effects, whereas a duration indicator collapses multiple annual measures into a single cumulative variable that assumes that each year of exposure has a similar influence.

Predictor	Description	Models					
		Yr6	Yr7	Yr8	Yr9	Yr10	Yr11
Ever IDACI (Yr6)	Whether a pupil has ever lived in an area classified as an area of high deprivation for children up to the year included in the model.	X					
Ever IDACI (Up to Yr7)			X				
Ever IDACI (Up to Yr8)				X			
Ever IDACI (Up to Yr9)					X		
Ever IDACI (Up to Yr10)						X	
Ever IDACI (Up to Yr11)							X
English is the first language	Binary indicator (yes or no).	X	X	X	X	X	X
Ever CLA (Yr6)	Whether a pupil has ever been considered by the local authority as a Children Looked After up to the year included in the model. This includes any child who has been under the care of a local authority for at least one day.	X					
Ever CLA (Up to Yr7)			X				
Ever CLA (Up to Yr8)				X			
Ever CLA (Up to Yr9)					X		
Ever CLA (Up to Yr10)						X	
Ever CLA (Up to Yr11)							X
KS2 reading level	Reading level at KS2	X	X	X	X	X	X
KS2 maths level	Maths level at KS2	X	X	X	X	X	X
KS4 attainment	KS4 (GCSE equivalent) exam results, with a focus on English, Maths, and overall attainment.						X
KS4 English results							X
KS4 Maths results							X

The frequencies of these predictors, the proportion of pupils with different numbers of risk factors, and their binary association with 12-month NEET experiences, for Yr11 are included in Chapter 4. The same information for Yr6 through Yr10 is found in Appendix B: Year 6 – Year 10 Model Fixed Effects.

Production of the Index

The coefficients estimated in the regression were converted into weights for the index indicators. This followed the approach proposed by Zedler et al. (2015; see also De Vellis and Thorpe, 2022) and already adopted in our earlier work (Crowley et al., 2023), which operationalised an index using longitudinal survey data.

The full description of the approach is included in Appendix 4 of the 2023 report (Crowley et al., 2023: 59-61), so here we offer only a brief outline. An index is a formative measure (De Vellis and Thorpe, 2022), which assumes that the concept it seeks to represent emerges from the sum of its different components, or indicators. These indicators do not necessarily have the same value: some may contribute more to shape the concept more strongly than others, resulting in more importance. For this reason, indicators in an index can be multiplied by weights, which ensure that the concept measured by the index does not over- or underestimate the importance of different indicators. More concisely, the formula for an index V based on n indicators I, multiplied by a weight w is:

$$V = w_1 I_1 + w_2 I_2 + \cdots + w_n I_n$$

One of the difficulties in the computation of an index is how to determine the values of the indicators' weights. In our index, we opted for the use of longitudinal data because it gave us the possibility to observe which pupils had experiences of NEET, and what risk factors they had. This means that we could use a regression model to produce coefficients for the different predictors that would be computationally equivalent to the indicators' weight.

This solution allowed us to determine the weights of the indicators, but also to solve some common methodological problems with the production of index, linked to redundancy and validity (see Crowley et al., 2023: 59-61, for a discussion on this).

To demonstrate how the index would work in practice, for now, let's ignore any potential effect of the local authority where the young adult lives and assume the simple case of a pupil in Year 11 with only two risk factors: having been classified as a "Child Looked After" and having been permanently absent from school in Year 6. Any other risk factor not experienced by the student would have a contribution of zero to the definition of their NEET risk index. The regression model reported that the two risk factors experienced by the pupil increased the likelihood of experiencing NEET status (see Table 7 in the next chapter):

- Young adults who had been classified as "Child Looked After" experienced a risk of being NEET that was 2.9 times greater than the risk of a young adult not classified as such.

- Young adults who had been permanently absent from school in Year 6 experienced a risk of being NEET 1.2 times greater than those who had not been permanently absent.

These figures are odds ratios, i.e. they show how the odds of becoming NEET compare between each group and its reference group: values above 1 indicate higher odds of being NEET, and the size of the number reflects how much higher those odds are relative to the comparison group. Those who have been classified as a looked-after child have 2.9 times greater odds of spending time NEET than those who have not, after accounting for the other risk factors included in the model.

The raw model coefficients for these estimates were, respectively, 1.06 and 0.19.[8] Given that the presence of the risk factors is reflected in the formula with the values of I being equal to 1, the overall raw NEET index value of the student was $1.06 * 1 + 0.19 * 1 = 1.25$. With the index having a raw range between -1.14 and 8.58, when shifting to the 0-100 scale used for the index, the pupil would have a NEET risk score of 24.6 out of 100.

[8] By "raw model coefficients" we mean the log-odds estimated by the logistic regression. Log-odds are simply a mathematical way of expressing how likely an outcome is, used because they make the model easier to estimate. They are not directly intuitive, which is why we convert them into odds ratios in the main text, as these are much easier to interpret.

A score of 24.6 equates to a fairly low risk of being NEET. Using the risk index with data from years 6 to 11, in our sample, pupils with risk scores between 20 and 30, 8% later went on to be NEET.

The advantages of not presenting a direct probability is that the index can still reflect pupils' relative risk, while not implying a level of predictive precision in estimating children's future life courses that is not appropriate here, given that the model includes only a subset of relevant risk factors (limited to those available in government administrative data) and is estimated using data collected under earlier system conditions (in particular, children passing through the educational system prior to the Coronavirus pandemic). Instead, the index provides a measure of relative vulnerability, ranging from low to high risk, without overstating the accuracy or certainty of the underlying prediction.

4. Results

4.1 Introduction

This chapter presents the core results of the modelling, demonstrating the proportion of NEET and the estimated impact of each risk factor, including how the estimated impact changes as NEET risk is predicted for Yr6 through to Yr11. We begin by examining descriptive statistics that show how each risk factor relates to NEET outcomes in the sample, demonstrating the variation in NEET rates across different groups of young people. We then present the outputs from the multilevel models for Year 11, covering both the fixed effects, which show how individual risk factors predict NEET status, and the random effects, which capture variations between local authorities. The findings reveal which factors are most strongly associated with NEET outcomes and how these relationships inform the weighting of indicators in the final index.

4.2 Descriptive statistics and NEET

The NEET Risk Index for Year 11 was based on the 23 risk factors included in Table 7. The sample sizes presented in the table highlight one of the benefits of using administrative data: even particular small subgroups of the population (such as children looked after) or groups that are usually difficult to interview in a survey project (such as individuals with profound, multiple, or severe learning difficulties) are represented in the data, with sample sizes sufficient to proceed with the analysis.

The second element of interest emerging in the data relates to the association between each risk factor and the outcome (being NEET). All the risk factors appear to be predicting variations in the prevalence of NEET rates in the sample. The biggest variations emerge around the GCSE attainment: Table 7 demonstrates that 4% of the young adults who have achieved 5+ A* - C (9 - 4), including in English and Maths, were NEET, compared to 76% of young adults with no passes or no exam results.

The equivalent descriptive statistics for each local authority are presented in Appendix H, Table 25.

Table 7. Proportions of NEET Pupils per Risk Factor

Variable	Category	Count	Percentage	Percentage NEET
Total	-	1,090,555	-	12
Absent for at least 10% of the time (Yr6)	Yes	7,901	<1	42
	No	1,082,654	99	12
Absent for at least 10% of the time (Yr7)	Yes	25,617	2	41
	No	1,064,938	98	12
Absent for at least 10% of the time (Yr8)	Yes	32,840	3	41
	No	1,057,715	97	11
Absent for at least 10% of the time (Yr9)	Yes	40,571	4	42
	No	1,049,984	96	11

Variable	Category	Count	Percentage	Percentage NEET
Absent for at least 10% of the time (Yr10)	Yes	49,540	5	44
	No	1,041,015	95	11
Absent for at least 10% of the time (Yr11)	Yes	71,151	7	41
	No	1,019,404	93	10
Excluded for a fixed term (Yr6)	Yes	6,455	<1	38
	No	1,084,100	99	12
Excluded for a fixed term (Yr7)	Yes	31,674	3	33
	No	1,058,881	97	12
Excluded for a fixed term (Yr8)	Yes	47,030	4	32
	No	1,043,525	96	11
Excluded for a fixed term (Yr9)	Yes	60,776	6	32
	No	1,029,779	94	11
Excluded for a fixed term (Yr10)	Yes	68,848	6	31
	No	1,021,707	94	11
Excluded for a fixed term (Yr11)	Yes	55,960	5	30
	No	1,034,595	95	11
Most recent SEN type (up to Yr11)	No SEN	923,994	79	8
	Autistic Spectrum Disorder	6,840	<1	42
	Behaviour, Emotional & Social Difficulties	26,717	6	34
	Moderate Learning Difficulty	67,702	7	27
	Other Difficulty/Disability	9,206	2	22
	Profound, multiple, or severe learning difficulties	5,727	<1	71
	Sensory Impairment	7,929	<1	29
	Specific Learning Difficulty	28,193	3	16
	Speech, Language and Communication Needs	14,247	1	22
SEN provision in Yr11	No SEN provision	838,344	77	8
	School or early years actions	211,185	19	23
	Statement	41,026	4	51
No. of years in receipt of free school meals (up to Yr 11)	Never	833,625	76	8
	1-2 years	83,586	8	21
	3 or more years	173,344	16	29
Ever in the lowest IDACI quintile (up to Yr11)	Yes	287,464	26	21
	No	803,091	74	10
Not speaking English as first language	English	959,372	88	13
	Not English	131,183	12	10
Ever classed as a looked-after child (up to Yr11)	Yes	13,130	1	52
	No	1,077,425	99	12
	Pupil at expected standard	872,830	80	9

Variable	Category	Count	Percentage	Percentage NEET
Pupil reading standard by the end of KS2	Pupil not at expected standard	160,727	15	30
	No valid KS2 reading award	8,542	<1	31
	Results not provided by school	48,456	4	11
Pupil maths standard by the end of KS2	Pupil at expected standard	800,066	73	8
	Pupil not at expected standard	234,782	22	26
	No valid KS2 maths award	8,610	<1	27
	Results not provided by school	47,097	4	10
Attainment: GCSE grades[9]	Achieved 5 or more GCSEs, grade A* - C incl. English and Maths	638,670	59	4
	Achieved 5 or more GCSEs, grade A* - C	252,781	23	16
	Achieved 5 or more GCSEs, grade A* - G	148,746	14	25
	Achieved 1 to 4 GCSEs, grade A* - G	35,375	3	53
	Achieved any pass	6,654	<1	68
	No results / no passes	8,329	<1	73
Achieved A* - C in GCSE English	Yes	742,340	68	6
	No	348,215	32	26
Achieved A* - C in GCSE Maths	Yes	733,741	67	5
	No	356,814	33	27

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2.

The descriptive statistics and the association with NEET status for the variables included in the other models (Yr6 through Yr10) but not in the Yr11 model are included in Appendix A: NEET Outcomes.

4.3 Model output

The output of a random-intercept multilevel model can be divided into two different parts. The first one – fixed-effect output – presents the effect of the predictor (or risk factors) across the sample, while holding all other predictors constant. The second – random effects – captures the change in the model intercept across different groups included in the analysis (local authority in our Year 11 models). The Year 11 model outputs will be presented below, highlighting in turn the fixed and the random effects, followed by a discussion concerning the models' predictive accuracy. The full model outputs for the Year 6 to Year 10 models can be found in Appendix B.

To aid in the interpretation of the findings, before we describe these results, the methods box below provides an introduction on how to interpret the key measures we present.

[9] A grade A* to C is equivalent to a grade 9 to 4 in the updated Department of Education grading system, for more information please see: https://www.gov.uk/government/publications/gcse-9-to-1-grade-scale-explained/gcse-9-to-1-grade-scale-explained

Methods explainer

Binary logistic regression
All the analysis we present in this report is based on a binary logistic regression. This is a statistical method used to predict the likelihood of a yes/no outcome, in this case, whether a pupil becomes NEET, based on a set of characteristics – here our risk factors for being NEET. It estimates how each factor increases or decreases the odds of the outcome, relative to a reference group.

Odds ratios (ORs)
An odds ratio shows how much more (or less) likely a group is to become NEET relative to the reference category (for example, men compared to women). They do this by comparing the odds of becoming NEET in one group with the odds in a reference group.

- OR = 1: no difference – the odds are the same.
- OR > 1: higher odds
- OR < 1: lower odds

For example, the odds ratio for pupils with a fixed-term exclusion in Year 11 is 1.2. This means their odds of becoming NEET are 1.2 times those of pupils with no exclusion in that year, after accounting for the other factors in the model.

Log-odds
Log-odds are the scale on which logistic regression estimates effects. Positive values mean higher NEET risk than the reference group; negative values mean lower risk. However, the substantive meaning of log-odds are not intuitive, so we convert them into odds ratios for interpretation.

Standard errors (SEs)
Standard errors show how precise an estimate is. Smaller SEs mean more precision; larger SEs mean greater uncertainty.

P-values
A p-value indicates how compatible the data are with the assumption that the true effect is zero, for example, the assumption there is no difference in how likely men and women are to be NEET. A small p-value (typically <0.05) suggests the observed effect would be unlikely if there were no real difference.

Fixed Effects

The model's fixed effects refer to the estimate of the regression coefficients and intercept across the full sample. Each coefficient captures the association between a predictor and the outcome (NEET status) once the influence of the other risk factors has been accounted for. The specific variation of the intercepts (mean differential risk of NEET against the average) in the different local authorities is separated into the random effects, discussed in the next sub-section.

