Vol. 36, No. 2 (2026) | DOI: 10.37190/ord/214108

OPEN ACCESS

Operations Research and Decisions

www.ord.pwr.edu.pl

OPERATIONS RESEARCH AND DECISIONS QUARTERLY

# Econometric modeling of unemployment rate in the United Kingdom: From classical ARIMA to exogenous and machine learning approaches

Van Hai Trieu Tran*[1] Tinh Minh Tu Tran[1]

[1] *Faculty of Information Systems, University of Information Technology, Vietnam National University, Ho Chi Minh City, Vietnam*

**Corresponding author, email address: trieutvh@uit.edu.vn*

**Abstract**

Unemployment is a key macroeconomic indicator for the labour market's health. Economic shocks, political changes, and structural shifts in the UK have shaped its dynamics. Using 326 monthly observations from 1997–2024 (UK Office for National Statistics), this study forecasts unemployment via ARIMA(1,1,1), ARIMAX, Random Forest, and XGBoost. Especially, ARIMA works for short-term predictions but misses structural breaks and non-linearities. ARIMAX, with gross value added as an exogenous variable, offers slight gains yet suffers from heteroskedasticity. XGBoost delivers the best performance by capturing nonlinear relationships, but direct interpretability is limited. The structural stability test was inconclusive, constraining regime-switching or rolling forecasts. Future research should address these limitations and integrate SHAP-based interpretability with feature significance analysis to better understand model behaviour and the drivers of unemployment.

**Keywords:** *forecasting, econometrics, ARIMA model, unemployment rate, machine learning, United Kingdom*

# 1. Introduction

*The unemployment rate* has been an important economic indicator. It shows the general health of an economy and helps policymakers assess how well economic strategies are working. With its diverse and intricate economy, the unemployment rate has seen many changes in the United Kingdom over recent decades. Variations in the unemployment rate have therefore nearly always reflected various economic and political happenings. The global financial crisis of 2008-2009, Brexit's aftermath, and problems associated with the coronavirus pandemic are among the issues that have since impacted how things are perceived regarding employment. According to the figures from the Office for National Statistics, the unemployment rate was 4.4% from February to April 2024—the highest rate since September 2021 [35]. Each event has had a lasting impact on the labour market in the United Kingdom. This shows

Received 24 April 2025, accepted 10 November 2025, published online 10 November 2025
ISSN 2391-6060 (Online)/© 2025 Authors

The costs of publishing this issue have been co-financed by the Department of Operations Research and Business Intelligence at the Faculty of Management, Wrocław University of Science and Technology, Wrocław, Poland

the need for accurate forecasting models to predict future unemployment trends. As the global economy becomes more interconnected and unstable, it is more important than ever to forecast unemployment rates accurately [2]. Policymakers depend on these forecasts to make informed decisions that can reduce the negative effects of economic downturns, stabilize the labour market, and encourage sustainable economic growth.

Some of the recent literature has shown that there is an increased interest in hybridizing conventional econometric models with machine learning for improved accuracy in forecasting at the macro level. Therefore, the Auto-Regressive Integrated Moving Average (ARIMA) model forecasts unemployment due to its robust theoretical foundation and accurate capture of temporal structure [29]. The ARIMA model is also empirically unfit since there are structural changes and exogenous shocks [18]. While attempting to resolve this limitation, the ARIMAX model incorporates GDP, interest rates, or oil prices as explanatory variables to improve forecasting performance. The model complied well in a forecasting study for developing countries [1].

Simultaneously, tree-based ensemble approaches, such as Random Forest and XGBoost, have been more favored by practitioners for modeling nonlinear linkages and intricate interactions inside economic systems. For instance, Gupta, Pierdzioch and Salisu showed that Random Forest outperformed traditional econometric models when forecasting UK unemployment under oil price uncertainty [19]. Furthermore, in a large-scale forecasting experiment involving U.S. output gaps, Sofianos et. al. found that XGBoost gave the most accurate macroeconomic forecasts [42]. In addition to providing better accuracy, these models can also manage significantly greater instability in economic conditions

Among the various models available, the ARIMA model, popularly applied in time series forecasting, was introduced by Box and Jenkins [5] in the 1970s and remains one of the most dependable tools, particularly in economic forecasting. Since the unemployment rate results from many determinants, the ARIMA model is beneficial for data analysis since it can capture both short- and long-term patterns. The prior research indicated the application of the ARIMA model in forecasting the unemployment rate across various countries. In the case of the UK, this model has proved very efficient in predicting short-term variations [45].

Historically, researchers have used econometric models like ARIMA due to their strong interpretability and statistical foundations. The UK labor market has notably spread substantial structural transformations in recent decades, encompassing the Global Financial Crisis, Brexit, and the COVID-19 pandemic. Concerns arise regarding the adequacy of solely using univariate time series models.

This paper aims to develop a benchmark forecasting model with a conventional ARIMA(1,1,1) specification. We improve this basic model by adding the important economic indicators, such as Gross Value Added (GVA), into an ARIMAX framework to show how these outside factors affect the results. We compare how well these econometric models predict outcomes by looking at their forecasting results alongside two modern data-driven methods: Random Forest and XGBoost. These machine learning models are well-suited for capturing complex, nonlinear relationships and interactions that may be present in labor market dynamics.

This research contrasts classical statistical methods with machine learning techniques to emphasize the trade-offs between model interpretability and forecast accuracy. Given the rapidly shifting economic environment, the findings offer insightful advice to analysts and policymakers on how to select appropriate forecasting tools. In light of these considerations, this study seeks to answer the specific research question: How well can the ARIMA, ARIMAX, Random Forest, and XGBoost approaches forecast the unemployment rate in the UK, and what do these forecasts mean for economic policy? The rest of the paper is structured as follows: Chapter 2 reviews the theory of previous research; Chapter 3 describes the research methodology, including data, research model, and others; Chapter 4 presents the study results and discussion; The final chapter concludes the paper.

## 2. Literature review

The unemployment rate remains a critical issue for countries due to its significant influence on the economy and financial stability; high unemployment can trigger recessions, crises, or economic downturns. Governments require reliable indicators to inform their policies and fiscal responses [2]. Funke was among the first to assess the out-of-sample performance of univariate ARIMA and multivariate VAR models on the German unemployment rate in the early 1990s [15]. Nowadays, there has been an increasing amount of literature on forecasting unemployment rates that has attracted the attention of researchers, as accurate prediction of indicators plays an important role in financial planning and national economic development [25].

