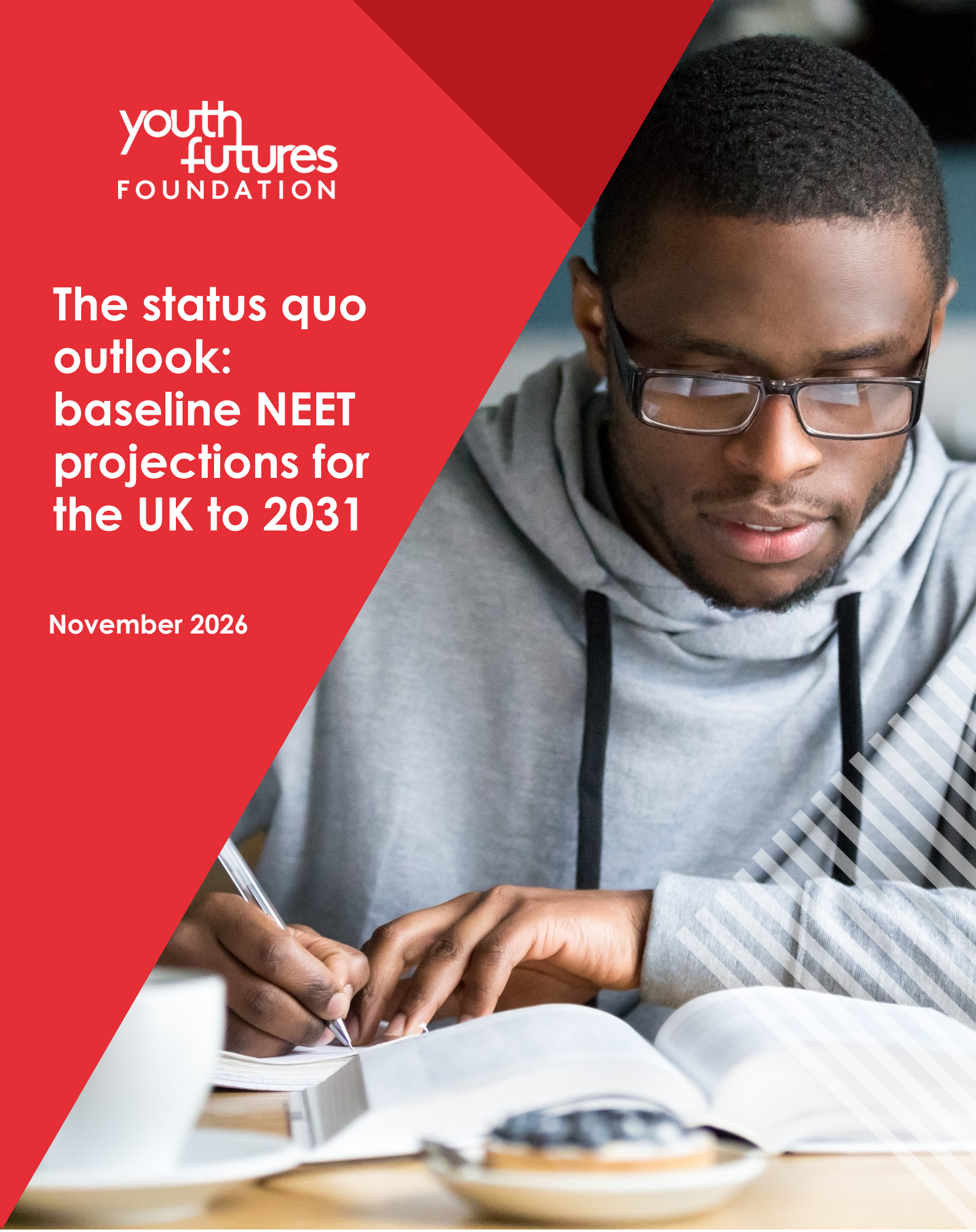
youth futures FOUNDATION

The status quo outlook: baseline NEET projections for the UK to 2031

November 2026



Five-year forecasts produced by the Economics and Analysis Team at Youth Futures Foundation

Arushi Bhasin, Senior Economist
Abigail Coxon, Principal Economist

youth futures FOUNDATION

Table of Contents

Executive Summary 2
Introduction 5
Methodology 7
Why SARIMAX? 8
Modelling Process 8
Baseline Assumptions 9
Why Some Known Drivers Were Excluded 9
Findings 11
Why the model produces flat NEET Forecasts 12
The Role of Historical Shocks and Policy Variables 13
Applications of the Model 14
Using the Model for Policy and Scenario Analysis 14
Structural Risks Beyond the Model: Potential Scenarios to Consider 14
Interpretation and Policy Implications 17
Model Strengths, Limitations and Improvements 19
Challenges in Modelling and Forecasting NEET Levels 19
Limitations to the SARIMAX Approach 19
Limitations Related to Exogenous Variables 20
Conclusion 24
References 26
Technical Appendices 30

Contact:

Get in touch

Youth Futures Foundation

Fivefields,
8 - 10 Grosvenor Gardens,
London
SW1W 0DH

For the latest version of projections, email:
analysis@youthfuturesfoundation.org

www.youthfuturesfoundation.org



Executive Summary

This report presents medium-term forecasts of the proportion of young people aged 16–24 in the UK who are not in employment, education, or training (NEET). Using a Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) model, the analysis generates quarterly projections of NEET levels from 2026 Q3 to 2031 Q3 and subsequently converts them to NEET rate forecasts using 2022-based ONS population projections.

The purpose of this exercise is twofold. First, the analysis presents a statistically sound baseline projection of NEET rates, estimated from long-run historical trends and key macroeconomic indicators. This modelling approach prioritises forecast accuracy and performed well when tested against two years of data held back from estimation. Although the model is not designed to run policy-led scenarios, it provides a stable and credible baseline from which external scenario assumptions can be overlaid ahead of major fiscal events, such as the Autumn Budget. These overlays enable analysts to explore the implications of alternative economic or policy developments, including adjustments to minimum wage policy, automation in youth-dense sectors, or rising health-related inactivity.

Second, the report complements the modelled baseline by assessing a separate set of emerging structural pressures that the model cannot capture. These include changes to youth health, and shifts in labour demand. Rather than extending the model itself, this part of the exercise qualitatively examines how these unmodelled drivers may influence NEET outcomes over the medium term. By setting out these risks alongside the baseline projection, the report provides policymakers with a fuller view of potential future trajectories and highlights where sustained youth inactivity could pose fiscal or social challenges. This qualitative assessment was first prepared alongside the original forecasts, ahead of the 2025 Autumn Budget. Evidence on several of these drivers, notably young people's health and the labour market effects of AI, has developed since then, and we have updated it where possible. Youth Futures Foundation has also since extended this modelling to produce NEET projections to 2036 under alternative economic scenarios (Coxon and Bhasin, 2026), and further economic modelling and forecasting (Wilson et al., 2026a), including upcoming work on young people's transitions into and out of NEET status. These are better suited to capturing some of these effects than the qualitative assessment presented here.

The findings suggest that, even under relatively optimistic assumptions about macroeconomic stability (as projected by the OBR) and the absence of new external shocks, the central forecast is for NEET rates to remain high and broadly flat – at around

13% (equivalent to approximately one million young people) through to 2031 Q3 – although uncertainty around this central forecast widens over time. The model offers a useful baseline for estimating the effects on future NEET rates from different policy interventions and different economic scenarios than those assumed in the current projections. Alongside the potential risks not captured in these forecasts, these findings highlight a concerning medium-term outlook and underscore the need to tackle the deeper, non-cyclical barriers to youth participation in education and work.

The model and accompanying analysis underwent a two-stage peer review process: the first, led by NatCen, focused on the code and technical data considerations; the second, conducted by NIESR, reviewed the economic assumptions, model interpretability, and overall write-up.

Why we are publishing this report. These forecasts extend Youth Futures' short-term NEET forecasting model (unpublished) to a five-year horizon. They were developed at pace at the request of colleagues in the Department for Work and Pensions (DWP) and the Department for Education (DfE), have since been used in government analysis, and are published here so that the methodology is transparent and available for others to refer to and use (see Introduction). This version uses data to April to June 2026. We update the forecasts as new data are release and the latest version is available on request.

Introduction

Background. This report sets out the methodology behind Youth Futures Foundation's five-year projections of NEET rates, which are produced using a SARIMAX model. Building on NEET forecasting work already in development, and at the request of colleagues in DWP and DfE, we extended the horizon to five years ahead of the 2025 Autumn Budget. The government has since used these projections in its internal analysis, and they are cited in the analytical annex of the 'Young People and Work: interim report'. A similar methodology now also underpins our short-term forecasts, which have performed well in predicting NEET outcomes a few quarters ahead.

We are publishing this report for transparency and reproducibility, so that anyone can understand and use these projections. The model and analysis were peer reviewed by experts at NatCen and NIESR. As with any long term projections, there are limitations, and we set these out in the section on model strengths, limitations and improvements. We have continued to develop the model since the original projections were produced, and we update them as new data are released.