Table 8. Estimated Impact of Risk Factors on NEET Status

Term	Level	Odds ratios	Log-odds	Std. Errors	p-value
Intercept (Odds)		0.03	-3.40	0.02	<0.001
Persistent absence Yr6	No (reference category)	-	-	-	-
	Yes	1.21	0.19	0.03	<0.001
Persistent absence Yr7	No (reference category)	-	-	-	-
	Yes	1.13	0.12	0.02	<0.001
Persistent absence Yr8	No (reference category)	-	-	-	-
	Yes	1.1	0.10	0.02	<0.001
Persistent absence Yr9	No (reference category)	-	-	-	-
	Yes	1.18	0.17	0.01	<0.001
Persistent absence Yr10	No (reference category)	-	-	-	-
	Yes	1.31	0.27	0.01	<0.001
Persistent absence Yr11	No (reference category)	-	-	-	-
	Yes	1.83	0.60	0.01	<0.001
Fixed-term exclusion Yr6	No (reference category)	-	-	-	-
	Yes	0.96	-0.04	0.03	0.1637
Fixed-term exclusion Yr7	No (reference category)	-	-	-	-
	Yes	0.93	-0.08	0.03	<0.001
Fixed-term exclusion Yr8	No (reference category)	-	-	-	-
	Yes	1.03	0.03	0.01	0.0139
Fixed-term exclusion Yr9	No (reference category)	-	-	-	-
	Yes	1.10	0.10	0.01	<0.001
Fixed-term exclusion Yr10	No (reference category)	-	-	-	-
	Yes	1.19	0.17	0.01	<0.001
Fixed-term exclusion Yr11	No (reference category)	-	-	-	-
	Yes	1.23	0.21	0.01	<0.001
Latest SEN type	No SEN (reference category)	-	-	-	-
	Autistic Spectrum Disorder	2.15	0.77	0.03	<0.001
	Behaviour, Emotional & Social Difficulties	1.28	0.25	0.01	<0.001
	Moderate Learning Difficulty	1.10	0.10	0.01	<0.001
	Other Difficulty/Disability	1.20	0.18	0.02	<0.001
	Profound, multiple, or severe learning difficulties	2.56	0.94	0.04	<0.001
	Sensory Impairment	1.81	0.59	0.03	<0.001
	Specific Learning Difficulty	0.83	-0.18	0.02	<0.001
	Speech, Language and Communication Needs	1.09	0.09	0.02	<0.001
SEN provision in Yr11	No provision (reference category)	-	-	-	-
	School or Early Years Action	1.30	0.26	0.01	<0.001
	Statement	2.20	0.79	0.02	<0.001
Number of years classed as FSM	0 (reference category)	-	-	-	-
	1 - 2 years	1.78	0.58	0.01	<0.001
	3 or more years	2.23	0.80	0.01	<0.001
	No (reference category)	-	-	-	-

Term	Level	Odds ratios	Log-odds	Std. Errors	p-value
Ever lived in lowest IDACI quintile	Yes	1.45	0.37	0.01	<0.001
Whether English is first language	English (reference category)	-	-	-	-
	Not English	0.62	-0.48	0.01	<0.001
Ever classed as Child looked after	No (reference category)	-	-	-	-
	Yes	2.89	1.06	0.02	<0.001
Reading standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	0.97	-0.03	0.01	<0.001
	No valid KS2 reading award	1.06	0.06	0.04	0.1062
	Results not provided by the school	1.06	0.06	0.08	0.4186
Maths standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.20	0.19	0.01	<0.001
	No valid KS2 maths award	1.14	0.13	0.04	<0.001
	Results not provided by the school	0.72	-0.33	0.08	<0.001
Attainment: GCSE grades	Achieved 5 or more GCSEs, grade A* - C incl. English and Maths	-	-	-	-
	Achieved 5 or more GCSEs, grade A* - C	1.49	0.40	0.02	<0.001
	Achieved 5 or more GCSEs, grade A* - G	1.94	0.66	0.02	<0.001
	Achieved 1 or more GCSE, grade A* - G	3.09	1.13	0.02	<0.001
	Achieved any pass	4.91	1.59	0.04	<0.001
	No results / no passes	5.34	1.68	0.04	<0.001
Passed GCSE English	Yes (reference category)	-	-	-	-
	No	1.37	0.31	0.01	<0.001
Passed GCSE Maths	Yes (reference category)	-	-	-	-
	No	1.51	0.41	0.01	<0.001

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2.

The analysis showed that Key Stage 4 attainment was the most important predictor of becoming NEET post-16, followed by being a looked-after child, being in receipt of free school meals, and having certain special educational needs.

The KS4 GCSE exam results are the most important predictor of NEET in Year 11. The odds of being NEET are 5.3 times higher for a young adult with no passes compared to the likelihood of incurring NEET for a young adult with five or more passes between A* and C, including Maths and English, holding all other predictors constant. Across all the categories of the GCSE grades predictor, the risk of NEET increases monotonically with a decrease in the exam results.

The risk of NEET for pupils who are classified as Child Looked After at some point between Year 6 and Year 11 was also particularly high. They experienced 2.9 times greater odds of experiencing NEET compared to young adults who have never been CLA, while holding all other predictors constant.

Young adults who had been in receipt of Free School Meals also had an increased likelihood of experiencing NEET spells lasting 12 or more months. Compared to those who had never been classified as FSM between Year 6 and Year 11, young adults who were classified as FSM in that period for 1-2 years had odds 1.8 times greater of being NEET, and those who were FSM for 3 or more years had a 2.2 times increase in their odds of being NEET, controlling for the other risk factors.

Finally, SEN and SEN provisions also predicted NEET in young adults. Those with autistic spectrum disorders and those with profound, multiple, or severe learning difficulties had an odds of NEET that increased respectively by a factor of 2.2 and 2.6 compared to those without SEN, with all other risk factors held fixed. The risk of NEET was lower compared to those with no SEN, only for those with "Specific learning difficulties." The category of specific learning difficulties includes difficulties in specific areas of cognition, such as dyslexia, dyscalculia, dyspraxia or other language disorders (Carroll et al., 2020). While this cannot be fully explained by the model, one potential explanation is that pupils with specific learning difficulties receive early, targeted support that helps sustain engagement and smooth their transition pathways, leading to a lower observed risk of NEET

These key predictors are the same as those identified in our earlier study (Crowley et al., 2023:31), based on survey data. This convergence between the two studies using slightly different academic cohorts, a different conceptualisation of NEET, and different data sources, provides further confidence in the relevance of these predictors as risk factors for NEET risk.

Other risk factors also played a role. Pupils who had ever lived (between Years 6 to 11) in an area within the lowest IDACI quintile, who had experienced a fixed term-exclusion from school after Year 9, or who had been persistently absent from school (in any year from Years 6 to 11) all faced an increased risk of being NEET. Academic attainment at KS2 also still mattered, after controlling for the effects of GCSE attainment – although to a lesser extent. In particular, lower grades at KS2 in Maths were associated with an increased risk of being NEET. Finally, not speaking English as a first language was found to act as a protective factor against becoming NEET (or, equivalently, pupils who did speak English as a first language had an increased risk of NEET status).

While the outputs for the other models (from Year 6 to Year 10) are included in Appendix B: Year 6 – Year 10 Model Fixed Effects, Table 9 offers a summary of how the odds change across the different models. As might be expected, a key element that appears is that all the key predictors (SEN type and provision, FSM, and CLA) have a far stronger association with NEET before Year 11, when most of their variance is captured by the GCSE grades (KS4 attainment). Table 9 also offers insights into the KS2 reading and maths attainments. Indeed, they are key NEET predictors up to Year 11, when their predictive power is completely absorbed by the GCSE grades.

Table 9. Estimated Impact of Risk Factors: Yr6 - Yr1

Predictors	Modelled odds ratios					
	Yr6	**Yr7**	**Yr8**	**Yr9**	**Yr10**	**Yr11**
(Intercept)	0.06	0.06	0.05	0.05	0.05	0.03

Predictors	Modelled odds ratios					
	Yr6	Yr7	Yr8	Yr9	Yr10	Yr11
Persistent absence Yr6	2.35	1.59	1.39	1.29	1.21	1.21
Persistent absence Yr7	-	2.32	1.64	1.38	1.25	1.13
Persistent absence Yr8	-	-	2.04	1.46	1.26	1.11
Persistent absence Yr9	-	-	-	2.14	1.49	1.18
Persistent absence Yr10	-	-	-	-	2.33	1.31
Persistent absence Yr11	-	-	-	-	-	1.83
Fixed-term exclusion Yr6	1.69	1.30	1.13	1.05	0.99	0.96
Fixed-term exclusion Yr7	-	1.71	1.27	1.10	1.01	0.93
Fixed-term exclusion Yr8	-	-	1.72	1.33	1.17	1.04
Fixed-term exclusion Yr9	-	-	-	1.69	1.33	1.10
Fixed-term exclusion Yr10	-	-	-	-	1.61	1.19
Fixed-term exclusion Yr11	-	-	-	-	-	1.23
SEN type: Autistic Spectrum Disorder	1.81	2.14	2.16	2.25	2.35	2.15
SEN type: Behaviour, Emotional & Social Difficulties	1.53	1.52	1.42	1.40	1.41	1.28
SEN type: Moderate Learning Difficulty	1.09	1.24	1.25	1.27	1.29	1.10
SEN type: Other Difficulty/Disability	1.04	1.15	1.17	1.24	1.26	1.20
SEN type: Profound, multiple, or severe learning difficulties	3.07	4.16	4.44	4.80	5.10	2.56
SEN type: Sensory Impairment	1.58	1.77	1.77	1.76	1.78	1.81
SEN type: Specific Learning Difficulty	0.78	0.86	0.87	0.89	0.91	0.83
SEN type: Speech, Language and Communication Needs	0.93	1.09	1.12	1.13	1.16	1.09
SEN provision: School or Early Years Action	1.49	1.40	1.40	1.42	1.46	1.30
SEN provision: Statement	3.36	2.98	3.03	3.10	3.22	2.20
No. FSM years: 1 - 2 years	2.67	2.60	2.28	2.12	2.00	1.78
No. FSM years: 3 or more years	-	-	2.73	2.62	2.52	2.23
Ever IDACI Lowest quintile	1.64	1.62	1.59	1.56	1.55	1.45
First language not English	0.49	0.49	0.50	0.52	0.54	0.62
Ever Child Looked After	3.96	3.53	3.33	3.20	3.15	2.89
KS2 Reading: Pupil not at the expected standard	1.45	1.36	1.31	1.28	1.25	0.97
KS2 Reading: No valid KS2 reading award	1.58	1.44	1.39	1.35	1.32	1.06
KS2 Reading: Results not provided by school	1.67	1.57	1.52	1.48	1.48	1.06
KS2 Math: Pupil not at the expected standard	2.04	1.99	1.97	1.93	1.89	1.20
KS2 Math: No valid KS2 maths award	1.81	1.66	1.58	1.54	1.49	1.14
KS2 Math: Results not provided by school	0.95	1.03	1.02	1.01	0.94	0.72
Achieved 5 or more GCSEs, grade A* - C	-	-	-	-	-	1.49
Achieved 5 or more GCSEs, grade A* - G	-	-	-	-	-	1.94
Achieved 1 or more GCSE, grade A* - G	-	-	-	-	-	3.09
Achieved any pass	-	-	-	-	-	4.91
No results / no passes	-	-	-	-	-	5.34
Passed GCSE English	-	-	-	-	-	1.37
Passed GCSE Maths	-	-	-	-	-	1.51

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Random Effects

Different from the fixed effects, which are consistent across the entire analysis sample, the random effects assume a different value for each group (local authority) included in the analysis. Across the different models, from Year 6 to Year 11, each student was assigned to the local authority where they lived during the school year 11. By including these random effects, the models take into account the students clustering in the areas where they live, assigning a different intercept to the model for each local authority. These represent deviations from the model's main intercept. In simpler terms, living in a specific local authority increases or decreases the mean risk of NEET identified across the sample.

These local-authority effects show whether an area's NEET risk is higher or lower than expected once the characteristics of its pupils are taken into account; a local authority can therefore have a high overall NEET rate but still show a low (or negative) random effect if its pupil composition already explains most of that risk.

For more technical readers, the analysis is based on random-intercept models. The random effects presented in Appendix D are the estimated intercept shifts (in log-odds units) for each local authority: positive values indicate higher-than-expected NEET risk after adjustment for pupil-level predictors, while negative values indicate lower-than-expected risk.

Table 10 offers a summary of the random effects across the different models. We computed the VPC, Variance Partition Coefficient, using the method proposed by Snijders and Bosker (2011) of considering the residual variance (level-1 variance, not explained by school or local authority groups) having a consistent value of 3.29.

Before adding predictors to the model (fixed-effect variables), local authorities accounted for 3.4% of the variation in NEET across England. The addition of the NEET risk factors brought down the variation associated with local authorities to 1.4-1.7%, which is quite low[10]. For reference, the actual distribution of NEET status by local authorities can be found in Appendix H.

Table 10. Random Effect Variations Over Time

Model	Variance		Variance Partition Coefficient (%)	
	Local authority	Residual	Local authority	Residual
NULL	0.11	3.29	3.4	96.6
YR6	0.05	3.29	1.4	98.6
YR7	0.05	3.29	1.4	98.6
YR8	0.05	3.29	1.4	98.6
YR9	0.05	3.29	1.4	98.6
YR10	0.05	3.29	1.5	98.5

[10] The local authority effect captures some geographic variation - specifically, differences between LAs after accounting for pupil characteristics. However, it won't capture finer-grained neighbourhood effects or geographic influences already reflected in the pupil-level variables.

YR11	0.06	3.29	1.7	98.3

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

In practice, these local-authority random effects can help users understand whether NEET risk in a particular area is higher or lower than would be expected once pupils' individual characteristics are taken into account. They quantify residual geographic variation in the model. This information can be used in two ways. First, when estimating a pupil's likelihood of becoming NEET, applying the relevant local-authority effect will provide a more accurate prediction by accounting for area-level influences not captured by the fixed-effect variables. These are considered in the calculation of the risk index. Second, the pattern of random effects provides a descriptive indication of how local authorities differ from one another after adjusting for pupil composition – identifying areas where the NEET risk associated with the local authority itself is unusually high or low.

4.4 Predictive accuracy

To provide a simple measure of predictive accuracy, Table 12 below shows the number of cases predicted to have either spent a 12-month period NEET or not using the Year 11 model, with a threshold of above or below 50% predicted probability of being NEET. Using this 50% threshold, the model achieved the following level of accuracy in its estimates:

- Overall, 89% of cases are correctly classified as either NEET or not NEET,
- Among cases that go on to spend a 12-month period NEET, 25% were accurately predicted,
- And among people who did not become NEET, 98% were accurately predicted.

Alternatively, one can look at how accurately the model classifies cases, among those it predicts to be NEET:

- Among individuals predicted to spend a 12-month period NEET, 64% did in fact become NEET.
- Among individuals predicted not to spend a 12-month period NEET, the prediction was accurate for 90%.

Although here we have illustrated the model's predictive accuracy using a 50% probability threshold, in a typical predictive-model setting, this cut-off could be adjusted depending on the balance one wishes to strike between correctly identifying future NEET cases and avoiding false positives. Lowering the threshold, for example, to a 30% probability threshold, would classify more pupils as at risk and increase the proportion of true NEET cases correctly identified. However, we do not recommend using the index as a strict classification tool – rather, we propose it is used to identify people with a heightened risk of NEET status (section 4.5 below).