As deep learning and machine learning techniques become more popular, several research papers have begun using these methods to predict global economic patterns. Researchers increasingly apply ML/DL to macroeconomic forecasting to capture nonlinearities and interactions [26]. In 2008, Milas and Rothman [28] observed that various models have analyzed macroeconomic variables over time. Consequently, methods now include regression, Random Forest [16], XGBoost [8], ANN [48], VAR [41], SVM [24], RNN [39], and LSTM [39, 49]. Out of the many possible methods, the ARIMA model stands out as the most popular and reliable tool for economic forecasting. A recent study by Mohamed found ARIMA (5,1,2) to be the best model in forecasting the GDP growth rate of Somalia [29]. Moreover, many other studies have utilised the ARIMA model to forecast economic indicators such as GDP, GNP growth, CPI, money supply, and unemployment rate [13, 41, 48, 49]. Although deep learning models typically require large datasets for effective training, the performance can be less reliable than the ARIMA model when applied to smaller datasets with limited ranges or periods [26].

However, the most significant weaknesses of ARIMA models are their failures to accommodate for exogenous macroeconomic factors. This paper applies the ARIMAX model to appropriate exogenous factors so that forecasting accuracy is improved. In the UK, labor markets are strongly driven by macroeconomic indicators among which gross value added plays a decisive role. GVA signals overall output from the economy and structural performance of industries, linking directly with trends in employment. Thus, its inclusion as an exogenous predictor can improve both forecast precision and policy relevance.

Box and Jenkins developed the ARIMA model in the 1970s, and it has proven to be a reliable method for dealing with time series data in economic investigation [5]. In 2015, the study by Vicente and colleagues used the ARIMA model to study the evolution of the Spanish unemployment rate, highlighting a significant upsurge due to the economic crisis [45]. Many studies have focused on forecasting economic growth in the European context. A study by Edlund and Karlsson also used ARIMA, transfer function, and VAR models to forecast Swedish unemployment [14]. Empirical evidence from Europe and other settings shows ARIMA and related models often perform well for short-term forecasts, while hybrid or ML-based approaches can improve accuracy when data richness and nonlinearity warrant it [2, 9, 24, 25].

The above explorations collectively emphasize the importance of accurately predicting macroeconomic indicators, particularly in anticipating a nation's future economic prospects via unemployment rates. Therefore, this study incorporates the interpretability of classic econometric models with the predictive power of data-driven approaches. It particularly enhances previous research by looking at ARIMA, ARIMAX, Random Forest, and XGBoost models, which helps evaluate the balance between how clear the models are, their theoretical basis, and how well they predict outcomes. This research will concurrently provide the best forecast model to assist businesses, policymakers, and governments in addressing current challenges and shaping more effective future policies.

# 3. Research methodology

## 3.1. Material and data

The Office of National Statistics website [35], an open-access data repository over the Internet, provided the data for this investigation. The unemployment rate is calculated as the number of unemployed persons aged 16 or over, actively seeking work divided by the total economically active population aged 16 or over. The dataset consists of 326 observations of the monthly unemployment rate for the United Kingdom between January 1997 and February 2024. We used the Python language for data analysis and partitioned the dataset into two parts: we used 80% for training and reserved 20% for testing. In addition to examining unemployment rates, the Gross Value Added was collected in the same period as the unemployment rate, which provides consistency in model input. GVA data were also retrieved from the Office for National Statistics [35].


**Figure 1.** Unemployment rate of the United Kingdom between 1/1997 and 2/2024

Figure 1 illustrates the UK unemployment rate has recorded vacillations over approximately 27 years in connection with some critical, pivotal economic and political events that affected the UK labor market. It fell from around 8% to below 5% in the four years between 1997 and 2001. Tony Blair and the Labour Party implemented robust economic policies during this period; they focused on education and health reform and introduced significant labor market changes, which significantly decreased unemployment and dependency on welfare [20].

There was global economic growth from 2001 to 2008, during which the unemployment rate was at about 5%, with a slight increase [21]. Increased immigration and the closure of major manufacturing firms such as MG Rover and the Peugeot plant in Ryton led to a slight increase in these figures, particularly in the West Midlands [31]. This was the setting within which the global financial crisis of 2008 brewed, setting off a deep recession with widespread job losses. Official unemployment stood at more than 2 million in 2009 and at a level of 2.5 million by 2010, giving an unemployment rate of 8% [21]. The unemployment rate peaked at 8% in 2012 before rapidly declining to below 5% by 2016. The economy's expansion following a period of financial downturns improved labor market conditions. Mark Carney, the Governor of the Bank of England, stated in 2013 that he would only raise interest rates if unemployment fell to 7% or below, thereby encouraging economic policies focused on employment growth.

Nonetheless, by late 2019, or early 2020, Brexit and the COVID-19 outbreak had started to slowly increase unemployment. Before the pandemic arrived, the United Kingdom had the lowest economic inactivity rate among the G7 countries, second only to Japan. The pandemic has significantly increased the economic inactivity rate, now leaving the country at the fourth-highest spot in the G7. The global pandemic of COVID-19 in 2020 caused a massive surge in unemployment, which has since moderately decreased. The increased openness of the virus pandemic has resulted in a tightening of the UK's labor market, partly due to a decrease in the number of EU migrants working in the UK. From 2020 to 2021, the COVID-19 pandemic caused an abrupt increase in the unemployment rate, which later began to recover. By 2024, the rate had risen slightly again due to pandemic-related restrictions and the current global economic challenges.

Furthermore, there were 1.53 million unemployed individuals in the UK from March to May 2024, according to the Office for National Statistics. This was up 133,000 compared to a year earlier. The unemployment rate was 4.4%, whereas it had been 4.0% a year previously. UK companies are now entering a super-tight labor market where job vacancies have just reached a record high, and the unemployment rate is low. This situation prompts an examination of Brexit's potential role in the UK's labor shortage. Brexit and changes to immigration policies have reduced the attractiveness of working in the UK for EU citizens, contributing to labor shortages and tightening the labor market. Economic and political upheavals have had a profound impact on the labor market, creating a complicated and varied picture of unemployment in the country.

## 3.2. Research framework development

### 3.2.1. The ARIMA model

The ARIMA model includes autoregressive (AR), moving average (MA), and difference (integration, I) [5], so the Box-Jenkins method is used. It describes the present value of a time series based on its own past values and previous error terms.

