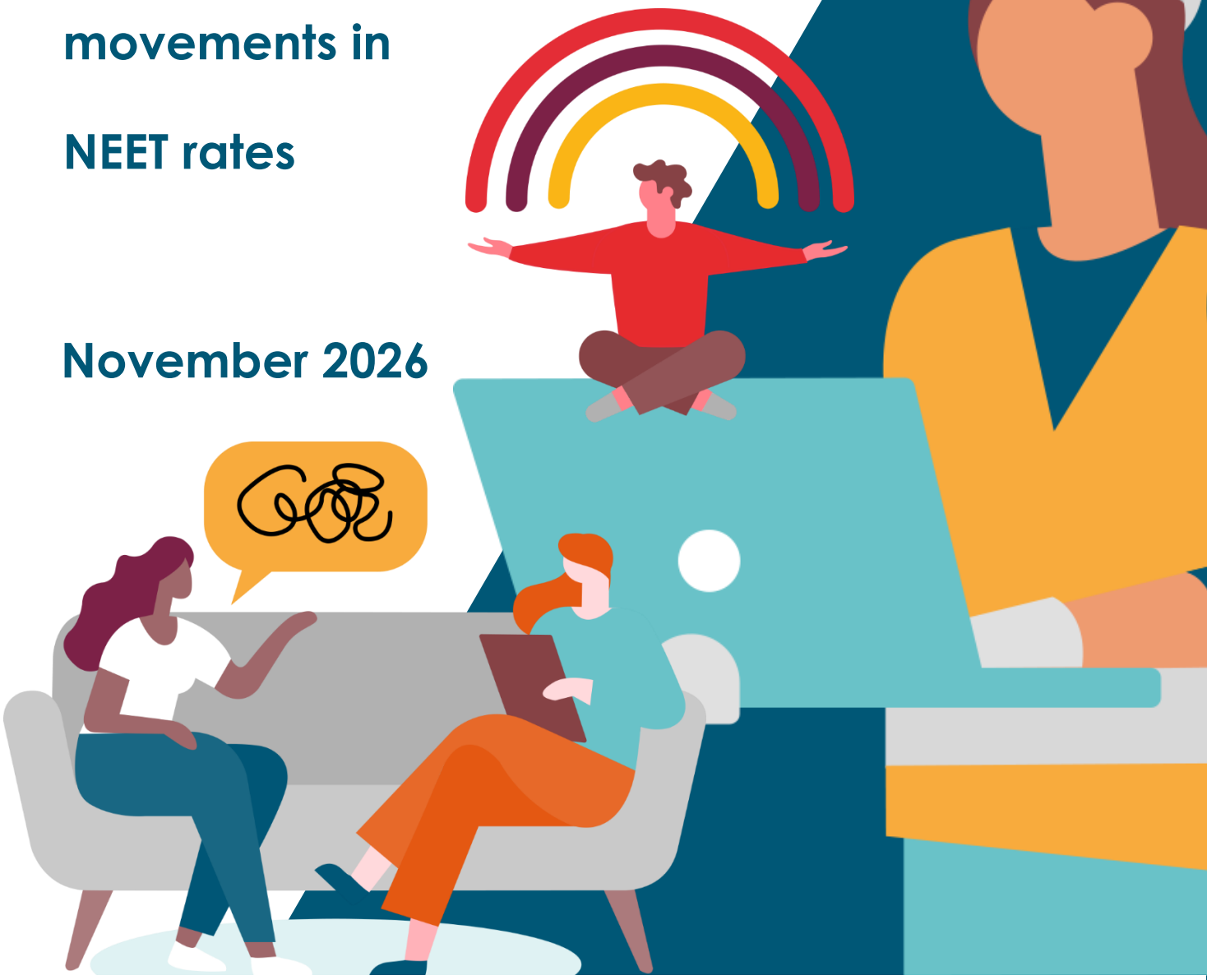
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Technical annexe for NEET forecasting: four-quarter forward-looking signals about likely movements in NEET rates

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Overview

This technical annexe report presents detailed methodological documentation and full analytical findings from modelling work commissioned by Youth Futures Foundation and undertaken by National Centre for Social Research to provide four-quarter-ahead signals about the likely trajectory of NEET rates.

The resulting forecasting tool is built primarily on the Labour Force Survey (LFS), the most widely used and officially recognised source of NEET statistics in the UK and is designed to enable new forecasts each quarter as new LFS data are released. To strengthen confidence in its predictions, the tool additionally draws on survey and administrative data from two complementary datasets to ensure the forecasts reflect underlying NEET trends.

Among the variables considered, unemployment rate, GDP and disability rate consistently improved short-term forecast accuracy across the models tested. These three factors were used in the final forecasting model. Adjusting for recent differences in reported NEET rates between LFS and the longitudinal study Understanding Society further strengthens forecasting accuracy, and the model therefore incorporates this as a fourth factor. The model forecasts that NEET rates will remain high through 2026 Q3 to 2027 Q2, with seasonally adjusted estimates ranging from 12.9% to 13.2% across the four quarters

This report set out the data sources, modelling approach, diagnostics, and limitations in full, ensuring transparency and supporting technical assurance. The tool itself comprises a series of analysis scripts for the statistical software R that enable the full forecasting process to be repeated in the future once updated data on NEET rates and external variables are made available.

The report is intended to be used alongside the short brief report, which focuses on headline results and implications for decision-making.

Developing a forecasting tool

The forecasting approach is built around a triangulated use of multiple national datasets, each serving a distinct purpose within the analysis:

- The **Labour Force Survey (LFS**) is used as the core forecasting dataset. It provides quarterly, nationally representative estimates of NEET rates for young people aged 16–24 and offers the most suitable balance of timeliness, frequency, and stability for short-term forecasting. The LFS is also one of the most widely used and reported sources for estimating NEET rates by a range of stakeholders. However, the LFS does have known data quality issues. The project aims to mitigate these issues by triangulating across several data sources.

- **Understanding Society (USoc)** is used as a secondary dataset to support triangulation. While USoc is more volatile and less well suited to producing precise short-term forecasts, it provides an independent check on which external drivers are consistently associated with changes in NEET rates, and whether signals identified in the LFS are replicated in a dataset with a different design and sampling structure. The deviation between LFS and USoc is explored in the final model as an exogenous variable, which is discussed in section 2.6.

- The **Longitudinal Education Outcomes (LEO**) dataset was incorporated in the final stage of the project. As an administrative dataset linking education, employment, and benefits records, LEO provides an additional and complementary source of evidence. Its primary role within this project is to support validation and robustness checking, rather than short-term forecasting.

A note on geographic scope

As the LEO data cover England only, the exploratory models for all three datasets were estimated on an England-only basis during the triangulation phase. This ensured that findings were directly comparable across sources, and as such any differences in variable performance could be attributed to differences in dataset design rather than differences in geographic coverage. However, the final forecasting model, which is based on the LFS and uses insights drawn from the triangulation process, covers the UK as a whole. This is consistent with the original project scope and with the primary purpose of the tool, which is to forecast the UK NEET rate as reported in the official ONS quarterly release. The shift from England to the UK for the final model is not expected to affect the validity of the triangulation findings: the economic factors that were useful in forecasting NEET movements in England during the exploratory phase, unemployment rate, GDP,

lagged disability rate, and the USoc–LFS deviation, operate at a UK-wide level and remain appropriate regressors in the final UK model.

In using these three separate datasets, this project aims to:

- account for potential effects of known data quality issues in the LFS (ONS, 2026), particularly those arising during and after the COVID-19 period,
- test the robustness of findings across datasets with different strengths and limitations, and
- avoid reliance on a single source when drawing conclusions about short-term NEET dynamics.

The objective was not to produce a single blended forecast, but to strengthen confidence in the signals that emerged from the LFS, to identify where findings were sensitive to data source or methodology, and to assess whether insights from alternative data sources suggested refinements or adjustments that improved the LFS forecasting approach.

The forecasting tool was developed in four stages, each with a different purpose:

Stage 1: Candidate variable identification. A longlist of potential exogenous variables was developed through theory, stakeholder input, expert review, and consideration of whether reliable future values could be obtained. This produced a shortlist of candidate variables that were taken forward for testing.

Stage 2: Exploratory modelling within each dataset. The candidate variables were tested separately within the Labour Force Survey (LFS), Understanding Society (USoc), and Longitudinal Educational Outcomes (LEO) datasets. At this stage, the objective was to identify which variables improved forecasting performance within each dataset, rather than to determine the final forecasting model.

Stage 3: Triangulation across datasets. The results of the three exploratory modelling exercises were then compared. Variables that repeatedly improved forecasting performance across multiple datasets were prioritised, while variables that only performed well in a single dataset were treated more cautiously. The purpose of triangulation was to identify forecasting signals that appeared robust across different sources of evidence.

Stage 4: Final model development. A final LFS-based forecasting model was then constructed. Variables that had either performed consistently across datasets or demonstrated strong performance within the LFS were taken forward and retested.

Additional refinements identified through triangulation, including the USoc-LFS NEET rate deviation variable, were also incorporated and evaluated. The final model was selected based on forecasting accuracy, model fit, robustness, and practical suitability for future updating.

Data

This section sets out the data used to develop the NEET forecasting models and explains how the data were prepared for analysis. It describes how each dataset enables measurement of NEET rates, outlines exogenous variables considered for inclusion, and explains the criteria used to assess their suitability for forecasting. The section also details the data preparation steps taken to ensure consistency across sources, including transformations applied to satisfy the assumptions of the forecasting approach. Together, these steps provide the foundation for the modelling approach.

Data for NEET rates

Central to the approach to forecasting is basing the model on the most robust, timely data to enable up-to-date forecasts of NEET estimates, and to supplement this approach with insights from additional data. All data was taken from 2009 Q1 onwards to ensure there was a consistent backstop of data that the models for each dataset were trained from and to ensure that the data included in each model captured the same economic changes. The pre-triangulation models were estimated on an England-only basis to ensure comparability across all three datasets, since LEO data covers England only. The final LFS-based model was then updated to cover the UK as a whole, to align with published ONS NEET statistics. The research utilised the following datasets:

Labour Force Survey (LFS). The LFS is a large, nationally representative survey conducted by the Office for National Statistics, providing quarterly NEET estimates for young people aged 16 to 24. The series used in the initial exploratory models spans 2009 Q1 to 2025 Q4, yielding approximately 68 quarterly observations. Its consistent quarterly frequency and sample size of over 5,000 young people make it well-suited to time series modelling, and it forms the core of the forecasting tool. Quarterly NEET estimates of young people aged 16 to 24 are readily available and published quarterly from the Office for National Statistics; no derivation of NEET status was required for the LFS data.

Understanding Society (USoc). USoc is a longitudinal household panel survey, collecting data from approximately 40,000 households and between three and six thousand young people per wave. The research team derived quarterly NEET estimates by splitting the annual sample, structured as calendar years, into quarters based on the date of fieldwork. The data was then grouped by quarter and the proportion of NEET young people in each quarter derived. This data was then joined, producing a series spanning 2009 Q1 to 2024 Q4 with an even distribution across quarters. Young people aged 16-25 were analysed using the USoc data, instead of 16–24-year-olds, due to limitations in the granularity and derivation of age categories. Appropriate USoc weights were applied to

make the estimates representative of young people aged 16-25 in the UK, as per the guidance on using the survey to represent subgroups of the population. Its smaller effective sample size produces a more volatile NEET series than the LFS, which is reflected in wider forecast uncertainty. Nonetheless, USoc provided an independent basis for triangulation and access to a broader set of individual-level socio-economic variables used during the NEET derivation that were not available in the LFS.

Longitudinal Education Outcomes (LEO). LEO is an administrative dataset linking individual educational records with subsequent employment and benefit outcomes for young people in England, covering between five and seven million individuals for a given quarter. Given that LEO's current coverage ends in 2021, its primary contribution was for historical comparison and validation rather than forward forecasting. The team derived NEET status using LEO by first identifying quarterly activity across higher education, further education, and employment spells using data from DWP. The research team then derived quarterly NEET estimates by aggregating the activity for all young people aged 16-24 from 2009 onwards and determining what proportion of each cohort was NEET. More details of the process for deriving NEET status using LEO can be found in Appendix A.

When deriving NEET status using LEO for the full cohort of young people, the approach used by the team was leading to a significant underestimation of young people whom the team could confidently say were in higher education from 2018 Q2 onwards. This meant that the NEET rates for 2018 Q3 onwards were substantially inflated and not representative of the true NEET rates for young people at that time. As LEO's primary role in the triangulation was backcasting, the decision was taken to restrict the LEO data from 2009 Q1 to 2018 Q1, to ensure the model only used time points that accurately derived NEET rates.

Candidate exogenous variables

Datasets like LFS, USoc or LEO do enable forecasts to be produced using only historic NEET estimates. However, a key benefit of the modelling approach used is the ability to incorporate additional data on relevant factors, referred to as exogenous variables (external variables), to enhance the accuracy and robustness of the forecasts.

The initial pool of candidate exogenous variables was drawn up through a combination of domain knowledge and structured input from stakeholders and external experts. The team then organised the exogenous variables around four thematic areas previously identified as relevant to NEET trends: macroeconomic conditions (including GDP, inflation, and unemployment); characteristics of different worker groups (including

educational attainment, disability, and demographic composition); sectoral and geographical factors; and policy changes.

Where publicly available projections existed, official sources were used for future exogenous variable values: unemployment and GDP forecasts were drawn from the Bank of England Monetary Policy Report. For the remaining candidate exogenous variables, where no such forecast was available, future values were generated using a separate SARIMA model fitted to the historical data series for each variable.

Candidate exogenous variables were proposed by both the research team and Youth Futures Foundation, and the resulting longlist was peer reviewed by two independent experts. Their feedback informed decisions about which variables were most theoretically justified and practically suitable for forecasting. For instance, this included prioritising variables for which reliable forward projections were publicly available.

This process produced a shortlist of six candidate exogenous variables that were then taken forward for testing to determine their suitability to be included in the forecasting models. This process is outlined in the Exogenous Variable Screening section.

The six candidate exogenous variables were:

- **Unemployment rate.** The quarterly unemployment rate for working-age adults aged 16 and over in the UK, drawn from the ONS published statistics. We sourced forward projections on unemployment from the Bank of England Monetary Policy Report.
- **Disability rate.** The proportion of adults in the UK with a disability or mental health condition, drawn from the LFS, which is published quarterly. As no publicly available forecast existed for this series, we applied a separate ARIMA model, fitted to the historical disability series, to generate future forecasts. The adult disability rate was preferred for practical reasons: it is published regularly and can be updated from publicly available data each quarter. By contrast, deriving a disability rate specifically for young people would require access to sensitive survey microdata, making routine updates to the forecasting tool substantially more difficult.
- **GDP.** Quarterly changes in the Total Production Index for the UK, used as a measure of aggregate economic output, sourced from the Bank of England. Forward projections were sourced from the Bank of England Monetary Policy Report.
- **Level 2 Attainment.** The proportion of young people achieving Level 2 qualifications in England, sourced from Department for Education statistics. We converted the annual attainment data to quarterly estimates using a cubic spline to plot the estimated values for each quarter between the reported yearly values. No publicly

available forecast exists for this series, so we applied a SARIMA approach to generate forecasted values to use. However, it should be noted that Level 2 Attainment is fundamentally an annual measure, with meaningful change concentrated around examination and resit periods. The ARIMA interpolation used to generate quarterly estimates smooths this pattern but does not introduce genuine within-year variation, which likely limits the variable's value as a quarterly forecasting signal – a pattern borne out in the cross-validation results.

- **Vacancies in sectors that disproportionately hire young people.** The number of available job vacancies across the UK in sectors most likely to attract young people, specifically those sectors that have a lower barrier to entry relating to skills or knowledge. This data was taken from the quarterly vacancy figures derived from the ONS Vacancy Survey. These included sectors such as hospitality, the care sector, and construction[1] (ONS, 2021; CIPD, 2024). No publicly available forecast exists for this series, so we applied a SARIMA approach to generate forecasted future values.

- **Proportion of young people aged 16 to 18.** The share of 16- to 18-year-olds falling within the 16-to-24 age band within England, sourced from ONS population estimates[2], which uses a range of administrative sources, including birth and death registries. This variable captures the demographic composition of the youth population, which is relevant because NEET status varies by age within the 16 to 24-year-old group. Forecasted values were sourced from the ONS Annual Population Survey population projections. This is also an important variable to consider because, since 2013, young people under the age of 18 have been legally required to be in full-time education, undertake an apprenticeship, or full-time employment combined with learning or training.

Several other variables were considered during the initial longlist stage, including earnings, benefit claimant counts, the proportion of young people entering higher education, and structural break variables for the 2008 financial crash. However, these were not taken forward to the screening stage due to a lack of credible forecasts or due to being too closely related to the NEET outcome itself, which could introduce endogeneity.

[1] The full list of considered sectors included accommodation & food services, wholesale & retail trade, vehicle repair, transport and storage, administrative and support services, entertainment and recreation, and other service activities. These sectors were considered as they had reduced barriers to entry for young people and were expected to hire disproportionately more young people than other sectors.
[2] More details on the methodology and underlying administrative data sources for the ONS population estimates can be found here: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates

Once a shortlist was identified, candidate exogenous variables were taken forward to formal statistical screening to ensure they were also technically robust to include in time-series forecasting.

Exogenous variable screening

To select suitable exogenous variables, the candidate variables were assessed against three criteria prior to permutation modelling: stationarity, multicollinearity, and cross-correlation with the NEET outcome series. These tests were conducted separately for each dataset to account for differences in the time periods available and the differences in each series, though results were broadly consistent across the three.

Stationarity

A key consideration in ARIMA-based forecasting is ensuring the time series has a stable average level and variation over time, referred to as stationarity. It is particularly important in SARIMAX forecasting because the model assumes past relationships remain consistent and would otherwise produce unreliable forecasts.