Table 11. Predicted NEET status by observed NEET status

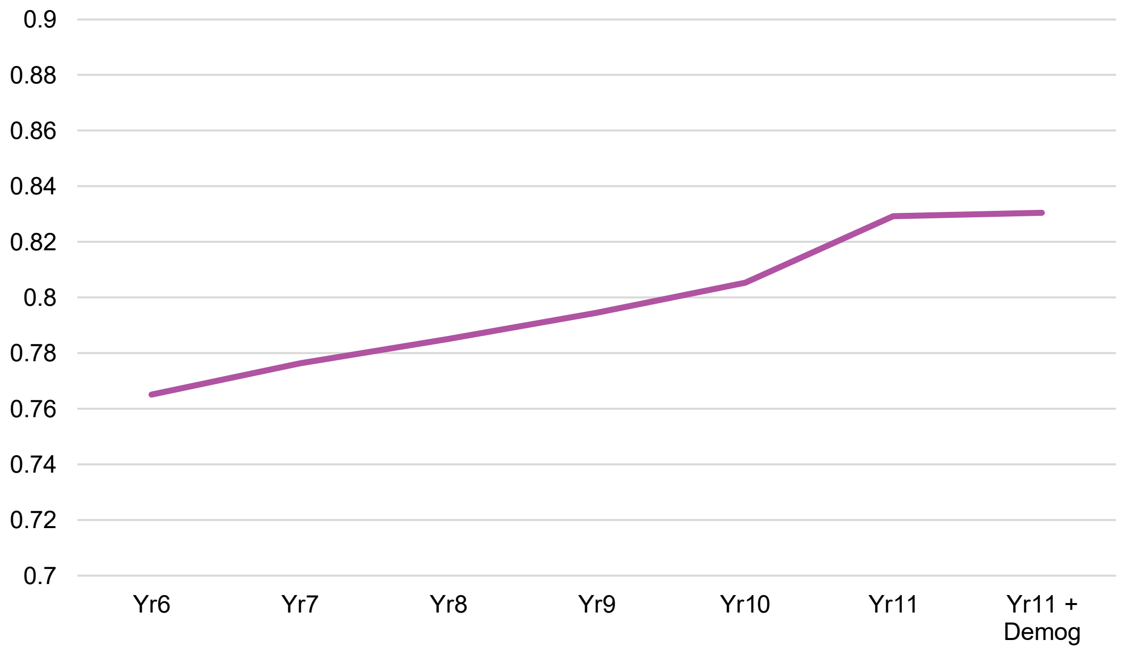
Predicted NEET Status	Observed NEET status	
	Did not spend a 12-month period NEET	Spent a 12-month period NEET
Predicted to not spend a 12-month period NEET	937,600	100,934
Predicted to spend a 12-month period NEET	18,808	33,213

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

The predictive accuracy of the models was then further assessed through the estimation of the AUROC curve, or Area Under the Receiving Operating Characteristic curve, for each single model. AUROC can assume values ranging from 0 to 1, with 1 representing maximum accuracy. Statistics above 0.80 are considered indicative of a good model (Zweig and Campbell, 1993). As expected, the accuracy of the models increased with later school years, almost linearly between Year 6 and Year 10, reaching a value above 0.80 from Year 10. The AUROC grows at a faster rate in the Year 11 model, reaching 0.83 once the GCSE grades are considered in the computation. The behaviour of the AUROC statistics supports the validity of the models, offering an empirical confirmation of how models based on later school years can more precisely predict NEET.

Interestingly, the AUROC statistics do not increase in the final Year 11 model that added the demographics, sex and ethnic background, in addition to the other risk factors already included in the model. This indicates that personal characteristics add very little explanation to the likelihood of experiencing NEET, over and above the risk factors included in the Year 11 model.

Figure 2. AUROC Plot of Model Accuracy



Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Out-of-sample validation

Out-of-sample validation is widely regarded as the gold standard for assessing the predictive performance of statistical models. It tests how well a model generalises to new cases not used during estimation and therefore provides a more robust indication of real-world performance than in-sample measures alone. While this was not feasible within the scope of the present analysis, we recommend that future research include out-of-sample validation, such as applying the model to a later cohort once that data becomes available, as an important next step in evaluating and strengthening the predictive accuracy of the NEET risk index.

4.5 Accuracy, uncertainty, and the role of professional judgement

Overall, the level of predictive accuracy achieved by these models is quite reasonable, particularly given the overall AUROC of 0.83. However, it is important to recognise that the model does not have access to all of the information needed to perfectly identify every child at risk of becoming NEET. This limitation must be kept in mind when the model is deployed in practice.

Practitioners should treat the model's output as one source of information when assessing a young person's likelihood of becoming NEET, rather than as a definitive or deterministic tool. Not all relevant risk factors are captured in administrative data, meaning that some young people who are genuinely at higher risk may receive a low predicted risk score. If, based on professional judgement, a practitioner believes that a young person requires additional support, a low-risk score should not be taken as conclusive evidence against providing that support. The model should contribute to decision-making, not replace it.

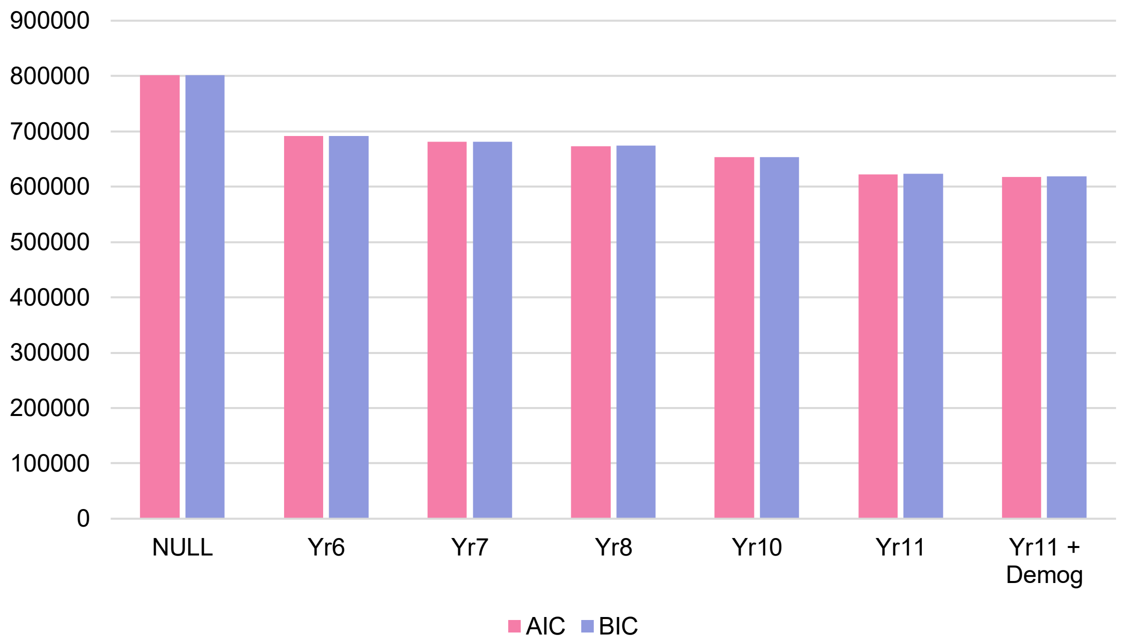
When interpreting predictive accuracy, it is also important to remember that a predicted probability reflects relative risk, not a categorical classification. For example, someone with a predicted 30% probability of experiencing a 12-month NEET spell is substantially above the baseline NEET risk rate of 12% in our sample. Using a threshold-based rule, such as classifying only those with a predicted probability of being NEET above 50% as "predicted NEET," misuses the model by forcing a binary yes/no interpretation that it was not designed to provide. The model is intended to highlight individuals whose likelihood of becoming NEET is elevated above the baseline, not to make definitive predictions about who will or will not become NEET.

How the tool is presented to practitioners will therefore be crucial. It needs to be clearly communicated that, even for individuals with strong risk factors, the model indicates an increased likelihood, not a certainty. The model's predictions should always be used alongside, and never in place of, professional judgement.

4.6 Further indicators of model fit

Further assessment of the models' predictive power can be the AIC and BIC parameters. These are indications of the model fit and model complexity. The more complex the model is, the better the predictions it generates are expected to be. However, in some instances, increasing the complexity of the model with additional variables does not make it better. AIC and BIC tend to decrease with the model's increased complexity. When the additional complexity leads to a large increase in goodness-of-fit to the data (indicating a better model), the AIC and BIC statistics are reduced to a larger extent compared to instances when the increased complexity does not greatly improve the goodness-of-fit of the model. **Error! Reference source not found.** shows how the AIC and BIC parameters changed a cross models, including this time also the null model; this is a model without predictors (NEET risk factors), but which includes the clustering by local authority.

Figure 3. Model AIC and BIC



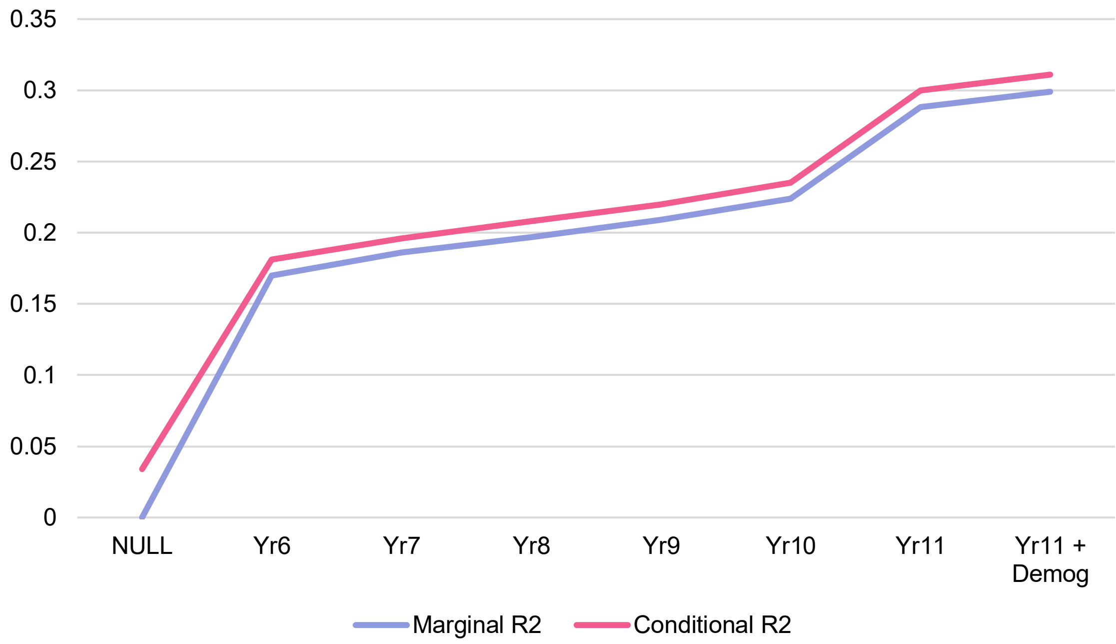
Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

As **Error! Reference source not found.** shows, both the AIC and BIC follow a similar pattern. The s trongest decreases of these parameters are observed when adding Year 6 risk factors to the null model, and in Year 11, when KS4 exam results are added as risk factors. Also in this case, the inclusion of demographic information – sex and ethnic background – leads to small gains in terms of goodness-of-fit to the data.

The R-squared of the models is a parameter that offers a further perspective on model evaluation. It indicates the proportion of the variance explained by the models, divided into marginal R-squared (variance explained attributable to fixed-effect only) and conditional R-squared (variance explained by both fixed and random effects). In simpler terms, the marginal R-squared explains how much of the difference in NEET can be explained by the risk factors, while the conditional R-squared considers both risk factors and local authority effects. These parameters are displayed in **Error! Reference source not found.** and confirm the picture that emerges from the other model statistics:

- The predictive power of the models is higher in later years than it is in earlier years;
- The Year 11 model is a strong improvement on the Year 10 due to the inclusion of KS4 exam results;
- The addition of demographics, such as sex and ethnic background, has a limited impact on the model's performance.

Figure 4. Model R^2 Values



Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

4.7 The role of sex and ethnicity

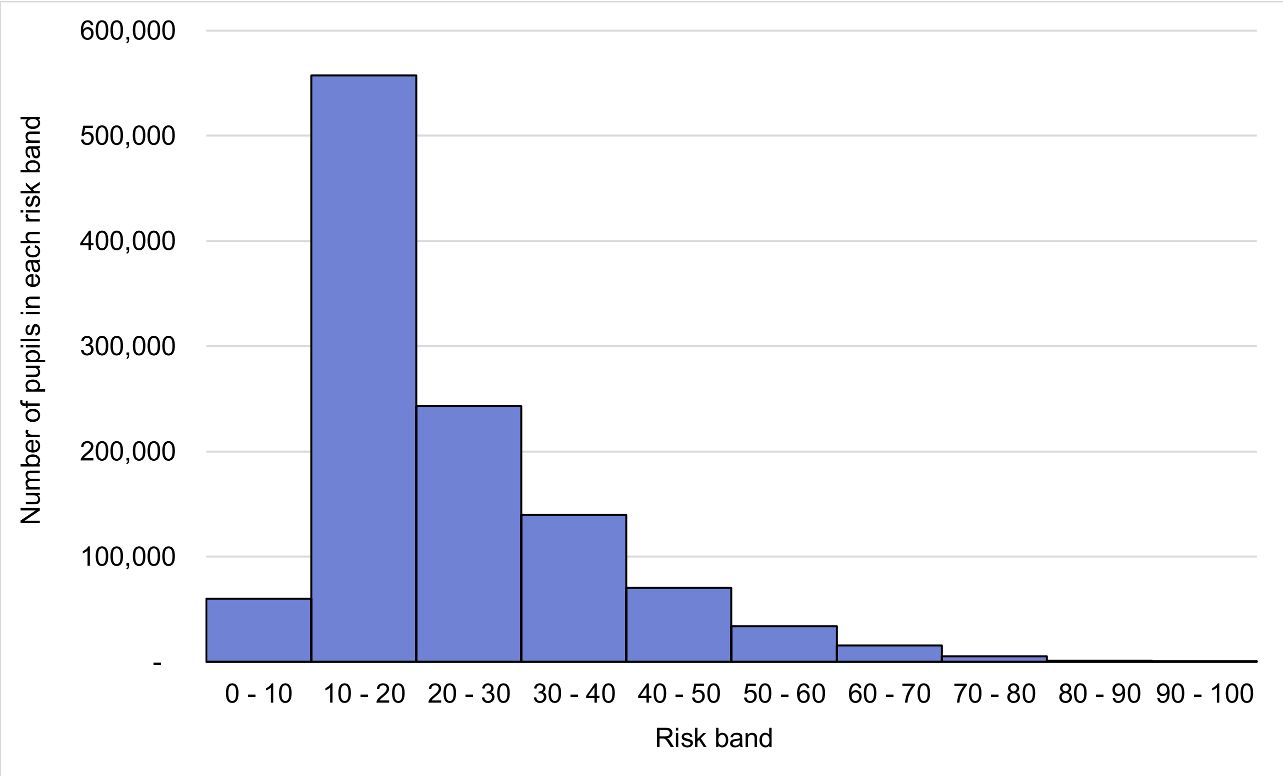
Across all the model evaluation measures discussed, the addition of the two demographic variables explored in this research – sex and ethnic background – contributed very little to predictive performance. As shown in the patterns of AIC and BIC, the greatest improvements in model fit occurred when substantive educational and behavioural risk factors – particularly Year 6 indicators and later KS4 results – were added.

By contrast, including sex and ethnicity resulted in only marginal changes to these metrics, indicating that they did not help the models meaningfully distinguish between young people who would later experience a NEET spell and those who would not. This conclusion is reinforced by the marginal and conditional R-squared statistics, which show very limited additional variance explained once demographic characteristics are introduced, and the minimal improvement in the model's AUROC value. Taken together, these findings suggest that sex and ethnicity did not enhance our ability to predict NEET outcomes in this sample, beyond the information already captured by the other educational and risk-factor variables.

4.8 Distribution of the risk index

The NEET risk index has been estimated for the sample of pupils used in this analysis, and the histogram below shows the distribution of pupils' index scores for the Year 11 model. The distribution is heavily skewed toward the lower end of the scale, with the largest concentrations of pupils scoring between 10–20 and 20–30, and only a very small proportion scoring above 60, which is to say that most pupils fall into relatively low-risk parts of the index, while only a small minority appear in the highest-risk range. This pattern and the substantive meaning of the risk band scores are described in more detail in chapter 5 (see Table 12 and Table 13).

