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# A persistent challenge: NEET projections for the UK to 2036 under alternative economic scenarios



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# Table of Contents


Table of Contents ..... 1

Executive summary ..... 4

Projections to 2036 ..... 6

Extreme sensitivity analysis ..... 8

Policy implications ..... 10

Interpreting the projections ..... 11

Technical documentation ..... 12

1. Model overview ..... 12

2. Data and candidate explanatory variables ..... 13

3. Treatment of stationarity and structural breaks ..... 14

4. Automated model selection ..... 15

4.1 Model specification ..... 15

4.2 Initial model screening ..... 15

4.3 Rolling-origin out-of-sample validation ..... 16

4.4 Selection of the preferred model ..... 17

5. Final model diagnostics ..... 19

6. Conditional out-of-sample performance of the final model ..... 19

7. Construction of economic scenarios ..... 20

7.1 Real GDP growth ..... 21

7.2 Unemployment ..... 23

7.3 Conversion of annual projections to quarterly non-seasonally adjusted series ..... 25

7.4 Deriving vacancy projections ..... 26

8. Producing the NEET scenario projections ..... 27

9. Seasonal adjustment of NEET forecasts ..... 27

10. Scenario decomposition ..... 27

11. Extreme sensitivity analysis ..... 28

12. Limitations ..... 29

Appendices ..... 32

Appendix A: Data and variable definitions ..... 32

**Appendix B: Modelling diagnostics and assumptions ..... 40**
B1. Structural break diagnostics for the NEET series ..... 40
B2. Transformation and stationarity diagnostics ..... 41
**Appendix C: Final model coefficients and diagnostics ..... 42**
C1. Coefficient estimates ..... 42
C2. Model fit and diagnostic statistics ..... 43
**Appendix D: Economic scenario assumptions ..... 45**
D1. Real GDP growth ..... 45
D2. Unemployment rate ..... 46
D3. Vacancy projections ..... 47
**Appendix E: Scenario decomposition ..... 48**
**Appendix F: NEET forecast outputs ..... 49**
**About the authors ..... 53**
**Acknowledgements ..... 54**

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# Executive summary

**Around one million young people in the UK are currently not in education, employment or training (NEET). With the number remaining persistently high, understanding how the wider economic environment could affect the scale of the challenge is important for policymakers and those supporting young people.**

This analysis explores how the size of the NEET population could change under different future economic and labour market conditions. The results suggest that changes to trends in the UK's economic outlook could make a meaningful difference to the number of young people who are NEET. However, even under more favourable economic conditions, the projected NEET population remains substantial.

By the end of 2036, the optimistic scenario projects around 1.01 million young people to be NEET, compared with approximately 1.07 million under the central scenario and 1.11 million under the pessimistic scenario. Across the full range of scenarios, NEET levels are projected to remain higher than current levels.

The main scenarios are designed to represent plausible economic pathways, drawing on external projections and established historical relationships rather than assuming severe economic shocks. The relatively narrow range of projected NEET outcomes across these scenarios reflects the fact that the scenarios represent changes within a plausible range of future economic conditions, rather than extreme departures from the central outlook. This means that the projections should be interpreted as illustrating how NEET levels could vary under different realistic economic conditions, rather than as capturing the full range of outcomes that could result from more severe or unexpected economic shocks.

The analysis also highlights the potential consequences of a more severe deterioration in economic conditions. This sensitivity test assumes that unemployment reaches its historical maximum and minimum rate since 2003 — 8.6% in Q3 2011 and 3.7% in Q1 and Q2 2022 — alongside a ±1 percentage point shock to GDP growth relative to the central scenario. Under the most adverse scenario, 1.33 million young people are projected to be NEET by the end of 2036 — around 261,000 more than under the central projection, and 347,000 more than the current NEET population.

This is not a prediction of what will happen, but illustrates the potential scale of the NEET challenge under particularly adverse economic assumptions characterised by a sharp decline in GDP growth and unemployment rising to and remaining at historically high levels. Taken together, the findings point to a dual challenge for youth employment policy. A stronger economy and healthier labour market could help limit the number of

young people who are NEET, but even under the more favourable scenario, the model projects that the NEET population would remain high at around one million. At the same time, the extreme sensitivity analysis illustrates how much further the NEET levels could rise, if economic conditions deteriorated severely.

The findings therefore provide important context for future youth employment policy. They suggest a need both to address the structural factors that prevent young people from participating in education and employment, and to ensure that support for young people can respond to changes in economic and labour market conditions.

The analysis uses a forecasting model to examine how the NEET population could evolve under different economic conditions. The results should therefore be interpreted as conditional scenarios rather than predictions or estimates of causal effects. They show how the NEET population could vary if the economic conditions specified in each scenario were to materialise and the historical relationships captured by the model were to continue. The projections also assume no major changes to the policy environment. Nor do they estimate the impact of individual policies or other interventions on NEET levels.

# Projections to 2036

The forecasting model was used to explore how the size of the NEET population could evolve under different economic conditions. We developed three scenarios: a central scenario, based on the Office for Budget Responsibility's (OBR) central projection for GDP growth and the average of independent unemployment rate forecasts compiled by the OBR; an optimistic scenario, representing more favourable economic and labour market conditions; and a pessimistic scenario, representing less favourable conditions.

The scenarios are designed to represent plausible changes in the economic outlook rather than deliberately extreme outcomes. The optimistic and pessimistic scenarios use the OBR's alternative unemployment projections, alongside GDP growth assumptions set above and below the OBR's central projection. The model also incorporates vacancy levels in the retail and hospitality sectors, which account for a disproportionately large share of employment among young people and therefore provide an indicator of labour demand in particularly relevant sectors. Sector-specific vacancy levels are projected based on their historical relationship with unemployment.

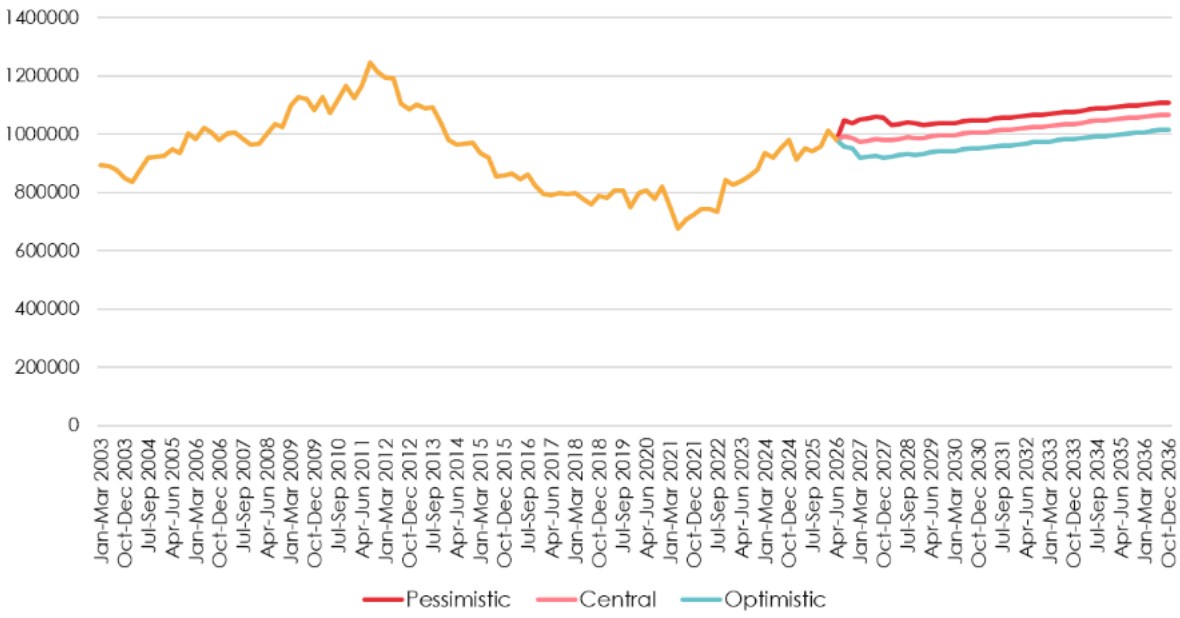
The projections are driven by two main elements. The first is the past pattern of the NEET series itself, including its tendency to change gradually over time and its regular seasonal pattern. The second is the economic and labour market conditions assumed in each scenario: GDP growth, unemployment and vacancies. The model also accounts for the effects of the COVID-19 pandemic and the raising of the education participation age to 18. Past patterns shape much of the level and direction of each projection, while the economic and labour market assumptions explain the differences between scenarios.

These factors are included because of how NEET levels have moved alongside them historically, and because they help the model forecast accurately. This does not mean they are the main drivers of young people being NEET. Other factors, such as health, education and the support available to young people, also play an important role but are not directly included in the model.

The resulting projections show how the NEET population could differ under these alternative economic conditions. Given the uncertainty associated with long-term projections, the estimates should be interpreted as illustrating the direction and broad scale of how NEET levels could vary under different economic conditions, rather than as precise estimates of the number of young people who could be affected.

**Figure 1: NEET projections are lower under a stronger economic scenario but remain high**

Projected number of people who are NEET under central, optimistic and pessimistic scenarios, seasonally adjusted, 2003 to 2036, ages 16-24, UK




Source: Labour Force Survey from the Office for National Statistics and outputs from Youth Futures Foundation SARIMAX modelling under different economic and labour market scenarios

Notes: See Section 13. Limitations and Appendix F for 95% confidence intervals around the central projection

Under the central scenario, the number of young people who are NEET is projected to be around 1.07 million by the end of 2036, compared with approximately 980,000 in April to June 2026. The projection is not uniform over the forecast period, but remains at a high level throughout.

The alternative economic scenarios produce a divergence in the projected NEET population. Under the optimistic scenario, stronger economic and labour market conditions are associated with a lower projected NEET population than under the central scenario. Under the pessimistic scenario, weaker conditions are associated with a higher projected NEET population.

By the end of 2036, the optimistic scenario projects around 1.01 million young people to be NEET, compared with approximately 1.07 million under the central scenario and 1.11 million under the pessimistic scenario. This represents around 53,000 fewer young people

under the optimistic scenario than the central projection, and around 42,000 more under the pessimistic scenario.

The difference between the optimistic and pessimistic scenarios is therefore around 95,000 young people by the end of 2036. While this is relatively modest compared with the overall projected size of the NEET population, it nevertheless represents a substantial number of young people.

The main scenarios show how the projected NEET population changes when the economic outlook is varied. Within the model, stronger GDP growth, lower unemployment and higher vacancies are associated with a lower projected NEET population, while weaker economic conditions are associated with a higher projected NEET population.