This report seeks to present baseline projections for the medium-term trajectory of NEET rates among young people aged 16–24 in the UK, drawing on two decades of historical data from the Labour Force Survey (LFS) and macroeconomic indicators. Using a Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) model, we generate quarterly projections of non-seasonally adjusted (NSA) NEET levels from Quarter 3 2026 through to Quarter 3 2031. These estimates were seasonally adjusted[1] and converted into NEET rates using population projections from the Office for National Statistics (ONS). The estimation sample covers the period Quarter 1 2003 to Quarter 2 2026, capturing multiple phases of economic and policy change, including the Global Financial Crisis, the COVID-19 pandemic, and the implementation of major education participation reforms. The model's explanatory variables were selected in 2025 using data to Quarter 1 2025. For this version, the model has been re-estimated with the same explanatory variables using Labour Force Survey data to Quarter 2 2026 (April to June 2026), with its ARIMA structure re-selected automatically on the updated data.

The exercise has two core objectives. First, it aims to provide empirically grounded baseline projections of NEET rates under a set of clearly specified assumptions. The projections produced by Youth Futures' modelling exercise aim to estimate future NEET rates under a "status quo" scenario – that is, projecting what NEET rates might look like

[1] Using X-13 SEATS US Census Bureau, 2025). See Appendix F for steps undertaken for seasonal adjustment and rate calculation of forecasts.

by Q3 2031 assuming no targeted government intervention, no significant economic shocks and a continuation of moderate economic growth as forecasted by the OBR.

Second, the report aims to contextualise the projections by highlighting key structural risks that, while not incorporated into the model due to data and methodological constraints, could be highly relevant as potential drivers of NEET trends over the next five years. These include, but are not limited to, the increasing number of school-aged children with special educational needs and disabilities (SEND) as well as changing impacts on labour demand for young workers driven by technological disruption (such as AI adoption) and changes to the National Minimum Wage and National Insurance policies. By setting out how these unmodelled dynamics may interact with or compound baseline trends, we aim to strengthen the model's utility as a forward-looking policy tool, enabling departments to consider a broader range of risks in their forecasting and intervention strategies.

In addition, the baseline serves as a foundation for policy scenario testing by stakeholders, particularly in the context of fiscal planning and policy development.

Methodology

The projections presented in this report are generated using a **Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX)** model (see Appendix A). At its core, SARIMAX is designed to use patterns in historical data to anticipate what might happen in the future. It does this by combining information from past values of the series (dependent variable), recurring seasonal cycles, and external factors that shape outcomes. This makes it particularly well suited to forecasting NEET levels, where persistence, seasonality, and wider economic conditions all play a role.

When the model was first developed in 2025, to determine which external factors should be included, we excluded the past two years of data (eight quarters from Q2 2023 to Q1 2025) when estimating the model. We then tested different versions of the model - with different combinations of external factors - by calculating the out-of-sample Mean Absolute Percentage Error (MAPE) for each. MAPE is a standard measure of forecast accuracy that expresses the average difference between predicted and actual values as a percentage. A lower MAPE means the model's forecasts are closer to reality. This approach provided a transparent way to identify which model is likely to produce the most accurate forecasts. For the forecasts in this report, the model was re-estimated on data to 2026 Q2 using the same explanatory variables.

The dependent variable is the quarterly NEET level (non-seasonally adjusted), derived from the ONS Labour Force Survey, covering the period Q1 2003 to Q2 2026. The chosen model includes four external (exogenous) variables, covering GDP growth and historical shocks or policy changes. These are listed below (see Appendix B for the variable dictionary):

- **Real GDP growth** (forecasts sourced from the OBR) captures the influence of macroeconomic conditions. (Office for Budget Responsibility, 2025).
- A variable for the **Global Financial Crisis** (2008–2009) accounts for structural breaks in NEET trends.
- The **COVID-19 stringency index** (Oxford Blavatnik School of Government, 2023) reflects the impact of lockdown restrictions.
- A variable for the **Education Participation Age reform** (2013–2015), capturing the effects of raising the education participation age in England.

The Technical Appendices provide further information on the model methodology.

Why SARIMAX?

The SARIMAX approach is well suited for this exercise for several reasons. First, it captures the strong autoregressive nature of NEET levels. Autoregressive means that the current value of a series depends on its past values. For example, a high NEET level last quarter increases the likelihood of a high NEET level this quarter. Second, it models seasonality explicitly, which is essential given the cyclical nature of youth engagement in education and employment. Third, and importantly, it allows for the incorporation of external shocks and policy changes, features that simpler time series models (e.g., linear extrapolation) cannot accommodate. Fourth, compared to machine learning approaches such as neural networks or ensemble methods, SARIMAX requires fewer data points and is more interpretable.

As well as a central projection, the model indicates the range within which actual figures are most likely to fall ("confidence intervals", calculated at the 95% level), offering a realistic picture of the level of uncertainty in its estimates. This is critical for stress testing because it enables policymakers to judge how resilient their plans are under different possible outcomes. These intervals reflect uncertainty in the model's estimates only. They do not capture uncertainty in the GDP forecasts used as inputs or in the choice of model, so the true range of uncertainty is likely to be wider. In addition, residual diagnostics for the model re-estimated on data to Q2 2026 show heavier tails than a normal distribution would imply. Because the intervals assume normally distributed errors, they are likely to be somewhat too narrow and should be read as indicative.

Modelling Process

We tested a wide range of potential drivers of NEET levels, including labour market indicators such as vacancies in key youth industries, policy changes including the raising of the education participation age, and major shocks such as COVID-19 and the 2008–09 financial crisis. Using a SARIMAX modelling framework, these variables were evaluated for their predictive power after stationarity tests and transformations (Appendix C), with selection guided by statistical criteria and forecast performance (see Appendix D).

All subsets of regressors were systematically evaluated, and each candidate model was tested against a range of diagnostics (Ljung-Box, Shapiro-Wilk, ARCH and VIF). Models passing all diagnostic checks were ranked by out-of-sample Mean Absolute Percentage Error (MAPE), which measures forecast accuracy. The Akaike Information Criterion (AIC) was specified as a tie-breaker in the event of identical MAPE values. This was not required in practice, as the best-performing model had a lower MAPE than any

alternative. This approach was peer-reviewed by NatCen, who confirmed it as a sound methodology. A second-stage peer review was then undertaken by a methods expert at NIESR.

The modelling process found that the most reliable predictors of future NEET levels were the levels from recent quarters and overall GDP growth. In other words, NEET trends are highly persistent: the level observed in the most recent quarter strongly shapes the likely trajectory in the coming quarters. GDP growth contributed a small adjustment (its coefficient was statistically significant only at the 10% level when the model was first estimated, and is not statistically significant at conventional levels in the model re-estimated on data to Q2 2026), but given the modest growth projected by the OBR over the model window, this effect on the forecast is limited. While other factors may be important in explaining historical NEET levels, they did not improve the model's ability to predict future quarterly changes and were therefore excluded from the baseline projections. The resulting projections serve as a baseline scenario, showing what NEET levels are likely to be if current trends and modest economic growth continue, and providing a foundation for exploring alternative scenarios.

Baseline Assumptions

The baseline projection is built on the following assumptions:

- GDP follows the OBR's central forecast trajectory (Office for Budget Responsibility, 2025).
- No major economic shocks or new pandemics occur during the forecast period.
- No significant structural transformations take place in the labour market (e.g., widespread automation).
- Health, demographic, and disability-related factors remain at current levels.

These assumptions make the baseline projections relatively optimistic, particularly given that forecasters assess a higher probability of GDP growth being weaker than expected (see Bank of England, 2025; NIESR, 2025).

Why Some Known Drivers Were Excluded

Certain factors that have affected NEET levels, such as vacancies, or structural labour market changes, did not improve the model's predictive performance. This does not mean they are unimportant in practice. Rather, the statistical relationship between these variables and NEET levels, or the data used to capture these relationships, is either inconsistent over time or insufficiently strong to predict quarter-to-quarter changes. Two

further factors, youth population and disability, were considered but not included in the final candidate set owing to a data-handling issue. Disability data was further difficult to use in a quarterly model since it is measured annually and would need to be smoothed to create quarterly estimates. This removes much of the short-term variation that could signal changes in NEET levels. Even with good quarterly data, changes in prevalence tend to occur gradually over multiple years rather than spiking from one quarter to the next, so their effect on NEET rates is largely a long-term trend.