As regards economic and financial series like unemployment, the typical characteristic is non-stationarity. As such, differencing is used to eliminate stochastic trends and ensure a stationary process that can be modeled [2, 29]. The non-seasonal ARIMA (*p*, *d*, *q*) model takes the following general form:

$$\Delta^d Y_t = c + \alpha_1 \Delta^d Y_{t-1} + \alpha_2 \Delta^d Y_{t-2} + \cdots + \alpha_p \Delta^d Y_{t-p} + \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \cdots + \varphi_q \varepsilon_{t-q} \qquad (1)$$

Alternatively, as stated by Kontopoulou [26], the model can be more compactly written as:

$$\Delta^d Y_t = c + \sum_{i=1}^{p} \alpha_i \Delta^d Y_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t \qquad (2)$$

$\Delta^d Y_t$ denotes the difference in value at time $t$.

This extended model application makes it possible to handle stationary and non-stationary time series data, making it a versatile tool for economic forecasting. To shape the unemployment rate using equation ( 1) and equation ( 2), we must regress the "Unemployment Rate" variable on its past values with lags *p* and $q$. Here's how the equation looks:

$$\Delta^d Unemployment\ Rate_t = c + \sum_{i=1}^{p} \alpha_i \Delta^d Unemployment\ Rate_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t \qquad (3)$$

$\Delta^d Unemployment\ Rate_t$ represents the differenced unemployment rate at time $t$.

According to the Box-Jenkins method [5], modeling is done in four steps: identification, estimation, diagnostics, and forecasting using the best model made in step two that passes the diagnostic tests done in step three.

#### 3.2.1.1 Model identification

The first section of this process is to model identification; its objective is to find the appropriate values for *p*, *d*, and $q$. At this point, we plotted the data and performed unit root tests to ensure that it was stationary. The current investigation utilizes Zivot-Andrews test [50], the Augmented Dickey-Fuller (ADF) test [12] and the Phillips-Perron (PP) test [38] to identify stationarity and white noise. We used partial autocorrelations (PACF), autocorrelations (ACF), and other statistical information to find the autoregressive (*p*) and moving average (*q*) parameters. This was done after figuring out the differencing order (*d*).

#### 3.2.1.2 Model estimation

There are numerous estimation methods available; however, based on the literature analysis, we utilize the Akaike Information Criterion (AIC) [3, 30] and the Bayesian Information Criterion (BIC) introduced by Schwarz [40]. This study uses BIC as a performance enhancer for AIC in selecting the best model among the available options. Here are the mathematical equations for these criteria:

$$AIC = 2m - 2\ln(L) \qquad (4)$$

and

$$BIC = \ln(n)m - 2\ln(L) \qquad (5)$$

where L is the model's maximum likelihood function, *m* is the number of parameters evaluated, and *n* is the number of observations (sample size).

#### 3.2.1.3 Model diagnostics

After selecting the optimal model through robust estimation methods, the subsequent phase of the analysis requires diagnostic checking to confirm the suitability and statistical significance of the estimated models for forecasting. This procedure focuses on the fitted model's residuals to see whether they resemble white noise. Firstly, the ADF approach checks stationarity in the full dataset to ensure the data is appropriate for the ARIMA model and it also aligns with studies by Vicente et al. [45]. The White test then seeks heteroskedasticity in a regression model [46].

Breusch-Pagan, another test for heteroscedasticity, determines whether the variance of the errors in a regression is dependent on the values of the independent variables [7]. The Ljung-Box test, also referred to as the Portmanteau checks, verifies the absence of autocorrelation in the residuals of a fitted model to guarantee the model's adequate representation of the data structure [27]. The Goldfeld-Quandt test is conducted to compare the variances of the residuals to check heteroscedasticity [17]. Subsequently, the Jarque-Bera (JB) test verified the normal distribution of the model's residuals which is regarded as a common assumption in time series analysis [22]. Finally, we consider the heteroscedasticity (H) test value in the best ARIMA model while using Python. This general test for detecting heteroskedasticity in the residuals of a regression model indicates issues that might affect the model's validity.

#### 3.2.1.4 Model forecasting

Finally, after passing all the tests in phases 2 and 3, and in alignment with the stationary univariate regression model's requirements, we utilize the verified ARIMA model for forecasting.

### 3.2.2. The ARIMAX model

From equation ( 2), the ARIMA model is expanded by adding external factors to create the Autoregressive Integrated Moving Average with Exogenous Variables model (ARIMAX). This adjustment allows the model to capture contemporaneous impacts of macroeconomic indicators, which is appropriate in an economic forecasting setting. We derive the general ARIMAX model as follows:

$$\Delta^d Y_t = c + \sum_{i=1}^{p} \alpha_i \Delta^d Y_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \sum_{k=1}^{r} \beta_k X_{k,t} + \varepsilon_t \tag{6}$$

$\beta_k$ corresponds to the coefficients of the exogenous variables $X_{k,t}$ reflecting their contemporaneous effect on the dependent variable.

As noted by Adu et al., the ARIMAX model improves short-term forecasting ability by including immediate drivers of economic activity, for example, policy or output indicators [1]. Starting from this generalised form, we build up an ARIMAX model specific to this research where we try to forecast the unemployment rate in the UK with the GVA exogenous macroeconomic indicator. This specific model is shown in equation ( 7) :

$$\Delta^d \textit{Unemployment Rate}_t = c + \sum_{i=1}^{p} \alpha_i \Delta^d \textit{Unemployment Rate}_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \beta_1 GVA_t + \varepsilon_t \tag{7}$$

$GVA_t$ represents economic output.

This formulation mirrors the structure used in equation ( 3) , extending it to allow for explanatory variables. The purpose is to see how outside factors affect the unemployment rate apart from its usual trends. So, the ARIMAX model offers a flexible yet strong way to capture both how the past values relate and the structural economic drivers in one forecasting model.

## 3.3. The machine learning models

Recently, machine learning (ML) approaches have gained popularity for forecasting the economy due to their flexibility, ability to model nonlinearity, and capacity to handle complex interactions among predictors. In this paper, we use two supervised learning methods, such as Random Forest (RF) and XGBoost (XGB), to model and predict the UK unemployment rate.

The choice of these two models is based on theoretical and empirical factors. Random Forest mitigates overfitting and excels in high-dimensional environments by consolidating predictions from a collection of decision trees [6]. XGBoost, an advanced gradient boosting method, offers higher predictive accuracy and more computational efficiency, especially for time series data in tabular form [10]. They all accurately represent the nonlinear relationships among macroeconomic factors. The general functional form for these ML regressors is:

$$\hat{y}_t = F(X_t) \tag{8}$$

$\hat{y}_t$ is the predicted unemployment rate at time $t$, $X_t = \{\mathrm{GVA}_t\}$ (in simplified cases). $F(\cdot)$ denotes the fitted function learned by the Random Forest or XGBoost model.