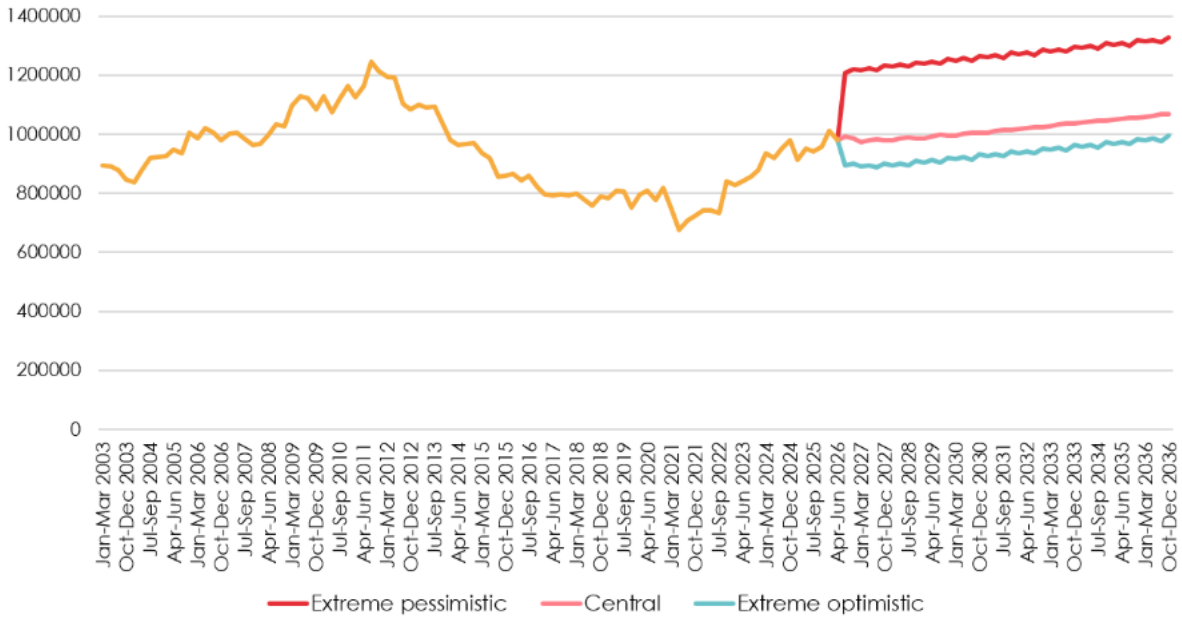
Of the economic and labour market assumptions, unemployment makes the largest contribution to the difference between the central and alternative scenarios, with smaller contributions from GDP growth and vacancies (see Appendix E). For example, in the optimistic scenario, the unemployment component accounts for around 46,000 of the 53,000 fewer NEET young people projected relative to the central scenario in 2036. These contributions describe how the model generates the difference between scenario projections and should not be interpreted as independent causal effects.

## Extreme sensitivity analysis

We also tested more extreme assumptions to assess how sensitive the projected NEET population is to large changes in economic conditions. These assumptions use the highest and lowest unemployment rates observed since 2003 — 8.6% in Q3 2011 and 3.7% in Q1 and Q2 2022 — alongside a ±1 percentage point shock to GDP growth relative to the central projection. Vacancy projections are again derived from the historical relationship between unemployment and vacancies.

**Figure 2: The NEET population could reach highest levels recorded under a severe economic shock**

Projected number of people who are NEET under extreme more-favourable and extreme less-favourable assumptions, seasonally adjusted, 2003 to 2036, ages 16-24, UK




Source: Labour Force Survey from the Office for National Statistics and outputs from Youth Futures Foundation SARIMAX modelling under different economic and labour market assumptions

The extreme assumptions produce a substantially wider range of modelled NEET outcomes. Under the extreme less-favourable assumptions, the projected NEET population reaches around 1.33 million by 2036, around 261,000 higher than under the central projection of 1.07 million. Under the extreme more-favourable assumptions, it sits at just under one million, approximately 74,000 fewer than the central projection.

This extreme sensitivity test illustrates the sensitivity of the NEET projections to large changes in economic conditions. The substantially larger increase under the extreme less-favourable assumptions highlights the potential scale of the NEET challenge under a severe deterioration in the wider economic and labour market environment.

Even under the extreme more-favourable assumptions, the projected NEET population remains substantially above the lowest levels recorded historically. Taken together, the extreme sensitivity analysis illustrates both the potential range of NEET outcomes under markedly different economic conditions and the persistence of a large projected NEET population even under the most favourable assumptions.

# Policy implications

The modelling points to three broad implications for youth employment policy.

**First, economic conditions are an important part of the context in which the NEET population evolves.** The main scenarios show that stronger economic and labour market conditions are associated with a lower projected NEET population, while weaker conditions are associated with a higher projected NEET population. This suggests that the scale and nature of support for young people may need to adapt to the wider economic environment. In periods of weaker labour market demand, this could include both measures to support young people to access and compete for available opportunities, and measures to increase the number of opportunities available to them. The balance between these approaches may need to reflect the conditions facing young people in the wider labour market.

**Second, the NEET challenge extends beyond the wider economic cycle.** Even under the optimistic scenario, around 1.01 million young people are projected to be NEET by the end of 2036. This indicates that the scale of the NEET challenge could remain substantial even under more favourable economic and labour market conditions, pointing to the importance of factors beyond the wider economic cycle. The modelling should therefore be considered alongside wider evidence on the factors affecting young people's participation in education and employment, including health, skills and education, access to employment opportunities and the effectiveness of employment support. These issues are explored in the interim report of the *Investigation into Young People and Work, led by Alan Milburn,* which highlights the range of structural factors contributing to young people's participation in education and work[1].

This is consistent with recent Resolution Foundation analysis, which finds that wider labour market conditions account for just over half of the rise in the 18–24 NEET rate since 2019, with the remainder corresponding closely to a rise in inactivity due to ill health or disability[2]. This helps explain why stronger economic conditions reduce the projected NEET population only modestly in the scenarios: the model's economic variables capture the cyclical component of NEET, but not health-related inactivity or other structural factors.

**Third, youth employment policy needs to be resilient to economic downturns.** The extreme sensitivity analysis illustrates that the modelled NEET population is substantially higher under the most adverse economic assumptions, reaching around 1.33 million by

[1] Young people and work: interim report - GOV.UK
[2] 28-lost-in-transition.pdf

2036. This highlights the potential value of maintaining sufficient capacity in youth employment support and being able to respond countercyclically - increasing support when economic conditions weaken and the need for support rises.

# Interpreting the projections

The scenarios show how the NEET population could evolve conditional on the specified economic conditions specified in each scenario and the historical relationships captured by the model continuing to hold. The model assumes no major changes in the underlying policy environment or other factors affecting young people's participation in education and employment over the projection period.

The model does not estimate the causal impact of individual youth employment policies or other interventions on NEET levels. Policies and programmes that have affected NEET outcomes during the historical period may be indirectly reflected in the model through the historical relationships on which the projections are based, but their individual contributions cannot be separately identified. Similarly, any effects of recently introduced policies are reflected in the projections only to the extent that they are already visible in the latest NEET data.

The model is therefore best viewed as a scenario and planning tool. It provides an indication of how the scale of the NEET population could vary under different economic circumstances and can provide a baseline for policy analysis, including by allowing separately estimated policy impacts to be considered alongside different economic scenarios.

# Technical documentation

The following section sets out the technical details of the modelling work underpinning the NEET projections, including a detailed description of the modelling approach, data, assumptions, scenario construction and validation processes used. It assumes some familiarity with economics, forecasting and statistical modelling techniques. While the preceding sections have aimed to present the underlying assumptions of the work clearly and in an accessible manner, this section is provided in the interests of methodological transparency and to help readers understand the scope, capabilities and limitations of the model.

## 1. Model overview

The projections are produced using a Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX) model. The model uses historical patterns in the ONS's quarterly NEET series alongside information on wider economic and labour-market conditions to project the future number of young people aged 16–24 who are not in education, employment or training.

The model takes three main types of inputs:

- Historical NEET levels, which allow the model to capture persistence and seasonal patterns in NEET;
- Explanatory variables, including real GDP growth, the UK unemployment rate, vacancy levels and selected structural indicators, which capture relationships between economic and labour-market conditions and NEET; and
- Future economic assumptions, supplied externally to the model, which determine the economic conditions under each scenario.

The model does not independently forecast the future values of these economic inputs. Instead, future GDP growth, unemployment and vacancy levels are specified as part of the economic scenarios and supplied to the fixed NEET model. The resulting NEET projections are therefore conditional projections: they show how the NEET population could evolve given the economic conditions assumed under each scenario. They should not be interpreted as unconditional forecasts of what will happen in the future, since different economic conditions would result in different NEET projections.

The SARIMAX approach is well suited for this exercise for several reasons. First, it captures the persistent nature of NEET levels, whereby the current value of a series is related to its past values. Second, it models seasonality explicitly, which is important given the cyclical nature of young people's participation in education and employment. Third, it allows observable external events, shocks and structural changes to be represented through exogenous variables where appropriate, which simpler time series models (e.g., linear extrapolation) cannot accommodate. Finally, compared to machine learning approaches such as neural networks or ensemble methods, SARIMAX requires fewer data points and is more interpretable.

The model captures historical relationships between NEET and economic and labour market conditions, as well as persistence in NEET levels. However, it does not explicitly model all of the factors that influence whether young people are in education, employment or training. In particular, structural factors such as health, education participation and other barriers to employment may affect NEET levels but are not separately projected by the model.

The projections should therefore be interpreted as estimates of how NEET could evolve under different economic conditions, rather than precise predictions of future NEET levels. Uncertainty also increases further into the projection period, and the results depend on the assumptions used to construct the economic pathways.

The modelling process comprised four main stages:

1. identification and preparation of candidate explanatory variables;
2. automated selection of the ARIMA and regression specification;
3. validation and diagnostic testing of the preferred model; and
4. production of conditional forecasts under economic scenarios.

The remainder of this technical documentation describes these stages in detail, including the data used, model specification and selection, validation and diagnostics, construction of the economic scenarios, and the limitations of the resulting projections.

## 2. Data and candidate explanatory variables

The dependent variable is the estimated number of young people aged 16–24 who are NEET in each quarter.

Candidate explanatory variables were selected based on economic theory and data availability, including whether reliable historical data were available over the period required for model estimation and whether suitable projections were available over the forecast period. Real GDP growth and the UK unemployment rate were included in every candidate specification because of their relevance to aggregate economic and labour market conditions.