To assess stationarity, ADF (Augmented Dickey-Fuller) and KPSS (Kwiatkowski–Phillips–Schmidt–Shin) tests were used. These tests assess whether a time series has a stable mean and variance over time and were applied to each candidate variable. We also examined first-differenced versions of each exogenous variable (represented as the change from the previous quarter to the next), and the tests were repeated. The original exogenous variables and the derived, differenced exogenous variables were then compared to assess which best achieved stationarity as shown in Table 1 below:

- GDP, unemployment, and disability achieved stationarity after first-order differencing. Unemployment was accepted despite a marginal ADF result, given that first-order differencing showed a genuine improvement in stationarity. This is explained further below.
- Results were less clear-cut for Level 2 Attainment and the proportion of young people aged 16 to 18: both showed marginal or inconsistent results across their original and differenced forms, with no clearly preferred specification. On the basis of these results, Level 2 Attainment and the proportion of young people were identified as potentially problematic for inclusion.

Table 1. Stationarity Assessment for Exogenous Candidate Variables by their Form (Original Compared with 1st Difference)

Variable	Form	ADF p-value	KPSS p-value	Stationary
Level 2 Attainment	original	0.209	0.016	No
Level 2 Attainment	1st diff	0.735	0.01	No
Disability	original	0.905	0.01	No
Disability	1st diff	0.016	>0.10	**Yes**
Proportion of young people aged 16-18	original	0.267	0.01	No
Proportion of young people aged 16-18	1st diff	0.972	0.02	No
GDP	original	0.42	0.078	No
GDP	1st diff	0.045	>0.10	**Yes**
Unemployment	original	0.162	0.01	No
Unemployment	1st diff	0.105	>0.10	Marginal (accepted)
Vacancies in sectors that hire young people	original	<0.01	0.01	Inconclusive
Vacancies in sectors that hire young people	1st diff	<0.01	>0.10	**Yes**
If ADF p < 0.05 and KPSS p > 0.05 then the series is stationary.				

Source: Authors' calculations.

Rather than excluding "borderline" variables—that is, those that narrowly underperformed in the stationarity testing—at this stage, all candidate exogenous variables were carried forward into the permutation modelling. This reflected a deliberate methodological decision, taken following a mid-project review, to move away from stricter pre-screening exclusions and instead allow cross-validation performance, specifically model fit and forecasting accuracy, to determine which variables contributed meaningfully to forecast accuracy. It also allowed the model selection process to be informed by theoretical considerations rather than solely statistical screening. Furthermore, it also enabled the full range of variable combinations to be explored, including any interactions between regressors that might not be apparent from univariate screening alone.

Multicollinearity

Variance Inflation Factors (VIF) were calculated for all candidate variables, and a correlation matrix was examined across the full set. Many exogenous variables that were considered were expected to have some underlying collinearity, such as the rate of unemployment and job availability. However, no combination of variables demonstrated problematic levels of collinearity, that is, a VIF score noteably greater than 5, and so no variables were excluded based on excessively high correlation.

Testing lagged relationships

During the testing of the exogenous variables, the project team explored whether a delayed relationship between a shift in an exogenous variable and a related change in NEET rates was present. This cross-correlation analysis identified one instance where a lagged specification outperformed a contemporaneous one: in the LFS, disability performed best when lagged by seven quarters, suggesting that disability prevalence is most strongly associated with reported NEET rates approximately seven quarters later. In USoc and LEO, disability performed best contemporaneously, that is, it performed best when it was not lagged. No other variables showed a lagged specification that meaningfully improved on including the exogenous variables as a same-quarter specification, and all remaining variables were therefore included contemporaneously.

Data preparation

Alongside the sourced set of candidate exogenous variables, additional variables were derived that aim to capture broader shifts in the economic landscape, rather than specific measures of related economic factors.

Prior to model estimation, structural breaks, where the statistical properties or underlying pattern of a time series change at a given point, in the NEET outcome series were

assessed for each dataset separately. Formal tests, including the Chow test of identified breaks, the recursive CUSUM test, and automatic Bai-Perron breakpoint detection, were used to identify whether and where statistically significant breaks were present. As the breaks were detected from the respective outcome series, the results differed between datasets. In the LFS, automatic breakpoint detection identified breaks at 2013 Q3 and 2020 Q4; these and the other identified breakpoints are further explained in Section **Error! R eference source not found.**. Binary variables were constructed to capture each post-break period.

In addition, a binary pulse variable – a record of a one-time event likely to have impacted the outcome – was constructed for both datasets, set to one in 2020 Q2, to capture the immediate impact of the COVID-19 pandemic on NEET rates in the quarter most directly affected. Unlike the step-change variables representing structural breaks in the underlying trend, this variable captures a discrete one-period shock rather than a persistent shift.

Table 2. Illustration of constructed binary variables

Quarter	Post 2013 Q3	Post 2020 Q4	COVID Shock
2013 Q1	0	0	0
2013 Q2	0	0	0
2013 Q3	**1**	0	0
2013 Q4	1	0	0
…	1	0	0
2020 Q1	1	0	0
2020 Q2	1	0	**1**
2020 Q3	1	0	0
2020 Q4	1	**1**	0

2021 Q1	1	1	0

Source: Authors' calculations.

The structural break variables and COVID-19 pulse variable were entered into the permutation modelling framework alongside the five substantive exogenous variables, allowing the model selection process to determine empirically whether including each improved forecast accuracy. Some of the structural breaks have a clear theoretical grounding, like those identified around the COVID period, whereas others do not. However, as the priority for the tool was to produce the most accurate forecasts, all structural breaks were carried forward and tested, prioritising those that improved forecasting accuracy. As binary indicators, they do not require the stationarity screening applied to the continuous exogenous variables.

Model creation

Building on the data and preparation steps described in the previous section, this section explains how the NEET forecasting models were specified and selected, with the approach applied to all three datasets. It outlines the Seasonal Autoregressive Integrated Moving Average with exogenous variables (SARIMAX) modelling approach used to capture trends, seasonality, and the influence of external conditions, and describes how model parameters were determined through a combination of diagnostic testing and automated selection. The section also sets out the criteria used to compare alternative model specifications, including measures of model fit and out-of-sample forecasting accuracy. Together, these steps explain how the final models were chosen to balance accuracy, robustness, parsimony, and practical usefulness for short-term forecasting.

Approach to model creation

Model specification and variable selection were carried out iteratively. First, the research team defined a long list of candidate external variables based on theory, data availability and suitability for short-term forecasting, and then screened these variables using tests of stationarity, multicollinearity and cross-correlation with NEET rates. Rather than excluding variables solely on screening results, the team took all shortlisted variables forward into permutation testing, fitting SARIMAX models for every possible combination of variables. In parallel, the team used manual diagnostics to set the seasonal structure of the model and applied auto-ARIMA within each permutation to select the remaining ARIMA parameters using AICc. Final model selection balanced forecast accuracy (MAPE), model fit (AICc), residual diagnostics, and consistency of selected variables across datasets, resulting in parsimonious specifications suitable for short-term forecasting.

The SARIMAX model combines an autoregressive time series structure (ARIMA) with a seasonal component (S) and one or more exogenous variables (X). In broad terms, the model uses the NEET rate's own recent history, its seasonal patterns, and the values of external variables over time to generate a forecast. The seasonal component accounts for the regular quarterly fluctuations in NEET rates, reflecting the cyclical patterns of education enrolment and labour market entry for young people, without requiring these to be removed from the series prior to modelling. As the model accounts for seasonality directly through seasonal differencing, non-seasonally adjusted data was used from the ONS. The final forecasting tool will produce both seasonally adjusted and unadjusted forecasts to support different reporting needs.

Model specification proceeded in two stages. First, manual diagnostics, including visual inspection of the NEET rate series and ACF and PACF plots, were used to establish the seasonal structure of the series. Residual plots for the exploratory models are included in Appendix B Diagnostic plots for exploratory LFS model, Appendix C: Diagnostic plots for exploratory USoc model, and Appendix D: Diagnostic plots for exploratory LEO model and full diagnostic plots for the final model are included in Appendix E: Diagnostic plots for final LFS model. This confirmed that seasonal differences at an annual period were appropriate for both datasets. Establishing this structure prior to automated comparison was important because auto-ARIMA does not always determine seasonal parameters reliably, particularly in shorter series, and mis-specifying the seasonal component can produce poorly fitting models regardless of how well the remaining parameters are chosen.

Second, an automated selection procedure, auto-ARIMA, was applied to each model permutation to determine the remaining order parameters. Rather than specifying these manually for every possible combination of exogenous variables, auto-ARIMA searched across feasible options and ranked the model specifications in order of lowest AICc. This was a practical necessity given the number of variable combinations being tested, as described in section **Error! Reference source not found.**.

Permutation testing of potential models

To identify which combination of exogenous variables produced the most accurate and robust forecasts, every possible subset of the candidate variables was fitted as a separate SARIMAX model for each dataset. Models were assessed using two quantitative criteria, AICc and MAPE, alongside manual inspection of residual diagnostics for the most promising candidates. Final selection, therefore, reflected a combination of in-sample fit, out-of-sample accuracy, and analytical judgement rather than a purely algorithmic choice. The order in which models were tested and selected was:

AICc (Corrected Akaike Information Criterion) was used to guide model specification. It measures in-sample goodness of fit whilst penalising complexity and is preferred over standard AIC for shorter time series, typically between 40 and 100 observations, as AICc applies a stronger small sample correction than standard AIC. The Bayesian Information Criterion (BIC) was produced during assessment and considered alongside other diagnostic criteria when examining promising candidates, but its heavier complexity penalty generally guided (as expected) towards models with fewer exogenous variables. Since exogenous variables allow the model to incorporate external information, retaining a richer set of these variables improves model robustness to future changes and gives end users the flexibility to introduce additional inputs to influence

future forecasts. As such, BIC was not used as a hard selection rule, but rather one part of a broader assessment of which exogenous variables should be retained.

MAPE (Mean Absolute Percentage Error) measures out-of-sample forecasting accuracy – how close forecasted values were to observed NEET rates. It is directly interpretable: an MAPE of 5% indicates that forecasts are, on average, 5% away from the observed value. MAPE was calculated using a four-quarter-ahead forecast horizon at multiple points in the historical series, with each forecast using only the data that would have been available up to that point, simulating the process of forecasting at that point in time. The resulting errors were then averaged to identify models that performed consistently across different periods rather than performing well at a single point by chance.

Two cross-validation approaches were used. The first is an expanding window, where the model is trained on a block of data (the first 40 quarters for LFS, first 35 for USoc and first 30 for LEO) and then re-estimated at each subsequent point in time, with the training window growing to include all available data up to that point. This mimics how the model would be used in practice, accumulating more information over time. The second is a sliding window, where a fixed-length block moves forward through the series, with older data dropping out as newer data is added. The sliding window acts as a robustness check: large differences in MAPE between the two approaches can indicate whether model performance depends on having more data overall or on having recent data specifically. RMSE was also calculated as a cross-check; given consistent forecast errors across permutations, it produced comparable model rankings to MAPE, and MAPE is reported as the primary measure given its interpretability.

The MAPE figures reported here reflect a broad model and variable selection process rather than the expected accuracy of the final forecasting tool. Two competing factors will shape real-world accuracy. The MAPE values reported here were calculated over a long historical evaluation period to support comparison of alternative model specifications and explanatory variables. Final model tuning will instead focus on minimising forecast error over a more recent expanding evaluation window that better reflects current economic and labour market conditions. This approach places greater emphasis on predictive performance under current economic and labour market conditions.

However, real-world use requires forecast values for exogenous variables such as GDP and unemployment, rather than the observed values used during model evaluation, introducing additional uncertainty. The net effect will depend on the balance between these two factors. For the final model, MAPE will be reported over a defined evaluation window, alongside performance on the most recent data as an indicator of near-term accuracy.

Consistency of Exogenous Variables was the third consideration, prioritising consistency of variables across datasets: where AICc and MAPE values were comparable between different model specifications, preference was given to specifications sharing a common variable set across the three datasets. We also manually reviewed the permutation results of those models that outperformed a base ARIMA to identify variables that appeared repeatedly among well-performing models within each dataset. A variable that performs well in a single specification may be capitalising on noise, but one that recurs across many strong permutations and across complementary datasets is more likely to reflect a robust forecasting relationship, rather than a relationship that is specific to one model specification.

Model diagnostics

Diagnostic checks on model residuals were used at three points in the modelling process. Residuals are the errors left over after the model has been fitted; examining them confirms whether any systematic patterns remain that the model has failed to capture. These checks were applied as an initial adequacy check on the baseline ARIMA (without exogenous variables); during variable selection, as part of manual inspection of promising candidate models; and on the final recommended model for each dataset.

For each, the Ljung–Box test was used to check for remaining patterns in the residuals, and Q–Q ("quantile-quantile") plots were inspected to assess that residuals were approximately normally distributed, a consideration of the data that supports the reliability of the forecast intervals. Models were considered adequate where no significant residual patterns were found.

A supplementary leave-one-out analysis was also carried out on the LFS model, removing each exogenous variable in turn to confirm it was contributing positively to forecast accuracy. Details are reported alongside the model results in Section 2.5.

Model selection

Through the variable selection process, the research team evaluated over 1,000 model permutations across the three datasets. A consistent core set of variables emerged as strong forecasting variables, out of the range of exogenous variables and model specifications that were tested.

Unemployment rate (ONS, 16+, first-differenced). Retained in all three datasets. It is the single most informative demand-side exogenous variable available at quarterly frequency with published forward projections and performed consistently well across permutations. It is not youth-specific, but changes in overall unemployment provide a

broad indicator of labour market conditions that may affect young people's opportunities to enter or remain in work. Unemployment and NEET status are related but distinct: a subset of unemployed people are by definition NEET, but the NEET group also includes economically inactive young people not counted in unemployment statistics, such as students.

Adult disability rate (LFS, first-differenced). Retained in LFS and USoc modelling, but with different lag structures. In the LFS, lagged disability performed well, as suggested by the cross-correlation analysis. The identified lag is not evidence of a causal relationship but it may be plausible that the onset of a disability or health condition is associated with reduced economic outcomes or becoming NEET, which typically unfolds over an extended period (Atwell, 2026). In USoc and LEO, the contemporaneous specification performed better, perhaps because the annual-to-quarterly conversion smooths out the temporal signal that allows a lag to be detected in the LFS. As no published forecast exists for this series, future values were generated using a separate ARIMA model. This introduces a secondary layer of forecast uncertainty that should be kept in mind when interpreting forecast interval widths, as they are not explicitly incorporated.

GDP (Total Production Index, first-differenced). Retained in the LFS recommended model and featured in some strong USoc and LEO specifications. It captures the broader macroeconomic cycle: economic contractions are generally expected to increase NEET rates, while recoveries are expected to reduce them. Models without structural breaks or COVID-19 incorporated tended to perform better when GDP was included, suggesting it may partly be capturing the economic disruption those binary variables otherwise account for.

Vacancies in sectors that hire young people: (ONS, first-differenced) appeared in a selection of well-performing models for all three datasets. For example, in the recommended LFS models, the inclusion of this EV produced a comparatively low AICc, only 1.5 points higher than the best-fitting model whilst showing a similarly low forecasting error to other well-performing models. As a result of it appearing in a selection of well-performing models, across the LFS, USoc, and LEO data, vacancies in sectors hiring young people were considered for the final model.

COVID-19 shock. Performed well across a selection of USoc models. However, it did not appear in many of the well-performing LFS models, and the COVID-19 shock was not applicable to the LEO data due to the available time frame of LEO estimates. Its inclusion prevents the model from treating the 2020 Q2 spike as a pattern to learn from, which would distort forecasts for future periods. It works alongside the structural break variables described in Section 2.2, which capture the longer-run shift in the series that followed the immediate disruption.

Structural breaks. Structural breaks (sudden changes in trend, mean, or variance) in NEET rates were included in the models to increase forecasting accuracy. In the model, these are included as binary variables, indicating whether the observation took place before or after that timepoint. Throughout the process for building each model, the underlying NEET rates were tested for structural breaks. Across the datasets, the following structural breaks were identified:

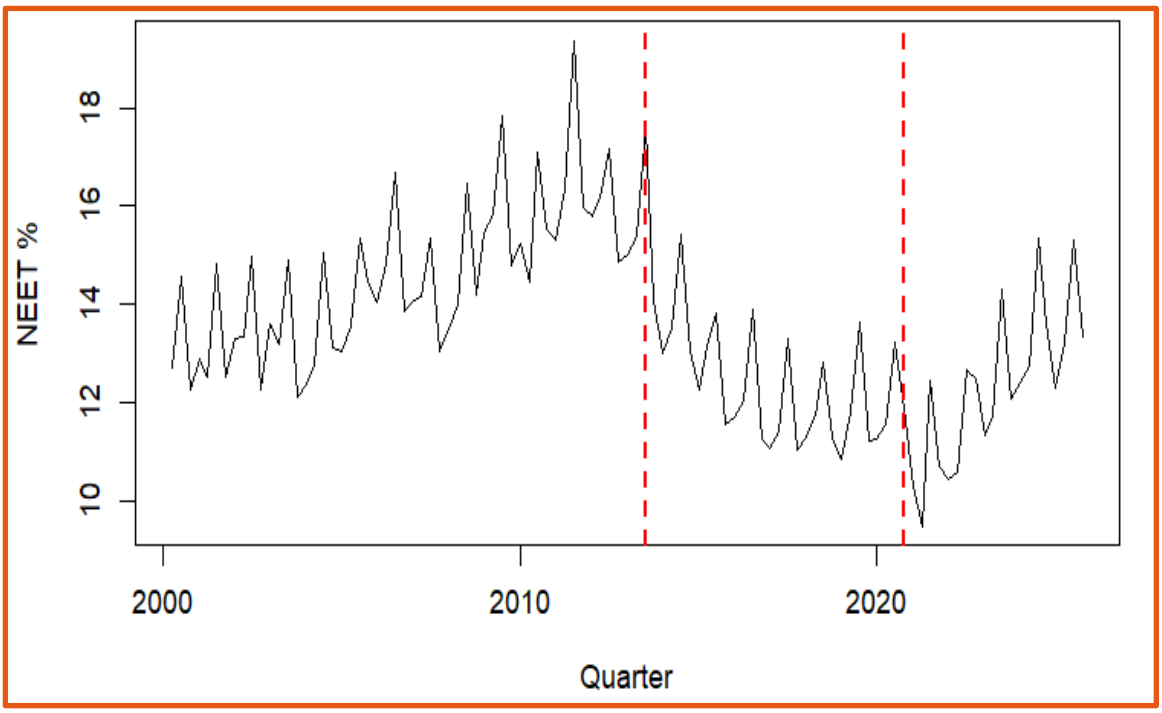
- **For LFS, two post-break step-change binary variables** were identified and appeared in the top-performing models. They were identified through automatic breakpoint detection and appeared in several of the better-performing models:
    - **2013 Q3 onwards,**
    - **2020 Q4 onwards.**

  The earlier structural break, 2013 Q3, was also identified in the LEO data. As the structural break variables in LFS performed consistently well across some of the top model permutations, both were included for testing for the final model.