**Random Forest** builds $B$ individual decision trees on bootstrapped samples and averages their predictions [11]:

$$\hat{y}_t^{\mathrm{RF}} = \frac{1}{B} \sum_{b=1}^{B} T_b(X_t) \tag{9}$$

$T_b$ is the prediction from the $b$-th decision tree.

**XGBoost** constructs an additive model of $K$ regression trees [10]:

$$\hat{y}_t^{\mathrm{XGB}} = \sum_{k=1}^{K} f_k(X_t), \quad f_k \in \mathcal{F} \tag{10}$$

$f_k$ is the $k$-th regression tree,

$\mathcal{F}$ is the space of regression trees.

The model is trained by minimising a regularised loss function combining prediction error and model complexity.

Models are trained with the same dataset used for ARIMA-based models, and hence predictive performance can be compared fairly. Nonlinearity and interaction effects that these models can capture provide an approach that complements econometric methods.

## 3.4. Performance valuation of models

An objective statistical measure of the forecasting performance of time series and machine learning models in predicting unemployment is required. Therefore, in this study, we apply standard regression evaluation metrics, which quantify prediction accuracy as well as model generalisability. The indicators of errors in forecasting chosen here are MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error) and the Coefficient of Determination $R^2$. These are probably the most traditionally used in empirical economics [1, 48].

Let $y_t$ represent the actual unemployment rate and $\hat{y}_t$ denote the predicted unemployment rate at time $t$, with $n$ representing the total number of observations.

**Mean Absolute Error (MAE)** measures the average magnitude of errors without considering their direction:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |y_t - \hat{y}_t| \tag{11}$$

**Mean Squared Error (MSE)** penalizes larger errors more severely, providing a quadratic loss measure:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2 \tag{12}$$

**Root Mean Squared Error (RMSE)** is the square root of MSE, representing the model's prediction error in the same units as the original variable:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \tag{13}$$

**Mean Absolute Percentage Error (MAPE)** provides a scale-independent accuracy measure, expressed as a percentage:

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n} \left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{14}$$

**R-squared ($R^2$)** evaluates how much of the variation in unemployment is explained by the model:

$$R^2 = 1 - \frac{\text{SS}_{\text{res}}}{\text{SS}_{\text{tot}}} = 1 - \frac{\sum_{t=1}^{n} (y_t - \hat{y}_t)^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2} \tag{15}$$

Where $\bar{y}$ is the mean of actual unemployment values, $\text{SS}_{\text{res}}$ is the residual sum of squares, and $\text{SS}_{\text{tot}}$ is the total sum of squares.

We apply the metrics uniformly across ARIMA, ARIMAX, Random Forest, and XGBoost models within the same sample and forecasting period. Lower values of MAE, MSE, RMSE, and MAPE with a higher $R^2$ value indicate better model performance in forecasting the unemployment rate.

# 4. Results and discussion

## 4.1. The ARIMA model

### 4.1.1. Model identification

To start with, we conducted a preliminary study by creating a graphical plot to examine the training dataset for the monthly unemployment rate between January 1997 and August 2018.


**Figure 2.** UK Unemployment Rate, 1/1997 - 8/2018

Figure 2 shows a decline from the late 1990s to 2008, a post-crisis rise surrounding the financial meltdown between 2008 and 2011, and a plunge following these years. With these distinct rises and falls, the time series is non-stationary.

This study used the Zivot–Andrews test [50] to detect possible structural changes associated with key events (e.g., Brexit, Covid-19), with findings shown in Table 1. Table 1 presents the test statistic, associated p-value, critical values, and the anticipated breakpoint.

**Table 1.** Zivot-Andrews Test

| Variable | Test Critical Values | | | Statistic | p-value | Estimated Breakpoint |
|---|---|---|---|---|---|---|
| | 1% | 5% | 10% | | | |
| Unemployment Rate | -5.276 | -4.811 | -4.566 | -3.808 | 0.473 | 2001-01-01 (Index 48) |

Table 1 reports the test statistic, corresponding p-value, critical values, and the estimated breakpoint. Since the test statistic is $-3.808$ and the p-value of $0.473$ is higher than the usual significance level of $5\%$, there is not enough statistical evidence to support any alternative to the null hypothesis of a unit root with a break. However, this test estimates a breakpoint for January 2001.

The estimated breakpoint fell in January 2001, which does not coincide with globally recognised economic shocks such as the Global Financial Crisis (2008), Brexit (2016), or the COVID-19 pandemic (2020). Structural shifts may relate to labour and welfare policies in the UK under Prime Minister Tony Blair, thereby generating a suspected structural change in the time series [20].

However, at this point, the Zivot-Andrews test, which has a statistic of $-3.808$, much higher than the usual significance thresholds (1%, 5%, or 10%), does not show strong statistical proof of a structural break. Therefore, this study has not applied any dummy variables or regime-switching methodologies. The research continues using the standard unit root tests—ADF and PP tests—to check whether the series is stationary or not [37].

Table 2 displays the statistical results from the ADF and PP unit root tests. Both tests confirmed that the data was not stationary with p-values greater than 0.05 when $d = 0$. Therefore, this study developed ARIMA models using differencing techniques to achieve stationarity. The unemployment rate variable had p-values of less than 5% in both tests after the first differencing ($d = 1$).

**Table 2.** The Result of Unit Root Test

| Variable | Test Methods | Differences (d) | 1% | 5% | 10% | Statistic | p-value | Results |
|---|---|---|---|---|---|---|---|---|
| Unemployment Rate | ADF test | $d = 0$ | -3.46 | -2.87 | -2.57 | -1.70 | 0.43 | Non-stationary |
| | PP test | $d = 0$ | -3.46 | -2.87 | -2.57 | -1.30 | 0.63 | Non-stationary |
| | ADF test | $d = 1$ | -3.46 | -2.87 | -2.57 | -3.99 | 0.00*** | Stationary |
| | PP test | $d = 1$ | -3.46 | -2.87 | -2.57 | -13.40 | 0.00*** | Stationary |

Note: Significance is statistical at 10% (*), 5% (**), 1% (***).

As shown in Figure 3 below, supporting statistical results demonstrate similar results with non-trending series. That means the ARIMA method suggests using $d = 1$, which is in line with the results that have already been published [2, 13, 29].