Additional candidate variables comprised:

- youth population levels;
- Adult disability rate;
- Vacancy (hospitality and retail) levels;
- a COVID-19 Stringency Index;
- a Global Financial Crisis indicator; and
- indicators for changes to the Education Participation Age.

Further details of the variables included in the process are provided in Appendix A.

## 3. Treatment of stationarity and structural breaks

Stationarity diagnostics and structural break tests were considered alongside economic theory when defining the candidate model specifications. Stationarity is an important assumption in ARIMA modelling, as non-stationary series can result in unreliable statistical relationships and forecasts if not appropriately treated.

Pre-modelling tests indicated that youth population, vacancies and disability may be non-stationary, or gave mixed results (see Appendix B). However, unit-root tests can have limited power in relatively short macroeconomic time series and can be affected by structural breaks. Differencing was therefore not imposed solely on the basis of these tests.

Instead, these variables were allowed to enter the model either in levels or in first-differenced form, but not both simultaneously. This allowed the model selection procedure to determine whether longer-run levels or shorter-run changes provided greater predictive value, while avoiding unnecessary differencing. Second differences were not considered, even where the tests suggested them, because higher-order

differencing can remove long-run information and amplify short-term variation unless there is strong evidence that it is required.

Structural break indicators were similarly treated as candidate regressors rather than being imposed in every model, allowing the model selection procedure to determine whether including each one improved the overall specification.

Further details of the stationarity and structural break tests are provided in Appendix B.

# 4. Automated model selection

## 4.1 Model specification

Regression models incorporating ARIMA processes and exogenous explanatory variables (ARIMAX models) were estimated for all admissible combinations of candidate explanatory variables.

For each regression specification, the ARIMA error process was selected using the auto.arima() function from the forecast R package. The procedure considered both seasonal and non-seasonal autoregressive and moving-average terms, with differencing determined using the ndiffs() and nsdiffs() procedures where appropriate.

An exhaustive search was used (stepwise = FALSE) so that all admissible ARIMA specifications within the defined search limits were evaluated. The ARIMA parameters were selected using the corrected Akaike Information Criterion (AICc).

To reduce the risk of overfitting given the relatively short quarterly time series and to maintain computational tractability, the search was restricted to:

- non-seasonal AR and MA orders of up to 3; and
- seasonal AR and MA orders of up to 1.

These restrictions allowed a broad range of relatively parsimonious quarterly ARIMA specifications to be considered without allowing unnecessarily complex error structures.

## 4.2 Initial model screening

Candidate models were screened before computationally intensive out-of-sample validation.

Models were retained for further consideration where they met the following criteria:

1. no strong evidence of residual autocorrelation, Ljung-Box p-value of at least 0.01 at lag 8;
2. economically plausible coefficient signs, with GDP growth negatively associated with NEET and unemployment positively associated with NEET;
3. minimum coefficient precision for GDP growth and unemployment, defined as an absolute t-statistic of at least 1.5; and
4. no evidence of severe multicollinearity, with variance inflation factors below 5.

The Ljung-Box threshold was used as a screening criterion rather than as a definitive test of model adequacy. The relatively conservative threshold was intended to exclude specifications showing strong evidence of residual autocorrelation while avoiding the exclusion of potentially useful forecasting models because of minor departures from white-noise residuals.

The coefficient sign and t-statistic criteria were also used as model-selection rules rather than conventional tests of causality or statistical significance.

## 4.3 Rolling-origin out-of-sample validation

The remaining candidate models were evaluated using rolling-origin time-series cross-validation.

Rather than relying on a single hold-out period, models were repeatedly re-estimated using an expanding historical training window historical data ending at six forecast origins:

- 2016 Q1;
- 2017 Q1;
- 2018 Q1;
- 2019 Q1;
- 2023 Q1; and
- 2024 Q1.

At each forecast origin, the model was estimated using all observations available up to and including that quarter, and an eight-quarter-ahead forecast was generated for the subsequent eight quarters. For example, the model estimated at the 2016 Q1 origin used

data through 2016 Q1 and was evaluated against outcomes from 2016 Q2 to 2018 Q1; the model estimated at the 2024 Q1 origin used data through 2024 Q1 and was evaluated against outcomes from 2024 Q2 to 2026 Q1.

Forecast accuracy was assessed using the Mean Absolute Percentage Error (MAPE). The cross-validation MAPE was calculated as the mean MAPE across the available forecast origins, providing an assessment of forecasting performance across multiple historical periods rather than relying on a single train-test split.

During rolling-origin validation, explanatory variables with no variation within a particular training window were excluded from that estimation window because their coefficients cannot be identified. For example, dummy variables that had a value of zero during the training window were excluded. The full specification was retained when estimating the preferred model using the complete historical sample.

## 4.4 Selection of the preferred model

To avoid selecting an unnecessarily complex model where predictive performance was effectively equivalent, models with a cross-validation MAPE within 5% of the best-performing specification were retained for further consideration. These models were then ranked according to four criteria, applied sequentially:

1. Number of explanatory variables – to favour more parsimonious specifications;
2. ARIMA model complexity – to favour simpler error structures where explanatory-variable complexity was equivalent;
3. Bayesian Information Criterion (BIC) – to favour models providing a better balance between model fit and complexity; and
4. Cross-validation MAPE – to distinguish between models where the preceding criteria were otherwise identical.

This approach prioritised parsimonious specifications where forecasting performance was sufficiently similar, while retaining models that satisfied the predefined statistical and economic plausibility criteria.

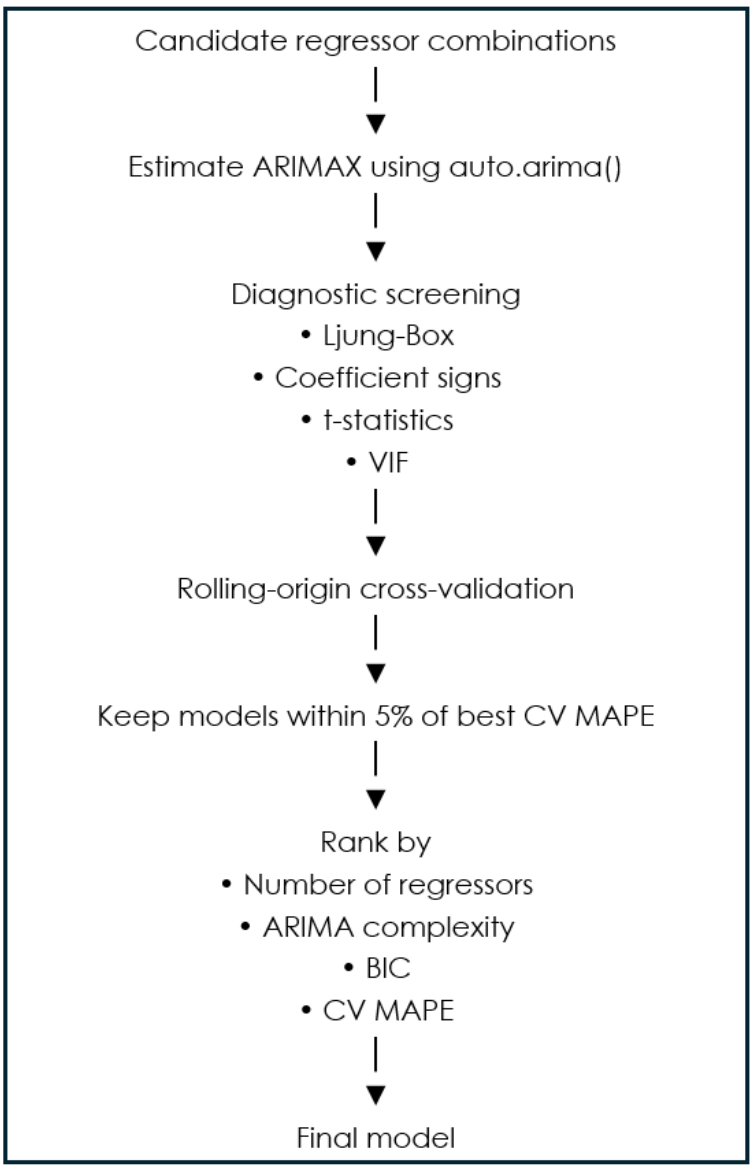
The preferred model was a regression with ARIMA errors with an ARIMA(0,1,1)(0,1,1)[4] error structure and five explanatory variables:

- real GDP growth;
- unemployment rate;
- vacancies;

- COVID-19 Stringency Index; and
- EPA18 indicator.

The model was estimated using the historical data available up to Q1 2026.

**Figure 3: Diagram of the automated model selection procedure**



# 5. Final model diagnostics

Following model selection, the preferred specification was re-estimated using the full historical sample and subjected to a further set of diagnostic checks.

These included:

- residual plots;
- residual ACF and PACF;
- Ljung-Box tests at lags 8, 12, 16 and 20;
- a Shapiro-Wilk test and Q-Q plot for residual normality; and
- an ARCH test for conditional heteroskedasticity.

The final model showed no evidence of residual autocorrelation. Ljung-Box p-values were 0.218, 0.367, 0.586 and 0.626 at lags 8, 12, 16 and 20 respectively.

The Shapiro-Wilk test returned a p-value of 0.248, providing no statistically significant evidence against normality. The ARCH test with four lags returned a p-value of 0.600, providing no evidence of conditional heteroskedasticity.

These diagnostics do not demonstrate that the model is a correct representation of the underlying data-generating process. Rather, they indicate that there was no strong evidence of the specific residual problems assessed by these tests.

# 6. Conditional out-of-sample performance of the final model

The final specification was evaluated using the same rolling-origin cross-validation procedure used during model selection.

The model successfully generated eight-quarter-ahead forecasts at all six forecast origins. The resulting mean out-of-sample MAPE was 3.73%.

This evaluation is conditional on the actual future values of the exogenous explanatory variables being available when generating each historical forecast. It therefore assesses the forecasting performance of the NEET model given the economic conditions that

subsequently occurred, rather than evaluating the accuracy of a complete forecasting system in which GDP, unemployment and vacancies would also need to be forecast.

The 3.73% MAPE should therefore not be interpreted as an estimate of the expected error of the final NEET projections. Actual future forecast errors will also depend on how closely the economic scenario assumptions correspond to the economic conditions that occur in practice.

Historical forecasting performance nevertheless provides useful evidence on the model's ability to translate economic conditions and historical NEET patterns into NEET forecasts. However, this performance is not a guarantee of equivalent accuracy over the future projection period, particularly where future economic conditions or relationships differ from those observed historically.

Further details of the final model coefficients and diagnostics are provided in Appendix C.