- **For USoc, one post-break step-change binary variable** from 2019 Q1 onwards appeared in several well-performing models; this break was identified through automatic breakpoint detection and retained on statistical grounds.

- **For LEO, two post-break step-change binary variables** were identified through automatic breakpoint detection and were retained and appeared in several of the better-performing models:
    - **2010 Q1 onwards,**
    - **2013 Q3 onwards.**

Figure 1. Structural Breaks Identified in LFS



Data source: Labour Force Survey, 2009 to 2025.

The structural breaks are illustrated in **Error! Reference source not found.** While e xploration of the causal reason for these structural breaks falls outside the scope of this research, the 2013 Q3 break, which appears consistently in both LFS and LEO, coincides with the introduction of the Raising the Participation Age (RPA) policy, which required all young people in England to remain in some form of education or training until their 18th birthday from September 2013. This provides one plausible policy explanation for the downward shift in NEET rates observed at that point.

One variable from the candidate shortlist that did not perform sufficiently well under cross-validation to be recommended for the final model specification was Level 2 Attainment. Although it appeared in the top-ranking model by AICc in USoc, this exogenous variable consistently produced poor out-of-sample MAPE scores across both datasets, suggesting that its in-sample correlation with NEET rates did not translate into consistent out-of-sample forecasting accuracy. This pattern is consistent with the stationarity concerns identified during screening (discussed in the Exogenous variable screening section): a variable that does not satisfy stationarity requirements in a reliable or consistent form may appear predictive within sample but may not be a dependable regressor of future values. Level 2 Attainment was therefore not recommended for either dataset.

Model Performance Across Datasets

This section summarises the modelling results produced for all three models and outlines how these inform the development of the final NEET forecasting tool. It presents the recommended model specifications for each dataset, explains the key differences in their forecasting performance, and highlights where the evidence aligns across sources. Together, these results provide an indication of which variables offer the strongest predictive value and how reliably each dataset can support short-term NEET forecasting. The best performing exogenous variables identified in this stage were taking forward to a further stage of testing, to inform the final model.

Labour Force Survey (LFS) results

Over 500 model combinations were tested for the LFS. The recommended model – GDP, unemployment, and lagged disability – was selected primarily on the basis of its model fit, reporting the lowest AICc, relatively low MAPE, ranging from 6.1% to 6.4%, and consistency with the best performing exogenous variables in the USoc models.

Table 3. Notable SARIMAX Results - Labour Force Survey

Exogenous Variables	N	AICc	Δ AICc	MAPE (Expanding)	MAPE (Sliding)
2013 Q3 Break, GDP, Unemployment Rate, Disability (lagged)	4	130.4	-	6.5	7.8
Unemployment Rate, Disability (lagged)	2	131.6	1.2	5.9	6.4
Youth Sector Vacancies, Unemployment Rate, Disability (lagged)	3	131.9	1.5	5.8	6.8
GDP, Unemployment Rate, Disability (lagged)	3	132.2	1.8	6.1	6.4

Source: Authors' calculations.

The model containing GDP, unemployment, and lagged disability produced one of the best in-sample fit (lowest AICc) and a relatively low forecasting error. This model was selected as the recommended model as it had comparable MAPE and AICc and included a similar combination of EVs as well-performing models in USoc and LEO. The addition of the 2013 structural break did marginally improve the model fit, reducing the AICc by 1.8, however, it did result in a notably worse forecasting accuracy across both the expanding and sliding MAPE. More complex models, incorporating additional binary break variables alongside GDP, show substantially worse fit with no corresponding accuracy gain. An expanding-window MAPE of 6.1% indicates that, on average, the recommended model's four-quarter-ahead forecasts are within approximately 6% of the observed NEET rate.

Understanding Society (USoc) results

Just over 250 model combinations were tested for USoc data[3]. The recommended model included COVID-19 shock, youth sector jobs and unemployment. It was selected on the basis of model fit showing the lowest AICc and relatively low MAPE amongst the USoc models and in line with exogenous variables that were selected for LEO data (youth sector jobs and unemployment) and LFS data (COVID-19 shock and unemployment) for consistency across the models.

The USoc results were less clear-cut than LFS. The best-fitting model by AICc consistently included COVID-19 shock, youth sector jobs and unemployment rates, indicating good performance for these candidate regressors. The top models by MAPE were closely grouped – all within around 2 AICc units of each other, which is a range where no specification clearly dominates. Overall, the selected model, which included COVID-19 shock, youth sector jobs and unemployment, was preferred for its model fit, relatively good accuracy and consistency with other models.

It should be highlighted that AICc values were not comparable between datasets. The substantially more negative figures in USoc reflect differences in the scale of the outcome variable rather than better model fit.

[3] The reduction in model permutations for the USoc data is due to the data only containing a one structural break.

Table 4. Notable SARIMAX Results – Understanding Society

Exogenous Variables	N	AICc	Δ AICc	MAPE (Expanding)	MAPE (Sliding)
COVID-19 Shock, Youth Sector Jobs, Unemployment Rate	3	262.5	-	17.1	17.1
COVID-19 Shock, Youth sector jobs, % of 16- to 18-year-olds, Unemployment Rate	4	263.6	1.1	17.9	20.3
COVID-19 Shock, Unemployment Rate	2	263.9	1.3	16.3	15.5
COVID-19 Shock, % of 16 to 18-year-olds, Unemployment Rate	3	263.9	1.4	16.0	19.4

Source: Authors' calculations.

The higher MAPEs across all USoc models, around 17% for the recommended specification, reflect the nature of the data rather than a weakness of the modelling approach. The USoc series is more volatile and is measured less frequently than LFS, which limits how precisely any model can forecast from it. USoc forecasts were therefore best read as annual signals rather than precise point estimates.

Longitudinal Educational Outcomes (LEO) results

Over 500 models were specified and tested for the LEO data. The recommended model contains consistently well-performing exogenous variables in both the LFS and USoc models, notably the number of vacancies in sectors that hire young people, the unemployment rate, and disability rate. The preferred model also demonstrated very good model fit, indicated by a very low delta AICc score, compared to the best-fitting model. The model also contained relatively low MAPE scores, indicating a higher level of forecasting accuracy compared to similar models.

Table 5. Notable SARIMAX Results - Longitudinal Educational Outcomes

Exogenous Variables	N	AICc	Δ AICc	MAPE (Expanding)	MAPE (Sliding)
Youth Sectors Jobs, Unemployment Rate, Disability	3	93.4	0.9	3.1	2.3
% of 16- to 18-year-olds, Unemployment Rate, Disability	4	94.5	1.9	3.6	2.9
GDP, Unemployment Rate, Disability	2	95.3	2.8	4.1	2.9
Youth Sectors Jobs, Unemployment Rate, Disability, 2010 Q1 Break	3	95.6	3.0	3.3	2.5

Source: Authors' calculations.

The well-performing LEO models produced some of the lowest MAPE scores of any models across the three datasets, indicating they have the best forecasting accuracy across all the model permutations tested. The substantial reduction in MAPE compared to both the LFS and USoc models may be related to the reduction in time points from which the MAPE scores are calculated, due to the reduced data availability of LEO. Additionally, the LEO data demonstrates some of the lowest variation in NEET rates both within and across years, indicating the increase in forecasting accuracy may be supported by the reduced variation in the underlying NEET rates.

Model performance

Section 2.4 presented the model selection results for each dataset individually. This section reports the structure and estimated coefficients of the three recommended models, and quantifies the contribution of the exogenous variables to forecast accuracy. Residual diagnostics for all three recommended models were satisfactory, with no significant remaining autocorrelation or departures from normality (see Section 2.4).

Forecast trajectories and forecast intervals are discussed in Section 2.5. The consistency of variable selection across datasets and implications for a consolidated model are discussed in Section 2.6.

Variable Contributions

Table 6 reports the estimated coefficients for the exogenous variables in each recommended model. As all the exogenous variables were standardised, the coefficients indicate the direction and relative strength of each variable's association with the NEET rate. Positive values indicate that increases in the regressor were associated with increases in the NEET rate; negative values indicate the opposite. Within each model, larger absolute values indicate a stronger association.

Table 6. Recommended Model Specification and Coefficients

	LFS	USoc	LEO
ARIMA Order	(0,1,2) (1,0,0) [4]	(0,1,1) (1,0,0) [4]	(0,1,0) (1,0,0) [4]
COVID-19 Shock	—	+9.0**	—
GDP	-0.2**	—	—
Unemployment Rate	+0.4**	+0.5*	+0.4**
Disability (lagged)	-0.1†	—	-0.2**
Youth Sector Jobs	—	+0.6†	-0.7†

Source: Authors' calculations. ** significant at 1%; * significant at 5%; † borderline (t-ratio between 1.5 and 2). All models specified in differenced form. Disability is lagged by seven quarters in the LFS model. COVID-19 Shock is a one-off binary variable and does not influence forecasts beyond the pandemic period.

All three models share the same seasonal structure and first differencing, with the LFS model including two moving average terms, USoc one, and LEO none. The ARIMA component captures the NEET rate's own recent history and seasonal pattern, forming the backbone of each forecast. The exogenous variables refine on top of this structure.

Unemployment rate is a clear and consistent regressor, appearing as a significant exogenous variable in each of the selected models. The direction is clear: higher unemployment rates were suggestive of higher NEET rates, as would be expected. The COVID-19 shock in USoc carries the largest coefficient of any variable (+9.02), reflecting the sharp pandemic-period spike. As a one-off binary pulse variable, it improves the fit of the historical series but does not influence forecasts going forward.

Disability is included in both the LFS and LEO models, with a negative coefficient in each case. In a differenced specification, this means that an increase in the rate of change of disability prevalence is associated with a decrease in the rate of change of the NEET rate. This could potentially be capturing the delayed effects of expanded identification or support provision, or for several other reasons. In the LFS model, this variable is lagged by seven quarters, consistent with the idea that these effects take time to materialise.

The number of vacancies in sectors that hire young people was borderline in significance in both models where it appeared and carried opposite signs. The LEO coefficient aligned with expectations, where greater job availability is associated with falling NEET rates, while the USoc sign was counterintuitive and likely reflected noise in a more volatile series. This variable should be interpreted with caution upon closer inspection, despite appearing in a number of high-performing models across USoc and LEO.

Contribution of Exogenous Variables

Across all three datasets, the recommended models outperformed the baseline ARIMA (without exogenous variables) on both AICc and cross-validation MAPE, confirming that the selected variables contribute to forecast accuracy beyond what the time series structure alone provides.

For the LFS model, where the improvement was most pronounced, a leave-one-out analysis was conducted to quantify the contribution of each variable individually. Each exogenous variable was removed in turn with the ARIMA structure held fixed, to isolate its effect on forecast accuracy.

Table 7. Leave-One-Out Variable Contributions, LFS Model

Variable Removed	MAPE	MAPE Increase	Share of EV Improvement
None (full model)	5.4	—	—

Unemployment Rate	7.2	+1.8	71%
Disability (lagged)	5.8	+0.4	18%
GDP	5.7	+0.3	11%
All exogenous variables (baseline ARIMA)	7.0	+1.6	—

Source: Authors' calculations.

All three variables contribute positively to forecast accuracy, with unemployment accounting for the majority of the improvement. Notably, removing unemployment alone produces worse accuracy than removing all exogenous variables entirely, indicating that disability and GDP can introduce noise when unemployment is not present to anchor the model. This underlines the central role of unemployment as the strongest individual regressor of NEET rates.

This analysis was conducted for the LFS model only, as the primary dataset intended for ongoing forecasting. The overall cross-validation results remain the primary evidence for variable selection across all three datasets.

NEET Forecasts

This section presents short-term forecasts of NEET rates derived from the three modelling approaches used in this study. It sets out the forecast trajectories for each dataset, explains how to interpret the point estimates and forecast intervals, and highlights key similarities and differences across sources. The section then compares the forecasts directly to assess the extent to which they provide consistent signals about likely movements in NEET rates over the coming year. Taken together, these results inform which forecasts are most suitable for decision-making and how evidence from multiple datasets can be interpreted alongside one another.

The forecasts in this section are exploratory model outputs used to compare data sources. The final production forecast, which incorporates triangulation-informed refinements, is presented in Section 2.6.

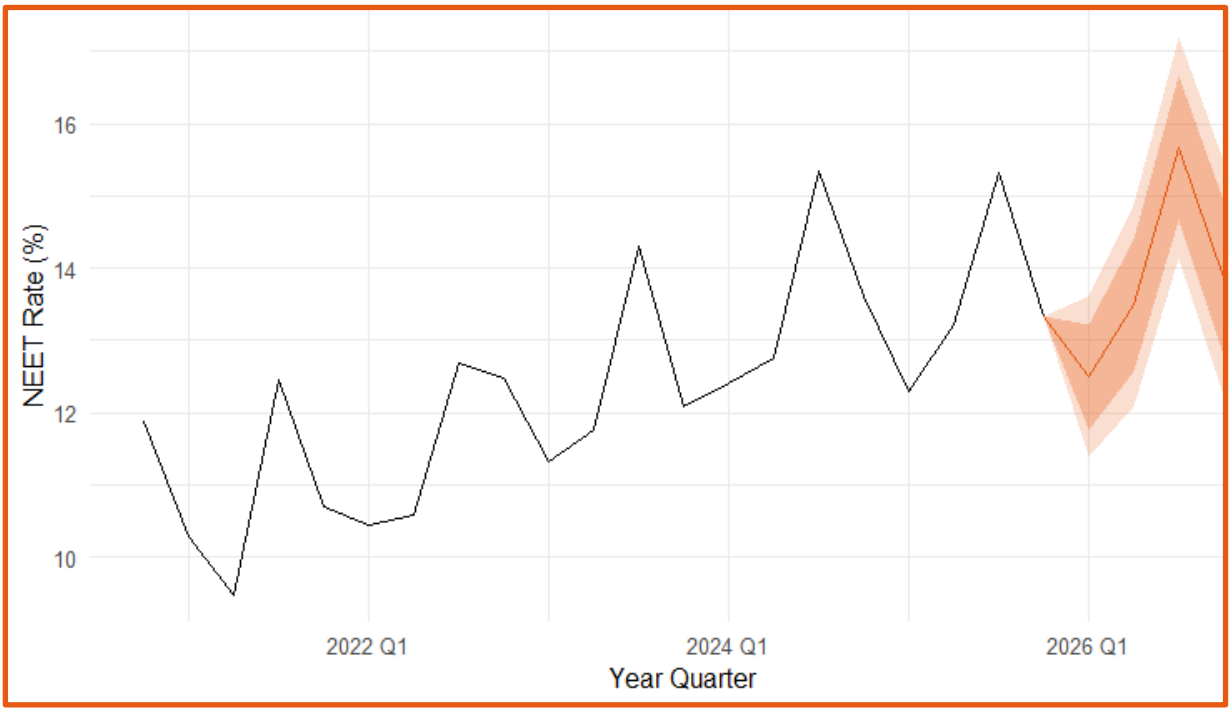
Forecasts were produced four quarters ahead of the most recently available NEET rate estimate at the time this stage of the analysis was conducted: 2026 Q1 to 2026 Q4 for the LFS, 2025 Q1 to 2025 Q4 for USoc, and 2018 Q2 to 2019 Q1 for LEO. Each forecast is accompanied by 80 and 95 per cent forecast intervals, which widen over the forecast horizon as uncertainty accumulates.

A note on seasonal adjustment. The forecasts presented in this section, for all three exploratory models (LFS, USoc, and LEO), are non-seasonally adjusted. This reflects the fact that the SARIMAX modelling approach accounts for seasonality directly within the model structure, making prior seasonal adjustment of the input series unnecessary. Seasonally adjusted forecasts are produced only for the final model (Section 2.6), as a post-hoc step to enable comparison with other published NEET figures. Throughout this report, all figures and tables are labelled accordingly: where seasonally adjusted, this is noted explicitly in the title and source note.

Labour Force Survey (LFS) forecast

The recommended LFS model produces forecasts for 2026 Q1 to 2026 Q4, four quarters beyond the most recently observed NEET rate. Point estimates are shown alongside 80 and 95 per cent forecast intervals, which do slightly increase as the model forecasts further ahead and the uncertainty accumulates. The 80 per cent interval represents the range within which the actual NEET rate would be expected to fall in around four out of five comparable forecast exercises.

Figure 2. Labour Force Survey Forecasted NEET Rate (Non-seasonally Adjusted)



Source: Data for 2009 to 2025 is from the Labour Force Survey. Data for the four quarters of 2026 are forecasts produced by the report authors. Shaded areas represent 80% and 95% forecast intervals.