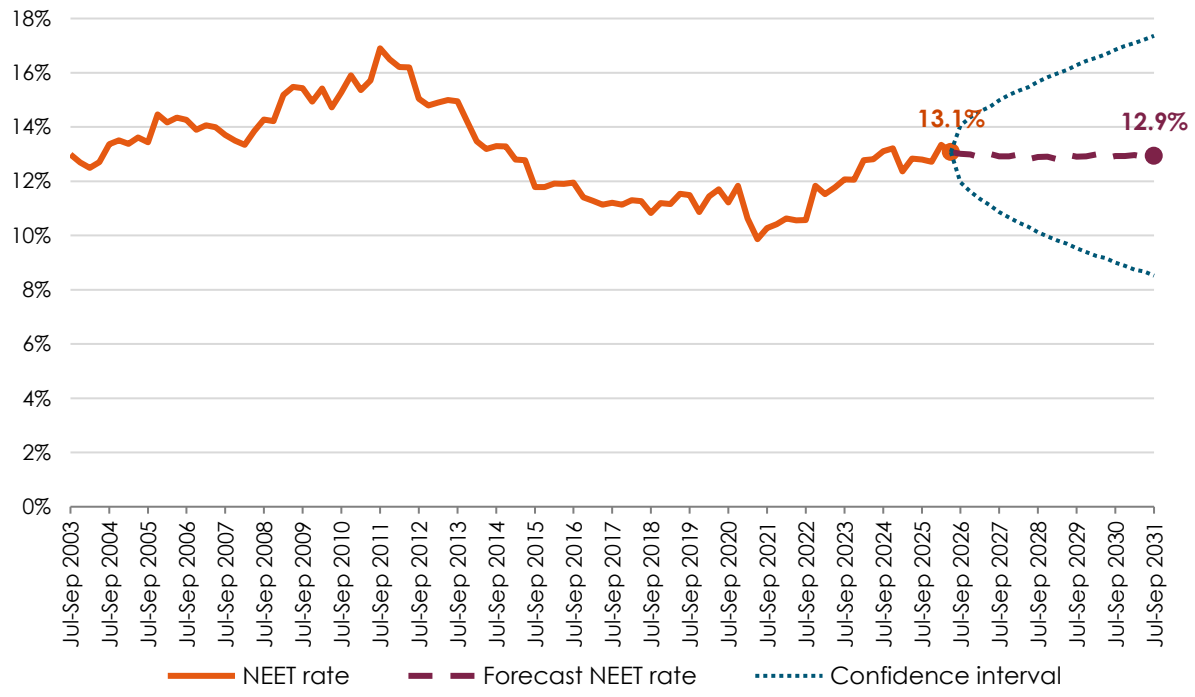
Similarly, structural labour market changes, such as automation, sectoral shifts, or regional economic restructuring, usually influence NEET levels slowly over time rather than causing abrupt quarterly fluctuations. SARIMAX modelling relies on correlations between successive quarters in the historical period. If a factor generally evolves slowly, its impact is effectively "smoothed out" in the quarterly model, and it will not emerge as a strong short-term predictor. Including variables with weak or unstable predictive power could reduce forecast accuracy, which is why the model focuses on the most robust predictors among those tested: recent NEET levels and GDP growth.

Findings

The central projection indicates that NEET rates will remain broadly flat at around 13% between July to September 2026 and July to September 2031. This equates to around one million young people remaining outside of education, employment or training, with the central estimates rising slightly from 985,000 to 1,008,000 over the period (see Tables E2 and E3 in Appendix E for quarterly forecasts of NEET levels and rates). The 95% interval around the central estimate widens over the forecast horizon, to roughly 8.5% to 17.4% (around 663,000 to 1.35 million young people) by July to September 2031. The central projection should be read alongside this uncertainty.

Figure 1: Baseline projections still leave around a million young people NEET

Percentage of young people aged 16 to 24 not in education, employment or training (NEET), UK, Jul-Sep 2003 to Apr-Jun 2026, and SARIMAX forecasts from Jul-Sep 2026 to Jul-Sep 2031



Source: Labour Force Survey from the Office for National Statistics; forecasts from Youth Futures Foundation analysis
Note: Projections are produced using a SARIMAX model; dotted lines show the upper and lower confidence interval. Appendix E provides further model outputs.

This model is designed to make predictions, not to explain the underlying causes of NEET rates. It is a simplified, top-down model that uses real GDP growth as an input and uses broad indicators to make predictions, rather than modelling the behaviour of individual

units. It does not capture the full set of factors that drive young people into or out of work, education, or training.

This has important implications for interpreting the results. For example, when we observe that the model's projections remain relatively flat, we can describe how it is using the GDP variable: higher GDP growth tends to be associated with slightly lower NEET levels, but we cannot conclude that changes in GDP directly cause changes in NEETs in the real world. The relationships in the model are correlational, not causal. In other words, the model shows patterns in the data rather than explaining why those patterns exist. The main purpose of this exercise is to produce reliable projections , so the focus should be on the projections themselves rather than trying to interpret the inner workings of the model as real-world mechanisms.

Why the model produces flat NEET Projections

The model's projections are relatively flat, and this can be understood by examining how it projects forward. The most significant contributor is the strong persistence of NEET levels. The AR(1) coefficient, which captures the relationship between one quarter and the next, is 0.85. This means that around 85% of any deviation from the model's expected path in one quarter carries over into the next, so shocks fade only slowly and current levels are strongly predictive of future outcomes. By contrast, the AR(2) term, which looks at the influence of two quarters ago, is small and not statistically significant, indicating that values from earlier periods contribute very little to the prediction.

Seasonality is handled through seasonal differencing (comparing each quarter with the same quarter a year earlier) and a seasonal moving average term, which together account for regular quarterly patterns such as seasonal labour market movements, but do not create long-term upward or downward trends. The GDP growth variable provides a modest adjustment: higher growth is associated with slightly lower NEET levels (although this coefficient is not statistically significant in the re-estimated model), but with projected growth being modest and stable, its contribution to the forecast is limited. Other variables, including COVID, the financial crisis, and education policy dummies, primarily captured historical shocks. Although none of these coefficients is individually statistically significant (Table E1), the specification including them produced the lowest out-of-sample forecast error in testing. They are not intended to influence forecasts beyond the period in which the event occurred. Consistent with this, the dummy variables and the COVID-19 stringency index were set to zero for all forecast periods (see Appendix B, Note 3).

Taken together, these dynamics mean that the model essentially carries forward the most recent NEET levels, adjusts slightly for GDP, and smooths seasonal effects. As a

result, the forecast trajectory remains fairly flat. The flatness of the forecast largely reflects the model's structure – it carries recent levels forward and has no mechanism for projecting new trends – so it should not be read as a sign of stability in a positive sense. Rather, it indicates that, absent new shocks or interventions, there is little in the recent data to suggest that NEET rates will fall from levels that are high relative to the past decade.

The Role of Historical Shocks and Policy Variables

Variables representing historical shocks and policy changes were included to improve the model's ability to explain past data. By accounting for these events, the model isolates the underlying dynamics of NEET persistence and GDP effects, leading to more reliable projections. For example, including the COVID-19 stringency index or the financial crisis variable helps ensure that unusual deviations in the historical record do not distort the estimation of regular trends. While these variables do not contribute directly to forecasts beyond the estimation period, they help to stabilise the estimated dynamics by reducing the extent to which past shocks influence predictions.

Applications of the Model

Using the Model for Policy and Scenario Analysis

The model provides a foundation for both baseline projections and scenario-based analysis. Scenario adjustments can be applied to explore the potential impact of factors that were not able to be captured directly in the model. For example, policymakers could overlay assumptions about rising long-term illness, changes in youth participation, or labour market shifts, adjusting the baseline projections upward or downward to reflect these scenarios. It is important to present these adjusted projections as scenarios, not as outputs from the SARIMAX model itself, preserving the integrity of the statistical baseline.

In this way, the model serves as a useful starting point for policy planning, allowing decision-makers to understand the expected trajectory of NEET levels while considering the potential influence of known or emerging factors.

These applications should be read in light of more recent work. The original forecasts and this report were prepared at pace ahead of the 2025 Autumn Budget. Since then, Youth Futures Foundation has developed the model further to produce NEET projections to 2036 under alternative economic scenarios, which add explanatory variables such as the unemployment rate and vacancies and allow future economic conditions to be varied directly within the model (Coxon and Bhasin, 2026). Forthcoming economic modelling, including work on young people's transitions into and out of NEET status, is intended to capture drivers such as health and labour demand more directly. For scenario analysis, these newer tools may be better suited than overlays applied to the baseline presented here.

Structural Risks Beyond the Model: Potential Scenarios to Consider

Although certain factors - such as disability prevalence or other influences not included as explicit variables - have affected NEET levels in the past, their effects are partially reflected in the historical NEET data the model uses. This means the forecasts implicitly incorporate some of the past impact of these factors. However, the model cannot account for future changes in these drivers, so any shifts in their prevalence or influence would not be captured in the projections.

The assessment in this section was first prepared in 2025, alongside the original forecasts and ahead of the 2025 Autumn Budget. Evidence on several of these drivers has progressed since then, so we have updated it below using more recent data and research. We have also added two further drivers that are not captured in the model: the rising cost of employing young people, and low qualifications and limited work experience.

There are several emerging risks that could plausibly raise NEET rates further in the medium term. These are discussed below to illustrate how the baseline can be used as a platform for policy stress-testing.

1. Increasing number of young people with SEND and poor mental health

Recent analysis of Labour Force Survey data shows that an increasing number of young people are economically inactive due to poor mental health and other health conditions (Youth Futures Foundation, 2025a; Youth Futures Foundation, 2025b). More s recent Youth Futures Foundation analysis of ONS Labour Force Survey data shows that the number of NEET young people who are economically inactive because of long-term sickness doubled between 2021 and 2026, reaching 249,000 in Q1 2026. Neurodevelopmental conditions, including autism and learning difficulties, are now the most commonly reported main health condition in this group (39% of cases) (Youth Futures Foundation, 2026a). If these trends persist, they could push NEET rates higher.