## 7. Construction of economic scenarios

The NEET model uses externally specified projections for three key economic and labour-market variables:

- real GDP growth;
- the unemployment rate; and
- sector-specific vacancy levels.

These variables capture different aspects of the economic environment that may affect NEET levels. GDP growth provides an indicator of overall economic conditions, while unemployment and vacancies provide information about conditions in the labour market. The scenarios vary these inputs around a central projection to examine how NEET levels could differ under relatively more and less favourable economic and labour-market conditions.

The central scenario provides the main projection, while optimistic and pessimistic scenarios combine assumptions in directionally consistent ways: stronger GDP growth with lower unemployment and higher vacancies in the optimistic scenario, and weaker GDP growth with higher unemployment and lower vacancies in the pessimistic scenario. Vacancy levels are subsequently derived from the unemployment pathways using their historical relationship, rather than being specified as independent assumptions.

This provides a structured sensitivity analysis of the NEET projections. The scenarios are intended to represent plausible alternative assumptions about future economic and labour-market conditions, rather than independent forecasts of the economy or estimates of the probability of particular outcomes. They therefore illustrate how the projected NEET population could vary if economic conditions are more or less favourable than assumed in the central scenario.

The GDP and unemployment pathways are constructed separately using different external projections and assumptions, rather than being jointly generated by a single macroeconomic model. Their timing and magnitude may therefore differ from those that would arise in a fully specified macroeconomic forecast. This does not affect their use as structured sensitivity assumptions for the NEET model, whose purpose is to examine the implications of relatively more and less favourable economic conditions rather than to forecast the joint evolution of the wider economy.

## 7.1 Real GDP growth

The central real GDP growth projection was taken from the Office for Budget Responsibility's *Long-term economic determinants*, published on 28 March 2026 as part of the 2026 *Economic and Fiscal Outlook*[3]. The OBR's long-term projections reflect the assumption that, once temporary output-gap effects have dissipated, economic growth becomes increasingly determined by the economy's underlying potential growth rate.

The high-growth and low-growth scenarios were constructed in-house as deviations from the OBR central projection. The high-growth scenario starts 0.45 percentage points above the central projection, while the low-growth scenario starts 0.65 percentage points below it. The asymmetric range is consistent with the approach taken by the OBR in its March 2026 Economic and Fiscal Outlook, which uses a larger near-term GDP deviation in its cyclical downside scenario than in its cyclical upside scenario. The values used here are nevertheless modelling choices for this analysis, intended to provide a meaningful differentiation in economic conditions, while avoiding a departure from the central projection that would be implausibly large for a sensitivity analysis of this type.

The deviations from the central projection then reduce by 0.02 percentage points per year, so that the alternative paths gradually converge towards the central projection. This allows the scenarios to represent differences in economic conditions that are larger over the near term but diminish over the longer term, rather than assuming a permanent

[3] Office for Budget Responsibility. (2026, March). Long-term economic determinants [Supporting document to the Economic and fiscal outlook]. https://obr.uk/download/long-term-economic-determinants-march-2026-economic-and-fiscal-outlook/.

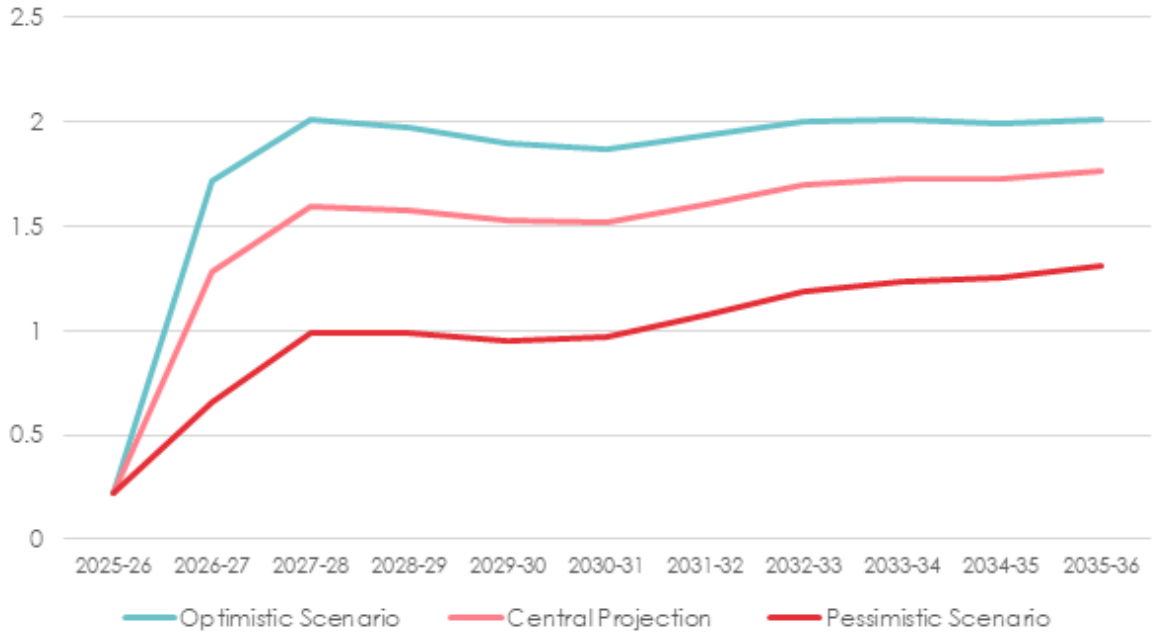
change in the economy's underlying long-run growth rate. The central projection itself remains unchanged.

The resulting scenarios are therefore:

- Central scenario: follows the OBR central projection.
- High-growth scenario: real GDP growth is initially stronger than the OBR central projection, with the difference gradually narrowing over time.
- Low-growth scenario: real GDP growth is initially weaker than the OBR central projection, with a larger initial deviation that gradually narrows over time.

None of the scenarios are intended to represent a permanent change in the long-run growth rate or to assign a probability to a particular economic outcome. The starting gaps and rate of convergence are modelling assumptions rather than estimates of the probability or expected magnitude of particular economic shocks. They are intended to provide a sufficiently differentiated range of economic conditions for assessing the sensitivity of the NEET projections.

**Figure 4: Wider pessimistic than optimistic GDP growth rate scenarios**
Trends in real GDP growth rate projections under "Optimistic", "Central" and "Pessimistic" scenarios, 2026-2036, UK



Source: Annual central real GDP growth rate projections from the Office for Budget Responsibility (2026). Optimistic and pessimistic scenarios calculated by Youth Futures Foundation drawing on economic theory.

Note: *The projections from OBR, along with alternative scenarios were converted into non-seasonally adjusted quarterly projections by Youth Futures Foundation to use as input data for the SARIMAX model of NEET levels.*

## 7.2 Unemployment

The unemployment scenarios are based on the OBR's *Economic and Fiscal Outlook 2026* and associated labour-market projections[4]. The central unemployment projection uses an average of external forecasts compiled by the OBR for the available projection period (See Table D, Appendix D). From 2031 onwards, the unemployment rate is held constant at its 2031 value to provide a stable long-run continuation of the available projection.

The alternative unemployment pathways use the OBR's projected cyclical and structural unemployment rates to represent relatively more and less favourable labour-market conditions (See Appendix D: Figure D1). The optimistic scenario uses the OBR's cyclical unemployment projection for 2026–2030, which reflects a relatively favourable labour-market environment with lower unemployment. The pessimistic scenario uses the OBR's structural unemployment projection, which results in higher unemployment over this period. Both pathways are held constant at their 2030 value from 2031 onwards.

The OBR's central unemployment forecast is designed to be consistent with its central GDP forecast and converges towards its long-run unemployment rate. We instead use the external average as the central assumption because this provides greater differentiation between the three unemployment pathways over the projection period. In particular, using the OBR central unemployment forecast alongside the cyclical and structural pathways would result in the pathways becoming increasingly similar over time. The external average provides an externally sourced central assumption while retaining a clearer distinction between the alternative labour-market conditions.

The resulting scenarios are therefore:

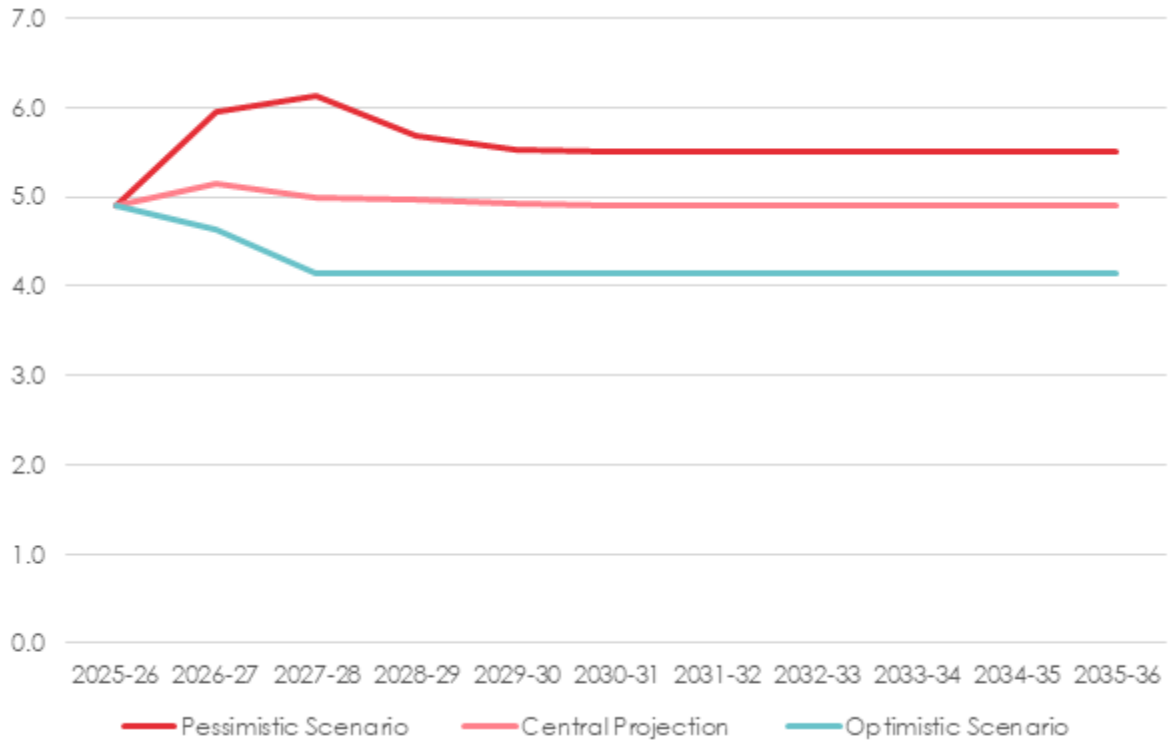
- Central scenario: uses the OBR external average for unemployment over the available projection period.