Table 8. Forecasted Labour Force Survey NEET Rates 2026 Q1 to Q4 (Non-seasonally Adjusted)

Time Point	NEET Rate	80% lower	80% upper	95% lower	95% upper
2025 Q4	13.3	-	-	-	-
2026 Q1	12.3	11.5	13.1	11.1	13.5
2026 Q2	13.2	12.3	14.1	11.8	14.6
2026 Q3	15.4	14.4	16.3	13.9	16.8
2026 Q4	13.5	12.6	14.5	12.0	15.0

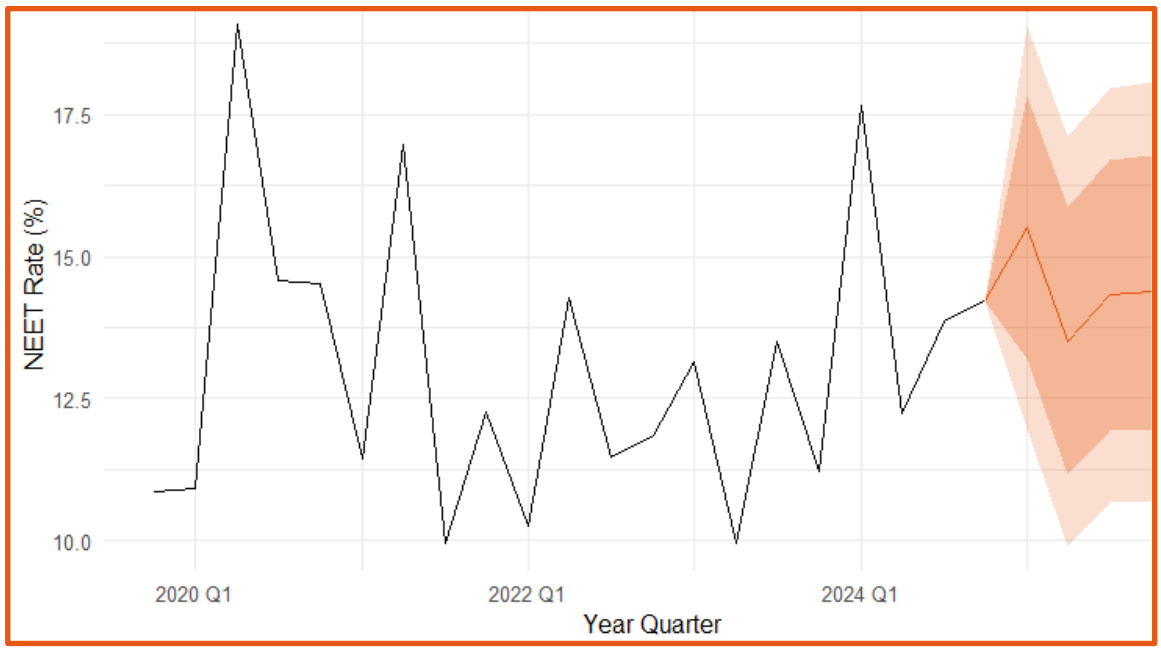
Source: Authors' calculations.

The LFS forecasts show a continued seasonality and a slight upwards trajectory in the short-term, with narrow forecast intervals reflecting the comparatively low volatility of the LFS series and the strength of the recommended model's cross-validation performance.

Understanding Society (USoc) forecast

The recommended USoc model produced forecasts for 2025 Q1 to 2025 Q4. The forecast trajectory is broadly flat, with wide forecast intervals that reflect the volatility of the underlying series. Given the interval widths, it is difficult to draw strong conclusions from a direct comparison with the LFS forecast; the two trajectories cannot meaningfully be said to agree or disagree. The value of the USoc modelling at this stage lies primarily in the consistency of its variable selection results with LFS, discussed in Section 2.6, rather than in the forecast trajectory itself.

Figure 3. Understanding Society Forecasted NEET Rate (Non-seasonally Adjusted)



Source: Data for years 2020 to 2024 is from Understanding Society. Data for the four quarters of 2025 are forecasts produced by the report authors. Shaded areas represent 80% and 95% forecast intervals.

Table 9. Forecasted Understanding Society NEET Rates 2025 Q1 to 2025 Q4 (Non-seasonally Adjusted)

Time Point	NEET Rate	80% lower	80% upper	95% lower	95% upper
2024 Q4	14.2	-	-	-	-

2025 Q1	15.3	12.9	17.6	11.7	18.8
2025 Q2	13.0	10.7	15.4	9.4	16.6
2025 Q3	13.6	11.3	16.0	10.0	17.2
2025 Q4	13.8	11.4	16.2	10.2	17.4

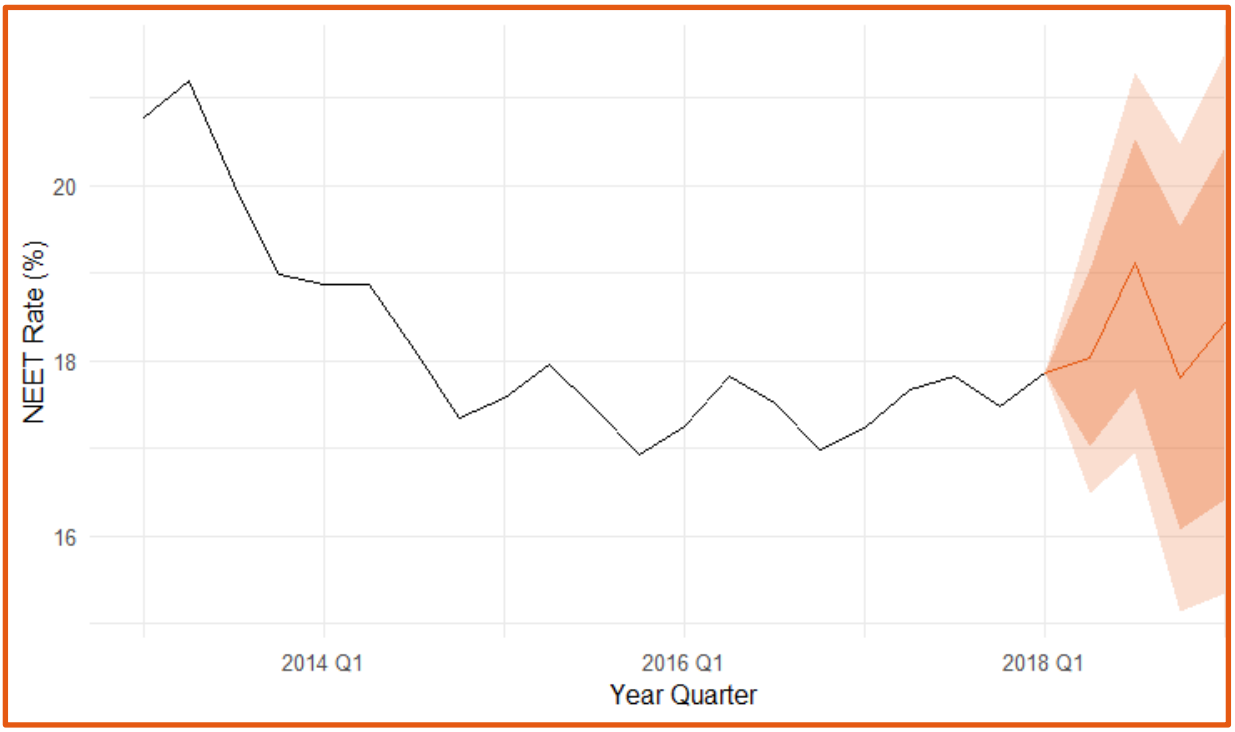
Source: Authors' calculations.

The forecast intervals are wider than those from the LFS model, reflecting the differences in data source and methodology. Comparison of the two forecast trajectories will inform the triangulation discussion in Section 2.6.

Longitudinal Educational Outcomes (LEO) forecast

The recommended model for LEO for 2018 Q2 through to 2019 Q1. The forecasted values showing a continued seasonality in the forecasted NEET rates, peaking in the second quarter of 2019. The forecasted values also carry forward the trend of consistently high NEET rates in LEO; this is expected, given the higher estimates in the training data. The forecasted values suggest a notable rise in the forecasted NEET rate in 2018 Q3, rising up to 19.1%, before the rate reduces back down and is more comparable to pre-forecast NEET rates.

Figure 4. Longitudinal Educational Outcomes Forecasted NEET Rate (Non-seasonally Adjusted)



Source: Data for years 2009 to 2018 is the authors' calculation based on Longitudinal Educational Outcomes data. Data for 2018 Q2 to 2019 Q1 are forecasts produced by the report authors. Shaded areas represent 80% and 95% forecast intervals.

Table 10. Forecasted Longitudinal Educational Outcomes values 2018 Q2 to 2019 Q2 (Non-seasonally Adjusted)

Time Point	NEET Rate	80% lower	80% upper	95% lower	95% upper
2018 Q1	17.9	-	-	-	-
2018 Q2	18.0	17.1	19.0	16.5	19.6
2018 Q3	19.1	17.7	20.5	16.9	21.3
2018 Q4	17.8	16.1	19.5	15.1	20.5
2019 Q1	18.4	16.4	20.4	15.4	21.5

Source: Authors' calculations.

Despite the LEO models containing some of the best forecasting accuracy, across all the models, the forecast intervals around the forecasted LEO rates were the largest of the three models. This is likely driven by the reduced volume of training data, leading to greater uncertainty in forecasted values.

Comparison Between the forecasts

Overall, the three datasets produce different levels of NEET rates, but they tell a broadly consistent story about recent trends and likely short-term movements. Differences in forecast levels and uncertainty largely reflect differences in data design, coverage and volatility, rather than conflicting underlying signals.

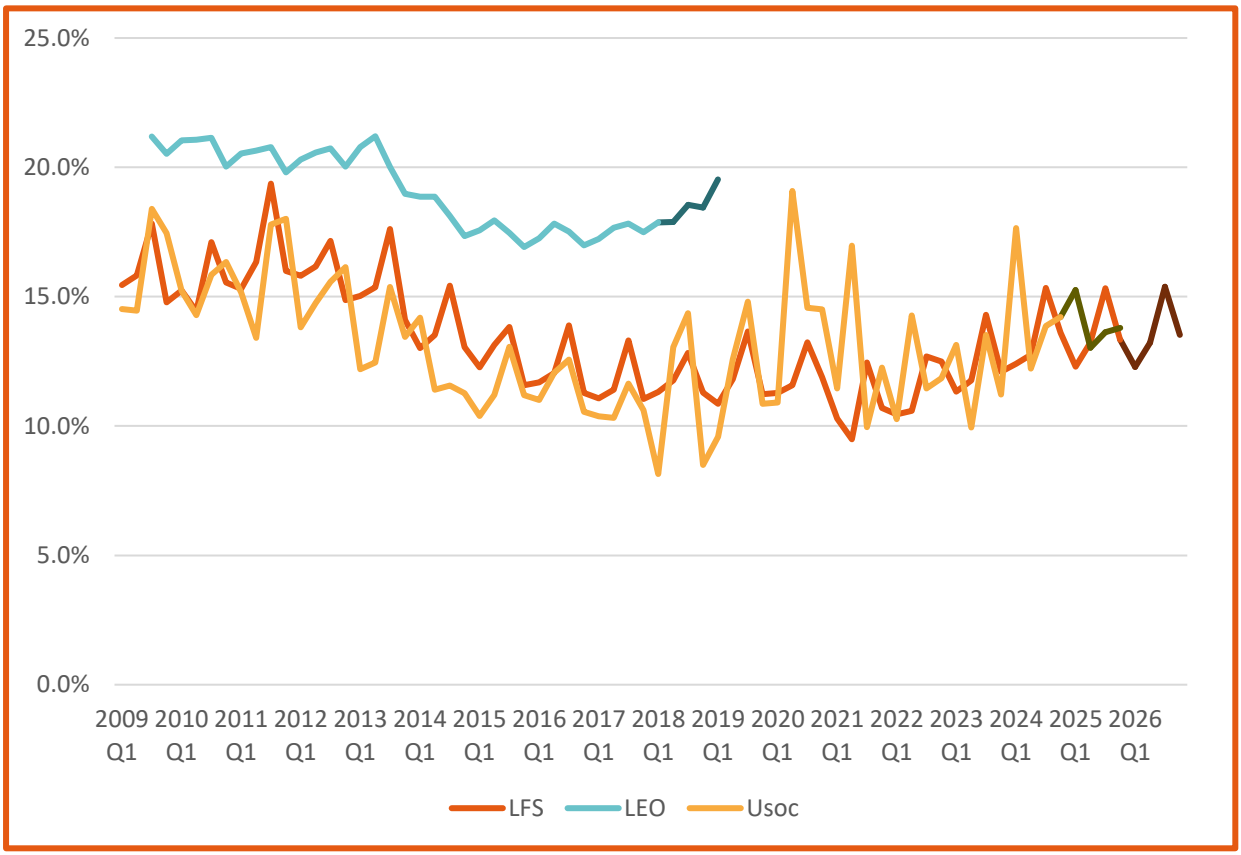
First, the datasets differ systematically in the level and volatility of reported NEET rates. LEO produces the highest NEET estimates across most periods. This likely reflects both the nature of the underlying data and the way NEET status must be derived from administrative records. Unlike survey-based measures, which rely on respondents reporting their current activity, LEO requires evidence of participation in education, employment, or benefits systems. Where such evidence is absent, individuals may be classified as NEET even if their activity is not fully captured within the administrative sources. In practice, this means that incomplete observation of education or employment activity is more likely to inflate NEET estimates than reduce them. Understanding Society reports lower NEET rates than the Labour Force Survey in earlier years but shows greater volatility, particularly after the COVID-19 period. This is likely driven by a combination of methodological factors. First, the quarterly USoc estimates are derived from a survey that was not originally designed to produce quarterly NEET statistics, and each quarter contains fewer observations than the LFS and is therefore more sensitive to sampling variation. Second, the quarterly series is constructed from fieldwork dates within annual survey waves, introducing additional variability that is not present in the purpose-built quarterly LFS estimates. As a result, individual quarters can move sharply even when underlying population changes are relatively modest. By contrast, the Labour Force Survey produces the most stable series and the lowest NEET estimates in recent years, which contributes to its narrower forecast intervals.

Despite these differences in level, the three series show similar long-run patterns. All datasets indicate falling NEET rates from around 2013, followed by a clear increase during and after the COVID-19 period. This consistency provides reassurance that the models were responding to shared underlying changes in youth labour market conditions rather than dataset-specific artefacts.

The forecast trajectories also show important similarities, particularly in how they extend recent trends forward. Across all three datasets, the forecasts carry through both within-year seasonality and the post-COVID upward shift in NEET rates. While the absolute levels differ, the direction of change in the forecasts broadly aligns with movements observed in the most recent reported data.

However, the degree of certainty around these forecasts varies markedly by dataset. The LFS forecasts have the narrowest forecast intervals, reflecting a greater number of available time points, reported quarterly frequency, and noticeably lower volatility of the series. Understanding Society forecasts have substantially wider intervals, meaning they should be interpreted primarily as indicating direction and relative risk rather than precise quarter-by-quarter estimates. LEO forecasts also have wide intervals, driven by the shorter time series available for modelling.

Figure 6. Reported and Forecasted NEET Rates for Each Model



Source: Data showing non-seasonally adjusted NEET estimates from Labour Force Survey data from 2009 to 2025, Understanding Society data from 2009 to 2024, and the authors' calculations based Longitudinal Educational Outcomes data for 2009 to 2018. Data for 2026 (LFS), 2025 (USoc) and 2018 Q2 to 2019 Q1 (LEO) are forecasts produced by the report authors.

Limitations

The forecasting models carry limitations inherent to common forecasting approaches, as well as risks specific to the data used.

All forecasts become less reliable further into the future, and forecast intervals should be considered alongside point estimates. Some variables, such as the disability rate, are themselves statistically modelled by producing forecasted values with ARIMAs, adding a further layer of uncertainty not captured in the forecast intervals.

Importantly, the forecasting approach is also inherently backwards-looking. Like all time-series forecasting methods, the models presented here learn from historical relationships between NEET rates and economic conditions, and project those relationships forward, even if the relationships may not hold true in the future. Major shocks, policy changes, or structural labour market shifts could disrupt this, as illustrated by the COVID-19 pandemic. This means forecast accuracy will be higher to the degree that current conditions persist, and lower to the degree that they do not. This is a property of short-term extrapolative forecasting generally, including approaches that incorporate more theory-driven drivers, rather than a specific limitation of the SARIMAX methodology used here. The inclusion of published forward projections for GDP and unemployment (from the Bank of England Monetary Policy Report) does provide some sensitivity to anticipated future economic conditions, but the forecasts are best understood as signals about the likely persistence of current trends rather than predictions of structural change. Users applying the tool during periods of significant economic transition should weight the forecast intervals accordingly and consider the forecasts alongside other sources of intelligence.

Data-specific risks also apply. Testing model specifications on relatively short series carries a risk of overfitting, though this is mitigated by selecting variables based on out-of-sample forecast performance and cross-dataset consistency. The LFS provides more stable estimates and therefore more precise forecasts, while Understanding Society is more volatile and should be treated as directional confirmation only. Both surveys experienced data quality challenges during the COVID-19 period, which may have introduced artificial volatility and contributed to the identification of structural breaks that reflect measurement issues rather than genuine shifts in NEET rates. Finally, some theoretically relevant variables could not be included due to data constraints or the absence of reliable forward projections.

One more practical limitation of this approach is the dependency on multiple data sources. In particular, the triangulation stage described below involves incorporating an indicator of the divergence between USoc and LFS NEET estimates as an exogenous

variable. This means that updating the forecasting tool requires a current USoc NEET estimate in addition to the LFS. Where USoc data are delayed or unavailable, this variable cannot be constructed, and the model would need to be run without it.