Figure 5. Risk Index distribution (Year 11 model)



Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

5. Constructing the NEET Risk Index

5.1 Introduction

This section provides practical guidance on calculating risk index scores and applying the index in local authority settings using data on current cohorts of children. We outline the four steps required to construct the index, explain how the scores can be rescaled for easier interpretation, and discuss appropriate uses of the index for both aggregated analysis and individual risk assessment.

5.2 Computation of Risk Index Scores

The log-odds in the output of the different models can be used in the production of six different risk indices, predicting the risk of facing NEET status for current pupils between school years 6 and 11. The index is a formative additive measure (DeVellis and Thorpe, 2021; Diamantopoulos and Winklhofer, 2001), meaning that the risk it monitors is formed by adding together the different items that represent risk factors.

There are four steps to follow for the construction of the developed risk index using the information included in this report.

1. The first step requires shaping the individual-level data owned by local authorities or included in administrative data controlled by the Department for Education, into a series of risk factors that are aligned to the way the variables were manipulated for this study. Information about this process is detailed in Appendix E: Risk Index Variable Definitions.

2. The second step is to add together the individual risk factors for each individual in the data. The values that should be assigned to the different risk factors are stored in Table 16, Table 17, Table 18, Table 19 and Table 20 in Appendix B: Year 6 – Year 10 Model Fixed Effects. We do not recommend including the main intercept of the model in the computation of the index, but to use only the values presented in Table 16 and Table 20. This is because the intercept is the same number for all young adults and, therefore, does not help differentiate between individuals.

3. The third step is to add the intercept value specific to the local authority where the young adult lives. These are listed in Table 21 in Appendix D: Local Authority Random Effects, for all years, from school year 6 to 11. This intercept allows to take into account for the specific risk of NEET imputable to a local area. It is the same for all young adults living in the same area.

4. In the last step, the result of the computation can be standardised to assume a more interpretable value ranging from 0 to 100, using this formula:

$$Rescaled\ value = \frac{Original\ Value - Minimum\ Original\ Value}{Maximum\ Original\ Value - Minimum\ Original\ Value} * 100$$

The values that should be used in the formula as “Minimum Original Value” and “Maximum Original Value” are different for the different years[11] and are presented in Table 24 in Appendix G.

When using the risk index, some users may prefer to use a categorical classification of the index instead of observing the risk on a continuous scale. Table 12 summarises NEET prevalence across banded risk scores from the Year 11 model. The distribution of pupils is heavily concentrated in the lower bands: around half fall in the 10–20 band (50%), and a further 22% fall in the 20–30 band, while only a very small proportion appear in the highest bands (e.g., 0.01% in the 90–100 band). NEET prevalence increases steadily with the risk index. In Table 12, the percentage NEET rises from 2% (0–10) to 82% (90–100). However, that extreme upper band has a small count (n=73), so figures at that edge of the distribution should be interpreted with caution

Given the uneven distribution in the index score seen in Table 12, we have also proposed a simple low, medium and high risk classification (in Table 13). In the low-risk category are pupils with risk scores of 0 to 30 – around three-quarters of the pupils in our sample (76%). The boundary for the low-risk group was set at 30 because this is the last risk band where the percentage of pupils who are NEET falls below the average NEET rate of 12% in our sample as a whole. The medium risk group includes those with a risk score of 30-60, who account for 22% of students, while the high-risk group includes all pupils with a score of 60 or more, and is by far the smallest group, about 2% of pupils. The NEET rates (those who had a 12-month period NEET) in these three groups were 4.5% in the low-risk category, 28% in the medium-risk group, and 71% in the high-risk group (Table 13).

The boundaries between the low, medium and high-risk groups are necessarily judgment-based. They reflect a balance between the distribution of scores, the underlying NEET rates, and the need for groupings that are interpretable and useful for policy. In particular, the distinction between the medium and high-risk groups involves setting a pragmatic threshold rather than identifying a natural break in the data.

[11] The minimum and maximum values used to rescale the index reflect the characteristics of the training cohorts. These values may change over time because the local-authority random effects, and to a lesser extent the underlying risk factors, will shift as new cohorts progress through the education system. In principle, the minimum represents a pupil with no recorded risk factors living in the local authority with the lowest estimated risk, while the maximum represents a pupil with all the highest-risk characteristics living in the authority with the highest estimated risk. This combination may not exist in practice, and an implemented model could therefore produce scores above 100.

Table 12. Proportion of NEETs by Banded Risk Score

Index Score (Banded)	Number of pupils in risk band	Percentage of pupils in risk band	Percentage NEET
0 to 10	59,889	5.3	2.0
10 to 20	557,199	49.5	2.7
20 to 30	243,201	21.6	8.1
30 to 40	139,724	12.4	18.0
40 to 50	70,054	6.2	34.4
50 to 60	33809	3.0	53.1
60 to 70	15,605	1.4	68.6
70 to 80	5,083	0.5	77.4
80 to 90	899	0.1	78.9
90 to 100	73	0.01	82.1

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Table 13. Proportion of NEETs by Risk Index Category

Risk Index Category	Risk Score	Number of pupils in risk category	Percentage of pupils in risk category	Percentage NEET
1. Low Risk	0 up to 30	860,289	76.43%	4.5
2. Medium Risk	30 up to 60	243,586	21.64%	27.7
3. High Risk	60 or higher	21,660	1.92%	71.3

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Example application

To give an example of how the risk index might be applied, Table 14 displays a hypothetical student with a range of risk factors. The estimated role of each risk factor in this child's log odds has been taken from the Year 11 model – so, we are assuming they are in Year 11 and have included risk factors that would only apply at that age (GCSE attainment). This person was persistently absent in years 6 and 7, they were on free school meals for three or more years, they have relatively low academic attainment, and they were also recorded as a looked-after child in at least one of their school years.

Table 14. Example application of risk index

Risk factors	Log odds
Persistent absence - Year 6	0.19
Persistent absence - Year 7	0.12
Number of years classed as FSM - 3 or more years	0.80
Ever classed as Child looked after - Yes	1.06
Not at the expected reading standard - KS2	-0.03

Not at the expected maths standard - KS2	0.19
Achieved 5 or more GCSEs, grade A* - G	0.66
Local authority - Blackpool	0.08
Sum of log odds	2.99

With this set of risk factors, this young person is likely to face an elevated risk of NEET. To calculate their risk score, the log odds associated with each risk factor that they experienced are summed – as shown in Table 14 – giving a total of 2.99. Those risk factors the student does not experience are effectively set to zero, so are not shown here.

This risk score is then normalised to range between zero and 100 using the formula described above. In the Year 11 model, the maximum possible value that could be scored from the raw log odds is 8.74, and the lowest possible value is -1.54.

$$44 = \frac{2.99 - -1.54}{8.71 - -1.54} * 100$$

When these values are plugged into the formula, along with this hypothetical pupil's score of 2.99 – the resulting risk index estimate is 44 – which is well above average and indicates a heightened risk of becoming NEET.

5.3 Uses of the Index

The new risk index can be used in an aggregated form to identify volumes of risk accumulated across young adults in certain clusters relevant for policy development and action. For example, it can be suitable for understanding how the risk varies by schools, by academic years, or by geographical entities, including small areas. It may be relevant to compare these analysis units by their mean or median risk to have a measure of centrality, by their standard deviation, to understand how spread out the risk is in a local setting, or by the thresholds discussed above, to understand the percentage of pupils and young adults that are in the low, mid, or low risk tiers.

Analysing NEET outcomes across socio-demographic characteristics, such as ethnicity or sex, can highlight where heightened risk is observed, which can be useful for understanding patterns that warrant further investigation or groups that need additional support. However, such findings must be interpreted with care. Differences in average risk between groups do not explain why those differences arise and should not be taken to imply that inherent characteristics – such as ethnic background – are responsible for higher or lower risk. Without appropriate framing, there is a risk that these analyses may inadvertently reinforce misleading or stigmatising assumptions. Clear caveats are therefore essential, ensuring that any observed disparities are understood as indicators of underlying structural, social, or contextual factors rather than attributes of the groups themselves.

The new risk index can also be used to understand whether specific individuals are at greater risk of NEET, so that specific support can be deployed in a local setting to shield them from this scarring social and economic outcome in early adulthood. Indeed, this is one of the primary uses of RONI (Department for Education, 2025).

Additionally, the new risk index also provides a consistent, evidence-based foundation for early identification from school year 6 onwards, available across all local authorities without requiring additional data collection. The index is based on educational risk factors captured in administrative data and, like all statistics models, provides probabilistic predictions rather than certainties. The index does not capture all aspects of a young person's life that may influence NEET outcomes. We therefore recommend pairing estimates with qualitative insights from school pastoral teams and caseworkers who work directly with pupils and young adults. This integrated approach – combining statistical evidence with professional knowledge of individual circumstances – enables more effective and appropriately targeted support than either approach could achieve alone.

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Appendices

Appendix A: NEET Outcomes

Table 15. NEET Outcomes by Risk Factors

Variable	Category	Count	Percentage	Percentage NEET
Ever in the lowest IDACI quintile (up to Yr6)	Yes	218,162	20	10
	No	872,393	80	22
Ever in the lowest IDACI quintile (up to Yr7)	Yes	246,255	23	10
	No	844,300	77	22
Ever in the lowest IDACI quintile (up to Yr8)	Yes	267,164	24	9
	No	823,391	76	21
Ever in the lowest IDACI quintile (up to Yr9)	Yes	274,338	25	9
	No	816,217	75	21
Ever in the lowest IDACI quintile (up to Yr10)	Yes	287,464	26	9
	No	803,091	74	21
Ever classed as CLA (up to Yr6)	Yes	5,540	<1	50
	No	1,085,015	99	12
Ever classed as CLA (up to Yr7)	Yes	6,560	<1	51
	No	1,083,995	99	12
Ever classed as CLA (up to Yr8)	Yes	7,690	<1	51
	No	1,082,865	99	12
Ever classed as CLA (up to Yr9)	Yes	9,230	<1	51
	No	1,081,325	99	12
Ever classed as CLA (up to Yr10)	Yes	11,150	<1	51
	No	1,079,405	99	12
Most recent SEN type (up to Yr6)	No SEN	923,994	85	9
	Autistic Spectrum Disorder	6,840	<1	43
	Behaviour, Emotional & Social Difficulties	26,717	2	33
	Moderate Learning Difficulty	67,702	6	27
	Other Difficulty/Disability	9,206	<1	20
	Profound, multiple, or severe learning difficulties	5,727	<1	67
	Sensory Impairment	7,929	<1	34
	Specific Learning Difficulty	28,193	3	17

Variable	Category	Count	Percentage	Percentage NEET
	Speech, Language and Communication Needs	14,247	1	25
Most recent SEN type (up to Yr7)	No SEN	907,467	83	9
	Autistic Spectrum Disorder	7,876	<1	42
	Behaviour, Emotional & Social Difficulties	32,232	3	34
	Moderate Learning Difficulty	71,899	7	28
	Other Difficulty/Disability	11,227	1	21
	Profound, multiple, or severe learning difficulties	5,398	<1	69
	Sensory Impairment	8,781	<1	33
	Specific Learning Difficulty	31,672	2.9	17
	Speech, Language and Communication Needs	14,003	1	24
Most recent SEN type (up to Yr8)	No SEN	895,569	82	8.9
	Autistic Spectrum Disorder	8,548	<1	41
	Behaviour, Emotional & Social Difficulties	38,469	4	33
	Moderate Learning Difficulty	73,305	7	28
	Other Difficulty/Disability	12,267	1	21
	Profound, multiple, or severe learning difficulties	5,386	<1	70
	Sensory Impairment	9,330	<1	32
	Specific Learning Difficulty	33,509	3	17
	Speech, Language and Communication Needs	14,172	1	23
Most recent SEN type (up to Yr9)	No SEN	883,275	81	9
	Autistic Spectrum Disorder	9,246	<1	41
	Behaviour, Emotional & Social Difficulties	46,157	4	34
	Moderate Learning Difficulty	73,783	7	27
	Other Difficulty/Disability	13,595	1	22
	Profound, multiple, or severe learning difficulties	5,398	<1	71
	Sensory Impairment	9,911	<1	31
	Specific Learning Difficulty	34,826	3	17
	Speech, Language and Communication Needs	14,364	1	23
Most recent SEN type (up to Yr10)	No SEN	870,915	80	8
	Autistic Spectrum Disorder	9,921	<1	41
	Behaviour, Emotional & Social Difficulties	54,434	5	34
	Moderate Learning Difficulty	73,846	7	27

Variable	Category	Count	Percentage	Percentage NEET
	Other Difficulty/Disability	14,983	1	22
	Profound, multiple, or severe learning difficulties	5,441	<1	71
	Sensory Impairment	10,416	<1	30
	Specific Learning Difficulty	36,169	3	16
	Speech, Language and Communication Needs	14,430	1	22
SEN provision in Yr6	No SEN provision	848,428	78	8
	School or early years actions	208,740	19	22
	Statement	33,387	3	50
SEN provision in Yr7	No SEN provision	850,203	78	8
	School or early years actions	204,341	19	22
	Statement	36,011	3	50
SEN provision in Yr8	No SEN provision	843,175	77	8
	School or early years actions	209,831	19	22
	Statement	37,549	3	50
SEN provision in Yr9	No SEN provision	840,161	77	8
	School or early years actions	211,234	19	22
	Statement	39,160	4	51
SEN provision in Yr10	No SEN provision	840,964	77	8
	School or early years actions	209,132	19	23
	Statement	40,459	4	51
No. of years in receipt of FSM (up to Yr 6)	Never	919,922	84	9
	1-2 years	170,633	16	29
	3 or more years	-	-	-
No. of years in receipt of FSM (up to Yr 7)	Never	888,378	81	9
	1-2 years	202,177	19	28
	3 or more years	-	-	-
No. of years in receipt of FSM (up to Yr 8)	Never	873,126	80	9
	1-2 years	101,958	9	25
	3 or more years	115,471	11	30
No. of years in receipt of FSM (up to Yr 9)	Never	858,290	79	8
	1-2 years	87,778	8	23
	3 or more years	144,487	13	30
No. of years in receipt of FSM (up to Yr 10)	Never	844,351	77	8
	1-2 years	85,873	8	22
	3 or more years	160,331	15	30

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Appendix B: Year 6 – Year 10 Model Fixed Effects