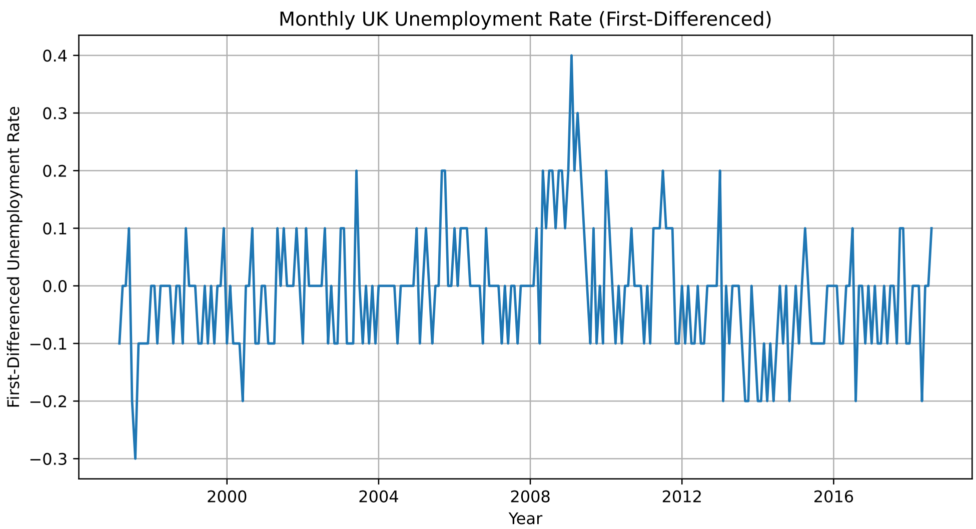


**Figure 3.** UK Unemployment Rate at First Difference

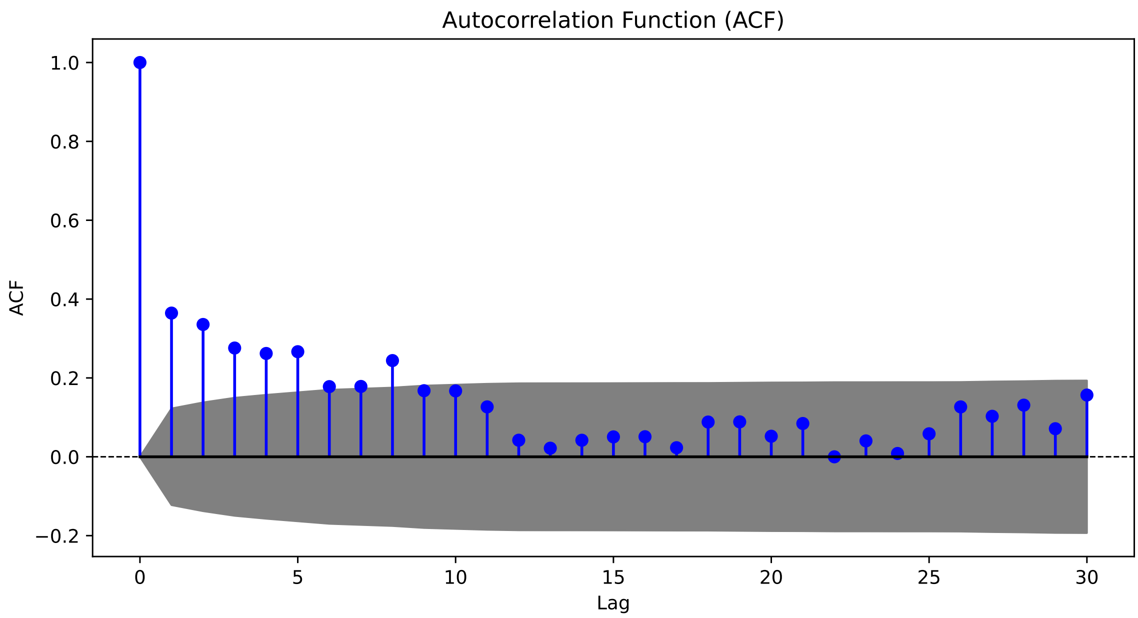


**Figure 4.** ACF of UK Unemployment Rate at First Difference

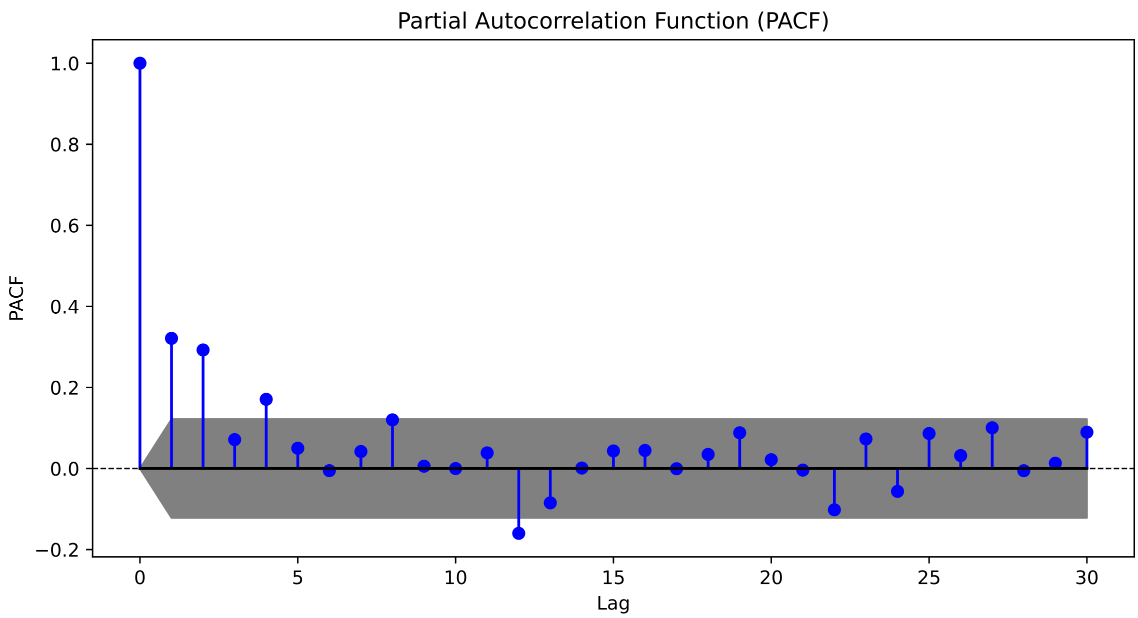


**Figure 5.** PACF of Unemployment Rate at First Difference

The next step is determining the other parameters, p and q, to complete the ARIMA model. Figure 4 and Figure 5 illustrate the initial variation in the unemployment rate value. These show the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). Researchers have already investigated the ARIMA model and found that it works best when p and q are within smaller intervals of 5 [24, 29]. That's why we chose PACF and ACF with five lags. As a consequence, the following appropriate models were selected for this study: (0,1,0), (0,1,1), (0,1,2), (0,1,3), (0,1,4), (0,1,5), (1,1,0), (1,1,1), (1,1,2), (1,1,3), (1,1,4), (1,1,5), (2,1,0), (2,1,1), (2,1,2), (2,1,3), (2,1,4), (2,1,5), (4,1,0), (4,1,1), (4,1,2), (4,1,3), (4,1,4), (4,1,5). We determine the best fit by comparing the AIC and BIC measures of the ARIMA model estimations.