Taken together, these caveats do not undermine the value of the modelling exercise, but they do highlight the importance of interpreting the forecasts as decision-support tools rather than definitive projections.

Model triangulation

This section brings together the modelling results from the three datasets to assess the extent to which findings converge across complementary sources, and what this means for the robustness of the final forecasting tool. The purpose of triangulation was not to blend three forecasts into one, but to stress-test and strengthen the LFS-based model by drawing on evidence from USoc and LEO – two complementary sources with different designs, populations, and limitations. The section covers three areas: the consistency of exogenous variable selection across the three datasets; what divergence between sources reveals about data quality and measurement; and the role of structural breaks in shaping model performance. It concludes by presenting the refined LFS forecasting model that resulted from this process.

Consistency of exogenous variables across datasets

This study uses three complementary datasets to model NEET rates, each with different design, coverage, and temporal resolution. No single source provides a complete picture: LFS offers the longest and most frequently updated series but faces known data quality concerns; USoc provides an independent household survey but with greater volatility and less frequent reporting; LEO draws on administrative records but covers a shorter time period and a different population.

Triangulation across these sources serves two purposes. First, it identifies where the evidence converges, strengthening confidence in findings that hold across datasets. Second, it highlights where sources diverge, which can itself be informative for the final model.

A key finding from the modelling is the degree of consistency in variable selection across the three datasets, despite substantial differences in design, sample size, and temporal resolution. Here we briefly summarise which variables appeared consistently across the exploratory LFS, USoc, and LEO models, how this informed decisions about which variables were taken forward for testing in the final model stage, and why some variables were ultimately retained while others were not.

- **Unemployment rate** is the strongest and most consistent regressor, appearing in all three recommended models with a positive coefficient and statistical significance in each case. In the LFS, when models were re-run, leaving a single predictor out at a time, it showed that including unemployment accounted for 71% of the total forecast improvement provided by the exogenous variables. Its consistent performance across datasets suggests it reflects a genuine predictive relationship with NEET rates rather than an artefact of any single source.

- **Disability rate** also performed consistently, appearing in both the LFS and LEO models with a negative coefficient in each case. In the LFS model, it was lagged by seven quarters, suggesting the relationship operates with a delay. The consistency of direction and significance across two complementary datasets strengthens the case for its inclusion.

- **Youth sector job availability** appeared in all three datasets, most frequently in USoc and LEO models, but with opposite signs and borderline statistical significance in both cases. The LEO coefficient aligns with expectations, where greater job availability is associated with falling NEET rates, while the USoc coefficient is counterintuitive and likely reflects noise in a more volatile series. As such, its individual contribution should be interpreted with caution. Its continued appearance in other high-performing models on the AICc-ranked leaderboard suggested that it was nonetheless worthwhile testing for inclusion in the final model.

- The **COVID-19 shock binary** variable was included in the USoc model only, where it substantially improved model fit for the pandemic period. As a one-off pulse variable, it does not influence forecasts going forward.

- **GDP** appeared only in the LFS model, where it made a small but genuine contribution to forecast accuracy.

Overall, the exogenous variables provide a refinement to forecast accuracy rather than a radical transformation. Across all three datasets, the ARIMA structure captures the bulk of the forecasting signal through trend, seasonality and recent history. The primary practical value of including exogenous variables is that they allow the forecasting tool to respond to changing economic conditions, such as a rise in unemployment or a contraction in GDP, rather than relying solely on the projection of past trends. This responsiveness is particularly important for a tool intended to support forward-looking policy decisions.

The forecast trajectories themselves were harder to compare directly. The USoc forecast is broadly flat with wide forecast intervals, making it difficult to draw strong conclusions from a comparison with the LFS trajectory. The intervals were wide enough that agreement or disagreement cannot be meaningfully established. LEO forecasts cover a different time period entirely, with low errors but wide intervals, and the forecast for the last reliable period shows an upwards tendency that is mirrored by the other sources. As such, USoc's and LEO's contributions were better understood through their insights for variable selection than through their forecast trajectories.

Integrating variation in NEET rates

The known data quality issues in LFS raised a concern about how the final model could be strengthened. Despite volatility in some years, USoc has tended to show lower NEET rates than LFS when rates were decreasing, and higher rates since the pandemic. This divergence may itself carry predictive information.

We used the difference in NEET rates between USoc and LFS as an additional regressor in the final model. The rationale is that both surveys are imperfect measures of the same underlying construct, the true UK NEET rate, each with distinct strengths and limitations. Where the two sources diverge, this divergence itself carries information: it signals that one or both sources may be temporarily departing from the underlying trend, whether due to sampling variation, fieldwork disruption, or other data quality factors. By including this deviation as a regressor, the model can adjust for periods when the LFS estimate appears to be moving out of step with the broader signal, using USoc as an independent cross-check. The variable is lagged by four quarters, due to the lag in data availability from Understanding Society, using the deviation from one year prior to the observation being predicted.

Testing observed structural breaks

Throughout the modelling process, candidate structural breaks were tested: points representing substantial changes in the pattern of the underlying data, such as a shift in the direction or level of the NEET rate. In the LFS models, a 2013 Q3 break marginally improved model fit but notably worsened forecast accuracy (see Table 4). In the LEO models, a 2010 Q1 break was tested but did not improve performance over the recommended specification (see Table 5). The COVID-19 shock binary variable in USoc was the most impactful, substantially improving fit for the pandemic period.

Some structural breaks have clear causal explanations, such as the pandemic. Others were harder to interpret and may represent the best single-point approximation of a longer-term shift in economic conditions. The structural breaks that were identified for the LFS data, 2013 Q3 and COVID shock, were taken forward for testing in the final model.

A refined Labour Force Survey (LFS) NEET forecasting model

Based on the recommendations discussed above, the research team produced a final LFS-based model, which formed the foundation of the forecasting tool that accompanied this work. The team built upon the exploratory LFS model, and the supplementary USoc and LEO models, by incorporating the following improvements:

1. The final model used a set of exogenous variables that either performed well within the exploratory models for LFS or performed consistently well across LFS, USoc and LEO.

2. The deviation in observed NEET rates between USoc and LFS datasets was included as an exogenous variable. This was constructed by calculating the difference in reported NEET rates between both data sources and then lagging the variable by four quarters to account for the delay in USoc data availability. Future values for the USoc data and this exogenous variable were then produced using a SARIMA forecast.

The final model was selected by prioritising forecasting accuracy, specifically in the more stable years post-COVID. As previously, the research team produced and tested every possible permutation of the final model. The team then selected the final model based primarily on minimising forecasting error, while ensuring the model also had a sufficiently good model fit to still be robust. The model the team selected had the lowest forecasting MAPE of all the permutations tested and contained:

- Lagged disability rate
- GDP,
- unemployment rate for working-age adults, and
- the deviation between USoc and LFS NEET rates.

Each variable retained in the final model improved forecasting accuracy. The inclusion of unemployment in the final model had the largest single improvement in forecasting accuracy, reducing the MAPE of the final model by 2.2 percentage points, compared to an equivalent model without it. The lagged disability rate and GDP also both made improvements to the forecasting accuracy: Compared to equivalent models excluding them, the lagged disability rate reduced the MAPE by 0.8 percentage points and GDP by 0.4 percentage point. Furthermore, the inclusion of USoc and LFS NEET rates deviation reduced the MAPE by 0.1 percentage points, compared to an equivalent permutation of the model that did not include it. The improvement made to forecasting accuracy by the USoc and LFS deviation was the smallest improvement of all the exogenous variables.

Other variables taken forward for testing in the final model stage, including vacancies in sectors that disproportionately hire young people and the structural break variables identified during the exploratory modelling stage, did not improve forecasting performance and were therefore not retained in the final model.

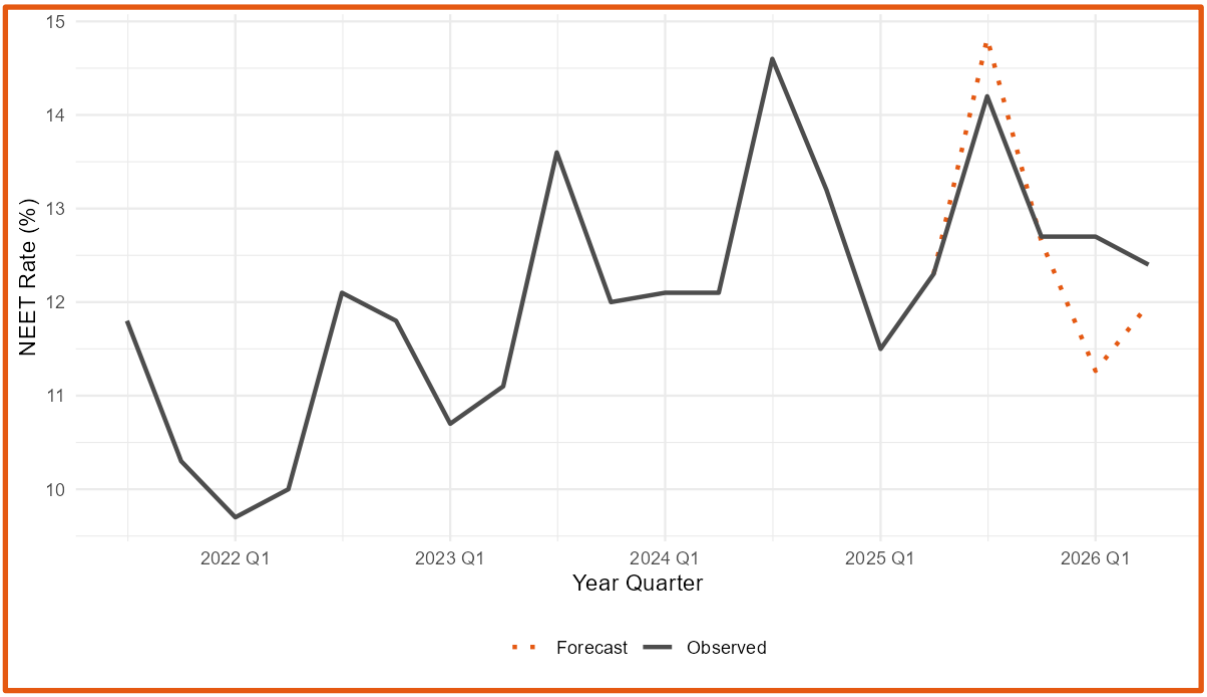
Table 11. Variable Contribution and Sensitivity Checks, Final Model

Variable Removed	MAPE Increase	Share of EV Improvement
Final model	—	—
Removing Unemployment Rate	+2.2	62.9%
Removing Disability Rate (lagged)	+0.8	22.9%
Removing GDP	+0.4	11.4%
Removing USoc and LFS Variation	+0.1	2.9%

Source: Authors' calculations.

This model produced an MAPE score of 4.9%, using an expanding window approach, which indicated relatively low forecasting error, and lower than those in the exploratory models, although comparisons should be made with caution due to the different evaluation windows. For completeness, the production model makes use of a 'holdout' window, the last four quarters of observed LFS NEET rates, as an additional check that displays what the most recent forecast would have been. Figure 6 shows this in practice: forecasted 2025 Q3 to 2026 Q2 LFS NEET rates are plotted against the reported values for that time period. The validation shows that the model performed reasonably well in predicting the NEET rates for that period, although the point estimates are initially slightly larger, they then drop slightly lower than the reported values from 2025 Q4 onwards. The model also correctly captured the within-year variation observed.

Figure 7. Validation of the Final Forecasting Model on the Reported 2025 LFS NEET Values



Source: Reported data from 2021 Q1 to 2026 Q2 taken from Labour Force Survey. The dotted orange line shows the final model forecasting values for 2025 Q3 to 2026 Q2, produced by the report authors. This 'last year' prediction is included in the production code for reference. The model contains unemployment, GDP, USoc and LFS variation, and lagged disability rate.

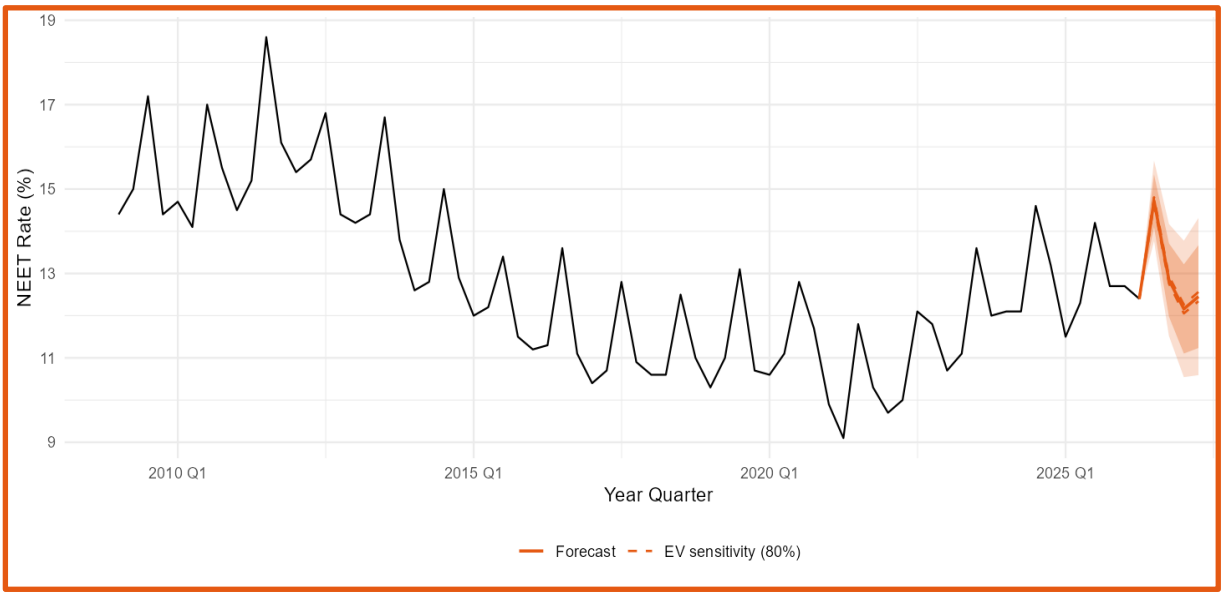
When forecasting forward to 2027 Q2, the model produced a forecast that continued both the overall annual trend for NEET rates from the previous four quarters and also captured the within-year seasonal variation. The forecasts, together with their 80% and 95% forecast intervals, are shown in Figure 8. The intervals are relatively narrow, which, alongside the model's low MAPE, indicates a reasonable degree of confidence in the point estimates.

A further improvement made to the final model was to quantify and display the additional uncertainty that arises when future values of some exogenous variables are themselves produced by a SARIMA model. In the exploratory models, the uncertainty around the values produced by SARIMAs, such as for disability rate, was not reflected anywhere in the forecast, so accuracy was overstated and the true uncertainty understated.

This additional uncertainty is shown in Figure 8 by the narrow-dashed orange bands around each forecasted point estimate. Rather than being folded into the main 80% and 95% intervals, it is presented as a sensitivity overlay: the forecast is re-run with the SARIMA-forecast exogenous variable set to the upper and lower bounds of its own 80%

forecast interval, and the resulting high and low NEET paths are plotted around the central forecast. In this example, the variation reflects the disability rate series, so the bands show how far the NEET forecast would shift if the disability rate turned out at the high or low end of its forecast range. The wider the bands, the more sensitive the forecast is to that variable's assumed path.

Figure 8. Plot of Non-seasonally Adjusted Forecasted NEET Rates produced by the Final Model



Source: Reported values for 2009 Q1 to 2026 Q2 taken from the Labour Force Survey. Forecasts for 2026 Q3 to 2027 Q2 were produced by the report authors. Shaded areas represent 80% and 95% forecast intervals. The dark orange dotted line around each forecasted point shows the sensitivity of forecasts according to 80% forecast intervals of exogenous variables created by the USoc and LFS variation EV. The model contains unemployment, GDP, USoc and LFS variation, and lagged disability rate.

Table 12.Non-seasonally Adjusted Forecasted NEET Rates from the Final Model

Time Point	NEET Rate	80% lower	80% upper	95% lower	95% upper
2026 Q2 (reported)	12.4	-	-	-	-
2026 Q3 (forecasted)	14.7	14.1	15.3	13.8	15.7

2026 Q4 (forecasted)	12.8	12.0	13.7	11.5	14.2
2027 Q1 (forecasted)	12.2	11.1	13.2	10.5	13.8
2027 Q2 (forecasted)	12.5	11.2	13.7	10.6	14.3

Source: Reported value for 2026 Q2 taken from the Labour Force Survey; values taken from 2026 Q3 to 2027 Q2 taken from the authors' calculations. The model contains unemployment rate, GDP, USoc and LFS deviation, and lagged disability rate.

Compared with the exploratory LFS forecast, the final model projects a similar pattern of NEET rates across 2026 Q3 to 2027 Q2. Both models suggest a peak in 2026 Q3 followed by a dip in 2027 Q1, before NEET rates again rise slightly towards the middle of 2027. The final model produces marginally more conservative estimates of NEET rates compared to the exploratory LFS model, reporting slightly lower NEET estimates in the latter two quarters of 2026. Both models also had similar levels of uncertainty around the estimates, which is expected given they were both estimated from the same LFS data.