Trends in special educational needs and disabilities (SEND) among school-age children point in the same direction. In January 2026, more than 1.8 million pupils in England had special educational needs, 5.2% more than a year earlier, and the number of pupils with an education, health and care (EHC) plan rose by 11.6% to around 538,500 (Department for Education, 2026). The odds of a young person with SEND becoming NEET are around 1.9 times those of a young person without SEND (Youth Futures Foundation, 2025c). Because today's pupils will move into the 16 to 24 age group over the coming decade, the effect of rising SEND identification on NEET rates is likely to build gradually during and beyond the forecast period rather than appear immediately.

2. Automation and Technological Change

Young workers are overrepresented in routine and entry-level roles that are most susceptible to automation. Studies by Autor (2015) and the OECD (2023) show that such jobs are particularly vulnerable to technological displacement. More recent evidence on generative AI suggests that it is already affecting hiring, especially for junior roles. UK evidence finds that employment in firms highly exposed to AI fell by around 4.5%, with a larger fall (5.8%) in low-seniority positions (Klein Teeselink, 2025). The evidence is not yet settled. However, other studies find no statistically significant relationship between AI

adoption and youth unemployment so far, which may reflect young people's concentration in sectors with low AI exposure, such as retail and hospitality, and causal evidence that separates the effects of AI from wider economic conditions remains limited (PwC, 2025; Youth Futures Foundation, 2026b). To help address this gap, Youth Futures Foundation has commissioned research on the current and future impacts of AI on young people's labour market outcomes and on the future of entry-level work, due to report in 2027. If the adoption of AI accelerates in the coming years, NEET rates may diverge from the baseline projections.

3. Declining Labour Demand

ONS data indicate that labour demand has continued to weaken. Vacancies fell to an estimated 691,000 in July to September 2026, 2.9% lower than in the previous quarter and the first time the total has been below 700,000 since early 2021. There were 2.4 unemployed people per vacancy in June to August 2026 (Office for National Statistics, 2026a), compared with around one per vacancy in 2022, indicating much greater competition for jobs (Youth Futures Foundation, 2026a). These are all-age figures, but there is evidence that the roles and sectors young people rely on have been particularly affected.

Around 43% of employed 16- to 24-year-olds work in retail and hospitality, compared with 16% of workers aged over 25, and hospitality vacancies fell by 46% between 2021 and 2025 (Youth Futures Foundation, 2025c). Employment has also fallen faster in industries that traditionally employ large numbers of young people, and entry-level vacancies fell 1.6 times more sharply than total vacancies over the year to early 2026 (12.8% compared with 8.1%) (Milburn, 2026; Youth Futures Foundation, 2026a). Further weakening in labour demand could reduce employment opportunities for young people and raise NEET rates over time.

Interpretation and Policy Implications

Taken together, the model findings and contextual evidence suggest that the outlook for NEET rates remains concerning. Although the baseline projection does not anticipate a sharp increase, the persistence of high NEET levels under relatively benign assumptions can be read as a signal of systemic stagnation, not stability.

This has several key implications for policymakers:

1. **Fiscal implications**: Persistent NEET levels entail long-term fiscal costs, including increased welfare expenditure, lost tax revenues, and reduced lifetime earnings for affected individuals. These costs compound over time and place pressure on future budgets.
2. **Macroeconomic recovery is not enough**: The model provides no indication that modest economic growth alone will reduce NEET levels, although this partly reflects the model's structure and the small, estimated effect of GDP growth. This is consistent with our more recent scenario-based projections, which find that NEET numbers remain high under every economic scenario considered, with a gap of only around 95,000 young people between the optimistic and pessimistic scenarios by 2036 (Coxon and Bhasin, 2026). Together with wider evidence, this underscores the need for structural interventions that address barriers beyond the business cycle.
3. **Urgency of intervention**: Wider evidence suggests that, without active policy measures, such as expanded mental health provision, targeted training and apprenticeship programmes, and wage or hiring subsidies for youth, NEET rates are unlikely to improve and may deteriorate (Milburn, 2026; Clegg et al., 2026; Coxon and Bhasin, 2026). Evaluated interventions of this kind, including Individual Placement and Support for people with mental health conditions, apprenticeships, and wage subsidies combined with training, have been found to improve employment outcomes (Nancarrow et al., 2023; Department for Work and Pensions, 2025; Youth Futures Foundation, n.d.).
4. **Strategic forecasting and stress-testing**: Departments such as DWP, DfE, and HM Treasury can treat the SARIMAX output as a baseline scenario for planning purposes. By layering structural risks on top of the projections, it is possible to construct higher-risk scenarios that can inform resource allocation, policy design, and fiscal contingency planning.

In short, the model is a decision-support tool: it offers a stable empirical foundation for assessing how different assumptions and interventions may shift the trajectory of youth labour market outcomes in the coming years.

Model Strengths, Limitations and Improvements

Challenges in Modelling and Forecasting NEET Levels

Forecasting NEET levels is inherently challenging because so many factors influence whether young people are in employment, education, or training. Beyond economic conditions, NEET status is affected by education participation and attainment, health and disability, labour market conditions and policies, social support systems, and personal circumstances. Each of these factors can change over time, interact with others, and vary in ways that are difficult to capture at a quarterly frequency.

Even well-resourced models, such as those used by the OBR to forecast unemployment, illustrate the complexity of labour market projections. The OBR integrates at least 20–30 major economic and labour market indicators, including GDP, employment by sector, earnings growth, job vacancies, and benefit claimants, using sophisticated modelling and expert judgment. A complete model for NEET rates would require even more variables than the OBR's unemployment model to account for economic inactivity, education-related behaviour, and individual-level vulnerabilities that are key drivers of youth NEET status.

Limitations to the SARIMAX Approach

The SARIMAX model provides a transparent, statistically validated approach to forecasting NEET levels. It is designed to limit overfitting, relies on formal diagnostic tests, and offers a baseline projection anchored in historical persistence and macroeconomic conditions. When tested, the model produced good forecasts for the previous two years of quarterly data, supporting its use for short-term projections (see Technical Appendices).

However, the model has limitations. Although SARIMAX can, in principle, capture long-term trends, the changing relationships between potential explanatory variables and NEET levels over time, combined with the lack of quarterly variation in some variables and data limitations, and data handling issues during model estimation mean that factors such as disability, structural labour market changes, and sectoral vacancies were not included in the model. As a result, the model does not capture slow-moving

changes that build up over several years, such as the steady rise in the number of young people with health conditions. If such trends continue, actual NEET rates could drift away from the flat baseline over time.. Flat projections should not be interpreted as indicating that NEET levels will remain static (especially given the wide confidence intervals); rather, they reflect a cautious projection based on historical patterns and modest economic growth. Structural shifts, unexpected shocks and policy changes could push NEET levels above or below the baseline.

Additionally, the automated model-selection procedures used in this analysis introduce a risk of multiple-testing and model-selection bias. In practice, this arises because a large number of candidate SARIMAX specifications—differing in their autoregressive structure, seasonal components, and choice of explanatory variables—are evaluated, and the model that performs best on a limited validation sample is selected. When many models are tested in this way, some may appear to perform well by chance alone, particularly when the out-of-sample period is short. As a result, the apparent forecasting performance of the selected model may be overstated relative to its true predictive ability.

While the approach used here incorporates out-of-sample testing to reduce this risk of overfitting (choosing a model that fits the historical data well but forecasts poorly), the validation window remains limited, increasing the possibility that model performance reflects sample-specific patterns rather than stable underlying relationships. Peer reviewers noted that this limitation could be addressed in future work by validating the chosen models against alternative data sources—such as different survey-based measures (like Understanding Society) or administrative data—or by holding out a longer period for validation or multiple validation periods. These extensions were not feasible within the timeframe of this project but would strengthen future iterations of the modelling. Similar work, forecasting NEET rates over the next year, triangulates estimates in LEO (admin) and survey data.

Limitations Related to Exogenous Variables

Even if the model were able to perfectly capture the relationship between exogenous variables and NEET levels, it still relies on having high-quality forecasts for those variables in order to produce accurate projections. For some factors, such as GDP, we can rely on the OBR forecasts, which draw on a wide range of economic indicators and employ sophisticated modelling techniques. However, this highlights the broader challenge: forecasting many of the variables that influence NEET levels is inherently difficult, particularly over multi-year horizons.

Variables such as sectoral vacancies, youth disability prevalence, or regional labour market conditions either lack reliable high-frequency projections or are affected by structural changes that are hard to anticipate. While models for short-term forecasts can leverage lagged relationships between exogenous variables and NEET rates (as done by Wilson et al., 2026b), the uncertainty in models for long-term forecasts grows with each additional forecasted year. The quality of the projection is highly dependent on the forecasts of the underlying exogenous variables, which makes careful interpretation essential when using SARIMAX for multi-year NEET projections.