[4] Economic and fiscal outlook – March 2026 - Office for Budget Responsibility

- Optimistic scenario: uses the OBR cyclical unemployment projection, representing lower unemployment and relatively more favourable labour-market conditions.
- Pessimistic scenario: uses the OBR structural unemployment projection, representing higher unemployment and relatively less favourable labour-market conditions.

**Figure 5: Cyclical upside as optimistic, structural unemployment rate as pessimistic and external average as central unemployment rate**

Trends in Unemployment rate projections under "Optimistic", "Central" and "Pessimistic" scenarios, 2026-2036, UK




Source: Annual central unemployment rate projections from the Office for Budget Responsibility (2026)'s "external average", Table D, Appendix D. Optimistic and pessimistic scenarios taken by the cyclical and structural unemployment rate projections by the OBR. Note: 2025 Unemployment rate is not a projection and is actual data from the Office for National Statistics. *The projections from OBR, along with alternative scenarios were converted into non-seasonally adjusted quarterly projections by Youth Futures Foundation to use as input data for the SARIMAX model of NEET levels.*

The unemployment pathways are not intended to represent alternative forecasts generated from a single internally consistent macroeconomic model. Rather, they provide externally grounded assumptions for examining how the projected NEET

population changes under different labour-market conditions. The use of the structural unemployment projection in the pessimistic scenario should similarly be interpreted as an assumption of persistently higher unemployment, rather than a forecast of a structural change in the relationship between unemployment and NEET levels.

Holding unemployment constant beyond the available external projection period is a pragmatic extrapolation assumption and should not be interpreted as a claim that unemployment would remain unchanged in practice.

## 7.3 Conversion of annual projections to quarterly non-seasonally adjusted series

Annual seasonally adjusted projections for unemployment rate and GDP as explained above, were disaggregated into quarterly non-seasonally adjusted projections using average historical quarter-specific deviations.

The GDP growth and unemployment rate projections used in the scenario analysis are available on an annual, seasonally adjusted basis. However, the NEET SARIMAX model is estimated at a quarterly frequency and uses non-seasonally adjusted quarterly series for its exogenous variables. The annual projections were therefore converted into quarterly NSA projections before being supplied to the model.

The conversion follows a seasonal-deviation approach. Historical quarterly NSA observations were first assembled for each variable. The COVID-19 period, 2020 and 2021, was excluded from the calculation of seasonal patterns because the exceptional disruption to economic activity and labour-market conditions during these years could distort the underlying within-year seasonal relationship.

For each year $y$, the annual average of the four quarterly NSA observations was calculated.

The seasonal deviation for each observation was then calculated as:

$$D_{y,q} = X_{y,q} - \bar{X}_y$$

The average seasonal deviation for each quarter was obtained by averaging the deviations for that quarter across the historical estimation period up to Q1 2026:

$$\bar{D}_q = \frac{1}{N_q} \sum_y D_{y,q}$$

where $\bar{D}_q$ is the average deviation for quarter $q$, and $N_q$ is the number of eligible observations for that quarter.

The annual seasonally adjusted forecast was then converted into a quarterly NSA forecast by adding the relevant historical average seasonal deviation:

$$\hat{X}_{y,q}^{NSA} = \hat{X}_{y}^{SA} + \bar{D}_q$$

Thus, the same annual forecast is distributed across the four quarters according to the typical historical seasonal pattern. These adjustments preserve the annual forecast approximately because the quarterly deviations are centred around zero. In other words, the quarterly series fluctuates around the annual projection without introducing an additional change in the underlying annual level.

## 7.4 Deriving vacancy projections

Vacancy level projections were derived from the historical relationship between unemployment and vacancies, commonly referred to as the Beveridge curve.

A log-linear distributed lag (ARDL) model was estimated using historical observations, excluding Q1 2020 to Q4 2022 because of the exceptional disruption associated with the COVID-19 pandemic. The model relates the log of vacancies to the previous quarter's log vacancy level and the current unemployment rate. This allows vacancy levels to adjust gradually in response to changes in unemployment, rather than moving immediately to the level implied by the historical unemployment–vacancy relationship.

The estimated model was then used to generate vacancy projections under each unemployment scenario. Forecasts were generated recursively, with the projected vacancy level in each quarter used as the lagged vacancy input for the following quarter.

This ensures that the scenarios are internally consistent: lower unemployment is associated with higher vacancies, while higher unemployment is associated with lower vacancies. The autoregressive component also allows the vacancy projections to transition smoothly from the latest observed vacancy level into the forecast period.

An important implication is that unemployment and vacancies should not be interpreted as independent scenario shocks. This is particularly relevant when interpreting the scenario decomposition, since part of the apparent vacancy contribution arises from the way vacancy assumptions are derived from unemployment.

Further details of the vacancy projections calculation are provided in Appendix D.

## 8. Producing the NEET scenario projections

For each scenario, the relevant future GDP growth, unemployment and vacancy projections were supplied to the fixed SARIMAX specification.

The model parameters were not re-estimated for each scenario. Instead, the same estimated model was used throughout, with only the future exogenous inputs varied between scenarios.

This means that differences between the scenario forecasts arise from the different assumed economic pathways rather than from differences in the estimated model itself.

The scenario forecasts should therefore be interpreted as conditional projections: they show how NEET levels differ within the model when the assumed future economic conditions are changed.

## 9. Seasonal adjustment of NEET forecasts

The SARIMAX model initially produces NEET forecasts on a non-seasonally adjusted basis.

Seasonal adjustment was subsequently applied to the central, optimistic and pessimistic forecasts using seasonal factors estimated from the historical and forecasted NEET series using X-13ARIMA-SEATS.

Seasonal factors were estimated from the central scenario series, comprising historical data and the central forecast, and the same factors were applied to all scenarios, including the extreme scenarios. Because the adjustment is additive, the difference between any two scenarios is identical on a seasonally adjusted and non-seasonally adjusted basis. This ensures that differences between scenarios reflect the underlying economic assumptions rather than the seasonal adjustment procedure.

## 10. Scenario decomposition

A decomposition was undertaken to examine how differences in the modelled economic inputs contribute to the difference between each alternative scenario and the central projection.

The decomposition is an attribution of the difference between the modelled scenario projections. The size of each contribution reflects both the relationship estimated by the model and the size and timing of the difference between the relevant economic input

under the alternative and central scenarios. It should therefore not be interpreted as a measure of the relative elasticity or inherent importance of each explanatory variable. The decomposition is not an estimate of the independent causal effect of each explanatory variable. This distinction is particularly important for vacancies because future vacancy levels are derived from unemployment through the Beveridge curve relationship. The unemployment and vacancy contributions therefore cannot be interpreted as independent economic effects.

The decomposition is consequently most useful for understanding how the model generates differences between scenarios and which changes in the scenario inputs contribute most to those differences.

Further details of the scenario decomposition are provided in Appendix E.

## 11. Extreme sensitivity analysis

A separate set of projections were developed to examine the sensitivity of the model to substantially more adverse and favourable economic conditions than those used in the main scenarios.

The extreme assumptions use the highest and lowest unemployment rates observed since 2003 - 8.6% in Q3 2011 and 3.7% in Q1 and Q2 2022 respectively - and are held constant throughout the projection period. A ±1 percentage point shock is applied to GDP growth relative to the central GDP path. Vacancy projections are derived from the historical relationship between unemployment and vacancies.

These assumptions are deliberately more extreme than those used in the principal scenarios. Although the unemployment levels are based on historical observations, holding these rates constant throughout the projection period is a constructed sensitivity assumption rather than a representation of a historical episode.

The extreme sensitivity analysis is not intended to represent likely future outcomes. Its purpose is to illustrate the range of NEET outcomes generated by the model under substantially different economic conditions and to assess the sensitivity of the projections to larger changes in the economic environment.

The results should therefore be interpreted as sensitivity analysis rather than as forecasts or probability estimates.

# 12. Limitations

Several limitations should be considered when interpreting the projections. These relate to the underlying data, the structure of the model, the selection of the final specification, the scenario assumptions, and the overall uncertainty surrounding the results.

**Underlying data uncertainty.** The historical NEET series is derived from the Labour Force Survey and is therefore subject to sampling variation, measurement error and revisions. These sources of uncertainty also affect the most recent observations, which form the starting point for the projections, and are not explicitly incorporated into the results.

**Dependence on historical relationships.** The model assumes that relationships estimated from the historical data remain informative over the projection period. Structural changes in the economy, the labour market or the relationship between economic conditions and youth participation could reduce the accuracy of the projections, particularly towards the end of the projection period.

**Cyclical and structural drivers of NEET.** The model is primarily designed to capture cyclical variation in NEET associated with changes in economic and labour market conditions. While it captures historical persistence in the NEET series, it does not explicitly model the structural factors that may influence participation over the longer term, such as young people's health, education participation, household circumstances and the support available to them. These factors are reflected in the projections only to the extent that they are captured indirectly through historical patterns in the data.

This is particularly relevant to the increase in NEET since 2019. Recent analysis by the Resolution Foundation suggests that much of the post-2019 increase not explained by wider labour market conditions corresponds to a rise in inactivity due to ill health or disability. The adult disability rate was tested as a candidate explanatory variable but was not retained in the final specification; a youth-specific health measure, with suitable projections, may better capture this channel and could be considered in future iterations. The projections should therefore not be interpreted as implying that improvements in economic conditions alone would reverse the recent increase in NEET.

**Population changes.** Youth population was considered as a candidate explanatory variable but was not retained in the final specification. Projected changes in the size of the 16–24 population therefore do not directly affect the projections, other than to the extent that past demographic trends are reflected in the historical NEET series.

**Model specification and validation.** The preferred model was selected from a large set of candidate specifications using predefined statistical, economic and forecasting-performance criteria. Other plausible specifications could produce different projections, and this model-selection uncertainty is not incorporated into the results. Although rolling-origin out-of-sample validation was used to reduce the risk of selecting a model that fits the historical data by chance, the number and length of the validation periods are limited, so measured forecasting performance may partly reflect patterns specific to those periods.

**External economic projections and scenario assumptions.** The scenarios depend on external economic projections and on additional assumptions used to convert them into quarterly series and extend them over the full projection horizon, including holding unemployment constant beyond the available projection period. Different assumptions about the future economic environment would produce different NEET projections.