Modelling of Seasonality and Seasonal Adjustment

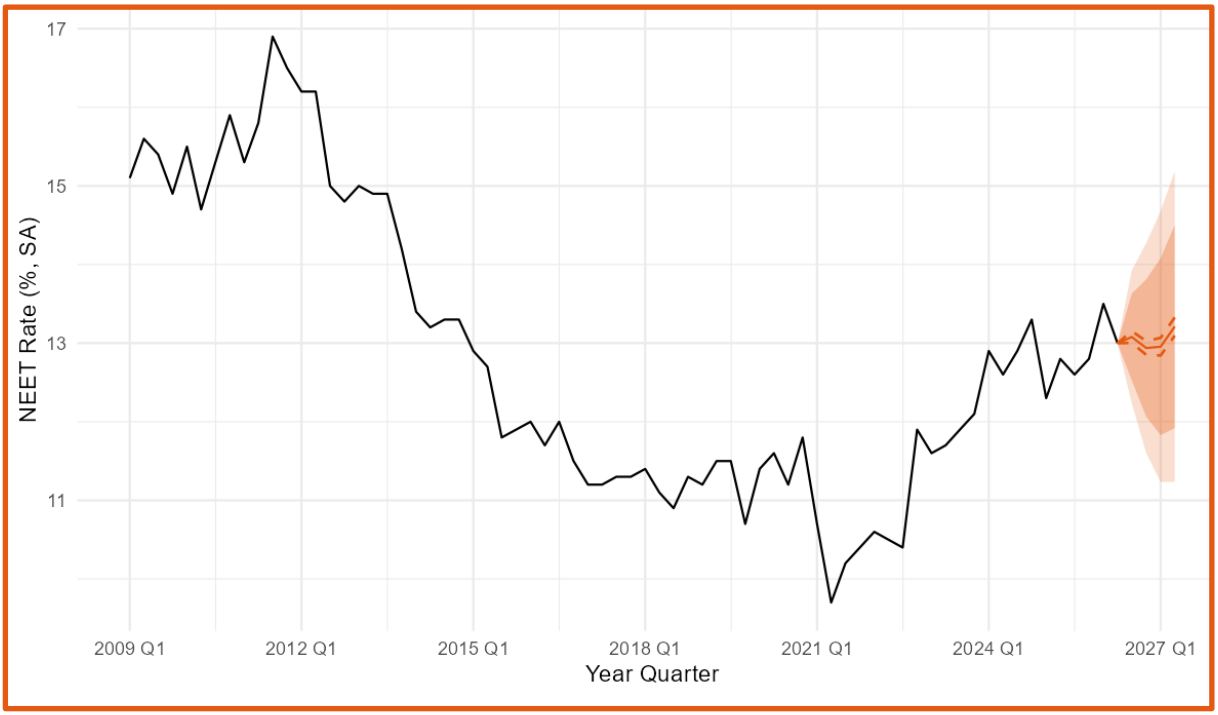
The NEET rate follows a strong and regular yearly cycle, peaking in the July–September quarter. To capture this pattern, the final production model includes Fourier terms, which allow a fixed quarterly seasonal pattern to be represented directly within the forecasting model. While some high-performing SARIMAX specifications did not explicitly model seasonality, incorporating Fourier terms ensured that seasonal effects were represented consistently in both forecasting and the subsequent production of seasonally adjusted estimates. Across the 28 model variations tested, this approach improved forecast accuracy in 24 cases and did not materially affect which exogenous variables were selected. (The production tool evaluates model specifications both with and without this addition when selecting the optimal model.)

The final production model therefore includes Fourier terms to represent seasonality when generating forecasts. However, these forecasts remain non-seasonally adjusted and therefore retain the expected within-year variation in NEET rates. To support comparison with other published NEET statistics, the research team also produced a seasonally adjusted version of the final forecast.

Seasonal adjustment removes the regular and predictable within-year fluctuations in NEET rates, such as those associated with the academic calendar and seasonal employment patterns. A post hoc seasonal adjustment was applied to the NEET rates produced by the final model using the X-13ARIMA-SEATS package in R (US Census Bureau, 2025). This approach was requested by Youth Futures due to previous use in producing seasonally adjusted rates.

Seasonal adjustment was carried out by fitting X-13ARIMA-SEATS to the full historical LFS NEET series to estimate its seasonal component, and deriving a seasonal factor for each quarter of the year. To adjust the four forecast quarters, the most recently observed factor for each quarter was carried forward and applied to the corresponding forecast value, holding the seasonal pattern constant at the level seen in the previous four quarters. This was preferred to averaging factors across the whole history because it keeps the adjustment aligned with the most recent seasonal pattern and avoids carrying forward older seasonal structure, including the atypical quarters around the COVID-19 disruption, that may no longer reflect current conditions.

Figure 9. Plot of Seasonally Adjusted Forecasted NEET Rates produced by the Final Model



Source: Data for 2009 Q1 to 2026 Q2 are from the Labour Force Survey seasonally adjusted estimates of NEET rates. Data for 2026 Q3 to 2027 Q2 are seasonally adjusted forecasts produced by the report authors. Shaded areas represent 80% and 95% forecast intervals. The model contains unemployment, GDP, USoc and LFS variation, and lagged disability rate.

Table 13. Seasonally Adjusted Forecasted NEET Rates from the Final Model

Time Point	NEET Rate	80% lower	80% upper	95% lower	95% upper
2026 Q2 (reported)	13.0	-	-	-	-
2026 Q3 (forecasted)	13.1	12.5	13.6	12.2	13.9
2026 Q4 (forecasted)	12.9	12.1	13.8	11.6	14.3
2027 Q1 (forecasted)	13.0	11.8	14.1	11.2	14.7
2027 Q2 (forecasted)	13.2	11.9	14.5	11.2	15.2

Source: Reported value for 2026 Q2 taken from the Labour Force Survey; values taken from 2026 Q3 to 2027 Q2 taken from the authors' calculations. The model contains unemployment, GDP, USoc and LFS deviation, and lagged disability rate.

Conclusion

What the research has achieved

This research demonstrates that short-term NEET forecasting is both reasonably accurate and policy relevant. By combining autoregressive time-series modelling with carefully selected exogenous variables, and triangulating findings across three distinct data sources, the analysis produced forward-looking signals more robust than any single model or dataset could provide alone. The final model achieved a mean absolute percentage error of 4.9%, a meaningful improvement on the 6.2% error of the pre-triangulation baseline and produced forecasts that correctly captured both the direction and within-year profile of recent NEET movements.

That accuracy rests on a deliberate triangulation strategy. NEET forecasting models were developed separately across three complementary data sources: the Labour Force Survey, Understanding Society, and the Longitudinal Educational Outcomes dataset. Variables that performed consistently well as factors associated with NEET rates across multiple datasets were prioritised for inclusion in the final Labour Force Survey model. This cross-dataset consistency provides stronger grounds for relying on these variables as credible components in a NEET forecasting model, rather than artefacts of any single data source, and increases confidence that the recommended model will respond reliably to the economic and social changes most likely to drive future shifts in NEET rates.

The project supports Youth Futures Foundation in addressing a recognised gap in the policy landscape: the absence of timely, forward-looking NEET estimates at a time when demand for such intelligence is high. The result is a forecasting model grounded in current economic conditions and a transparent, reproducible methodology that can be updated and re-run at each quarterly data release.

Recommended use of the forecasting tool

A forecasting tool produced in the statistical computing language R has been prepared for Youth Futures Foundation, enabling the full process to be repeated as updated data become available. It is designed to produce updated four-quarter-ahead forecasts (with 80% and 95% forecast intervals) at each new Labour Force Survey quarterly data release, without requiring substantial changes to the underlying model.

The tool's recommended use is as one source of intelligence among others: a structured, evidence-based input to discussions about likely future NEET trajectories, not a definitive projection. Forecast intervals should always accompany point estimates, and outputs should be interpreted alongside current economic conditions and expert judgement.

The tool cannot anticipate abrupt structural breaks or major policy shocks; scenario-based analysis is more appropriate for exploring such contingencies. The tool also enables scenario testing as alterations can be made to underlying exogenous variables to simulate potential policy changes, and the subsequent effect on NEET forecasts can be assessed. Importantly, the forecasting tool has been developed and validated for four-quarter-ahead forecasts. The reported MAPE and other performance metrics should therefore be interpreted as evidence of performance at that horizon only. Users wishing to extend the forecast window beyond four quarters should do so with caution and should re-run the validation process using the longer forecast horizon to confirm that forecasting performance remains acceptable. This is particularly important because forecast uncertainty accumulates over time and some exogenous variables must themselves be forecasted.

At a time when labour market conditions remain uncertain, this tool provides a credible, timely, and transparent basis for forward-looking policy planning. Used appropriately, it supports more proactive planning, better-informed resource allocation, and more resilient decision-making across organisations working to reduce NEET rates.

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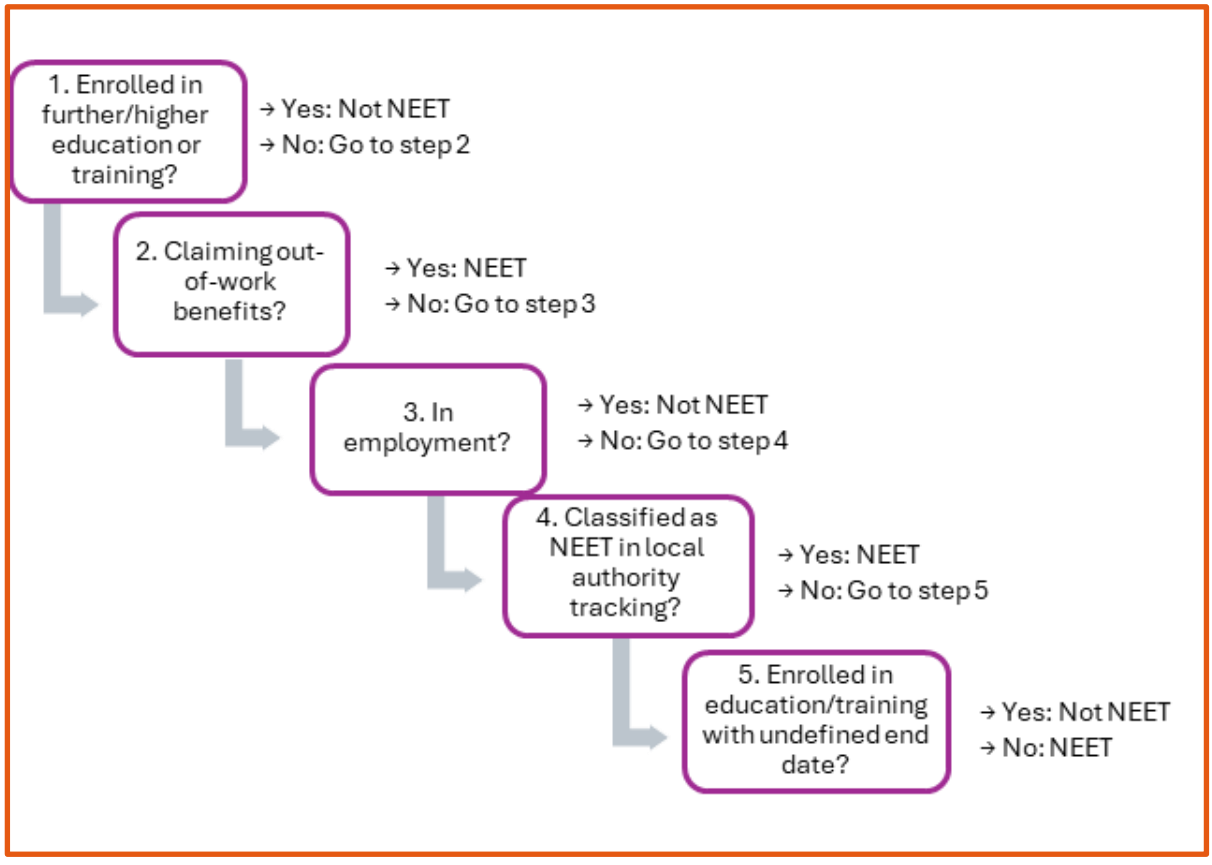
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Appendices

Appendix A: Derivation of NEET status in LEO

The outcome of the analysis, experiences of NEET status, was conceptualised following the methodology applied by the Department for Education for the study of NEET on LEO data (2018)[1]. This followed a hierarchical process for each month (the first condition to apply determined whether the individual was classified as NEET):

Figure 10. Hierarchical Process for Deriving NEET Status in LEO

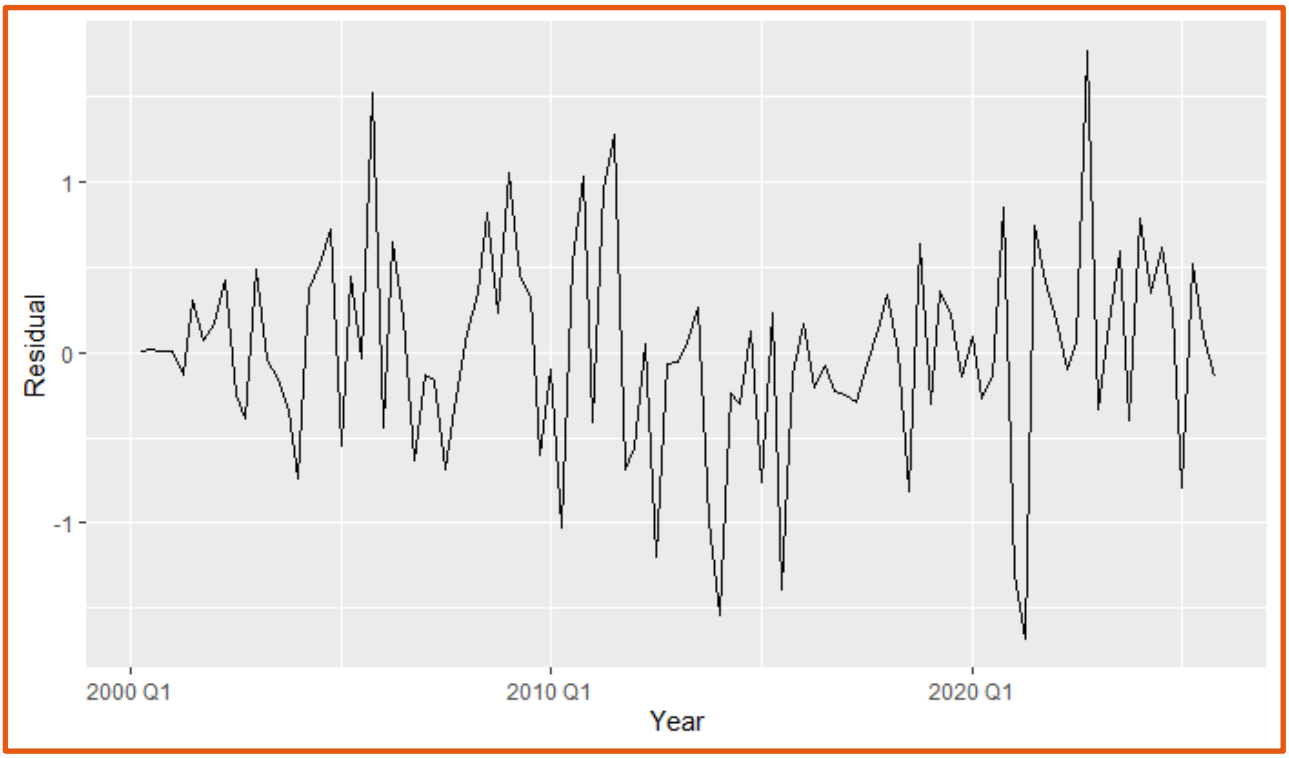


A cross-sectional snapshot of NEET status was then taken from the beginning of each quarter; this produced quarterly measures of NEET status for the whole cohort across all suitable years of LEO data. This approach is consistent with how NEET status is measured in the LFS and Understanding Society and will allow the forecast of each model to be comparable.

Due to the approach used to derive participation in higher education, the research team encountered data issues using the latter years of LEO, from 2018 onwards. This is likely due to the derivation requiring a complete spell in education to confidently attribute participation in higher education to a case. Therefore, the team's approach led to a significant underestimation of HE numbers in the latter years of LEO and therefore, inflated NEET estimates. As LEO's primary role in the forecasting was historical comparison, NEET estimates from LEO were only used from 2009 Q1 up until 2018 Q1.