Table 16. Year 10 Model Fixed Effects

Term	Level	Odds	Log-odds	Std. Errors	p-value
(Intercept)		0.05	-3.08	0.02	<0.001
Persistent absence Yr6	No (reference category)	-	-	-	-
	Yes	1.21	0.19	0.03	<0.001
Persistent absence Yr7	No (reference category)	-	-	-	-
	Yes	1.25	0.22	0.02	<0.001
Persistent absence Yr8	No (reference category)	-	-	-	-
	Yes	1.26	0.23	0.02	<0.001
Persistent absence Yr9	No (reference category)	-	-	-	-
	Yes	1.49	0.40	0.01	<0.001
Persistent absence Yr10	No (reference category)	-	-	-	-
	Yes	2.33	0.85	0.01	<0.001
Fixed-term exclusion Yr6	No (reference category)	-	-	-	-
	Yes	0.99	-0.01	0.03	0.683
Fixed-term exclusion Yr7	No (reference category)	-	-	-	-
	Yes	1.01	0.01	0.02	0.475
Fixed-term exclusion Yr8	No (reference category)	-	-	-	-
	Yes	1.17	0.16	0.01	<0.001
Fixed-term exclusion Yr9	No (reference category)	-	-	-	-
	Yes	1.33	0.29	0.01	<0.001
Fixed-term exclusion Yr10	No (reference category)	-	-	-	-
	Yes	1.61	0.47	0.01	<0.001
Latest SEN type	No SEN (reference category)	-	-	-	-
	Autistic Spectrum Disorder	2.35	0.85	0.03	<0.001
	Behaviour, Emotional & Social Difficulties	1.41	0.34	0.01	<0.001
	Moderate Learning Difficulty	1.29	0.25	0.01	<0.001
	Other Difficulty/Disability	1.26	0.23	0.02	<0.001
	Profound, multiple, or severe learning difficulties	5.10	1.63	0.04	<0.001
	Sensory Impairment	1.78	0.58	0.03	<0.001
	Specific Learning Difficulty	0.91	-0.10	0.02	<0.001
	Speech, Language and Communication Needs	1.16	0.15	0.02	<0.001
SEN provision in Yr10	No provision (reference category)	-	-	-	-
	School or Early Years Action	1.46	0.38	0.01	<0.001
	Statement	3.22	1.17	0.02	<0.001
	0 (reference category)	-	-	-	-

Term	Level	Odds	Log-odds	Std. Errors	p-value
Number of years classed as FSM	1 - 2 years	2.00	0.69	0.01	<0.001
	3 or more years	2.52	0.93	0.01	<0.001
Ever lived in lowest IDACI quintile	No (reference category)	-	-	-	-
	Yes	1.55	0.44	0.01	<0.001
Whether English is first language	English (reference category)	-	-	-	-
	Not English	0.54	-0.62	0.01	<0.001
Ever classed as Child looked after	No (reference category)	-	-	-	-
	Yes	3.15	1.15	0.02	<0.001
Reading standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.25	0.22	0.01	<0.001
	No valid KS2 reading award	1.32	0.28	0.04	<0.001
	Results not provided by the school	1.48	0.39	0.07	<0.001
Maths standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.89	0.64	0.01	<0.001
	No valid KS2 maths award	1.49	0.40	0.04	<0.001
	Results not provided by the school	0.94	-0.06	0.07	0.425

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Table 17. Year 9 Model Fixed Effects

Term	Level	Odds	Log-odds	Std. Errors	p-value
(Intercept)		0.05	-3.01	0.02	<0.001
Persistent absence Yr6	No (reference category)	-	-	-	-
	Yes	1.29	0.25	0.03	<0.001
Persistent absence Yr7	No (reference category)	-	-	-	-
	Yes	1.38	0.33	0.02	<0.001
Persistent absence Yr8	No (reference category)	-	-	-	-
	Yes	1.46	0.38	0.02	<0.001
Persistent absence Yr9	No (reference category)	-	-	-	-
	Yes	2.14	0.76	0.01	<0.001
Fixed-term exclusion Yr6	No (reference category)	-	-	-	-
	Yes	1.05	0.05	0.03	0.109
Fixed-term exclusion Yr7	No (reference category)	-	-	-	-
	Yes	1.10	0.09	0.02	<0.001
Fixed-term exclusion Yr8	No (reference category)	-	-	-	-
	Yes	1.33	0.28	0.01	<0.001
	No (reference category)	-	-	-	-

Term	Level	Odds	Log-odds	Std. Errors	p-value
Fixed-term exclusion Yr9	Yes	1.69	0.52	0.01	<0.001
Latest SEN type	No SEN (reference category)	-	-	-	-
	Autistic Spectrum Disorder	2.25	0.81	0.03	<0.001
	Behaviour, Emotional & Social Difficulties	1.40	0.33	0.01	<0.001
	Moderate Learning Difficulty	1.27	0.24	0.01	<0.001
	Other Difficulty/Disability	1.24	0.21	0.02	<0.001
	Profound, multiple, or severe learning difficulties	4.80	1.57	0.04	<0.001
	Sensory Impairment	1.76	0.57	0.03	<0.001
	Specific Learning Difficulty	0.89	-0.12	0.02	<0.001
	Speech, Language and Communication Needs	1.13	0.12	0.02	<0.001
SEN provision in Yr9	No provision (reference category)	-	-	-	-
	School or Early Years Action	1.42	0.35	0.01	<0.001
	Statement	3.10	1.13	0.02	<0.001
Number of years classed as FSM	0 (reference category)	-	-	-	-
	1 - 2 years	2.12	0.75	0.01	<0.001
	3 or more years	2.62	0.96	0.01	<0.001
Ever lived in lowest IDACI quintile	No (reference category)	-	-	-	-
	Yes	1.56	0.45	0.01	<0.001
Whether English is first language	English (reference category)	-	-	-	-
	Not English	0.52	-0.66	0.01	<0.001
Ever classed as Child looked after	No (reference category)	-	-	-	-
	Yes	3.20	1.16	0.02	<0.001
Reading standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.28	0.24	0.01	<0.001
	No valid KS2 reading award	1.35	0.30	0.03	<0.001
	Results not provided by the school	1.48	0.39	0.07	<0.001
Maths standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.93	0.66	0.01	<0.001
	No valid KS2 maths award	1.54	0.43	0.04	<0.001
	Results not provided by the school	1.01	0.01	0.07	0.935

Table 18. Year 8 Model Fixed Effects

Term	Level	Odds	Log-odds	Std. Errors	p-value
(Intercept)		0.05	-2.95	0.02	<0.001
Persistent absence Yr6	No (reference category)	-	-	-	-
	Yes	1.39	0.33	0.03	<0.001
Persistent absence Yr7	No (reference category)	-	-	-	-
	Yes	1.64	0.49	0.02	<0.001
Persistent absence Yr8	No (reference category)	-	-	-	-
	Yes	2.04	0.72	0.01	<0.001
Fixed-term exclusion Yr6	No (reference category)	-	-	-	-
	Yes	1.13	0.12	0.03	<0.001
Fixed-term exclusion Yr7	No (reference category)	-	-	-	-
	Yes	1.27	0.24	0.02	<0.001
Fixed-term exclusion Yr8	No (reference category)	-	-	-	-
	Yes	1.72	0.54	0.01	<0.001
Latest SEN type	No SEN (reference category)	-	-	-	-
	Autistic Spectrum Disorder	2.16	0.77	0.03	<0.001
	Behaviour, Emotional & Social Difficulties	1.42	0.35	0.01	<0.001
	Moderate Learning Difficulty	1.25	0.22	0.01	<0.001
	Other Difficulty/Disability	1.17	0.16	0.03	<0.001
	Profound, multiple, or severe learning difficulties	4.44	1.49	0.03	<0.001
	Sensory Impairment	1.77	0.57	0.03	<0.001
	Specific Learning Difficulty	0.87	-0.14	0.02	<0.001
	Speech, Language and Communication Needs	1.12	0.11	0.02	<0.001
SEN provision in Yr8	No provision (reference category)	-	-	-	-
	School or Early Years Action	1.40	0.33	0.01	<0.001
	Statement	3.03	1.11	0.02	<0.001
Number of years classed as FSM	0 (reference category)	-	-	-	-
	1 - 2 years	2.28	0.82	0.01	<0.001
	3 or more years	2.73	1.01	0.01	<0.001
Ever lived in lowest IDACI quintile	No (reference category)	-	-	-	-
	Yes	1.59	0.46	0.01	<0.001
Whether English is first language	English (reference category)	-	-	-	-
	Not English	0.50	-0.69	0.01	<0.001
Ever classed as Child looked after	No (reference category)	-	-	-	-
	Yes	3.33	1.20	0.03	<0.001
Reading standard by the end of KS2	Expected standard (reference category)	-	-	-	-

Term	Level	Odds	Log-odds	Std. Errors	p-value
	Not at the expected standard	1.31	0.27	0.01	<0.001
	No valid KS2 reading award	1.39	0.33	0.03	<0.001
	Results not provided by the school	1.52	0.42	0.07	<0.001
Maths standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.97	0.68	0.01	<0.001
	No valid KS2 maths award	1.58	0.46	0.04	<0.001
	Results not provided by the school	1.02	0.02	0.07	0.745

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Table 19. Year 7 Model Fixed Effects

Term	Level	Odds	Log-odds	Std. Errors	p-value
(Intercept)		0.06	-2.90	0.02	<0.001
Persistent absence Yr6	No (reference category)	-	-	-	-
	Yes	1.59	0.46	0.03	<0.001
Persistent absence Yr7	No (reference category)	-	-	-	-
	Yes	2.32	0.84	0.02	<0.001
Fixed-term exclusion Yr6	No (reference category)	-	-	-	-
	Yes	1.30	0.26	0.03	<0.001
Fixed-term exclusion Yr7	No (reference category)	-	-	-	-
	Yes	1.71	0.53	0.01	<0.001
Latest SEN type	No SEN (reference category)	-	-	-	-
	Autistic Spectrum Disorder	2.14	0.76	0.03	<0.001
	Behaviour, Emotional & Social Difficulties	1.52	0.42	0.02	<0.001
	Moderate Learning Difficulty	1.24	0.21	0.01	<0.001
	Other Difficulty/Disability	1.15	0.14	0.03	<0.001
	Profound, multiple, or severe learning difficulties	4.16	1.43	0.03	<0.001
	Sensory Impairment	1.77	0.57	0.03	<0.001
	Specific Learning Difficulty	0.86	-0.15	0.02	<0.001
	Speech, Language and Communication Needs	1.09	0.09	0.02	<0.001
SEN provision in Yr7	No provision (reference category)	-	-	-	-
	School or Early Years Action	1.40	0.33	0.01	<0.001
	Statement	2.98	1.09	0.02	<0.001
Number of years classed as FSM	0 (reference category)	-	-	-	-
	1 - 2 years	2.60	0.95	0.01	<0.001

Term	Level	Odds	Log-odds	Std. Errors	p-value
	3 or more years[12]	NA	NA	NA	NA
Ever lived in lowest IDACI quintile	No (reference category)	-	-	-	-
	Yes	1.62	0.48	0.01	<0.001
Whether English is first language	English (reference category)	-	-	-	-
	Not English	0.49	-0.70	0.01	<0.001
Ever classed as Child looked after	No (reference category)	-	-	-	-
	Yes	3.53	1.26	0.03	<0.001
Reading standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.36	0.31	0.01	<0.001
	No valid KS2 reading award	1.44	0.36	0.03	<0.001
	Results not provided by the school	1.57	0.45	0.07	<0.001
Maths standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.99	0.69	0.01	<0.001
	No valid KS2 maths award	1.66	0.50	0.03	<0.001
	Results not provided by the school	1.03	0.03	0.07	0.701

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Table 20. Year 6 Model Fixed Effects

Term	Level	Odds	Log-odds	Std. Errors	p-value
(Intercept)		0.06	-2.81	0.02	<0.001
Persistent absence Yr6	No (reference category)	-	-	-	-
	Yes	2.35	0.86	0.03	<0.001
Fixed-term exclusion Yr6	No (reference category)	-	-	-	-
	Yes	1.69	0.53	0.03	<0.001
Latest SEN type	No SEN (reference category)	-	-	-	-
	Autistic Spectrum Disorder	1.81	0.60	0.03	<0.001
	Behaviour, Emotional & Social Difficulties	1.53	0.43	0.02	<0.001
	Moderate Learning Difficulty	1.09	0.09	0.01	<0.001
	Other Difficulty/Disability	1.04	0.04	0.03	0.1832
	Profound, multiple, or severe learning difficulties	3.07	1.12	0.03	<0.001
	Sensory Impairment	1.58	0.46	0.03	<0.001
	Specific Learning Difficulty	0.78	-0.25	0.02	<0.001

[12] Pupils cannot be classified as FSM for 3 or more years after Yr6 in Yr7.

Term	Level	Odds	Log-odds	Std. Errors	p-value
	Speech, Language and Communication Needs	0.93	-0.07	0.02	0.0042
SEN provision in Yr6	No provision (reference category)	-	-	-	-
	School or Early Years Action	1.49	0.40	0.01	<0.001
	Statement	3.36	1.21	0.02	<0.001
Number of years classed as FSM	0 (reference category)	-	-	-	-
	1 - 2 years	2.67	0.98	0.01	<0.001
	3 or more years[13]	NA	NA	NA	NA
Ever lived in lowest IDACI quintile	No (reference category)	-	-	-	-
	Yes	1.64	0.49	0.01	<0.001
Whether English is first language	English (reference category)	-	-	-	-
	Not English	0.49	-0.71	0.01	<0.001
Ever classed as Child looked after	No (reference category)	-	-	-	-
	Yes	3.96	1.38	0.03	<0.001
Reading standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	1.45	0.37	0.01	<0.001
	No valid KS2 reading award	1.58	0.46	0.03	<0.001
	Results not provided by the school	1.67	0.51	0.07	<0.001
Maths standard by the end of KS2	Expected standard (reference category)	-	-	-	-
	Not at the expected standard	2.04	0.71	0.01	<0.001
	No valid KS2 maths award	1.81	0.59	0.03	<0.001
	Results not provided by the school	0.95	-0.05	0.07	0.4925

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

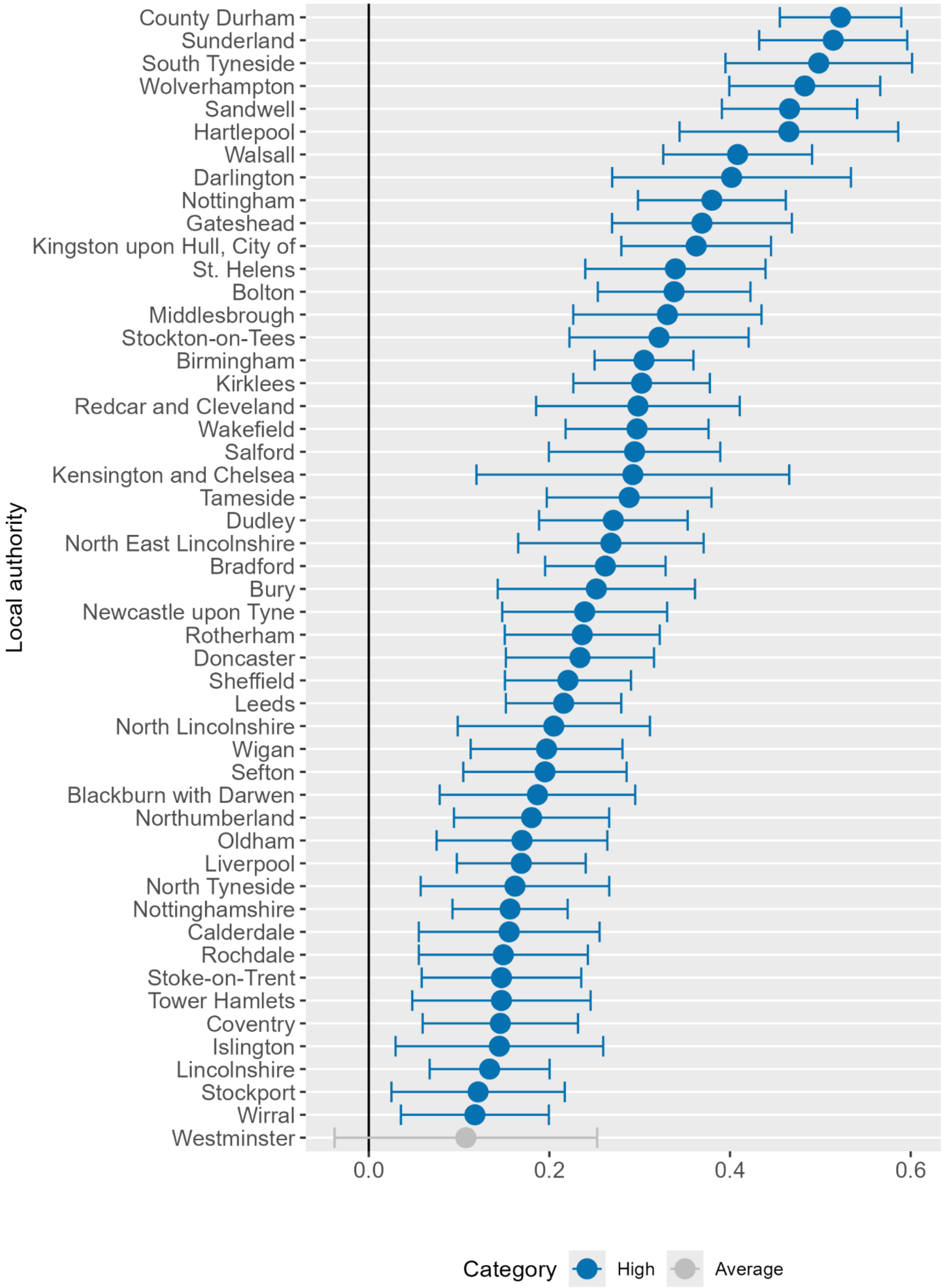
[13] Pupils cannot be classified as FSM for 3 or more years after Yr6 in Yr7.