Other Limitations

A key limitation of this analysis is the reliance on the Labour Force Survey (LFS) at a time when known data quality issues are affecting its accuracy and stability. These issues introduce additional uncertainty into the NEET estimates used for modelling and may weaken the model's ability to detect reliable relationships between NEET trends and the exogenous variables considered during model selection (See appendix G for further limitations and caveats). Our more recent short-term forecasting work addresses this by triangulating the LFS with other survey and administrative data, including an adjustment for the gap between LFS and Understanding Society NEET estimates, which improved forecast accuracy (Wilson et al., 2026a & 2026b). This was not feasible to incorporate within the timeframe of these five-year projections.

A further limitation relates to the forecast horizon. These forecasts extend a model developed and validated for short-term forecasting to a five-year horizon, and the extension was carried out at pace to meet a policy deadline. The model's accuracy was tested over a two-year hold-out period only, so its performance at longer horizons has not been assessed and is likely to be lower; the widening forecast intervals only partly reflect this. The explanatory variables were also selected using data to Q1 2025 and have not been re-tested with the more recent data, and no new out-of-sample test was run for the re-estimated model, so the reported forecast accuracy relates to the original selection.

Suggested Directions for Further Model Development

1. Broader Use of Available Data Sources
Quarterly data on disability (and other relevant characteristics) are available through the LFS two-quarter longitudinal panel, which extends further back to 2003. Quarterly OBR projections of real GDP are also accessible. These sources were not incorporated in the current iteration due to time constraints, but they provide opportunities to enrich the model and enhance robustness in future extensions. Future iterations can test whether

these sources increase the predictive accuracy of the model and capture their underlying quarterly relationship with NEET levels.

2. Incorporating Emerging Labour Market Drivers (e.g., AI and Automation)
Future iterations should account for emerging determinants of labour demand, including the effects of AI, automation, and other technological transitions on youth employment. Although data availability and literature are still developing, these drivers are increasingly shaping labour market trajectories and are likely to have material implications for NEET rates over the next decade.

3. Improving Long-Horizon Forecasting Methodology
ARIMA-based approaches (including SARIMAX) are less well suited to longer-term forecasting horizons (e.g., five-year projections), particularly in settings characterised by structural change. Alternative approaches—such as structural time series models, system dynamics models, or agent-based modelling—should be explored for long-run scenario development and policy simulation.

Additional Methodological Considerations

5. Balancing Stationarity Requirements and Information Preservation

In this analysis, stationarity was assessed using conventional statistical tests alongside an additional criterion that prioritised transformations associated with lower rolling variance, with the aim of improving short-term forecast stability. However, peer review highlighted that this approach may increase the risk of over-differencing, as variance reduction is not explicitly balanced against potential information loss. Excessive differencing can remove meaningful low-frequency variation and reduce the interpretability of relationships between NEET levels and explanatory variables.

A potential improvement would be to adopt the simplest transformation necessary to achieve stationarity—guided primarily by standard unit root tests and visual inspection—while reserving additional variance-based criteria for sensitivity analysis rather than model selection. Explicitly setting out the rationale for any departures from conventional practice, and presenting alternative specifications where appropriate, would further strengthen confidence in the modelling approach.

6. Selection and Specification of Exogenous Macroeconomic Regressors

Further improvements could be made in the selection and justification of exogenous regressors included in the model. In particular, while real GDP growth was included as a parsimonious proxy for overall macroeconomic conditions, peer review highlighted that this choice implicitly assumes that only changes in real economic growth are relevant for

NEET dynamics. This may limit interpretability, as labour market outcomes for young people can improve even in periods where real GDP growth is weak or neutral—for example, due to targeted fiscal interventions, changes in labour demand in youth-intensive sectors, or policy-driven employment programmes operating alongside higher inflation.

Although this assumption is less problematic for short-term forecasting—provided that real GDP growth demonstrably improves predictive performance—it constrains the economic interpretation of the model. A useful extension would therefore be to test alternative or complementary macroeconomic indicators such as nominal GDP growth, sectoral employment growth, youth unemployment rates, vacancy measures, or policy-relevant labour market indicators, and to compare their forecasting performance and interpretability against the baseline specification.

Situating the choice of exogenous variables more explicitly within the existing literature on youth labour market dynamics and NEET transitions would also strengthen the conceptual grounding of the model and clarify how the selected regressors relate to established empirical findings.

7. Testing Statistical Significance of Forecast Performance Differences

A final methodological improvement raised through peer review relates to the evaluation of forecast accuracy. While forecast performance was compared using MAPE values, the analysis did not test whether observed differences in predictive accuracy are statistically significant. Applying a formal test for forecast differentials—such as the Diebold-Mariano (1995) test—would allow for a more rigorous comparison between model specifications and clarify whether improvements in forecast performance (e.g., when including exogenous regressors) are statistically distinguishable from noise. This would also help assess whether any of the SARIMAX variants statistically outperform a simple AR(1) benchmark, thereby strengthening the justification for the final model choice and supporting more confident interpretation of the role of exogenous drivers in NEET forecasting.

Conclusion

This report has presented a medium-term projection of youth NEET rates in the UK using a SARIMAX model grounded in two decades of historical data and a set of macroeconomic indicators. It offers a baseline view of how NEET rates may evolve under relatively stable economic conditions, with projections suggesting that rates remain broadly flat at around 13% through to Q3 2031. While this does not indicate further deterioration, it also points to a continued risk of persistently high levels of youth NEET rates in the absence of significant structural change.

More broadly, this work represents one of the first attempts to develop a transparent, empirically grounded medium-term projection of youth NEET rates in the UK. In doing so, it highlights both the value and the limitations of applying time-series methods to complex social outcomes. While the model provides a useful statistical baseline and a consistent reference point for policy discussion, it also makes clear the extent to which important drivers of NEET outcomes: such as health, labour demand shifts, and technological change—remain difficult to incorporate within this framework, particularly over longer horizons. Forecasting NEETs with its explanators entails having reliable forecasts of those explanators. In a rapidly evolving youth labour market, capturing this would require robust data and evidence.

The primary value of these projections, hence, lies not only in its central estimate but in its role as a starting point for further analysis. It provides a structured foundation from which alternative scenarios can be explored, allowing policymakers and analysts to test how different assumptions—whether related to economic conditions, policy interventions, or population characteristics—might alter future trajectories.

Looking ahead, this work underscores the need for continued development in both methodology and data. Improving the robustness of NEET forecasting will likely require combining time-series approaches with complementary modelling techniques, including those that can better capture structural relationships, distributional effects and behavioural dynamics. It also points to the importance of strengthening the underlying data infrastructure, including the integration of survey and administrative sources, to improve both measurement and model inputs.

As such, this analysis should be seen as part of an evolving analytical programme. Its contribution lies in establishing a transparent baseline, clarifying the limits of current approaches, and helping to shape the next phase of work aimed at better understanding—and ultimately improving—youth labour market outcomes.

Since they were first produced, these projections have informed analysis across government. We will continue to update them as new data become available, and we

encourage anyone using them to contact us for the latest version and for guidance on how best to apply them.

References

Autor, D. (2015). "Why Are There Still So Many Jobs?" *Journal of Economic Perspectives*, 29(3), 3–30. https://economics.mit.edu/sites/default/files/inline-files/Why%20Are%20there%20Still%20So%20Many%20Jobs_0.pdf

Bank of England. (2025). *Monetary Policy Report – May 2025*. https://www.bankofengland.co.uk/-/media/boe/files/monetary-policy-report/2025/may/monetary-policy-report-may-2025.pdf

Brynjolfsson, E., Chandar, B., & Chen, R. (2025). *Canaries in the coal mine? Six facts about the recent employment effects of artificial intelligence*. Stanford Digital Economy Lab working paper.

Chiacchio, F., Petropoulos, G., & Pichler, D. (2018). *The impact of industrial robots on EU employment and wages: A local labour market approach*. Bruegel Working Paper 02/2018. Bruegel. https://www.bruegel.org/working-paper/impact-industrial-robots-eu-employment-and-wages-local-labour-market-approach

Clegg, A., Cominetti, N., Diniz, J., Judge, L., & Stone, I. (2026). *Lost in transition: An examination of why the UK NEET rate is high and rising*. Resolution Foundation. https://doi.org/10.63492/cxo2244

Coxon, A., & Bhasin, A. (2026). *A persistent challenge: NEET projections for the UK to 2036 under alternative economic scenarios*. Youth Futures Foundation. https://youthfuturesfoundation.org/publication/a-persistent-challenge-neet-projections-for-the-uk-to-2036-under-alternative-economic-scenarios/

Department for Education. (2026). *Special educational needs in England: Academic year 2025/26*. https://explore-education-statistics.service.gov.uk/find-statistics/special-educational-needs-in-england/2025-26

Department for Work and Pensions. (2025). *What works to support disadvantaged groups towards employment? Research report*. https://www.gov.uk/government/publications/what-works-to-support-disadvantaged-groups-towards-employment

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3), 253–263.