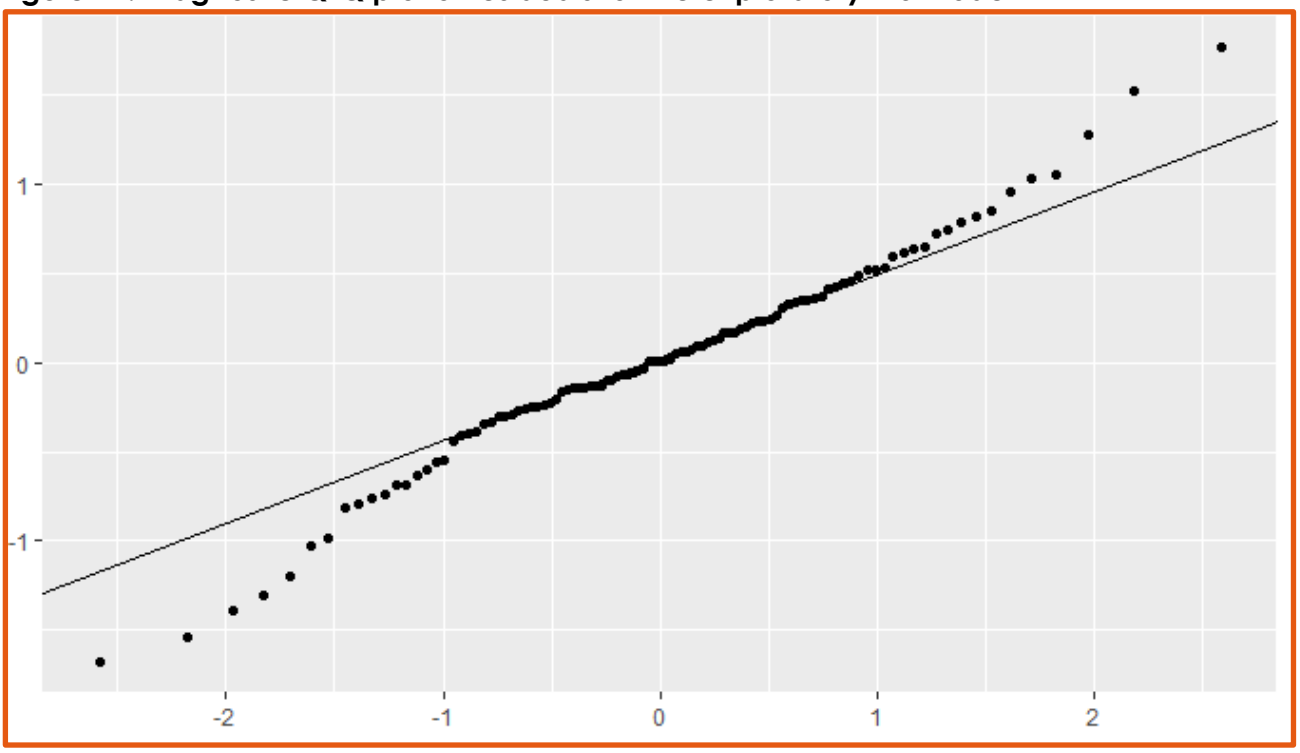
Appendix B Diagnostic plots for exploratory LFS model

Figure 11. Diagnostic residuals of the exploratory LFS model



Source: Labour Force Survey, 2009 Q1 to 2025 Q4

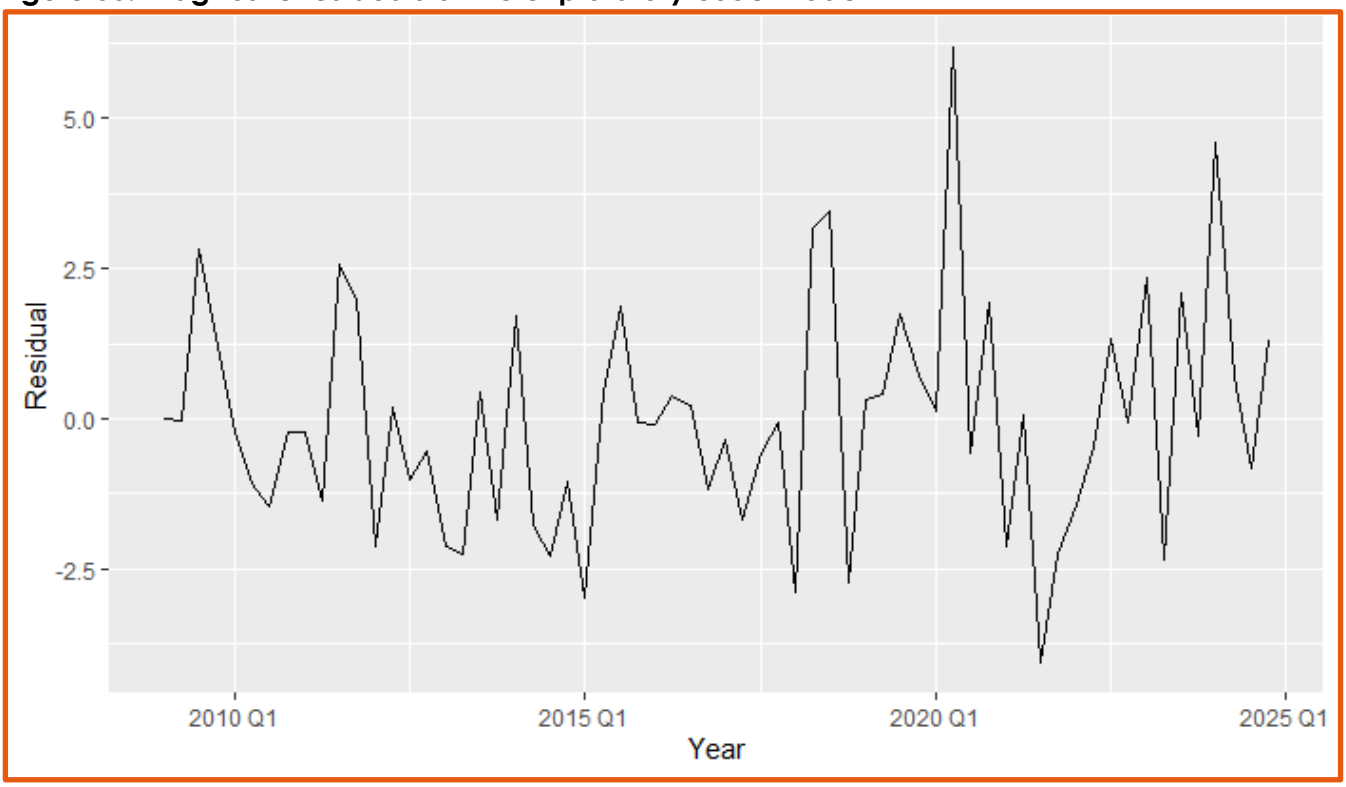
Figure 12. Diagnostic Q-Q plot of residuals for the exploratory LFS model



Source: Labour Force Survey, 2009 Q1 to 2025 Q4

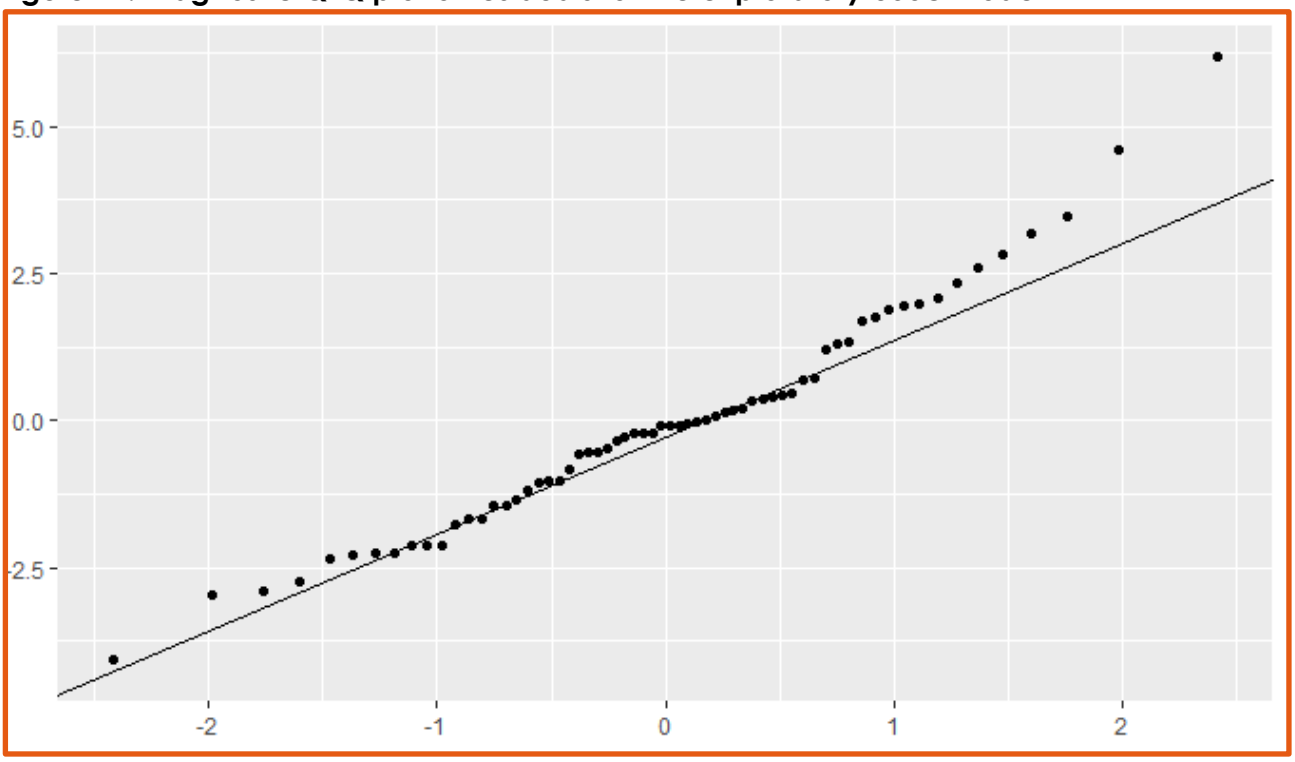
Appendix C: Diagnostic plots for exploratory USoc model

Figure 53. Diagnostic residuals of the exploratory USoc model



Source: Understanding Society, 2009 Q1 to 2024 Q4

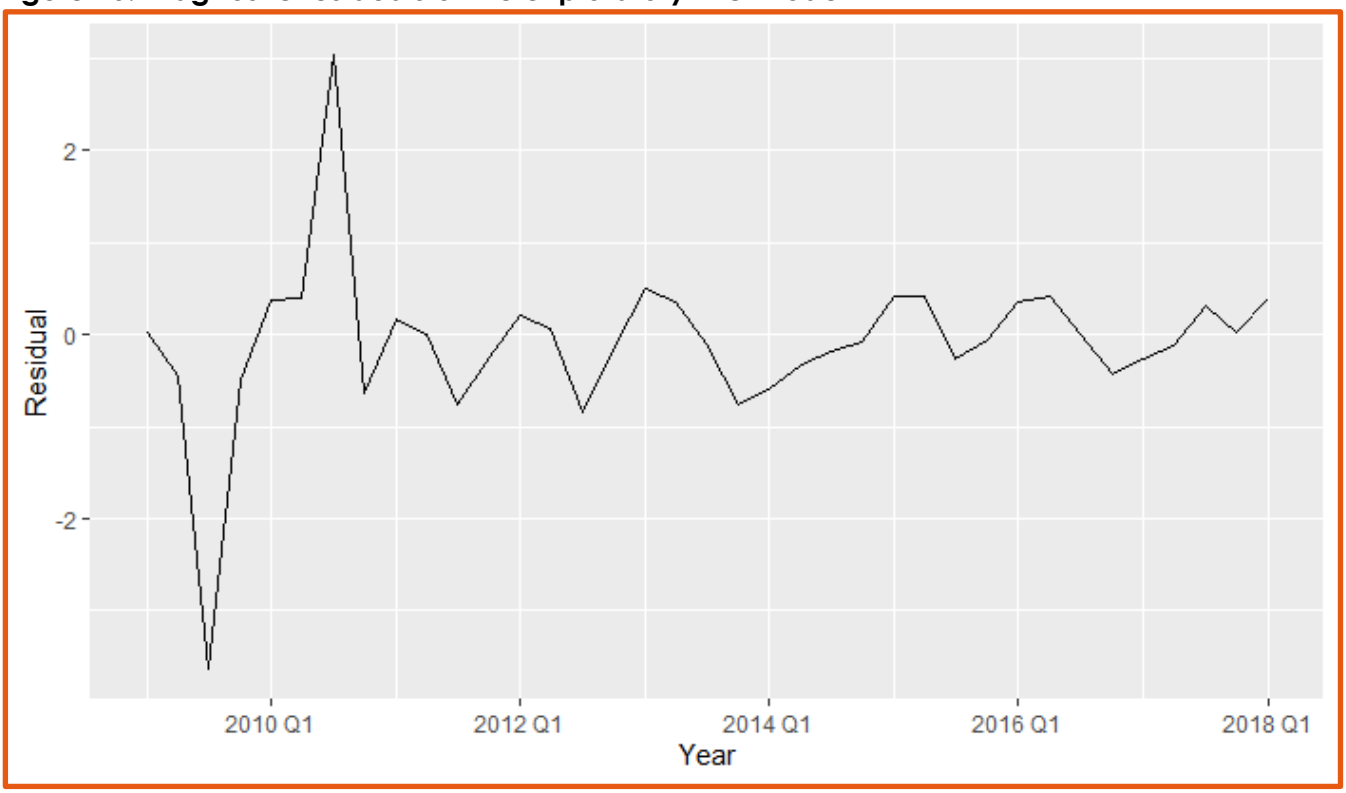
Figure 14. Diagnostic Q-Q plot of residuals for the exploratory USoc model



Source: Understanding Society, 2009 Q1 to 2024 Q4.

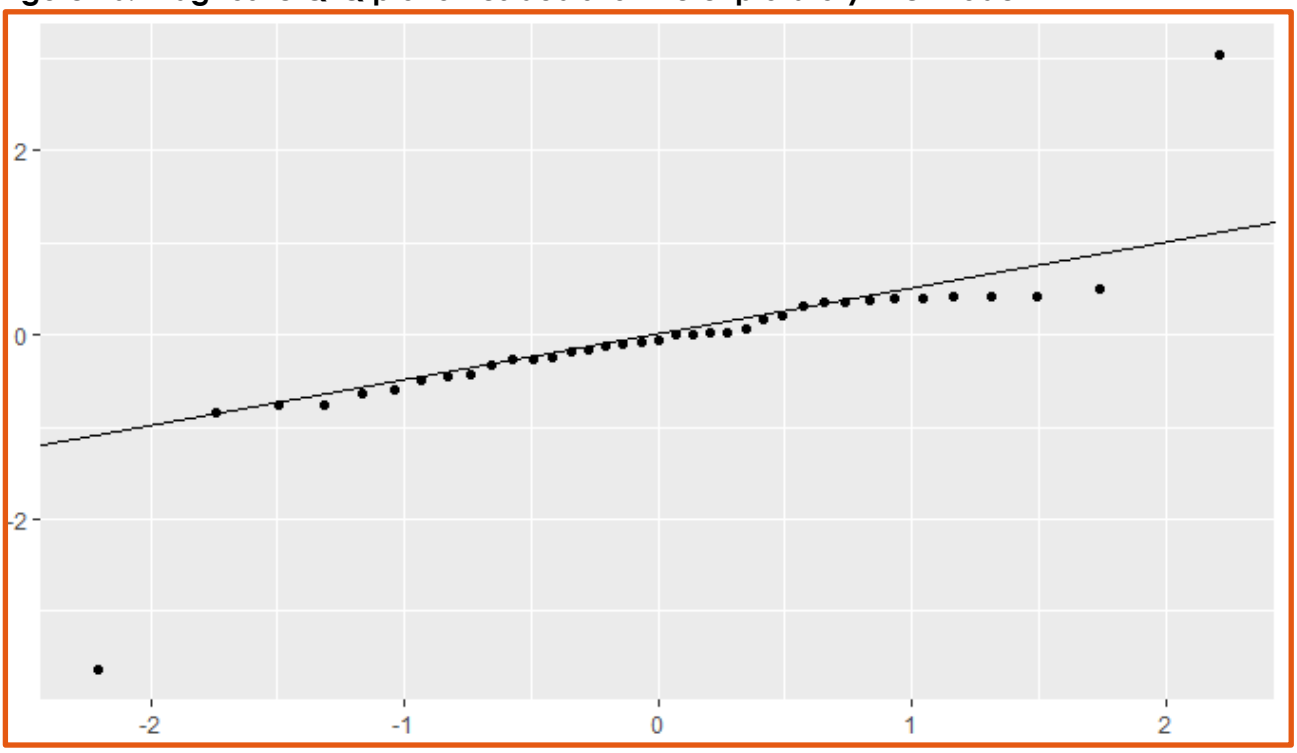
Appendix D: Diagnostic plots for exploratory LEO model

Figure 15. Diagnostic residuals of the exploratory LEO model



Source: Longitudinal Educational Outcomes, 2009 Q1 to 2018 Q1.

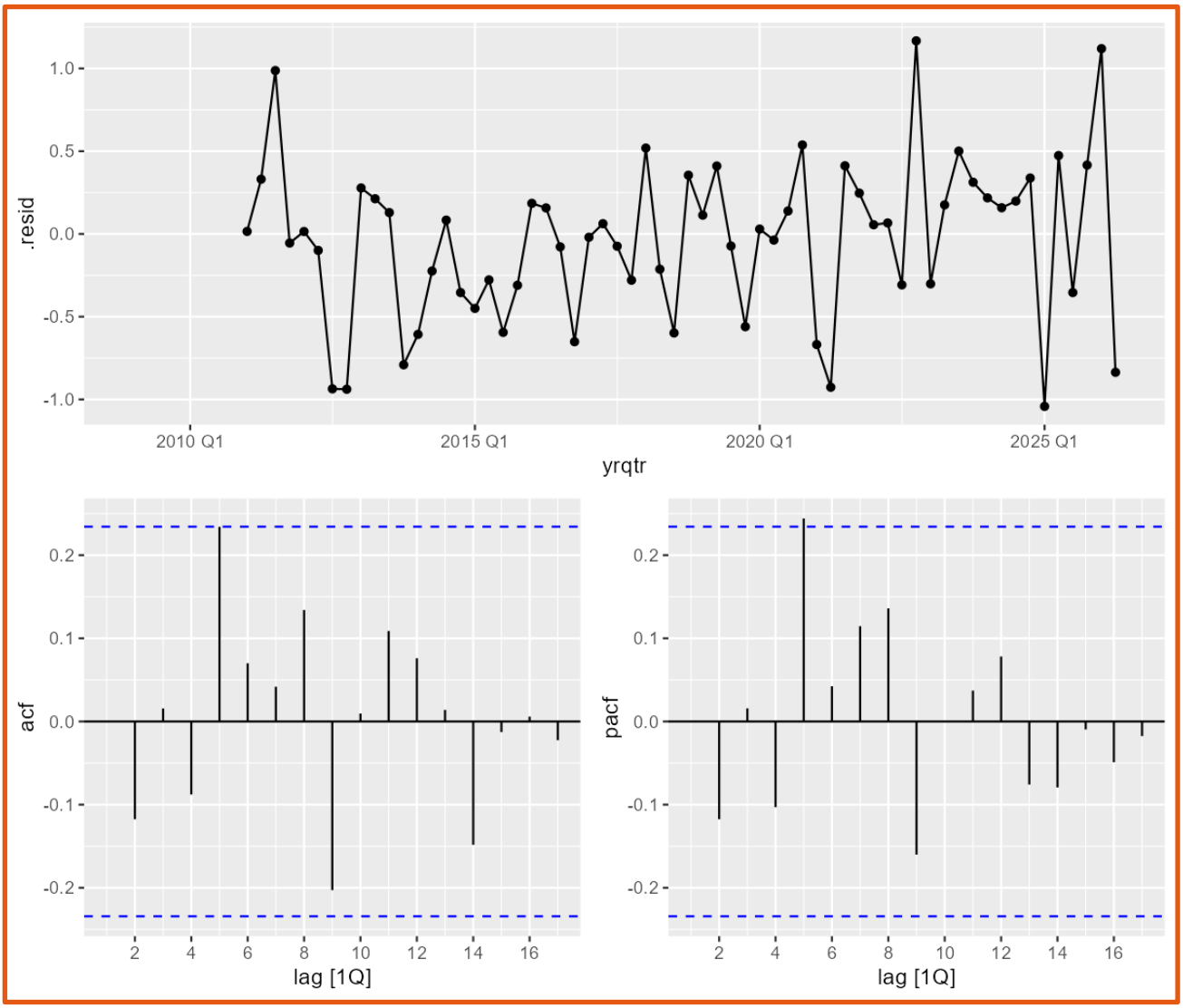
Figure 16. Diagnostic Q-Q plot of residuals for the exploratory LEO model



Source: Longitudinal Educational Outcomes, 2009 Q1 to 2018 Q1.