### 4.1.2. Model estimation

This part looks at the models picked in Step 2 using AIC and BIC to identify which is better for predicting the unemployment rate. Other researchers [26, 29] have also used these criteria in their studies. Table 3 summarizes the results for all those models.

**Table 3.** Evaluation of Different ARIMA Models Following AIC and BIC Criteria

| Model | AIC | BIC | Model | AIC | BIC | Model | AIC | BIC |
|---|---|---|---|---|---|---|---|---|
| ARIMA(0,1,0) | -458.75 | -455.19 | ARIMA(1,1,2) | -517.17 | -502.95 | ARIMA(2,1,4) | -511.89 | -487.00 |
| ARIMA(0,1,1) | -483.13 | -476.01 | ARIMA(1,1,3) | -515.42 | -497.63 | ARIMA(2,1,5) | -511.44 | -482.99 |
| ARIMA(0,1,2) | -497.18 | -486.51 | ARIMA(1,1,4) | -513.85 | -492.51 | ARIMA(4,1,0) | -511.17 | -493.38 |
| ARIMA(0,1,3) | -499.02 | -484.79 | ARIMA(1,1,5) | -513.10 | -488.20 | ARIMA(4,1,1) | -513.74 | -492.40 |
| ARIMA(0,1,4) | -499.94 | -482.16 | ARIMA(2,1,0) | -509.31 | -498.64 | ARIMA(4,1,2) | -511.34 | -486.45 |
| ARIMA(0,1,5) | -506.63 | -485.29 | ARIMA(2,1,1) | -517.18 | -502.95 | ARIMA(4,1,3) | -515.01 | -486.55 |
| ARIMA(1,1,0) | -496.69 | -489.57 | ARIMA(2,1,2) | -515.15 | -497.37 | ARIMA(4,1,4) | -510.36 | -478.35 |
| ARIMA(1,1,1) | **-519.12** | **-508.45** | ARIMA(2,1,3) | -513.47 | -492.13 | ARIMA(4,1,5) | -510.31 | -474.74 |

The best model is ARIMA(1,1,1).

**Table 4.** Parameter Estimation of ARIMA(1,1,1) of Unemployment Rate

| | Coefficient | Standard Error | z | p-value |
|---|---|---|---|---|
| AR (1) | 0.911 | 0.036 | 265.558 | 0.000 |
| MA (1) | -0.690 | 0.063 | -10.957 | 0.000 |

According to the results in Table 3 and Table 4, the most appropriate model is ARIMA(1,1,1), which has the smallest AIC and BIC. Hence, based on equation ( 3), the following equations are for the ARIMA(1,1,1) model:

$$\Delta^1 \mathit{Unemployment\ Rate}_t = 0.911 \cdot \Delta^1 \mathit{Unemployment\ Rate}_{t-1} - 0.690 \cdot \varepsilon_{t-1} + \varepsilon_t \tag{16}$$

$$\mathit{Unemployment\ Rate}_t = 1.911 \cdot \mathit{Unemployment\ Rate}_{t-1} - 0.911 \cdot \mathit{Unemployment\ Rate}_{t-2} - 0.690 \cdot \varepsilon_{t-1} + \varepsilon_t \tag{17}$$

### 4.1.3. Model diagnostics

To discover whether the previously selected model is adequate and reliable, we proceed to the following phase in the Box-Jenkins procedure, diagnostic checking. This research conducted many tests to validate the model assumptions and verify that the residuals align with white noise. Table 5 below demonstrates the reliability of the approach using diagnostic tests for ARIMA(1,1,1).

**Table 5.** Results of Diagnostic Tests

| No. | Diagnostic Tests | Test Statistic | p-value | Conclusion |
|---|---|---|---|---|
| 1 | Augmented Dickey-Fuller (ADF) test | -7.98 | 0.000 | Stationary |
| 2 | White test | 1.684 | 0.431 | No Heteroskedasticity |
| 3 | Breusch-Pagan | 1.666 | 0.197 | No Heteroskedasticity |
| 4 | Portmanteau (Ljung-Box) test | 0.00 | 0.950 | No autocorrelation |
| 5 | Goldfeld-Quandt test | 0.022 | 0.999 | Homoskedasticity |
| 6 | Jarque-Bera (JB) test | 1.33 | 0.510 | Normally Distributed |
| 7 | Heteroskedasticity (H) test | 1.05 | 0.810 | No Heteroskedasticity |

The diagnostic tests to ensure the ARIMA(1,1,1) model is right show that the residuals meet the model's assumptions about their reliability. An ADF test statistic by the model developed resulted in $-7.98$ with a p-value of $0.000$, which is enough evidence that indeed the series is stationary after differencing. It is a guarantee that the model is a stationary time series upon which ARIMA modeling is highly dependent. The p-values from the White test and the Breusch-Pagan test were, respectively, $0.431$ and $0.197$; hence, there is no evidence of heteroscedasticity. The Portmanteau (Ljung-Box) test's p-value was $0.95$, which proves that there is no significant autocorrelation in the residuals. This is a positive sign that our model correctly describes the structure of the autocorrelation in the data. The Goldfeld-Quandt test returned a p-value of $0.99$, which shows homoscedasticity; this evidence proves that the model is strong enough to handle variance correctly across the dataset. A similar indication comes from the Jarque-Bera normality test, as its p-value was $0.510$, implying that the distribution of residuals is indeed normal, validating model assumptions. The heteroscedasticity (H) test p-value was $0.81$, which backs up our earlier evidence that the residuals do not show any heteroscedasticity. That means the variance does not change over time. Overall, these results suggest that the ARIMA(1,1,1) model is appropriate for forecasting the unemployment rate since it fulfills some necessary conditions for predictions to be right: stationarity, no autocorrelation, and normal distribution of residuals with constant variance.

Table 6 presents the estimation and diagnostic results for the selected ARIMA(1,1,1) model based on key results from prior tables.