International Monetary Fund. (2026). *Real Gross Domestic Product (GDP) for United Kingdom [NGDPRNSAXDCGBQ]*. Retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/NGDPRNSAXDCGBQ

Kanabar, R., & Ayoubkhani, D. (2012, November). *Approaches to the seasonal adjustment of labour market flows*. Office for National Statistics. https://doczz.net/doc/8411002/approaches-to-the-seasonal-adjustment-of-labour-market-flows

Klein Teeselink, B. (2025). *Generative AI and labor market outcomes: Evidence from the United Kingdom*. SSRN. https://doi.org/10.2139/ssrn.5516798

Milburn, A. (2026). *Young people and work: Interim report*. Department for Work and Pensions. https://www.gov.uk/government/publications/young-people-and-work-interim-report

Nancarrow et al. (2023). *The impact of wage subsidies on the employment of disadvantaged and/or marginalised young people: Rapid evidence assessment technical report*. Institute for Employment Studies for Youth Futures Foundation.

Nau, R. (n.d.). *Introduction to ARIMA models*. Duke University. https://people.duke.edu/~rnau/411arim.htm

NIESR. (2025). *National Institute UK Economic Outlook – Summer 2025*. National Institute of Economic and Social Research. https://niesr.ac.uk/wp-content/uploads/2025/08/JC883-NIESR-Outlook-Summer-2025-UK-v6-1.pdf

OECD (2023). *Artificial Intelligence and the Labour Market*. OECD Publishing. https://books.google.co.uk/books/about/OECD_Employment_Outlook_2023_Artificial.html?id=89PKEAAAQBAJ&redir_esc=y

Office for Budget Responsibility. (2025). *Labour market: Economy forecast*. https://obr.uk/forecasts-in-depth/the-economy-forecast/labour-market

Office for National Statistics. (2024). *Young people not in education, employment or training (NEET), UK: November 2024*. https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unemployment/bulletins/youngpeoplenotineducationemploymentortrainingneet/november2024

Office for National Statistics. (2025). *Vacancies by industry (single month estimates)*. https://www.ons.gov.uk/employmentandlabourmarket/peoplenotinwork/unempl

oyment/datasets/x06singlemonthvacanciesestimatesnotdesignatedasnationalstatistics

Office for National Statistics. (2026a). *Vacancies and jobs in the UK: October 2026*. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/jobsandvacanciesintheuk/october2026

Office for National Statistics. (2026b). *Labour market overview, UK: October 2026*. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/uklabourmarket/october2026

Oxford Blavatnik School of Government. (2023). *COVID-19 Government Response Tracker*. https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker

PwC. (2025). *Youth Employment Index 2025 – Topic in focus: Is the rise of artificial intelligence leading to the displacement of young workers in the UK?*. PwC UK.

US Census Bureau. (2025). *X-13ARIMA-SEATS seasonal adjustment program*. https://www.census.gov/data/software/x13as.html

Wilson, C., Beardsworth, S., Khriakova, E., Moller Vallgarda, L., & Ruisch, B. (2026a). *NEET forecasting brief: Four quarter forward-looking signals about likely movements in the UK NEET rate. NEET forecasting brief: four quarter forward-looking signals about likely movements in the UK NEET rate - Youth Futures Foundation*

Wilson, C., Beardsworth, S., Khriakova, E., Moller Vallgarda, L., & Ruisch, B. (2026b). *Technical annexe for NEET forecasting brief: Four quarter forward-looking signals about likely movements in the UK NEET rate. Technical annexe for NEET forecasting brief: four quarter forward-looking signals about likely movements in the UK NEET rate - Youth Futures Foundation*

Department for Work and Pensions. (n.d.). *Family Resources Survey: Stat-Xplore*. https://stat-xplore.dwp.gov.uk/webapi/jsf/dataCatalogueExplorer.xhtml

Federal Reserve Bank of St. Louis. (n.d.). *Gross Domestic Product (GDP)*. FRED. https://fred.stlouisfed.org/series/GDP/

Youth Futures Foundation (2025a). Trends in young people not in education, employment or training (January – March 2025). Youth Futures Foundation. https://youthfuturesfoundation.org/publication/trends-in-young-people-not-in-education-employment-or-training-january-march-2025/

Youth Futures Foundation (2025b). *Understanding drivers of recent trends in young people's mental health*. https://youthfuturesfoundation.org/publication/report-understanding-drivers-of-recent-trends-in-young-peoples-mental-health/

Youth Futures Foundation (2025c). *Youth Employment 2025 Outlook*. https://youthfuturesfoundation.org/publication/youth-employment-2025-outlook/

Youth Futures Foundation (2026a). *NEET Trends Analysis (Q1 2026): What is driving the NEET rate?*. https://youthfuturesfoundation.org/publication/neet-trends-analysis-2026-q1-what-is-driving-the-neet-rate/

Youth Futures Foundation (2026b). *Call for research proposals: Impact of artificial intelligence on the youth labour market*. https://youthfuturesfoundation.org/opportunity/call-for-proposals-ai-and-the-youth-labour-market/

Youth Futures Foundation (n.d.). *Youth Employment Toolkit*. https://youthfuturesfoundation.org/tools/youth-employment-toolkit/

Technical Appendices

Appendix A: A Brief Method Note on ARIMA Models

SARIMAX Models

A SARIMAX model (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables) is an extension of ARIMA and is widely applied to economic and social indicators such as GDP, inflation, population, and labour market metrics including employment and unemployment (Nau, n.d.).

ARIMA components

- AR (AutoRegressive): Relationship between an observation and its past values.
- I (Integrated): Differencing applied to remove trends and achieve stationarity.
- MA (Moving Average): Relationship between an observation and past forecast errors.

How SARIMAX extends ARIMA

- Incorporates seasonality (e.g., quarterly NEET level patterns linked to school term cycles).
- Allows exogenous variables, enabling the model to capture drivers such as policy changes, economic conditions, or demographic factors.
- Uses iterative forecasting, generating one-step-ahead predictions and feeding them forward for longer-horizon results.

Strengths

- Captures recurring seasonal patterns.
- Incorporates external drivers, improving accuracy and interpretability.
- Transparent and widely used in economic and social forecasting.
- Strong short-to-medium–term performance.

Limitations

- Accuracy declines for long-term horizons.
- Assumes historical patterns persist.
- Requires consistent, high-quality time series data.
- Exogenous variable selection can be complex.
- Iterative forecasts accumulate error; direct forecasts avoid this but require more data and offer less visibility over intermediate trends.

Since SARIMAX models with different combinations of exogenous variables can perform very differently, we compared candidate models on how accurately they forecast data held back from estimation, using the Mean Absolute Percentage Error (MAPE).

Mean Absolute Percentage Error (MAPE)

MAPE is calculated as the average of the absolute percentage errors between observed and forecasted values: $MAPE = (1/n)\ \Sigma_t\ |(Actual_t - Forecast_t) / Actual_t| \times 100$. A lower MAPE indicates a more accurate forecast. Out-of-sample MAPE was the primary metric used to select the preferred model specification because it directly measures how closely forecasts match data not used in estimation, which is particularly relevant when choosing a baseline for policy scenario testing.

Appendix B: Data, Sources and Transformations

Table B1: Historic data variable dictionary

NEET driver	Variable	Inclusion intuition
Labour demand	Non-seasonally adjusted UK real GDP growth rate	Real GDP growth is a key indicator of overall economic performance and labour demand. Periods of stronger growth are typically associated with job creation and better labour market opportunities for young people, while recessions or slowdowns often coincide with rising unemployment and inactivity among this group.
	Non-seasonally adjusted hospitality and retail vacancy levels	Proxy for youth labour demand, which is especially important to understand unemployment trends post-COVID. Hospitality and retail have the highest concentration of jobs occupied by young people and is more relevant to the NEET population due to low entry requirements.
Labour supply	Youth disability levels (ages 16 to 24)	To capture health-related labour market pressures. In the absence of this variable, the model would ignore a major driver of recent inactivity trends and could wrongly attribute the post-2020 rise to other factors or simply extrapolate from recent data without accounting for the underlying health-driven component.

NEET driver	Variable	Inclusion intuition
Demographic pressures	Non-seasonally adjusted UK youth population levels (ages 16 to 24)	i) The size of the youth population directly affects the number of young people who could potentially be NEET. ii) Larger cohorts may face greater competition for jobs and training opportunities, increasing NEET risk, while smaller cohorts may benefit from tighter labour markets or more targeted support.
Historic shocks	Global Financial Crisis	The Global Financial Crisis created an exceptional labour market shock beyond what GDP growth captures, with hiring freezes, credit constraints, and structural disruptions amplifying unemployment. Including a crisis dummy (Q2 2008–Q2 2009) helps isolate this extraordinary effect and prevents it from being misattributed to normal GDP–unemployment dynamics.
	COVID-19 stringency index	The COVID-19 stringency index captures the intensity of government restrictions that directly affected the labour market, such as lockdowns and business closures. Including it helps the model separate pandemic-related shocks from underlying unemployment trends, improving both interpretation and forecast accuracy.
	Education Participation age from 16 to 17	The policy change (raising the minimum education participation age) created a structural shift in the youth labour market by delaying young people's entry into employment or unemployment.