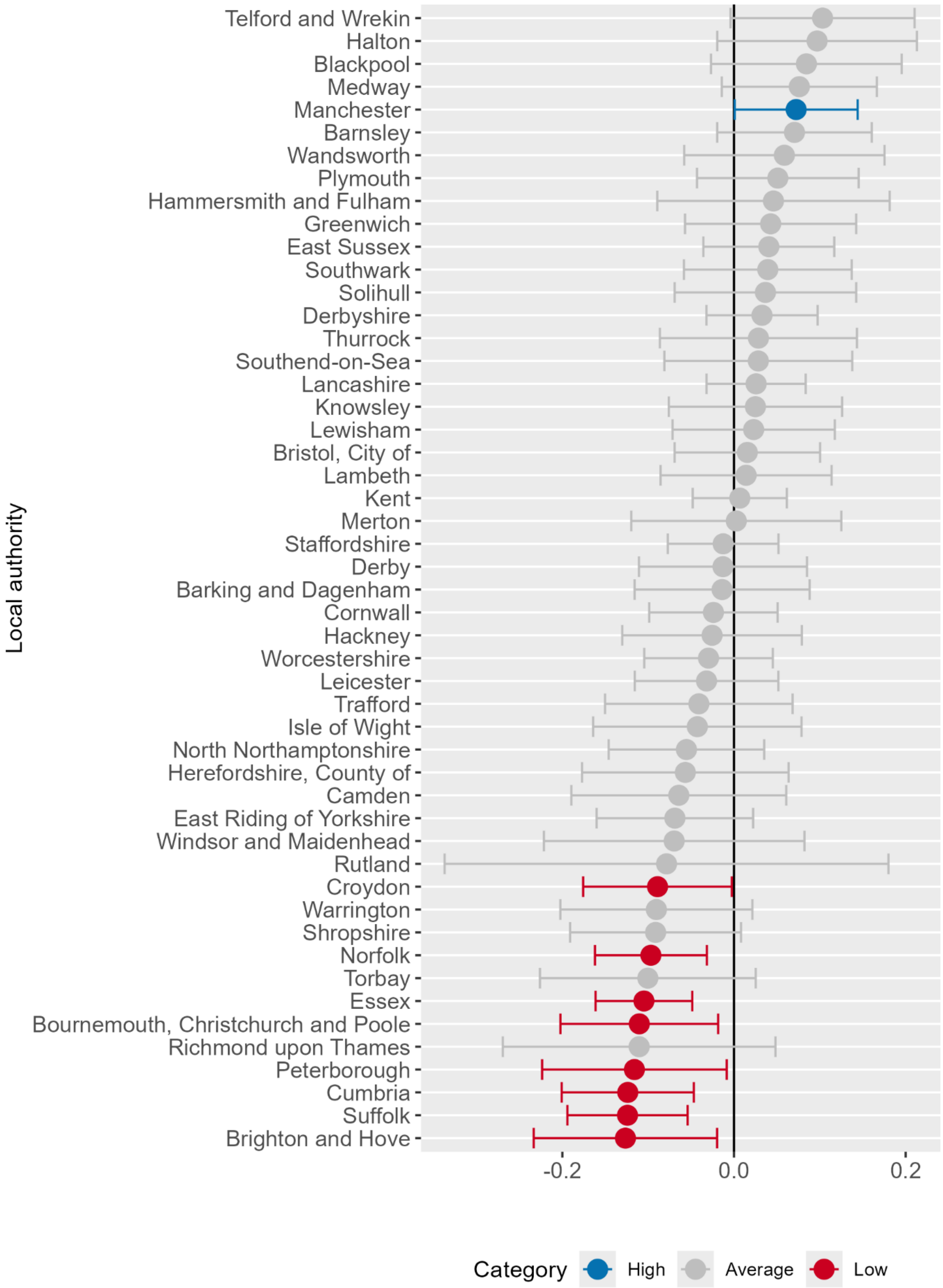
Appendix C: Local Authority NEET Variation

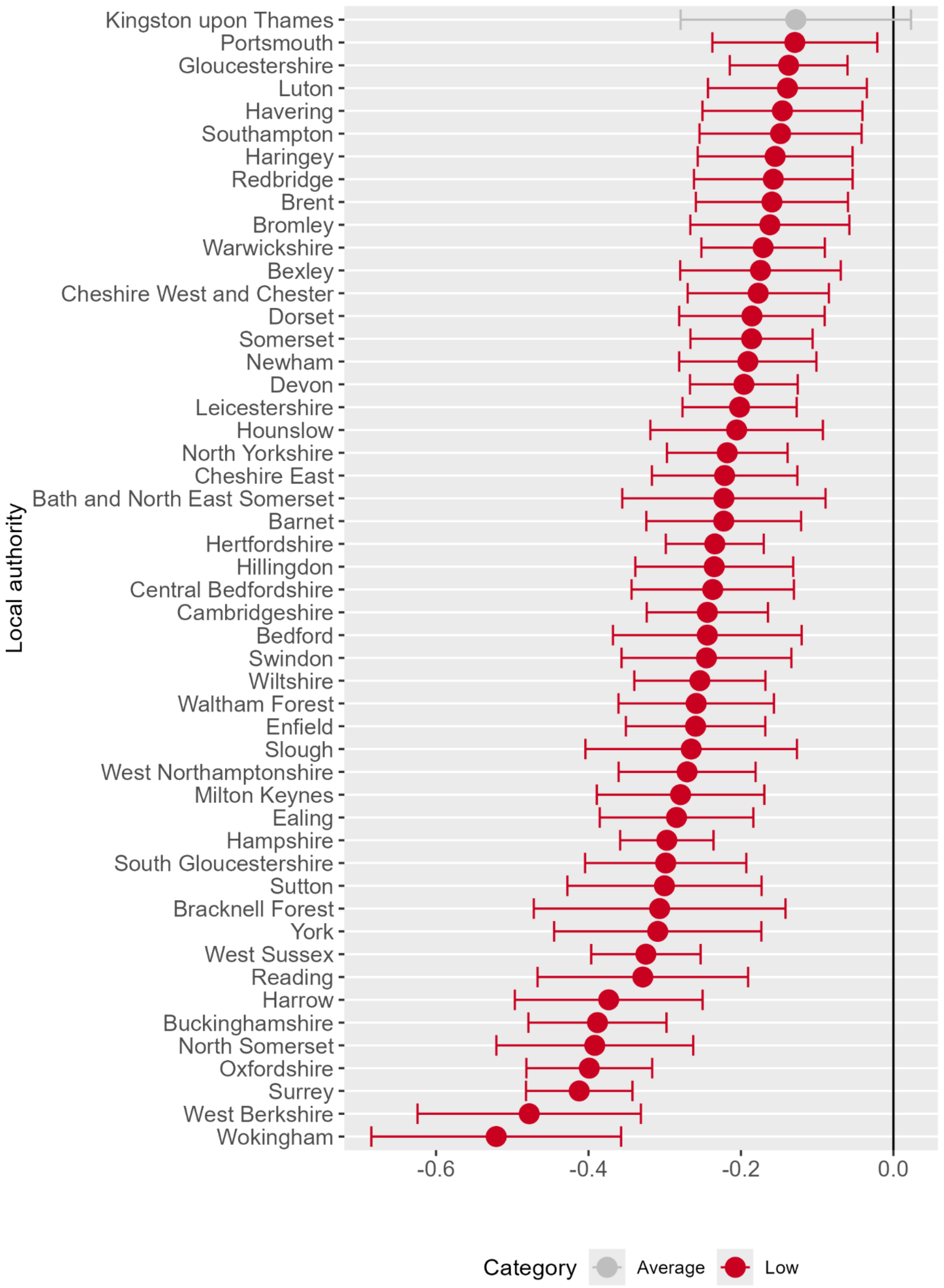
Figure 6 shows the variation in log-odds of NEET risk for the different local authorities in Year 11, net of the fixed effects in the model – that is over and above the nature of the pupil composition measured by those variables. The figure is colour-coded, showing local authorities with an effect that is statistically significant in red (higher than zero) or blue (lower than zero). Local authorities with effects that are not statistically significant are marked in grey. The ranking of the different local authorities provides further face-value validity to the model: local authorities in areas that are economically more deprived are associated with an elevated risk of NEET, while local authorities in more affluent areas are associated with a reduction of the mean NEET risk. Blackpool ranks 53rd and does not have a statistically significant variation of the mean risk, indicating that the greater prevalence of NEET rates seen in the area can be explained primarily by pupils' characteristics.

The estimated random effects for each local authority are presented in Appendix D; these log-odds values are required for calculating the risk index when applying the model to future data. To give a sense of the remaining variation in NEET risk across local authorities after adjusting for the pupil-level factors included in the model, we converted these log-odds into predicted probabilities. This indicates that area-level variation corresponds to a difference of roughly 2 to 5.5 percentage points in the likelihood of experiencing a 12-month NEET period.

Figure 6. Local Authority Random Effects from the Year 11 NEET Risk Model



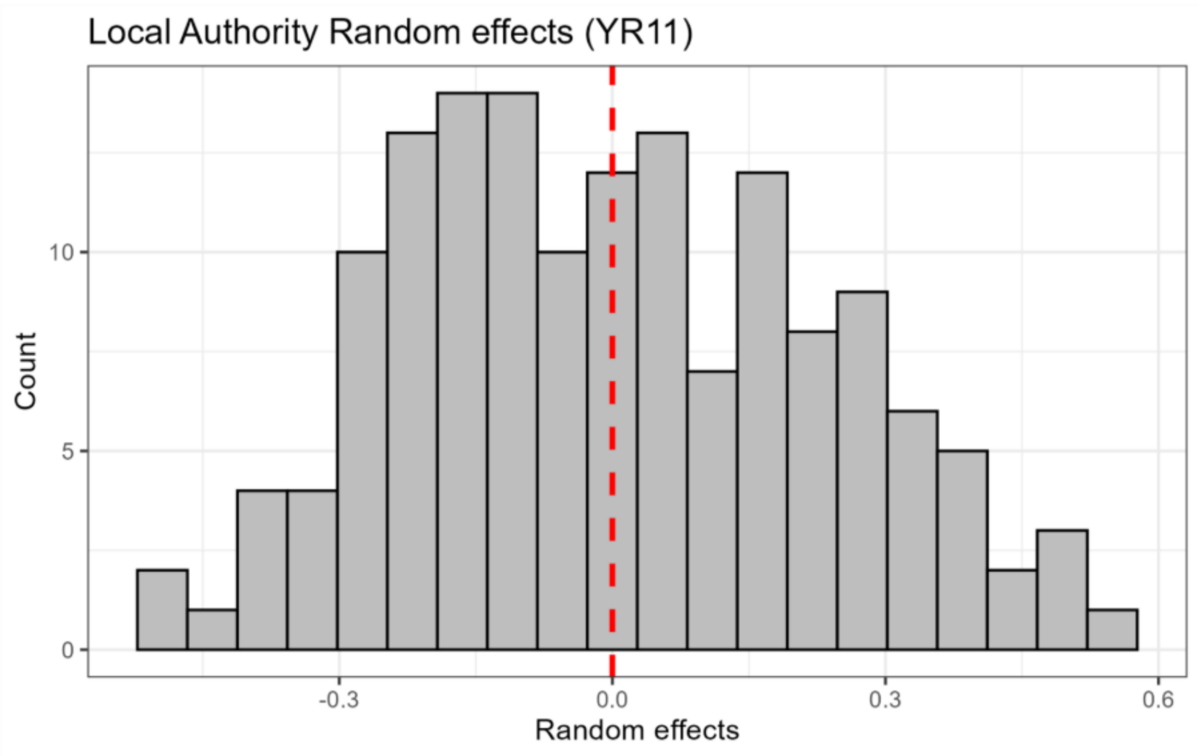

Local authority
Telford and Wrekin
Halton
Blackpool
Medway
Manchester
Barnsley
Wandsworth
Plymouth
Hammersmith and Fulham
Greenwich
East Sussex
Southwark
Solihull
Derbyshire
Thurrock
Southend-on-Sea
Lancashire
Knowsley
Lewisham
Bristol, City of
Lambeth
Kent
Merton
Staffordshire
Derby
Barking and Dagenham
Cornwall
Hackney
Worcestershire
Leicester
Trafford
Isle of Wight
North Northamptonshire
Herefordshire, County of
Camden
East Riding of Yorkshire
Windsor and Maidenhead
Rutland
Croydon
Warrington
Shropshire
Norfolk
Torbay
Essex
Bournemouth, Christchurch and Poole
Richmond upon Thames
Peterborough
Cumbria
Suffolk
Brighton and Hove
-0.2
0.0
0.2
Category
High
Average
Low



Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

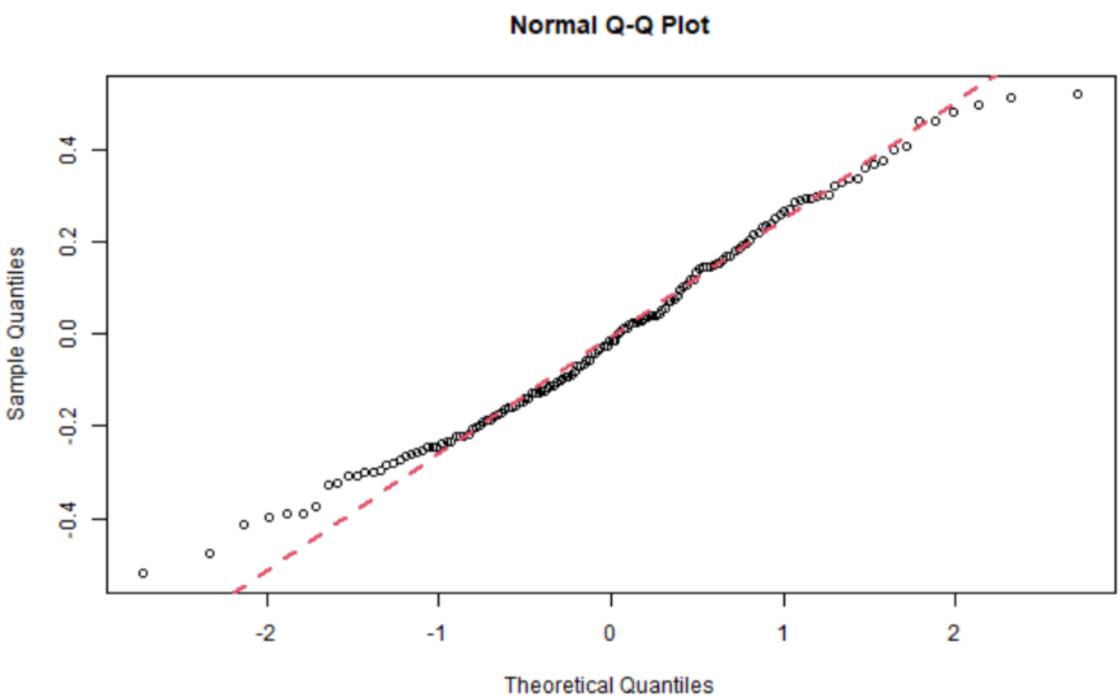
Appendix D: Local Authority Random Effects

Figure 7. Local Authority Random Effects (Yr 11)



Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Figure 8. Quartile- Quartile Plot of Yr11 Model Residuals



Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Table 21. Random Effects for Index Computation

Local Authority	NULL	YR6	YR7	YR8	YR9	YR10	YR11
Barking and Dagenham	0.06	0.04	-0.01	-0.05	-0.07	-0.04	-0.01
Barnet	-0.36	-0.21	-0.23	-0.24	-0.24	-0.26	-0.22
Barnsley	0.32	0.12	0.12	0.13	0.15	0.17	0.07
Bath and North East Somerset	-0.32	-0.16	-0.14	-0.14	-0.14	-0.15	-0.22
Bedford	-0.16	-0.19	-0.16	-0.14	-0.16	-0.17	-0.24
Bexley	-0.38	-0.27	-0.28	-0.27	-0.26	-0.23	-0.17
Birmingham	0.40	0.25	0.21	0.18	0.19	0.19	0.3
Blackburn with Darwen	0.16	0.17	0.17	0.16	0.17	0.19	0.19
Blackpool	0.34	0.19	0.16	0.13	0.13	0.15	0.08
Bolton	0.31	0.35	0.30	0.28	0.29	0.30	0.34
Bournemouth, Christchurch and Poole	-0.11	0.01	0.00	-0.01	-0.02	-0.03	-0.11
Bracknell Forest	-0.53	-0.30	-0.30	-0.28	-0.30	-0.30	-0.31
Bradford	0.34	0.31	0.30	0.29	0.30	0.31	0.26
Brent	-0.15	-0.15	-0.17	-0.20	-0.20	-0.21	-0.16
Brighton and Hove	0.11	0.05	0.03	0.01	-0.02	-0.06	-0.13
Bristol, City of	0.25	0.06	0.06	0.07	0.08	0.05	0.02
Bromley	-0.41	-0.30	-0.30	-0.28	-0.27	-0.26	-0.16
Buckinghamshire	-0.69	-0.35	-0.35	-0.35	-0.35	-0.35	-0.39
Bury	-0.05	0.09	0.12	0.13	0.14	0.18	0.25
Calderdale	0.07	0.15	0.16	0.16	0.17	0.16	0.16
Cambridgeshire	-0.32	-0.12	-0.11	-0.13	-0.15	-0.15	-0.24
Camden	0.25	-0.04	-0.08	-0.1	-0.11	-0.12	-0.06
Central Bedfordshire	-0.36	-0.18	-0.13	-0.11	-0.11	-0.13	-0.24
Cheshire East	-0.34	-0.15	-0.14	-0.13	-0.14	-0.17	-0.22
Cheshire West and Chester	-0.11	-0.08	-0.10	-0.11	-0.12	-0.14	-0.18
Cornwall	-0.10	-0.06	-0.03	0.00	0.02	0.02	-0.02
County Durham	0.47	0.37	0.38	0.38	0.38	0.40	0.52
Coventry	0.25	0.17	0.14	0.11	0.09	0.09	0.15
Croydon	-0.12	-0.13	-0.15	-0.15	-0.14	-0.15	-0.09
Cumbria	-0.11	-0.07	-0.03	-0.02	-0.03	-0.04	-0.12
Darlington	0.35	0.29	0.28	0.29	0.30	0.31	0.40
Derby	0.04	0.01	0.00	0.01	0.03	0.02	-0.01
Derbyshire	-0.04	0.07	0.09	0.09	0.09	0.09	0.03
Devon	-0.28	-0.16	-0.15	-0.13	-0.13	-0.12	-0.20
Doncaster	0.32	0.24	0.21	0.20	0.21	0.21	0.23
Dorset	-0.35	-0.13	-0.10	-0.07	-0.06	-0.06	-0.19
Dudley	0.20	0.24	0.28	0.27	0.27	0.26	0.27
Ealing	-0.34	-0.28	-0.31	-0.32	-0.33	-0.33	-0.28
East Riding of Yorkshire	-0.19	-0.06	-0.05	-0.03	-0.02	-0.01	-0.07
East Sussex	0.01	0.06	0.05	0.06	0.06	0.05	0.04
Enfield	-0.16	-0.23	-0.23	-0.25	-0.24	-0.27	-0.26

Essex	-0.21	-0.08	-0.08	-0.08	-0.07	-0.07	-0.10
Gateshead	0.36	0.23	0.27	0.29	0.30	0.33	0.37
Gloucestershire	-0.31	-0.11	-0.11	-0.10	-0.10	-0.09	-0.14
Greenwich	0.21	-0.06	-0.09	-0.09	-0.09	-0.08	0.04
Hackney	0.23	-0.18	-0.17	-0.17	-0.15	-0.14	-0.03
Halton	0.27	0.02	0.05	0.06	0.06	0.05	0.10
Hammersmith and Fulham	0.25	-0.08	-0.11	-0.09	-0.08	-0.08	0.05
Hampshire	-0.40	-0.23	-0.23	-0.24	-0.24	-0.24	-0.30
Haringey	0.08	-0.17	-0.14	-0.16	-0.15	-0.17	-0.16
Harrow	-0.63	-0.37	-0.36	-0.40	-0.42	-0.42	-0.37
Hartlepool	0.63	0.47	0.49	0.49	0.51	0.50	0.47
Havering	-0.39	-0.21	-0.21	-0.21	-0.19	-0.14	-0.15
Herefordshire, County of	-0.22	-0.08	-0.06	-0.04	-0.03	-0.03	-0.06
Hertfordshire	-0.47	-0.21	-0.21	-0.21	-0.22	-0.22	-0.23
Hillingdon	-0.33	-0.18	-0.22	-0.23	-0.24	-0.23	-0.24
Hounslow	-0.34	-0.22	-0.23	-0.23	-0.22	-0.22	-0.21
Isle of Wight	0.14	0.09	0.12	0.12	0.12	0.14	-0.04
Islington	0.41	0.02	0.03	0.03	0.05	0.08	0.14
Kensington and Chelsea	0.23	0.10	0.07	0.06	0.09	0.09	0.29
Kent	-0.01	-0.01	0.00	0.00	-0.01	-0.02	0.01
Kingston upon Hull, City of	0.62	0.44	0.39	0.40	0.41	0.42	0.36
Kingston upon Thames	-0.50	-0.20	-0.19	-0.18	-0.17	-0.18	-0.13
Kirklees	0.13	0.28	0.30	0.30	0.30	0.33	0.30
Knowsley	0.43	0.01	0.03	0.07	0.08	0.09	0.02
Lambeth	0.23	-0.1	-0.14	-0.15	-0.15	-0.15	0.01
Lancashire	-0.07	0.00	0.01	0.02	0.03	0.05	0.03
Leeds	0.33	0.34	0.33	0.31	0.28	0.25	0.22
Leicester	0.19	0.12	0.08	0.07	0.06	0.03	-0.03
Leicestershire	-0.35	-0.14	-0.10	-0.09	-0.10	-0.12	-0.20
Lewisham	0.22	0.00	-0.02	-0.02	-0.02	-0.01	0.02
Lincolnshire	-0.05	0.08	0.10	0.11	0.11	0.11	0.13
Liverpool	0.50	0.07	0.08	0.08	0.10	0.12	0.17
Luton	-0.14	-0.12	-0.14	-0.15	-0.14	-0.16	-0.14
Manchester	0.56	0.10	0.09	0.06	0.04	0.03	0.07
Medway	0.05	0.08	0.07	0.07	0.07	0.07	0.08
Merton	-0.16	0.01	-0.02	-0.04	-0.05	-0.08	0.00
Middlesbrough	0.64	0.32	0.33	0.35	0.33	0.34	0.33
Milton Keynes	-0.32	-0.23	-0.24	-0.24	-0.25	-0.25	-0.28
Newcastle upon Tyne	0.47	0.17	0.17	0.18	0.17	0.18	0.24
Newham	-0.05	-0.12	-0.21	-0.23	-0.23	-0.23	-0.19
Norfolk	-0.05	-0.05	-0.03	-0.03	-0.02	-0.02	-0.10
North East Lincolnshire	0.45	0.29	0.24	0.23	0.24	0.24	0.27
North Lincolnshire	0.18	0.13	0.17	0.17	0.17	0.19	0.20
North Northamptonshire	-0.09	-0.03	-0.01	0.00	-0.01	0.00	-0.06
North Somerset	-0.47	-0.30	-0.30	-0.29	-0.29	-0.31	-0.39

North Tyneside	0.12	0.07	0.09	0.12	0.13	0.14	0.16
North Yorkshire	-0.43	-0.21	-0.17	-0.17	-0.18	-0.19	-0.22
Northumberland	0.20	0.16	0.19	0.21	0.20	0.19	0.18
Nottingham	0.76	0.47	0.44	0.44	0.43	0.40	0.38
Nottinghamshire	0.03	0.11	0.12	0.12	0.13	0.13	0.16
Oldham	0.14	0.18	0.19	0.19	0.20	0.21	0.17
Oxfordshire	-0.42	-0.32	-0.31	-0.30	-0.31	-0.33	-0.4
Peterborough	0.09	0.05	0.03	0.02	0.00	-0.02	-0.12
Plymouth	0.10	0.03	0.04	0.04	0.05	0.06	0.05
Portsmouth	0.22	0.09	0.04	0.04	-0.01	-0.04	-0.13
Reading	-0.20	-0.18	-0.20	-0.23	-0.25	-0.26	-0.33
Redbridge	-0.42	-0.15	-0.17	-0.19	-0.20	-0.21	-0.16
Redcar and Cleveland	0.47	0.34	0.34	0.34	0.35	0.35	0.3
Richmond upon Thames	-0.38	-0.11	-0.11	-0.12	-0.12	-0.14	-0.11
Rochdale	0.27	0.19	0.18	0.18	0.19	0.19	0.15
Rotherham	0.32	0.22	0.22	0.22	0.20	0.21	0.24
Rutland	-0.32	-0.11	-0.09	-0.08	-0.07	-0.06	-0.08
Salford	0.41	0.19	0.19	0.19	0.22	0.26	0.29
Sandwell	0.55	0.47	0.45	0.43	0.42	0.42	0.47
Sefton	0.13	0.14	0.16	0.17	0.18	0.20	0.20
Sheffield	0.36	0.26	0.24	0.23	0.22	0.22	0.22
Shropshire	-0.22	-0.08	-0.05	-0.04	-0.03	-0.05	-0.09
Slough	-0.42	-0.23	-0.24	-0.25	-0.26	-0.28	-0.27
Solihull	-0.15	-0.03	-0.03	-0.01	-0.01	-0.03	0.04
Somerset	-0.27	-0.10	-0.09	-0.08	-0.09	-0.09	-0.19
South Gloucestershire	-0.48	-0.27	-0.24	-0.22	-0.21	-0.20	-0.30
South Tyneside	0.55	0.36	0.38	0.38	0.37	0.41	0.50
Southampton	0.12	-0.05	-0.12	-0.15	-0.19	-0.19	-0.15
Southend-on-Sea	0.12	0.13	0.10	0.09	0.09	0.08	0.03
Southwark	0.28	-0.09	-0.11	-0.11	-0.12	-0.15	0.04
St. Helens	0.40	0.33	0.33	0.35	0.37	0.38	0.34
Staffordshire	-0.15	-0.03	0.00	0.02	0.02	0.04	-0.01
Stockport	-0.04	0.05	0.07	0.08	0.09	0.09	0.12
Stockton-on-Tees	0.43	0.32	0.34	0.37	0.36	0.35	0.32
Stoke-on-Trent	0.39	0.16	0.15	0.15	0.16	0.15	0.15
Suffolk	-0.15	-0.11	-0.06	-0.03	-0.04	-0.01	-0.12
Sunderland	0.51	0.36	0.40	0.41	0.41	0.43	0.51
Surrey	-0.55	-0.35	-0.35	-0.35	-0.37	-0.37	-0.41
Sutton	-0.54	-0.35	-0.36	-0.36	-0.36	-0.36	-0.30
Swindon	-0.23	-0.09	-0.11	-0.14	-0.13	-0.14	-0.25
Tameside	0.28	0.31	0.32	0.31	0.32	0.34	0.29
Telford and Wrekin	0.16	0.08	0.09	0.08	0.06	0.05	0.10
Thurrock	-0.03	-0.11	-0.12	-0.1	-0.08	-0.04	0.03
Torbay	0.01	-0.05	-0.04	-0.06	-0.07	-0.06	-0.10
Tower Hamlets	0.27	-0.03	-0.01	0.01	0.01	0.03	0.15

Trafford	-0.25	-0.12	-0.12	-0.13	-0.14	-0.14	-0.04
Wakefield	0.30	0.26	0.27	0.26	0.26	0.26	0.30
Walsall	0.43	0.42	0.43	0.42	0.41	0.40	0.41
Waltham Forest	-0.16	-0.21	-0.26	-0.27	-0.27	-0.28	-0.26
Wandsworth	0.13	0.05	-0.01	-0.02	-0.02	-0.02	0.06
Warrington	-0.25	-0.13	-0.10	-0.11	-0.12	-0.10	-0.09
Warwickshire	-0.30	-0.16	-0.14	-0.14	-0.13	-0.15	-0.17
West Berkshire	-0.62	-0.46	-0.44	-0.42	-0.41	-0.42	-0.48
West Northamptonshire	-0.24	-0.18	-0.17	-0.17	-0.19	-0.22	-0.27
West Sussex	-0.39	-0.22	-0.22	-0.22	-0.23	-0.25	-0.32
Westminster	0.19	0.06	0.00	-0.01	-0.02	-0.05	0.11
Wigan	0.13	0.11	0.14	0.16	0.18	0.20	0.20
Wiltshire	-0.35	-0.18	-0.15	-0.13	-0.13	-0.15	-0.25
Windsor and Maidenhead	-0.49	-0.13	-0.09	-0.07	-0.07	-0.09	-0.07
Wirral	0.19	-0.07	-0.05	-0.04	-0.02	0.02	0.12
Wokingham	-0.91	-0.55	-0.54	-0.54	-0.52	-0.53	-0.52
Wolverhampton	0.53	0.43	0.41	0.41	0.41	0.43	0.48
Worcestershire	-0.11	-0.03	0.00	-0.01	-0.02	-0.02	-0.03
York	-0.52	-0.34	-0.31	-0.30	-0.29	-0.29	-0.31

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Appendix E: Risk Index Variable Definitions

Table 22. List of Risk Variables

Risk factor	Description
Persistent absence Fixed-term exclusion	This is a binary measure (“Yes” or “No”) for each school year up to the year for which the model is computed (e.g. in the Yr7 risk index, the variables for both Yr6 and Yr7 should be included). Persistent absence refers to pupils who have been absent at least 10% of the time.
SEN type	We found inconsistencies in this variable over time (probably due to the school, and type of school, that was reporting the information). For this reason, our models are based on the “latest” SEN type (i.e. if a student was classified as SEN at least once, we take the latest type of SEN known). Only students who have always been classified as not having SEN were classified in the analysis as “No SEN”. We used eight categories of SEN, as highlighted in the models’ outputs presented in this report.
SEN provision	This is the SEN provision offered to the student in the year of the risk index. This is the SEN provision offered to the student in the year of the risk index. Due to changes in SEN provisions since the years used in our analysis, we proposed to apply the following change to the variable labels: • School of early years actions =SEN support. • Statement = EHCP.
Number of years classed as FSM	This is the sum of the years a student was classed as FSM from year 6 onwards. The resulting number of years is grouped in two categories (1-2 years, or 3 or more).