**Table 6.** Summary of ARIMA(1,1,1) model estimation and diagnostics

| Component | Result / Statistic | Interpretation |
|---|---|---|
| Selected model | ARIMA(1,1,1) | Lowest AIC/BIC among tested models |
| AR(1) coefficient | 0.911 ($p < 0.01$) | Significant positive autocorrelation |
| MA(1) coefficient | $-0.690$ ($p < 0.01$) | Significant moving-average term |
| AIC / BIC | $-519.12$ / $-508.45$ | Best fit across candidates |
| ADF test | $-7.98$ ($p = 0.000$) | Stationary residuals |
| Ljung–Box | $p = 0.950$ | No autocorrelation |
| White / BP test | $p > 0.1$ | No heteroskedasticity |
| Jarque–Bera | $p = 0.510$ | Normal residuals |

### 4.1.4. Model forecasting

After the diagnostic test was completed, this study continues to forecast the unemployment rate for the test dataset using the ARIMA (1,1,1) model in Figure 6. Table 7 compares predicted and actual values of the test dataset between September 2018 and February 2024. The forecasted unemployment rate has a more consistent trend than the actual test dataset. This characteristic is widespread in ARIMA models, which are linear and often generalize trends while attenuating short-term variations. The model forecasts the unemployment rate trajectory but may not account for abrupt changes or shocks in the test dataset.


**Figure 6.** UK Forecasted Unemployment Rate Based on Test Dataset

**Table 7.** Actual vs Predicted Values Over Time

| Month | Actual | Predicted | Month | Actual | Predicted | Month | Actual | Predicted |
|---|---|---|---|---|---|---|---|---|
| Sep-18 | 4.1 | 4.105 | Jul-20 | 4.4 | 4.154 | May-22 | 3.8 | 4.161 |
| Oct-18 | 4.0 | 4.110 | Aug-20 | 4.6 | 4.154 | Jun-22 | 3.6 | 4.161 |
| Nov-18 | 4.0 | 4.115 | Sep-20 | 5.0 | 4.155 | Jul-22 | 3.6 | 4.161 |
| Dec-18 | 3.9 | 4.119 | Oct-20 | 5.2 | 4.155 | Aug-22 | 3.7 | 4.161 |
| Jan-19 | 4.0 | 4.123 | Nov-20 | 5.2 | 4.156 | Sep-22 | 3.8 | 4.161 |
| Feb-19 | 3.8 | 4.126 | Dec-20 | 5.3 | 4.156 | Oct-22 | 3.9 | 4.161 |
| Mar-19 | 3.8 | 4.129 | Jan-21 | 5.2 | 4.157 | Nov-22 | 3.9 | 4.161 |
| Apr-19 | 3.8 | 4.132 | Feb-21 | 5.0 | 4.157 | Dec-22 | 3.9 | 4.161 |
| May-19 | 3.9 | 4.135 | Mar-21 | 4.9 | 4.158 | Jan-23 | 4.0 | 4.161 |
| Jun-19 | 3.9 | 4.137 | Apr-21 | 4.8 | 4.158 | Feb-23 | 4.0 | 4.161 |
| Jul-19 | 3.9 | 4.139 | May-21 | 4.8 | 4.158 | Mar-23 | 3.9 | 4.161 |
| Aug-19 | 3.9 | 4.141 | Jun-21 | 4.7 | 4.159 | Apr-23 | 4.0 | 4.161 |
| Sep-19 | 3.8 | 4.143 | Jul-21 | 4.6 | 4.159 | May-23 | 4.2 | 4.161 |
| Oct-19 | 3.8 | 4.145 | Aug-21 | 4.5 | 4.159 | Jun-23 | 4.3 | 4.161 |
| Nov-19 | 3.7 | 4.146 | Sep-21 | 4.4 | 4.159 | Jul-23 | 4.3 | 4.161 |
| Dec-19 | 3.9 | 4.148 | Oct-21 | 4.3 | 4.160 | Aug-23 | 4.1 | 4.161 |
| Jan-20 | 3.9 | 4.149 | Nov-21 | 4.2 | 4.160 | Sep-23 | 4.0 | 4.161 |
| Feb-20 | 4.1 | 4.150 | Dec-21 | 4.2 | 4.160 | Oct-23 | 4.0 | 4.161 |
| Mar-20 | 4.1 | 4.151 | Jan-22 | 4.1 | 4.160 | Nov-23 | 3.9 | 4.161 |
| Apr-20 | 4.1 | 4.152 | Feb-22 | 3.9 | 4.160 | Dec-23 | 4.1 | 4.161 |
| May-20 | 4.1 | 4.153 | Mar-22 | 3.8 | 4.160 | Jan-24 | 4.2 | 4.161 |
| Jun-20 | 4.1 | 4.105 | Apr-22 | 3.8 | 4.160 | Feb-24 | 4.3 | 4.161 |

Particularly, the ARIMA (1,1,1) model is then applied to the whole dataset to make predictions for the next three years, from March 2024 to February 2027. The findings indicated that the ARIMA (1,1,1) model provides a reliable forecast of the unemployment rate. The predicted values and confidence intervals showed a slight increase in the unemployment rate over the following three years in Figure 7 and Table 8.