NEET driver	Variable	Inclusion intuition
		A step dummy captures this once-off, permanent level shift in unemployment/NEET rates after the reform, controlling for the fact that changes from that point onward are partly policy-driven rather than cyclical or trend-based.
	Education Participation age from 17 to 18	As above

Table B2: Data Sources and Transformations

Variable	Data source	Transformations required
Quarterly real GDP growth (NSA)*	IMF (historic estimates); OBR (projections)	GDP levels were converted into rates
Monthly hospitality and retail vacancies (NSA)	ONS	Quarterly estimates were calculated by taking a 3-month average
Youth population levels (NSA)	ONS	N/A
Global Financial Crisis dummy	Q2 2008 to Q2 2009 equal 1; 0 otherwise	N/A
COVID-19 stringency index	University of Oxford	Quarter values were calculated from averaging daily values
Education Participation age from 16 to 17 dummy	Q3 2013 to Q2 2015 equal 1; 0 otherwise	N/A

Variable	Data source	Transformations required
Education Participation age from 17 to 18 dummy	Q3 2015 onwards equal 1; 0 otherwise	N/A
Disability levels (NSA)	Family resource survey (FRS)	Quarterly estimates were calculated by smoothing the annual change equally across quarters

Notes: -

1. *NSA stands for Non-seasonally adjusted.
2. We have assumed population levels to be acyclical, consistent with the OBR's methodology (see OBR Labour Market Forecast).
3. Quarterly disability levels are available in the LFS microdata. FRS was used due to time constraints in delivery. Future iterations of Youth Futures' NEET forecasting models seek to use the LFS.
4. Forecasts of final exogenous variables included in the model were obtained from the OBR (for GDP projections) and the ONS (2022-based population projections, to convert NEET levels to rates).
5. The dummy variables for the Global Financial Crisis and the education participation age reform were set to 0 for all forecast periods, as they were at the end of the estimation sample, and the COVID-19 stringency index was also set to 0. This is consistent with the status quo assumption explained in the report.
6. Pre-testing versions of the model or the "theoretical model" included vacancies as well as variables capturing AI/automation. These variables were excluded due to unavailability of reliable forecasts and competing evidence in literature to fabricate data. Due to time constraints, the authors refrained from constructing scenario-based variables and including them into separate models.

Note B1: Transforming GDP projections

We converted OBR annual SA GDP level projections into quarterly Non-seasonally adjusted growth rates.

Method: -

1. Collected pre-2020 quarterly Non-seasonally adjusted growth rates.
2. Calculated each year's mean growth.
3. Computed quarterly deviations from the yearly mean.

4. Averaged deviations for each quarter to obtain **seasonal factors**.

5. For each projected quarter:
   Quarterly_NSA_Growth = Annual_SA_Growth + Seasonal_Deviation[Quarter]

Rationale: -

- Assumes historical seasonal deviations remain valid.
- Aligns future quarterly movements with established seasonal patterns.
- Growth rates calculated as:
  $[(GDP_t - GDP_{t-1}) / GDP_{t-1}] \times 100$

Appendix C: Stationarity tests and transformations

Stationarity is essential for reliable SARIMAX estimation. Before estimating SARIMAX models, we ensured that all-time series variables are stationary. Stationarity, defined as a constant mean, variance, and autocorrelation structure over time, is necessary to avoid spurious regression results and unreliable forecasts.

We first examined each regressor for characteristics such as exponential growth or non-constant variance, applying appropriate variance-stabilising transformations (e.g., log transformations) when needed. Stationarity was formally assessed using tests: the Augmented Dickey–Fuller (ADF) test, which tests for the presence of a unit root, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, which tests for stationarity.

To select the most appropriate transformation for each regressor that failed the tests, we first identified all transformations and differencing orders that produced stationary series according to the ADF and KPSS tests. Among these stationary candidates, we chose the version that exhibited the lowest variance instability, measured by the average rolling standard deviation over a short window. This approach prioritised series that are not only stationary but also smooth and stable in their variability, reducing noise and improving the reliability of subsequent SARIMAX model estimation.

Table C1: Variables and Stationarity transformations Applied

Variable	Stationarity transformation
Youth population levels (NSA)	Log, differenced twice
Disability levels (NSA)	Log; differenced once
Monthly hospitality and retail vacancies (NSA)	Log

Appendix D: Model selection

All possible subsets of regressors—including the null model with no regressors—were systematically evaluated. For each subset, an ARIMAX model was estimated using auto.arima with stepwise selection and approximation to improve computational efficiency. Model performance was assessed both in-sample and out-of-sample (Q2 2023–Q1 2025) using the Mean Absolute Percentage Error (MAPE). Only models passing key diagnostic checks—including the Ljung-Box test for residual autocorrelation, the Shapiro-Wilk test for normality, an ARCH test for conditional heteroskedasticity, and variance inflation factor (VIF < 5 for subsets with multiple regressors)—were retained.

The chosen model was selected based on the model that provided the lowest out-of-sample MAPE. The Akaike Information Criterion (AIC) was specified as a tie-breaker in the event of identical MAPE values, but this was not needed in practice because the selected model had a lower out-of-sample MAPE than any alternative. The selected model had an out-of-sample MAPE of 4.08% over Q2 2023 to Q1 2025. Inspection of residual plots were undertaken for final checks.

For this report, the model was re-estimated on data from Q1 2003 to Q2 2026 using the same four explanatory variables, with the ARIMA orders re-selected by auto.arima on the updated data. auto.arima selected the same ARIMA orders as the original model, ARIMA(2,0,0)(0,1,1)[4], with no drift term. No new out-of-sample test was run for the re-estimated model, so the out-of-sample MAPE reported above relates to the model as originally estimated. Residual diagnostics for the re-estimated model (Appendix E) show heavier tails than a normal distribution, so its forecast intervals should be treated as indicative.

Appendix E: Final model outputs

Figure E1: SARIMAX Residuals, Auto-correlation and Partial Autocorrelation Charts

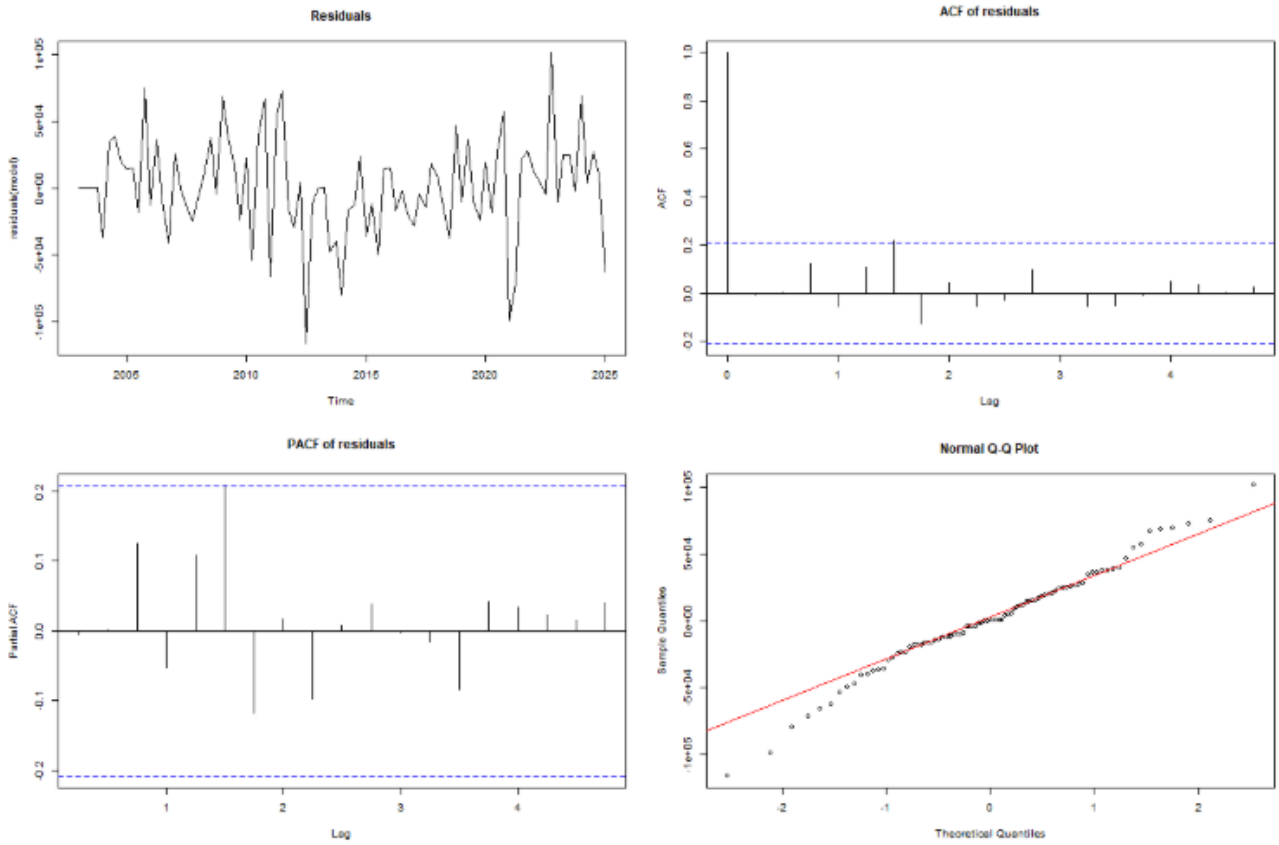


Table E1: SARIMAX Regression Outputs

Term	Estimate	StdError	tValue	pValue
ar1	0.9074	0.1117	8.121	0
ar2	0.0334	0.1136	0.294	0.7686
sma1	-0.7386	0.0841	-8.781	0
real_gdp_growth	-1771.4713	1044.164	-1.697	0.0898
covid_string	-52.7318	550.6047	-0.096	0.9237
gfc_dummy	17553.3364	26256.0675	0.669	0.5038

Term	Estimate	StdError	tValue	pValue
epa17_dummy	36339.1719	25093.2935	1.448	0.1476

Note E1: Model Specification Table

Statistic	Estimate
Model Specification	ARIMA(2,0,0)(0,1,1)[4] (with regression errors)
Error Variance (σ^2)	1.627×10^9
Log-Likelihood	-1020.16
AIC	2056.32
AICc	2058.22
BIC	2075.86

The following tables set out the historic NEET levels and rates for young people aged 16 to 24 in the UK, alongside five-year SARIMAX forecasts and their upper and lower confidence bounds. They accompany Figure 1 in the main report.