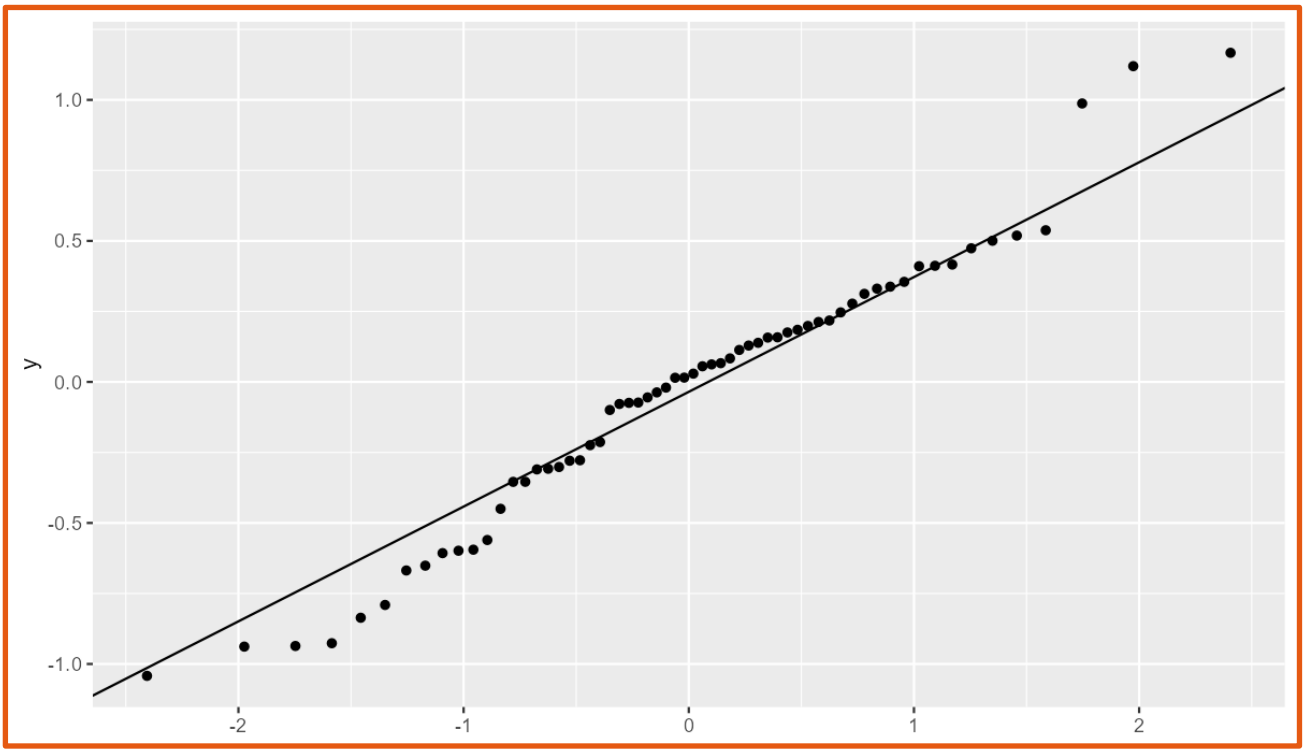
Appendix E: Diagnostic plots for final LFS model

Figure 17. Diagnostic ACF and PACF plots of the final LFS model



Source: Labour Force Survey, 2009 Q1 to 2026 Q2.

Figure 18. Diagnostic Q-Q plot of residuals for the final LFS model



Source: Labour Force Survey, 2009 Q1 to 2026 Q2.

Appendix F: LFS - Full Model Results

Table 16. Cross-validation results for the top 35 exploratory LFS model permutations

Rank	Model Specification	N	AICc	Δ AICc	MAPE Expanding	MAPE Sliding
1	COVID Shock + 2020 Q4 Break + Unemployment + Disability	4	126.33	-	6.20	6.28
2	COVID Shock + 2013 Q3 Break + 2020 Q4 Break + Unemployment + Disability	5	128.87	2.54	6.66	8.14
3	COVID Shock + 2020 Q4 Break + % 16 - 18-year-olds + Unemployment + Disability	5	130.03	3.70	6.58	7.16
4	2013 Q3 Break + GDP + Unemployment + Disability	4	130.43	4.10	6.53	7.82
5	2020 Q4 Break + GDP + Unemployment + Disability	4	131.53	5.20	5.70	6.71
6	Unemployment + Disability	2	131.63	5.30	5.89	6.38
7	Youth Sector Jobs + Unemployment + Disability	3	131.95	5.62	5.78	6.78
8	GDP + Unemployment + Disability	3	132.16	5.84	6.10	6.42
9	2020 Q4 Break + Youth Sector Jobs + Unemployment + Disability	4	132.29	5.96	6.36	6.68
10	COVID Shock + Youth Sector Jobs + GDP + Unemployment + Disability	5	133.12	6.79	6.10	6.58
11	Youth Sector Jobs + GDP + Unemployment + Disability	4	133.13	6.80	6.05	7.16
12	2013 Q3 Break + 2020 Q4 Break + Youth Sector Jobs + Unemployment + Disability	5	133.41	7.08	6.97	7.72
13	2013 Q3 Break + Youth Sector Jobs + Unemployment + Disability	4	133.51	7.18	5.96	7.21
14	COVID Shock + Youth Sector Jobs + Unemployment + Disability	4	133.86	7.54	6.31	6.48
15	Level 2 Attainment + GDP + Unemployment + Disability	4	134.00	7.68	6.48	8.21

16	% 16 -18-year-olds + Unemployment + Disability	3	134.02	7.69	6.27	6.15
17	2013 Q3 Break + 2020 Q4 Break + GDP + Unemployment + Disability	5	134.22	7.90	6.79	7.60
18	2013 Q3 Break + Unemployment + Disability	3	134.27	7.94	6.43	8.22
19	COVID Shock + 2020 Q4 Break + GDP + Unemployment + Disability	5	134.37	8.04	5.82	6.84
20	Youth Sector Jobs + Level 2 Attainment + Unemployment + Disability	4	134.50	8.17	6.04	8.05
21	2020 Q4 Break + Youth Sector Jobs + GDP + Unemployment + Disability	5	134.50	8.18	6.77	7.05
22	Youth Sector Jobs + % 16 -18-year-olds + Unemployment + Disability	4	134.54	8.21	6.11	6.61
23	COVID Shock + 2013 Q3 Break + Youth Sector Jobs + GDP + Unemployment + Disability	6	134.57	8.24	6.47	6.86
24	% 16 -18-year-olds + GDP + Unemployment + Disability	4	134.60	8.27	6.64	6.44
25	2013 Q3 Break + Youth Sector Jobs + GDP + Unemployment + Disability	5	134.60	8.28	6.36	8.40
26	COVID Shock + 2020 Q4 Break + Youth Sector Jobs + Unemployment + Disability	5	134.62	8.30	6.58	6.86
27	COVID Shock + GDP + Unemployment + Disability	4	134.75	8.42	6.25	6.53
28	2020 Q4 Break + Youth Sector Jobs + % 16 -18-year-olds + Unemployment + Disability	5	134.91	8.58	7.20	6.98
29	2020 Q4 Break + Youth Sector Jobs + Level 2 Attainment + Unemployment + Disability	5	134.96	8.64	6.91	7.61
30	2013 Q3 Break + Level 2 Attainment + GDP + Unemployment + Disability	5	135.27	8.95	6.74	8.55
31	COVID Shock + 2013 Q3 Break + Youth Sector Jobs + Unemployment + Disability	5	135.52	9.19	6.86	6.92
32	Youth Sector Jobs + Level 2 Attainment + GDP + Unemployment + Disability	5	135.53	9.21	6.64	8.37

33	Youth Sector Jobs + % 16 -18-year-olds + GDP + Unemployment + Disability	5	135.72	9.40	6.81	7.65
34	2013 Q3 Break + % 16 -18-year-olds + GDP + Unemployment + Disability	5	135.75	9.42	7.11	8.23
35	COVID Shock + Youth Sector Jobs + % 16 -18-year-olds + GDP + Unemployment + Disability	6	135.85	9.53	6.74	7.43

Source: Authors' calculations

Appendix G: USoc - Full Model Results

Table 17. Cross-validation results for the top 35 exploratory USoc model permutations

Rank	Model Specification	N	AICc	Δ AICc	MAPE Expanding	MAPE Sliding
1	COVID Shock + Youth Sector Jobs + Unemployment	3	262.52	-	17.14	17.14
2	COVID Shock + Youth Sector Jobs + % 16-18-year-olds + Unemployment	4	263.64	1.12	17.86	20.32
3	COVID Shock + Unemployment	2	263.86	1.34	16.25	15.49
4	COVID Shock + % 16-18-year-olds + Unemployment	3	263.89	1.37	15.96	19.36
5	COVID Shock + % 16-18-year-olds + GDP	3	264.20	1.68	17.53	18.37
6	COVID Shock + 2019 Q1 Break + Youth Sector Jobs + Unemployment	4	264.33	1.81	17.30	16.84
7	COVID Shock + Youth Sector Jobs + GDP	3	264.45	1.93	17.18	16.33
8	COVID Shock + GDP	2	264.47	1.95	17.50	16.48
9	COVID Shock + % 16-18-year-olds	2	264.54	2.02	16.01	18.02
10	COVID Shock + Youth Sector Jobs + Level 2 Attainment + Unemployment	4	264.75	2.23	17.70	15.54
11	COVID Shock + Youth Sector Jobs + GDP + Unemployment	4	264.76	2.24	17.73	17.14
12	COVID Shock	1	264.85	2.33	17.37	16.63
13	COVID Shock + Level 2 Attainment + GDP	3	265.02	2.50	17.59	16.20
14	COVID Shock + Youth Sector Jobs + Unemployment + Disability	4	265.03	2.51	17.04	16.88

15	COVID Shock + Youth Sector Jobs	2	265.03	2.51	16.92	16.01
16	COVID Shock + Youth Sector Jobs + % 16-18-year-olds + GDP	4	265.11	2.59	18.04	19.38
17	COVID Shock + Level 2 Attainment + Unemployment	3	265.15	2.63	16.91	14.65
18	COVID Shock + Youth Sector Jobs + % 16-18-year-olds	3	265.56	3.04	17.06	18.15
19	COVID Shock + 2019 Q1 Break + Unemployment	3	265.67	3.15	16.37	15.48
20	COVID Shock + % 16-18-year-olds + GDP + Unemployment	4	265.77	3.25	17.27	19.71
21	COVID Shock + GDP + Unemployment	3	265.77	3.25	16.91	15.51
22	COVID Shock + Level 2 Attainment	2	265.85	3.33	17.41	16.43
23	COVID Shock + Level 2 Attainment + % 16-18-year-olds + GDP	4	265.85	3.33	17.74	19.27
24	COVID Shock + Youth Sector Jobs + % 16-18-year-olds + GDP + Unemployment	5	265.87	3.35	18.86	21.28
25	COVID Shock + Youth Sector Jobs + Level 2 Attainment + GDP	4	265.98	3.46	17.88	16.40
26	COVID Shock + Level 2 Attainment + % 16-18-year-olds + Unemployment	4	266.08	3.56	16.55	19.47
27	COVID Shock + Youth Sector Jobs + Level 2 Attainment + % 16-18-year-olds + Unemployment	5	266.22	3.70	17.65	21.37
28	COVID Shock + Youth Sector Jobs + % 16-18-year-olds + Unemployment + Disability	5	266.26	3.74	18.04	22.39
29	COVID Shock + Unemployment + Disability	3	266.28	3.76	16.32	15.38
30	COVID Shock + 2019 Q1 Break + Youth Sector Jobs + GDP	4	266.29	3.77	17.03	16.36
31	COVID Shock + 2019 Q1 Break	2	266.30	3.78	17.49	15.51

32	COVID Shock + 2019 Q1 Break + GDP	3	266.37	3.85	16.97	15.78
33	COVID Shock + 2019 Q1 Break + Youth Sector Jobs	3	266.38	3.86	17.22	15.35
34	COVID Shock + Level 2 Attainment + % 16-18-year-olds	3	266.42	3.90	16.32	18.89
35	COVID Shock + % 16-18-year-olds + Unemployment + Disability	4	266.43	3.91	16.46	19.46

Source: Authors' calculations

Appendix H: LEO cross-validation results

Table 18. Cross-validation results for the top 35 exploratory LEO model permutations

Rank	Model Specification	N	AICc	Δ AICc	MAPE Expanding	MAPE Sliding
1	Unemployment + Disability	2	92.57	-	3.31	2.11
2	Youth Sector Jobs + Unemployment + Disability	3	93.44	0.87	3.05	2.34
3	Youth Sector Jobs +% 16 - 18-year-olds + Disability	3	93.61	1.04	2.82	2.63
4	Level 2 Attainment + Unemployment + Disability	3	94.44	1.86	5.76	5.15
5	% 16 - 18-year-olds + Unemployment + Disability	3	94.47	1.89	3.60	2.85
6	Unemployment	1	94.74	2.17	3.05	2.32
7	Unemployment + Disability + 2010 Q1 Break	3	94.93	2.36	3.01	2.38
8	Youth Sector Jobs + Level 2 Attainment + Disability	3	95.01	2.44	6.09	6.55
9	Youth Sector Jobs + Level 2 Attainment + Unemployment + Disability	4	95.18	2.61	5.44	5.08
10	GDP + Unemployment + Disability	3	95.34	2.77	4.12	2.93
11	% 16 - 18-year-olds + Unemployment	2	95.39	2.82	2.78	2.50
12	Youth Sector Jobs + Level 2 Attainment +% 16 - 18-year-olds + Disability	4	95.40	2.83	6.75	3.76
13	Youth Sector Jobs + Unemployment + Disability + 2010 Q1 Break	4	95.58	3.01	3.25	2.51
14	Level 2 Attainment + Unemployment + Disability + 2010 Q1 Break	4	95.65	3.08	7.38	6.14
15	Level 2 Attainment + Unemployment	2	95.77	3.20	7.51	5.78
16	Youth Sector Jobs + % 16 - 18-year-olds + Unemployment + Disability	4	96.11	3.54	3.48	2.72
17	% 16 - 18-year-olds + Unemployment +2013 Q3 Break	3	96.21	3.64	2.49	3.18

18	Youth Sector Jobs + GDP + Unemployment + Disability	4	96.31	3.74	3.83	2.81
19	Youth Sector Jobs + Level 2 Attainment + Disability + 2010 Q1 Break	4	96.43	3.86	7.74	6.69
20	Youth Sector Jobs + Unemployment	2	96.62	4.05	3.09	2.34
21	Youth Sector Jobs + Level 2 Attainment + Unemployment + Disability + 2010 Q1 Break	5	96.68	4.10	6.95	5.95
22	% 16 - 18-year-olds + Unemployment + Disability + 2010 Q1 Break	4	96.74	4.16	4.44	2.90
23	Youth Sector Jobs + Disability	2	96.77	4.19	2.56	2.99
24	Youth Sector Jobs + Disability + 2010 Q1 Break	3	96.93	4.36	5.00	4.13
25	Youth Sector Jobs +% 16 - 18-year-olds + GDP + Disability	4	96.96	4.39	3.96	3.24
26	Youth Sector Jobs + % 16 - 18-year-olds + Disability + 2010 Q1 Break	4	97.00	4.43	5.04	3.35
27	Youth Sector Jobs + % 16 - 18-year-olds + Disability + 2013 Q3 Break	4	97.08	4.51	3.86	2.95
28	Level 2 Attainment + GDP + Unemployment + Disability	4	97.15	4.58	6.65	5.86
29	Unemployment + 2010 Q1 Break	2	97.21	4.64	3.05	2.32
30	% 16 - 18-year-olds + Unemployment + Disability +2013 Q3 Break	4	97.25	4.68	3.50	3.52
31	GDP + Unemployment	2	97.27	4.70	4.39	3.49
32	Level 2 Attainment + % 16 - 18-year-olds + Unemployment + Disability	4	97.49	4.92	5.56	2.84
33	% 16 - 18-year-olds + GDP + Unemployment + Disability	4	97.57	5.00	3.59	2.31
34	GDP + Unemployment + Disability + 2010 Q1 Break	4	97.78	5.21	4.15	3.34
35	Youth Sector Jobs + Level 2 Attainment + Unemployment	3	97.89	5.32	7.51	5.79

Source: Authors' calculations

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