**Consistency of economic scenario pathways.** Because the GDP and unemployment pathways are constructed separately, their timing and magnitude may not be fully consistent with one another. Future iterations could use a more integrated framework, such as the OBR's cyclical upside and downside scenarios with their implied GDP paths where available, an Okun's Law relationship, or a simple vector autoregression (VAR), to ensure greater consistency between the GDP and unemployment assumptions across scenarios.

**Extreme sensitivity analysis assumptions.** The extreme sensitivity analysis applies symmetric ±1 percentage point shocks to GDP growth relative to the central path, while unemployment is fixed at its historical maximum or minimum. In practice, severe downturns may involve larger deviations in GDP than equivalent upturns, so the extreme less-favourable assumptions may not capture the full range of outcomes associated with a more severe deterioration. The results should be interpreted as sensitivity tests based on the specified assumptions, rather than as an exhaustive assessment of the effects of a severe economic shock.

**Uncertainty around the projections.** The scenario projections are point estimates. The differences between them reflect alternative assumptions about future economic conditions and should not be interpreted as a measure of forecast uncertainty.

Statistical prediction intervals for the central projection are presented in Appendix F. These capture uncertainty associated with the estimated model, conditional on the specified values of the explanatory variables, but do not incorporate uncertainty in the GDP, unemployment and vacancy projections or in the choice of model specification. Even so, they widen considerably over the projection period: by Q4 2036, the central

non-seasonally adjusted projection of 1.06 million has a 95% prediction interval of 569,000 to 1.5 million, a range of nearly one million (Table F2, Appendix F).

The scenarios are instead intended to show how NEET could evolve under different economic conditions, conditional on the historical relationships captured by the model. Future iterations could complement the forecasting framework with modelling of key structural drivers, particularly those associated with economic inactivity, to better understand how these factors may affect the longer-term trajectory of NEET.

**Population changes.** The model does not explicitly include projected changes in the size of the 16–24 population as a driver of the NEET forecast. Youth population was considered as a candidate explanatory variable during model selection but was not included in the final specification, as it did not improve the model sufficiently relative to alternative specifications. The projected change in the NEET population should therefore not be interpreted as being driven by demographic change alone.

# Appendices

## Appendix A: Data and variable definitions

This appendix provides further detail on the data used in the forecasting model, including the definition, source, frequency and treatment of each variable

***Table A1: Variables included in the modelling process***

| S.No | Variable | Description | Reason for inclusion | Source | Transformations required | Treatment in model |
|---|---|---|---|---|---|---|
| 1. | NEET population (NSA) | Number of people aged 16–24 who are not in education, employment or training | Dependent variable | ONS | N/A | Dependent variable |
| 2. | Real GDP growth (NSA) | Quarterly real GDP growth | Real GDP growth is a key indicator of overall economic performance and labour demand. Periods of stronger growth are typically associated with job | IMF | GDP levels were converted into rates | Included in all candidate models |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | creation and better labour market opportunities for young people, while recessions or slowdowns often coincide with rising unemployment and inactivity among this group. | | | |
| 3. | Unemployment rate (NSA) | Unemployment rate (aged 16+). The share of adults who are out of work and actively seeking employment | Although it is not youth specific, movements in general unemployment often signal broader labour market pressures that also affect young people's opportunities to enter | ONS | N/A | Included in all candidate models |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | or remain in work. | | | |
| 4. | Youth population (NSA) | Population aged 16–24 | i) The size of the youth population directly affects the number of young people who could potentially be NEET.<br><br>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. | ONS | N/A | Candidate explanatory variable; not included in the final model |

| | | | | | | |
|---|---|---|---|---|---|---|
| 5. | Disability rate | Proportion of adults reporting a disability | To capture health-related labour market pressures.<br><br>In the absence of this variable, the model could ignore a major driver of recent inactivity trends and could attribute the post-2020 rise to other factors or simply extrapolate from recent data without accounting for the underlying health-driven component. | LFS micro-data | N/A | Candidate explanatory variable; not included in the final model |

| | | | | | | |
|---|---|---|---|---|---|---|
| 6. | Vacancies (NSA) | Monthly hospitality and retail vacancies (NSA) | Proxy for youth labour demand, which is especially important to understand unemployment trends post-COVID.<br><br>Hospitality and retail have the highest concentration of jobs occupied by young people and are more relevant to the NEET population due to low entry requirements. | ONS | Quarterly estimates were calculated by taking a 3-month average | Candidate explanatory variable; included in the final model |
| 7. | COVID-19 Stringency Index | Indicator capturing restrictions associated | The COVID-19 stringency index | University of Oxford | Quarter values were calculated from | Candidate structural-break variable; |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | with the COVID-19 pandemic | captures the intensity of governme nt restrictions that directly affected the labour market, such as lockdowns and business closures. Including it helps the model separate pandemic-related shocks from underlying unemploy ment trends, improving both interpretati on and forecast accuracy. | | averaging daily values | included in the final model |
| 8. | Global Financial Crisis indicator | Indicator for the Global Financial Crisis period | The Great Financial Crisis created an exception | Q2 2008 to Q2 2009 | N/A | Candidate structural-break variable; not |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | al labour market shock beyond what GDP growth captures, with hiring freezes, credit constraints, and structural disruptions amplifying unemployment. Including a crisis dummy helps isolate this extraordinary effect and prevents it from being misattributed to normal GDP–unemployment dynamics. | equal 1;<br><br>0 otherwise | | included in the final model |
| 9. | EPA indicators | Indicators capturing changes to the Education | The policy change (raising the minimum education | i) Q3 2013 to Q2 2015 | Lagged t-1 due to school term start dates | Candidate structural-break variables; EPA17 ; not |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | Participation Age<br><br>I) from 16 to 17 dummy<br><br>ii) from 17 to 18 dummy | participation age) created a structural shift in the youth labour market by delaying young people's entry into employment or unemployment.<br><br>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 | equal 1;<br><br>0 otherwise<br><br>ii) Q3 2015 onwards equal 1;<br><br>0 otherwise | | included in the final model; EPA18 included in the final model |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | cyclical or trend-based. | | | |

# Appendix B: Modelling diagnostics and assumptions

## B1. Structural break diagnostics for the NEET series

***Table B1: Structural break tests for the historical NEET series***

| Test | Statistic / result | Interpretation |
|---|---|---|
| SupF test | 64.90 | Strong evidence against parameter stability |
| SupF p-value | <0.001 | Rejects the null hypothesis of parameter stability |
| Bai-Perron optimal specification | 4 breaks | Four-break specification selected using BIC |

***Table B2: Estimated structural break dates***

| Break | Quarter | Treatment in modelling |
|---|---|---|
| 1 | 2008 Q2 | Global Financial Crisis indicator considered |
| 2 | 2013 Q3 | Education Participation Age-related indicator considered |
| 3 | 2016 Q4 | No intervention variable introduced |

| | | |
|---|---|---|
| 4 | 2022 Q2 | COVID-19 indicator considered |

The Bai-Perron procedure identified four estimated breakpoints. Where these corresponded to identifiable economic or policy events, intervention variables were included as candidate regressors in the automated model selection process. The 2016 Q4 breakpoint was not associated with a sufficiently clear intervention and was not represented by a separate indicator.

The stationarity diagnostics informed the candidate specifications but were not applied mechanically. Level and first-differenced versions of youth population, vacancies and disability were therefore evaluated during model selection, while GDP growth was retained in levels. Unemployment was retained in levels because it is a principal economic scenario variable and modelling its first difference would change the interpretation of the scenario assumptions. Second differences were not considered as candidate regressors.

## B2. Transformation and stationarity diagnostics

***Table B3:* Summary of time series diagnostics and modelling decisions for explanatory variables**

| Variable | Variable type | Box-Cox λ | Transformation | Level (0 differences) | First difference | Second difference | Initial recommendation | Final modelling approach |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth | Rate (%) | N/A | None | ADF: 0.010KPSS: 0.100Stationary | Stationary | Stationary | Retain in levels | Included as a required regressor in all candidate models. |
| Youth population | Count | 2.000 | None | ADF: 0.484 KPSS: 0.057 Diagnostics required | ADF: 0.852 KPSS: 0.026 Needs differencing | ADF: 0.010 KPSS: 0.100 Stationary | Second difference | Both the level and first-differenced versions were included as candidate regressors during automated model selection. |
| Vacancies | Count | 0.882 | None | ADF: 0.010 KPSS: 0.038 Diagnostics required | ADF: 0.010 KPSS: 0.100 Stationary | Stationary | First difference | Both the level and first-differenced versions were included as candidate |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | | regressors during automated model selection. |
| Disability rate | Rate (%) | N/A | None | ADF: 0.921 KPSS: 0.010 Needs differencing | ADF: 0.010 KPSS: 0.025 Diagnostics required | ADF: 0.010 KPSS: 0.100 Stationary | Second difference | Both the level and first-differenced versions were included as candidate regressors during automated model selection. |
| UK unemployment rate | Rate (%) | N/A | None | ADF: 0.377 KPSS: 0.010 Needs differencing | ADF: 0.015 KPSS: 0.100 Stationary | Stationary | First difference | Included as a required regressor in all candidate models. |

Note (1): Neither variable produced a Box-Cox parameter sufficiently close to zero to support a logarithmic transformation. The explanatory variables were therefore retained on their original scales.

Note (2): For the ADF test, a low p-value provides evidence against a unit root; for the KPSS test, a low p-value provides evidence against stationarity.