Table E2: Historic NEET levels and forecasts with confidence intervals

Number of young people aged 16 to 24 not in education, employment or training (NEET), seasonally adjusted, UK, Jan-Mar 2026 to Apr-Jun 2026, and SARIMAX forecasts from Jul-Sep 2026 to Jul-Sep 2031

Quarter	NEET level	Lower confidence bound	Upper confidence bound
Jan-Mar 2026 (actual)	1,002,000	–	–
Apr-Jun 2026 (actual)	985,000	–	–
Jul-Sep 2026	985,000	905,000	1,064,000
Oct-Dec 2026	986,000	882,000	1,090,000

Quarter	NEET level	Lower confidence bound	Upper confidence bound
Jan-Mar 2027	981,000	865,000	1,110,000
Apr-Jun 2027	995,000	851,000	1,126,000
Jul-Sep 2027	991,000	833,000	1,149,000
Oct-Dec 2027	993,000	819,000	1,166,000
Jan-Mar 2028	1,000,000	806,000	1,180,000
Apr-Jun 2028	988,000	796,000	1,193,000
Jul-Sep 2028	996,000	782,000	1,210,000
Oct-Dec 2028	998,000	771,000	1,225,000
Jan-Mar 2029	992,000	760,000	1,236,000
Apr-Jun 2029	1,006,000	751,000	1,248,000
Jul-Sep 2029	1,001,000	739,000	1,263,000
Oct-Dec 2029	1,002,000	729,000	1,275,000
Jan-Mar 2030	1,008,000	718,000	1,285,000
Apr-Jun 2030	998,000	711,000	1,296,000
Jul-Sep 2030	1,005,000	700,000	1,309,000
Oct-Dec 2030	1,006,000	690,000	1,321,000
Jan-Mar 2031	1,009,000	680,000	1,329,000
Apr-Jun 2031	1,004,000	674,000	1,340,000
Jul-Sep 2031	1,008,000	663,000	1,352,000

Source: Labour Force Survey from the Office for National Statistics; forecasts from Youth Futures Foundation analysis.
Note: Forecasts are produced using a SARIMAX model. Confidence bounds apply to forecast quarters only; a dash means not applicable. Figures are rounded to the nearest thousand.

Table E3: Historic NEET rates and forecasts with confidence intervals

Percentage of young people aged 16 to 24 not in education, employment or training (NEET), UK, Jan-Mar 2026 to Apr-Jun 2026, and SARIMAX forecasts from Jul-Sep 2026 to Jul-Sep 2031

Quarter	NEET rate	Lower confidence bound	Upper confidence bound
Jan-Mar 2026 (actual)	13.3%	–	–
Apr-Jun 2026 (actual)	13.1%	–	–
Jul-Sep 2026	13.0%	12.0%	14.1%
Oct-Dec 2026	13.0%	11.6%	14.4%
Jan-Mar 2027	12.9%	11.4%	14.6%
Apr-Jun 2027	13.0%	11.1%	14.7%
Jul-Sep 2027	12.9%	10.9%	15.0%
Oct-Dec 2027	12.9%	10.7%	15.2%
Jan-Mar 2028	13.0%	10.5%	15.3%
Apr-Jun 2028	12.8%	10.3%	15.5%
Jul-Sep 2028	12.9%	10.1%	15.7%
Oct-Dec 2028	12.9%	10.0%	15.8%
Jan-Mar 2029	12.8%	9.8%	16.0%
Apr-Jun 2029	13.0%	9.7%	16.1%
Jul-Sep 2029	12.9%	9.5%	16.3%
Oct-Dec 2029	12.9%	9.4%	16.4%
Jan-Mar 2030	13.0%	9.3%	16.6%
Apr-Jun 2030	12.8%	9.2%	16.7%
Jul-Sep 2030	12.9%	9.0%	16.8%
Oct-Dec 2030	12.9%	8.9%	17.0%
Jan-Mar 2031	13.0%	8.7%	17.1%
Apr-Jun 2031	12.9%	8.7%	17.2%

Quarter	NEET rate	Lower confidence bound	Upper confidence bound
Jul-Sep 2031	12.9%	8.5%	17.4%

Source: Labour Force Survey from the Office for National Statistics; forecasts from Youth Futures Foundation analysis.
Note: Forecasts of NEET levels were produced using a SARIMAX model and converted to NEET rates using 2022-based ONS population projections (see Appendix F). Confidence bounds apply to forecast quarters only (and not actual estimates); a dash means not applicable. Rates are rounded to one decimal place.

Appendix F: Steps Undertaken for Seasonal adjustment and rate calculation of forecasts

Seasonal adjustment was applied using X-13ARIMA-SEATS Seasonal Adjustment Program in R (US Census Bureau, 2025), a methodology similar to the one used by the ONS to seasonally adjust the Labour Force Survey (Kanabar and Ayoubkhani, 2012).

Step 1: Preparing the data

We constructed a quarterly time series of NEET levels from Q3 2001 to Q2 2026 using the Non-seasonally adjusted estimates from the Labour Force Survey, extended to Q3 2031 using our model outputs.

Step 2: Seasonal adjustment of the historical series

We ran the `seas()` function in R to decompose the Non-seasonally adjusted NEET series into trend, seasonal, and irregular components. Depending on the transformation selected by the algorithm, an additive decomposition was used (where the seasonal component is subtracted from the Non-seasonally adjusted series). This produced a seasonally adjusted central series, free from recurring within-year fluctuations.

Step 3: Extracting seasonal factors

The seasonal component was explicitly calculated to derive a set of quarterly seasonal factors. These factors represent the recurring patterns in NEET levels that are not attributable to trend or shocks (for example, education leavers entering or leaving the labour market at particular times of year).

Step 4: Applying adjustment to forecasts and confidence intervals

The same seasonal factors were then applied not only to the forecast central estimates but also to the forecast confidence intervals. This ensures that the entire forecast distribution is consistently adjusted for seasonality, rather than only the mean. In practice, the upper and lower bounds were transformed using the same additive or multiplicative seasonal factors as the central forecast, so that the confidence intervals remain aligned with the adjusted central series.

Step 5: Turning into rates

We used 2022-based annual UK population projections for age 16 to 24 from NOMIS - ONS, and assumed uniform quarterly growth due to the absence of seasonal patterns in historic data, and smoothed the transition from LFS estimates to the projections.

Appendix G: Further caveats and limitations

- Due to time constraints, the effect of lagged exogenous variables (e.g. GDP growth or policy reforms influencing NEETs with a delay) was not fully explored. This may understate the true effect of some drivers.

- NEET estimates come from the Labour Force Survey, which has margins of error. Revisions to ONS data could shift the baseline.
- GDP projections are taken from the OBR forecast that was available when the model was first developed in 2025 and have not been updated to reflect subsequent OBR forecasts. Using the latest projections could change the forecasts slightly, although the estimated effect of GDP growth on the forecast is small.

About the authors

Arushi Bhasin is a Senior Economist at Youth Futures Foundation, specialising in forecasting, economic modelling and labour market analysis. She has a background in economics, with experience applying econometric and impact evaluation methods to inform public policy, at research think tanks and UNICEF. Arushi leads Youth Futures projects on NEET forecasting, Artificial Intelligence, and economic analysis of the youth labour market. She is currently leading Youth Futures' research on AI's impact on labour demand, skill requirements, progression and distributional outcomes for young people. She is also the technical lead on Youth Futures' local NEET transitions model, which will forecast NEET rates by modelling young people's flows into and out of education, employment, training and NEET status, and project the distributional impact of policies.

Abigail Coxon is a Principal Economist at Youth Futures Foundation, specialising in quantitative research, economic forecasting and modelling, labour market analysis and inequalities. She has extensive experience applying quantitative methods and developing official statistics to inform public policy at the Office for National Statistics and has led on several projects at Youth Futures projects, including the development of models to identify young people at risk of becoming NEET (RONI), research into the drivers of mental health challenges among young people, and economic forecasting. Abigail is currently leading Youth Futures' work to develop a local NEET transitions model, designed to help national and local government understand where NEET outcomes are heading, for whom, and which policies would make the biggest difference.