Even in the lowest IDACI quintile	This variable is a binary indicator (“Yes” or “No”) reporting if a student has ever lived in the lowest IDACI quintile (area deprivation for children) since school year 6.
Ever classed as Looked After Child	This variable is a binary indicator (“Yes” or “No”) reporting if a student has ever been classed as CLA since school year 6.
KS2 Reading KS2 Maths	This variable reports the results of the KS2 award related to reading or maths for pupils. We used four categories. The first two related to having achieved or not the expected standards, the third category flags pupils with awards not valid. The last category captures instances when the school did not provide information.
KS4 Attainment	The GCSE attainment of the students was captured in six categories, presented in the models’ outputs. We included in the model additional variables measuring if the student has passed the GCSE in English (“Passed” or “Not passed”) and Math.

Appendix F: Risk Factor Fixed Effects

Table 23. Risk Factor Estimates for Index Computation (Fixed Effects)

Risk factor	YR6	YR7	YR8	YR9	YR10	YR11
Persistent absence Yr6	0.86	0.46	0.33	0.25	0.19	0.19
Persistent absence Yr7	-	0.84	0.49	0.33	0.22	0.12
Persistent absence Yr8	-	-	0.72	0.38	0.23	0.10
Persistent absence Yr9	-	-	-	0.76	0.40	0.17
Persistent absence Yr10	-	-	-	-	0.85	0.27
Persistent absence Yr11	-	-	-	-	-	0.60
Fixed-term exclusion Yr6	0.53	0.26	0.12	0.05	-0.01	-0.04
Fixed-term exclusion Yr7	-	0.53	0.24	0.09	0.01	-0.08
Fixed-term exclusion Yr8	-	-	0.54	0.28	0.16	0.03
Fixed-term exclusion Yr9	-	-	-	0.52	0.29	0.10
Fixed-term exclusion Yr10	-	-	-	-	0.47	0.17
Fixed-term exclusion Yr11	-	-	-	-	-	0.21
SEN type: Autistic Spectrum Disorder	0.60	0.76	0.77	0.81	0.85	0.77
SEN type: Behaviour, Emotional & Social Difficulties	0.43	0.42	0.35	0.33	0.34	0.25
SEN type: Moderate Learning Difficulty	0.09	0.21	0.22	0.24	0.25	0.10
SEN type: Other Difficulty/Disability	0.04	0.14	0.16	0.21	0.23	0.18
SEN type: Profound, multiple, or severe learning difficulties	1.12	1.43	1.49	1.57	1.63	0.94
SEN type: Sensory Impairment	0.46	0.57	0.57	0.57	0.58	0.59
SEN type: Specific Learning Difficulty	-0.25	-0.15	-0.14	-0.12	-0.10	-0.18
SEN type: Speech, Language and Communication Needs	-0.07	0.09	0.11	0.12	0.15	0.09
SEN provision: School or Early Years Action	0.40	0.33	0.33	0.35	0.38	0.26
SEN provision: Statement	1.21	1.09	1.11	1.13	1.17	0.79
No. FSM years: 1 - 2 years	0.98	0.95	0.82	0.75	0.69	0.58
No. FSM years: 3 or more years	-	-	1.01	0.96	0.93	0.80
Ever IDACI Lowest quintile	0.49	0.48	0.46	0.45	0.44	0.37
First language not English	-0.71	-0.70	-0.69	-0.66	-0.62	-0.48
Ever Child Looked After	1.38	1.26	1.20	1.16	1.15	1.06
KS2 Reading: Pupil not at the expected standard	0.37	0.31	0.27	0.24	0.22	-0.03
KS2 Reading: No valid KS2 reading award	0.46	0.36	0.33	0.30	0.28	0.06
KS2 Reading: Results not provided by school	0.51	0.45	0.42	0.39	0.39	0.06
KS2 Math: Pupil not at the expected standard	0.71	0.69	0.68	0.66	0.64	0.19
KS2 Math: No valid KS2 maths award	0.59	0.50	0.46	0.43	0.40	0.13
KS2 Math: Results not provided by school	-0.05	0.03	0.02	0.01	-0.06	-0.33

Risk factor	YR6	YR7	YR8	YR9	YR10	YR11
GCSE grades: achieved 5+ A* - C (9 - 4)	-	-	-	-	-	0.40
GCSE grades: achieved 5+ A* - G (9 - 1)	-	-	-	-	-	0.66
GCSE grades: achieved 1+ A* - G (9 - 1)	-	-	-	-	-	1.13
GCSE grades: achieved any pass	-	-	-	-	-	1.59
GCSE grades: No results / no passes	-	-	-	-	-	1.68
Passed GCSE English	-	-	-	-	-	0.31
Passed GCSE Maths	-	-	-	-	-	0.41

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Appendix G: Index Value Ranges

Table 24. Year 6 – Year 11 Index Value Ranges

School Year	Minimum original value	Maximum original value
Yr6	-1.38	8.26
Yr7	-1.21	8.93
Yr8	-1.23	9.29
Yr9	-1.20	9.49
Yr10	-1.21	9.67
Yr11	-1.54	8.71

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

Appendix H: Local authority sample sizes and NEET rates

Table 25. Observed NEET rates for each local authority

Local authority	Percentage of cases in Local Authority	Local authority sample size	Percentage NEET for a period of 12 months or more	Number of cases NEET for a period of 12 months or more
Barking and Dagenham	0.40	4,086	13.3	544
Barnet	0.53	5,417	9.2	501
Barnsley	0.51	5,236	16.3	853
Bath and North East Somerset	0.30	3,074	9.1	281
Bedford	0.31	3,174	10.8	343
Bexley	0.52	5,367	8.9	475
Birmingham	2.16	22,115	17.6	3,885
Blackburn with Darwen	0.34	3,524	14.2	502
Blackpool	0.30	3,038	16.6	503
Bolton	0.59	6,086	16.0	976
Bournemouth, Christchurch and Poole	0.62	6,320	11.4	721
Bracknell Forest	0.20	2,089	7.3	153
Bradford	1.12	11,451	16.5	1,892
Brent	0.46	4,708	11.2	525
Brighton and Hove	0.39	4,011	13.8	552
Bristol, City of	0.60	6,197	15.4	955
Bromley	0.57	5,805	8.7	505
Buckinghamshire	0.95	9,714	6.9	666
Bury	0.38	3,906	11.7	456
Calderdale	0.45	4,584	13.0	598
Cambridgeshire	1.05	10,780	9.3	1,007
Camden	0.22	2,247	15.3	343
Central Bedfordshire	0.53	5,478	8.8	484
Cheshire East	0.69	7,109	9.0	639
Cheshire West and Chester	0.66	6,783	11.1	756
Cornwall	1.06	10,823	11.2	1,211
County Durham	1.06	10,849	18.4	1,991
Coventry	0.59	6,016	15.7	947
Croydon	0.69	7,093	11.1	788
Cumbria	1.03	10,565	11.1	1,177
Darlington	0.20	2,023	16.1	326
Derby	0.47	4,839	13.0	628
Derbyshire	1.60	16,401	11.8	1,935
Devon	1.43	14,668	9.6	1,415
Doncaster	0.66	6,725	16.3	1,098
Dorset	0.67	6,849	9.0	617
Dudley	0.70	7,143	14.6	1,046

Ealing	0.53	5,437	9.3	503
East Riding of Yorkshire	0.68	7,014	10.4	726
East Sussex	0.96	9,864	12.5	1,233
Enfield	0.62	6,399	10.9	700
Essex	2.85	29,242	10.3	3,014
Gateshead	0.40	4,088	16.8	686
Gloucestershire	1.14	11,716	9.4	1,097
Greenwich	0.39	3,993	15.7	626
Hackney	0.33	3,373	15.7	528
Halton	0.28	2,891	15.6	451
Hammersmith and Fulham	0.17	1,790	15.6	280
Hampshire	2.46	25,256	8.6	2,184
Haringey	0.38	3,906	13.4	523
Harrow	0.41	4,221	7.2	305
Hartlepool	0.21	2,186	21.0	460
Havering	0.54	5,489	8.6	472
Herefordshire, County of	0.34	3,485	10.0	349
Hertfordshire	2.18	22,351	8.2	1,840
Hillingdon	0.52	5,366	9.0	482
Hounslow	0.40	4,133	9.5	391
Isle of Wight	0.27	2,815	13.8	389
Islington	0.24	2,469	18.3	451
Kensington and Chelsea	0.10	996	15.3	152
Kent	2.76	28,335	12.6	3,569
Kingston upon Hull, City of	0.52	5,334	21.2	1,132
Kingston upon Thames	0.24	2,489	7.6	190
Kirklees	0.89	9,115	13.8	1,261
Knowsley	0.37	3,767	17.7	666
Lambeth	0.38	3,869	15.5	598
Lancashire	2.40	24,605	11.6	2,855
Leeds	1.37	14,037	16.5	2,315
Leicester	0.63	6,484	15.0	973
Leicestershire	1.32	13,484	9.0	1,215
Lewisham	0.45	4,567	15.3	699
Lincolnshire	1.42	14,540	11.9	1,733
Liverpool	0.86	8,808	19.0	1,677
Luton	0.45	4,585	11.1	507
Manchester	0.81	8,321	20.4	1,697
Medway	0.58	5,936	13.2	781
Merton	0.29	3,013	10.9	329
Middlesbrough	0.30	3,062	21.4	654
Milton Keynes	0.45	4,563	9.2	419
Newcastle upon Tyne	0.46	4,748	18.6	884
Newham	0.56	5,717	12.2	697
Norfolk	1.57	16,121	11.9	1,915

North East Lincolnshire	0.36	3,690	18.2	672
North Lincolnshire	0.36	3,738	14.6	545
North Northamptonshire	0.64	6,594	11.5	760
North Somerset	0.36	3,668	7.8	286
North Tyneside	0.41	4,191	13.8	580
North Yorkshire	1.15	11,818	8.5	1,004
Northumberland	0.64	6,527	14.5	945
Nottingham	0.49	5,069	23.5	1,193
Nottinghamshire	1.59	16,345	12.7	2,078
Oldham	0.49	5,001	14.0	702
Oxfordshire	1.03	10,596	8.3	878
Peterborough	0.35	3,588	13.8	495
Plymouth	0.50	5,149	13.7	704
Portsmouth	0.35	3,635	15.1	548
Reading	0.24	2,442	10.8	264
Redbridge	0.55	5,636	8.6	482
Redcar and Cleveland	0.28	2,846	18.7	532
Richmond upon Thames	0.20	2,088	8.7	182
Rochdale	0.48	4,873	15.5	754
Rotherham	0.60	6,128	16.4	1,006
Rutland	0.05	557	9.0	50
Salford	0.41	4,179	17.4	727
Sandwell	0.70	7,226	19.7	1,420
Sefton	0.57	5,819	13.8	802
Sheffield	1.00	10,283	16.9	1,736
Shropshire	0.55	5,680	10.1	575
Slough	0.26	2,681	8.4	226
Solihull	0.47	4,824	10.7	518
Somerset	1.00	10,283	9.7	998
South Gloucestershire	0.58	5,927	7.9	468
South Tyneside	0.32	3,330	19.8	659
Southampton	0.38	3,866	14.2	550
Southend-on-Sea	0.34	3,452	14.2	490
Southwark	0.39	4,018	16.4	658
St. Helens	0.39	3,979	17.5	695
Staffordshire	1.75	17,892	10.8	1,926
Stockport	0.56	5,728	11.9	682
Stockton-on-Tees	0.39	4,038	18.1	729
Stoke-on-Trent	0.51	5,248	17.5	920
Suffolk	1.33	13,626	11.0	1,493
Sunderland	0.59	6,017	19.0	1,145
Surrey	1.84	18,850	7.5	1,405
Sutton	0.38	3,923	7.7	302
Swindon	0.41	4,194	10.1	423
Tameside	0.50	5,145	15.8	814

Telford and Wrekin	0.36	3,716	14.3	532
Thurrock	0.34	3,501	12.1	425
Torbay	0.26	2,679	12.4	332
Tower Hamlets	0.37	3,820	16.0	610
Trafford	0.45	4,633	10.1	470
Wakefield	0.73	7,440	16.1	1,200
Walsall	0.60	6,114	18.0	1,102
Waltham Forest	0.46	4,676	10.7	499
Wandsworth	0.27	2,792	14.5	406
Warrington	0.44	4,551	10.0	454
Warwickshire	1.02	10,414	9.4	983
West Berkshire	0.30	3,039	6.8	208
West Northamptonshire	0.74	7,564	9.8	743
West Sussex	1.49	15,262	8.6	1,320
Westminster	0.14	1,464	15.3	224
Wigan	0.70	7,145	13.8	986
Wiltshire	0.87	8,969	9.0	810
Windsor and Maidenhead	0.23	2,358	7.8	185
Wirral	0.70	7,198	14.9	1,074
Wokingham	0.29	2,928	5.3	155
Wolverhampton	0.53	5,479	19.7	1,080
Worcestershire	1.12	11,447	11.3	1,289
York	0.32	3,275	7.6	248

Source: Longitudinal Educational Outcomes (LEO) Standard Extract V2

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