# Appendix C: Final model coefficients and diagnostics

## C1. Coefficient estimates

***Table C1: Final model coefficient estimates***

| Variable | Estimate | Standard error | t-statistic | p-value |
|---|---|---|---|---|
| MA(1) | -0.373 | 0.124 | -3.003 | 0.003 |
| Seasonal MA(1) | -0.838 | 0.069 | -12.184 | <0.001 |
| Real GDP growth | -2,797.154 | 1,013.759 | -2.759 | 0.006 |

| | | | | |
|---|---|---|---|---|
| Unemployment rate | 60,381.423 | 11,839.990 | 5.100 | <0.001 |
| Vacancies | -0.496 | 0.189 | -2.621 | 0.009 |
| COVID-19 Stringency Index | -1,653.988 | 494.790 | -3.343 | <0.001 |
| EPA18 indicator | -60,142.952 | 28,266.967 | -2.128 | 0.033 |

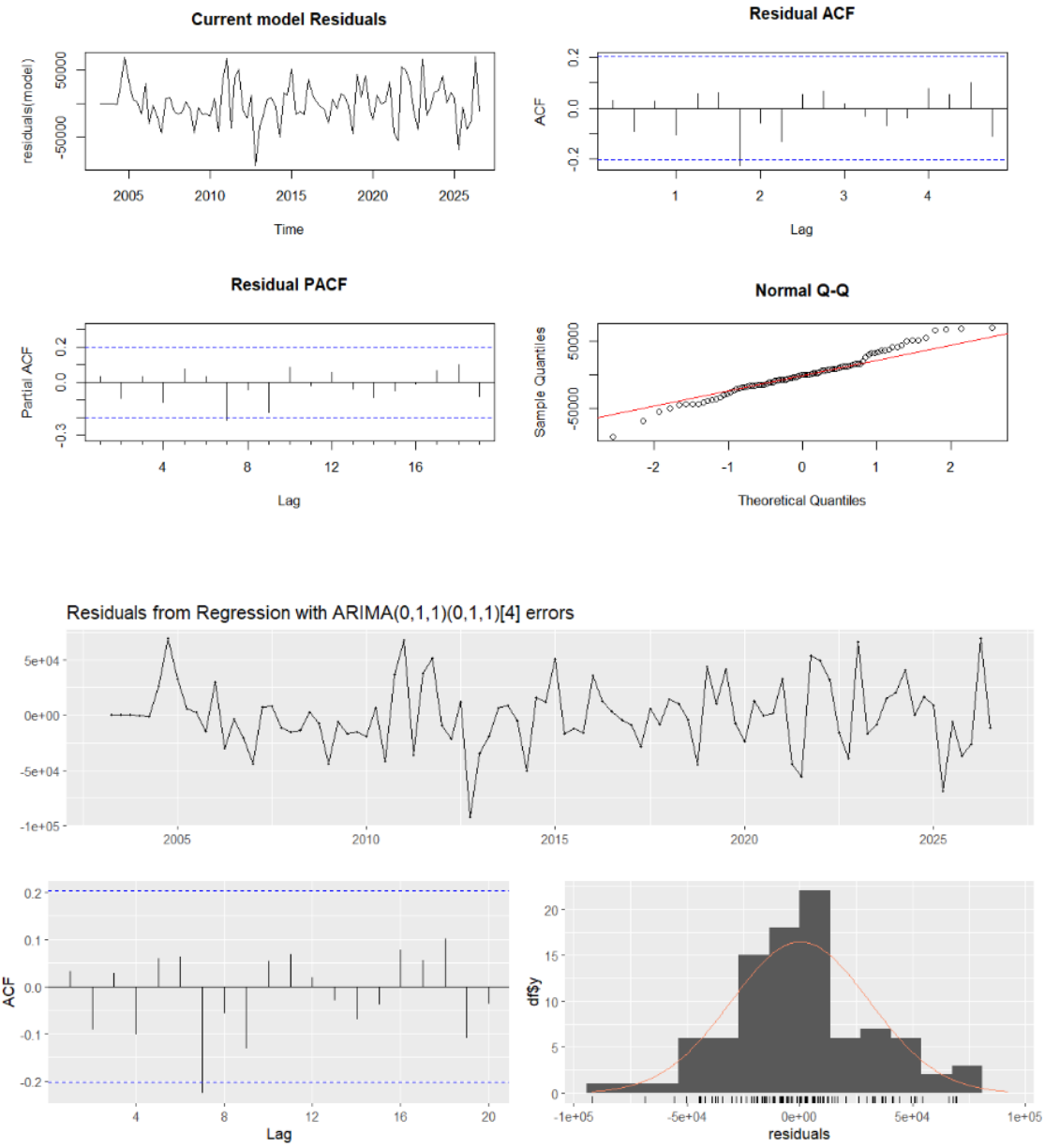
## C2. Model fit and diagnostic statistics

***Table C2: Final model diagnostics***

| Diagnostic | Result | Interpretation |
|---|---|---|
| AIC | 2,093.9 | Information criterion used alongside other model-selection criteria |
| CV MAPE | 3.73% | Out-of-sample forecasting performance |
| Ljung-Box, lag 8 | p = 0.218 | No evidence of residual autocorrelation |
| Ljung-Box, lag 12 | p = 0.367 | No evidence of residual autocorrelation |
| Ljung-Box, lag 16 | p = 0.586 | No evidence of residual autocorrelation |
| Ljung-Box, lag 20 | p = 0.626 | No evidence of residual autocorrelation |

| | | |
|---|---|---|
| Shapiro-Wilk | p = 0.248 | No evidence against residual normality |
| ARCH(4) | p = 0.600 | No evidence of conditional heteroskedasticity |

***Figure C1: Residual diagnostics for the final model***



# Appendix D: Economic scenario assumptions

## D1. Real GDP growth

***Table D1: Real GDP growth scenario construction***

| Scenario | Initial deviation from central | Annual change in deviation | Convergence |
|---|---|---|---|
| Central | 0.00 pp | — | — |
| Optimistic / high growth | +0.45 pp | -0.02 pp per year | Deviation tapers towards zero |
| Pessimistic / low growth | -0.65 pp | +0.02 pp per year | Deviation tapers towards zero |

Note: Scenario deviations are modelling assumptions and are not estimates of the probability or expected size of future economic shocks.

***Table D2: Real GDP growth rate forecasts from OBR's long-term economic determinants***

| Time Period | Real GDP growth projection |
|---|---|
| 2023-24 | 0.10 |
| 2024-25 | 1.46 |
| 2025-26 | 1.15 |
| 2026-27 | 1.29 |
| 2027-28 | 1.60 |
| 2028-29 | 1.58 |
| 2029-30 | 1.52 |
| 2030-31 | 1.52 |
| 2031-32 | 1.60 |
| 2032-33 | 1.69 |
| 2033-34 | 1.72 |
| 2034-35 | 1.72 |
| 2035-36 | 1.76 |

## D2. Unemployment rate

The unemployment scenarios were based on the OBR's *Economic and Fiscal Outlook 2026* and associated labour-market projections.

***Table D3: Unemployment scenario construction***

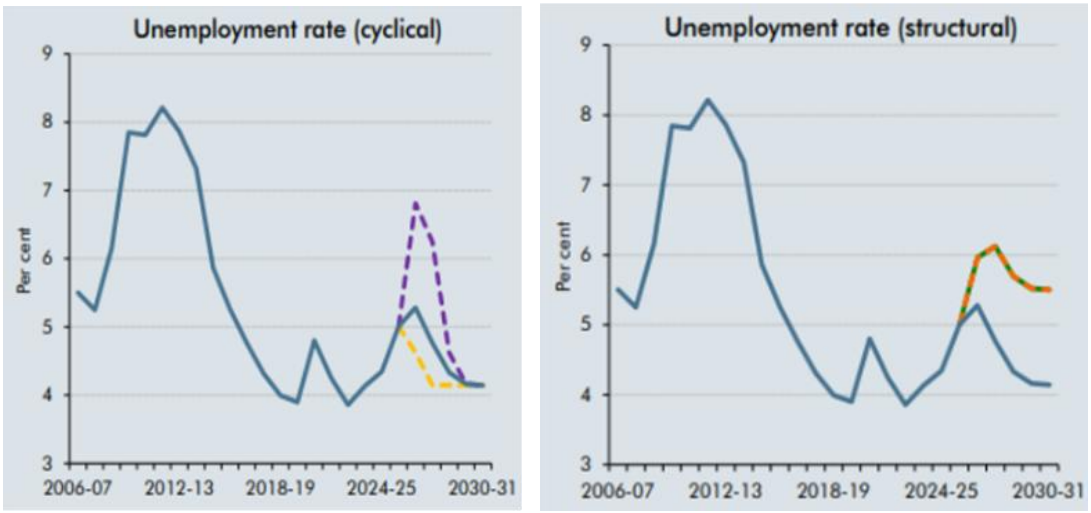
| Scenario | Source / construction | Treatment beyond external projection |
|---|---|---|
| Central | OBR compiled external averaged projections | Held constant at 2031 value |
| Optimistic | OBR's more favourable (cyclical) unemployment pathway | Held constant at 2031 value |
| Pessimistic | OBR's less favourable (structural) unemployment pathway | Held constant at 2031 value |

Note: The unemployment pathways are based on the OBR's *Economic and Fiscal Outlook 2026* and associated labour-market projections. The unemployment rate is held constant at its 2031 value for the remainder of the forecast period.

***Table D4: OBR's economic and fiscal outlook data***

| Unemployment rate projections | 2026 | 2027 | 2028 | 2029 | 2030 |
|---|---|---|---|---|---|
| OBR | 5.3 | 4.9 | 4.4 | 4.2 | 4.1 |
| Bank of England | 5.3 | 5.3 | 5.1 | - | - |
| External Average | 5.2 | 5.0 | 5.0 | 4.9 | 4.9 |

***Figure D1: OBR's unemployment scenarios***



Source: Office for Budget Responsibility Economic and Fiscal Outlook 2026

## D3. Vacancy projections

The model is estimated as an ARDL(1,0) specification, in which current vacancies depend on vacancies in the previous quarter and the current unemployment rate. The short-run coefficient on unemployment (−0.036) captures the immediate effect of a change in unemployment. Because vacancies adjust gradually, the long-run effect is larger: a one percentage point increase in the unemployment rate is associated with a fall of approximately 9% in vacancies once adjustment is complete.

***Table D5: Beveridge curve ARDL(1,0) regression results (short-run coefficients)***

| Variable | Estimate | Standard error | t-statistic | p-value |
|---|---|---|---|---|
| Constant | 4.605 | 1.200 | 3.84 | <0.001 |
| Lagged log vacancies | 0.630 | 0.096 | 6.57 | <0.001 |
| Unemployment rate | -0.036 | 0.014 | -2.65 | 0.010 |

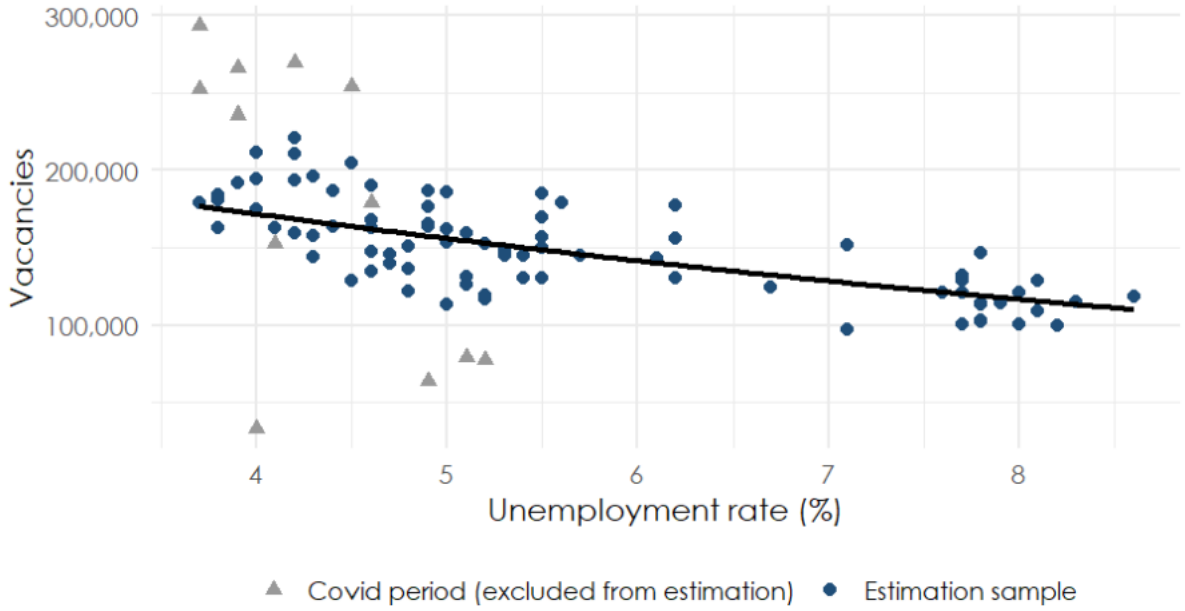
***Table D6: Implied long-run Beveridge curve relationship***

| Variable | Estimate | Standard error | t-statistic | p-value |
|---|---|---|---|---|
| Long-run constant | 12.441 | 0.135 | 92.46 | <0.001 |
| Long-run unemployment rate | -0.097 | 0.023 | -4.16 | <0.001 |

***Table D7: Beveridge curve regression diagnostics***

| Diagnostic | Result |
|---|---|
| $R^2$ | 0.713 |
| Adjusted $R^2$ | 0.706 |
| Number of observations | 81 |
| F-statistic | 97.07 |
| p-value | <0.001 |

***Figure D2: Beveridge curve: Observed vacancies and fitted long-run relationship***




# Appendix E: Scenario decomposition

***Table E1: Decomposition of model contributions and differences between scenarios, 2036***

| Component | *Contribution to central model* | *Optimistic vs central scenarios* | *Pessimistic vs central scenarios* |
|---|---|---|---|
| Unemployment | 285,080 | -46,238 | 35,880 |
| GDP growth | -10,994 | -699 | 1,259 |
| Vacancies | -78,517 | -6,053 | 4,397 |
| COVID-19 Stringency Index | 0 | – | – |
| EPA18 dummy | -60,143 | – | – |
| Total | 135,426 | -52,990 | 41,536 |

Note: The decomposition shows the contribution of each model component to the modelled NEET outcome and the change between scenarios. The total contribution shown for the central scenario does not represent the total projected NEET population, as it excludes the ARIMA error components. Scenario differences are decomposed into the contributions arising from changes in the specified economic inputs.

# Appendix F: NEET forecast outputs

***Table F1: Projected seasonally adjusted NEET population under the scenarios***

| Time period | Main Central | Main Optimistic | Main Pessimistic | Extreme more-favourable | Extreme less-favourable |
|---|---|---|---|---|---|
| 2026 Q3 | 992864 | 958548 | 1045408 | 893080 | 1205730 |
| 2026 Q4 | 984555 | 949307 | 1038448 | 899445 | 1219754 |
| 2027 Q1 | 973810 | 917650 | 1048711 | 890022 | 1215424 |
| 2027 Q2 | 977857 | 920651 | 1053890 | 894712 | 1223435 |
| 2027 Q3 | 982463 | 924602 | 1059185 | 886841 | 1217703 |
| 2027 Q4 | 978293 | 919952 | 1055524 | 899512 | 1231740 |
| 2028 Q1 | 979129 | 921939 | 1030780 | 894599 | 1227695 |
| 2028 Q2 | 984257 | 926918 | 1035444 | 901155 | 1234801 |
| 2028 Q3 | 989190 | 931801 | 1040043 | 894118 | 1228112 |
| 2028 Q4 | 986657 | 929171 | 1037353 | 908772 | 1242985 |
| 2029 Q1 | 987068 | 931898 | 1029230 | 904564 | 1238915 |
| 2029 Q2 | 992115 | 936982 | 1033988 | 911203 | 1245641 |
| 2029 Q3 | 996635 | 941568 | 1038294 | 903852 | 1238346 |
| 2029 Q4 | 995018 | 939930 | 1036588 | 919491 | 1254020 |
| 2030 Q1 | 995736 | 942330 | 1037636 | 915167 | 1249717 |
| 2030 Q2 | 1000657 | 947297 | 1042528 | 921692 | 1256256 |
| 2030 Q3 | 1004753 | 951464 | 1046576 | 913924 | 1248496 |
| 2030 Q4 | 1003813 | 950508 | 1045650 | 930247 | 1264825 |
| 2031 Q1 | 1006107 | 952873 | 1047879 | 925671 | 1260252 |
| 2031 Q2 | 1010835 | 957604 | 1052604 | 931954 | 1266538 |

| | | | | | |
|---|---|---|---|---|---|
| 2031 Q3 | 1014667 | 961481 | 1056406 | 923890 | 1258475 |
| 2031 Q4 | 1014310 | 961091 | 1056073 | 940777 | 1275363 |
| 2032 Q1 | 1016610 | 963450 | 1058314 | 936195 | 1270781 |
| 2032 Q2 | 1021050 | 967888 | 1062757 | 942183 | 1276770 |
| 2032 Q3 | 1024702 | 971579 | 1066381 | 933934 | 1268521 |
| 2032 Q4 | 1024766 | 971607 | 1066470 | 951238 | 1285825 |
| 2033 Q1 | 1027224 | 974124 | 1068871 | 946812 | 1281399 |
| 2033 Q2 | 1031501 | 978397 | 1073151 | 952636 | 1287224 |
| 2033 Q3 | 1034993 | 981927 | 1076615 | 944226 | 1278813 |
| 2033 Q4 | 1035363 | 982261 | 1077011 | 961837 | 1296424 |
| 2034 Q1 | 1037929 | 984885 | 1079520 | 957518 | 1292105 |
| 2034 Q2 | 1041984 | 988935 | 1083577 | 963119 | 1297707 |
| 2034 Q3 | 1045403 | 992393 | 1086968 | 954636 | 1289223 |
| 2034 Q4 | 1046019 | 992973 | 1087611 | 972492 | 1307080 |
| 2035 Q1 | 1048496 | 995507 | 1090030 | 968084 | 1302671 |
| 2035 Q2 | 1052373 | 999381 | 1093911 | 973508 | 1308096 |
| 2035 Q3 | 1055758 | 1002803 | 1097267 | 964991 | 1299578 |
| 2035 Q4 | 1056512 | 1003522 | 1098048 | 982985 | 1317573 |
| 2036 Q1 | 1059063 | 1006075 | 1100598 | 978652 | 1313239 |
| 2036 Q2 | 1062973 | 1009980 | 1104510 | 984108 | 1318696 |
| 2036 Q3 | 1066282 | 1013328 | 1107792 | 975515 | 1310103 |
| 2036 Q4 | 1067094 | 1014104 | 1108630 | 993567 | 1328155 |

***Table F2: Non-seasonally adjusted central projection and lower and upper 95% confidence intervals***

| Quarter | Central | Lower95 | Upper95 |
|---|---|---|---|
| | | | |
| 2026 Q3 | 1108173 | 1044097 | 1172249 |
| 2026 Q4 | 975799 | 900162 | 1051437 |
| 2027 Q1 | 913875 | 828222 | 999527 |
| 2027 Q2 | 930851 | 836238 | 1025464 |
| 2027 Q3 | 1098645 | 991375 | 1205916 |
| 2027 Q4 | 969202 | 852212 | 1086192 |
| 2028 Q1 | 918759 | 792796 | 1044721 |
| 2028 Q2 | 937264 | 802928 | 1071600 |
| 2028 Q3 | 1106059 | 960112 | 1252007 |
| 2028 Q4 | 977238 | 821901 | 1132574 |
| 2029 Q1 | 926385 | 762195 | 1090574 |
| 2029 Q2 | 945119 | 772531 | 1117706 |
| 2029 Q3 | 1114063 | 930149 | 1297977 |
| 2029 Q4 | 985329 | 791974 | 1178684 |
| 2030 Q1 | 934851 | 732494 | 1137207 |
| 2030 Q2 | 953634 | 742660 | 1164607 |
| 2030 Q3 | 1122611 | 900315 | 1344906 |
| 2030 Q4 | 993895 | 761958 | 1225833 |
| 2031 Q1 | 945024 | 703830 | 1186218 |
| 2031 Q2 | 963867 | 713759 | 1213974 |

| | | | |
|---|---|---|---|
| 2031 Q3 | 1132881 | 871325 | 1394437 |
| 2031 Q4 | 1004189 | 732725 | 1275653 |
| 2032 Q1 | 955313 | 674289 | 1236337 |
| 2032 Q2 | 974165 | 683897 | 1264433 |
| 2032 Q3 | 1143185 | 841275 | 1445095 |
| 2032 Q4 | 1014497 | 702379 | 1326614 |
| 2033 Q1 | 965798 | 643795 | 1287800 |
| 2033 Q2 | 984651 | 653060 | 1316242 |
| 2033 Q3 | 1153672 | 810208 | 1497136 |
| 2033 Q4 | 1024984 | 670998 | 1378970 |
| 2034 Q1 | 976363 | 612158 | 1340567 |
| 2034 Q2 | 995216 | 621073 | 1369358 |
| 2034 Q3 | 1164237 | 777969 | 1550505 |
| 2034 Q4 | 1035550 | 638440 | 1432660 |
| 2035 Q1 | 986808 | 579144 | 1394473 |
| 2035 Q2 | 1005661 | 587710 | 1423612 |
| 2035 Q3 | 1174683 | 744343 | 1605023 |
| 2035 Q4 | 1045995 | 604491 | 1487499 |
| 2036 Q1 | 997373 | 544980 | 1449765 |
| 2036 Q2 | 1016226 | 553202 | 1479250 |
| 2036 Q3 | 1185248 | 709564 | 1660931 |
| 2036 Q4 | 1056560 | 569393 | 1543727 |

# About the authors

**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.

**Arushi Bhasin** is a Senior Economist at Youth Futures Foundation, specialising in data analysis, forecasting, economic modelling and youth labour market analysis. She has a background in economics, with experience applying econometric and impact evaluation methods to inform public policy, and leads Youth Futures projects on NEET forecasting, the impact of AI on the young people's employment outcomes, and economic analysis of the youth labour market.

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