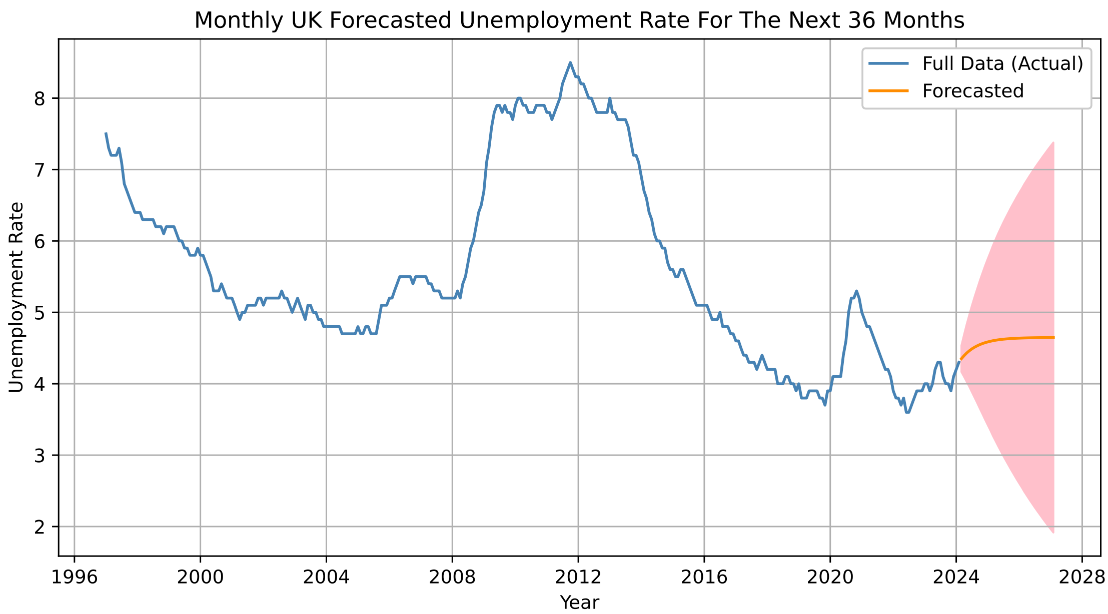


**Figure 7.** Monthly UK Forecasted Unemployment Rate for The Next 36 Months

**Table 8.** Monthly UK Forecasted Unemployment Rate for the Next 36 Months

| Month | Forecast | Lower CI | Upper CI | Month | Forecast | Lower CI | Upper CI |
|---|---|---|---|---|---|---|---|
| Mar-24 | 4.35 | 4.17 | 4.53 | Sep-25 | 4.63 | 2.85 | 6.41 |
| Apr-24 | 4.39 | 4.10 | 4.69 | Oct-25 | 4.63 | 2.79 | 6.48 |
| May-24 | 4.43 | 4.03 | 4.83 | Nov-25 | 4.64 | 2.73 | 6.54 |
| Jun-24 | 4.46 | 3.96 | 4.97 | Dec-25 | 4.64 | 2.66 | 6.61 |
| Jul-24 | 4.49 | 3.88 | 5.10 | Jan-26 | 4.64 | 2.60 | 6.67 |
| Aug-24 | 4.51 | 3.81 | 5.22 | Feb-26 | 4.64 | 2.55 | 6.74 |
| Sep-24 | 4.53 | 3.73 | 5.33 | Mar-26 | 4.64 | 2.49 | 6.80 |
| Oct-24 | 4.55 | 3.65 | 5.45 | Apr-26 | 4.64 | 2.43 | 6.86 |
| Nov-24 | 4.56 | 3.57 | 5.55 | May-26 | 4.64 | 2.37 | 6.91 |
| Dec-24 | 4.58 | 3.50 | 5.65 | Jun-26 | 4.64 | 2.32 | 6.97 |
| Jan-25 | 4.59 | 3.42 | 5.75 | Jul-26 | 4.64 | 2.27 | 7.02 |
| Feb-25 | 4.60 | 3.35 | 5.84 | Aug-26 | 4.65 | 2.21 | 7.08 |
| Mar-25 | 4.60 | 3.27 | 5.93 | Sep-26 | 4.65 | 2.16 | 7.13 |
| Apr-25 | 4.61 | 3.20 | 6.02 | Oct-26 | 4.65 | 2.11 | 7.18 |
| May-25 | 4.62 | 3.13 | 6.10 | Nov-26 | 4.65 | 2.06 | 7.23 |
| Jun-25 | 4.62 | 3.06 | 6.18 | Dec-26 | 4.65 | 2.01 | 7.28 |
| Jul-25 | 4.62 | 2.99 | 6.26 | Jan-27 | 4.65 | 1.96 | 7.33 |
| Aug-25 | 4.63 | 2.92 | 6.33 | Feb-27 | 4.65 | 1.92 | 7.38 |

## 4.2. The ARIMAX model

This study augments the univariate ARIMA model with the GVA exogenous variable, henceforth referred to as an ARIMAX (1,1,1) specification, to reflect the short-run impacts of macroeconomic drivers on the unemployment rate beyond autoregressive behaviour grounded in prior literature, where labour market conditions are driven by macroeconomic indicators [1, 2, 9]. Table 9 summarises the results of the estimation of the ARIMAX model.

**Table 9.** Summary of ARIMAX Model Estimation

| | Coefficient | Standard Error | z | p-value |
|---|---|---|---|---|
| GVA | -0.0287 | 0.012 | -2.353 | 0.019 |
| AR(1) | 0.9103 | 0.037 | 24.294 | 0.000 |
| MA(1) | -0.7063 | 0.067 | -10.491 | 0.000 |

The coefficient of GVA is negative and significant at 5% (p-value = 0.019). The finding implies that higher economic output leads to a lower rate of unemployment; this result conforms to Keynesian theory and empirical findings in labour economics.

This observation confirms and broadens what the ARIMA model (section 4.1) had found, which already caught strong autocorrelation structures. The AIC ($-522.139$) and BIC of the ARIMAX model ($-507.911$) indicate a slightly better fit than the ARIMA model (AIC = $-519.119$), suggesting that adding GVA only slightly improves prediction accuracy.

**Table 10.** ARIMAX Model Diagnostic Tests

| No. | Diagnostic Tests | Test Statistic | p-value | Conclusion |
|---|---|---|---|---|
| 1 | Augmented Dickey-Fuller (ADF) test | -7.978 | 0.000 | Stationary |
| 2 | White test | 11.0734 | 0.004 | Heteroskedasticity |
| 3 | Breusch-Pagan | 4.330 | 0.037 | Heteroskedasticity |
| 4 | Portmanteau (Ljung-Box) test | 0.010 | 0.920 | No autocorrelation |
| 5 | Goldfeld-Quandt test | 0.013 | 1.000 | Homoskedasticity |
| 6 | Jarque-Bera (JB) test | 2.56 | 0.280 | Normally Distributed |
| 7 | Heteroskedasticity (H) test | 1.000 | 0.990 | No Heteroskedasticity |

Residual diagnostics are shown in Table 10. The model successfully passes nearly all standard tests conducted on it. Results indicate that there is no residual autocorrelation; hence, the time series dynamics are validated (p-value = 0.920). The results of the Jarque-Bera test (p-value = 0.280) confirm the normality of the residuals, and the Goldfeld–Quandt test signifies the existence of homoskedasticity. Heteroskedasticity undermines the reliability of standard errors and statistical inferences in the White and Breusch-Pagan tests (p-value $< 0.05$). Consequently, this issue may arise from unrecognised structural changes or economic disturbances not included by the ARIMAX model.

## 4.3. The machine learning models

In addition to evaluating selected models such as ARIMA and its variations, this paper brings in two ensemble-based machine learning methods to predict the UK unemployment rate, namely Random Forest and XGBoost. As such, we selected them due to their proficiency in handling nonlinear connections and complex feature interactions found in macroeconomic data. Table 11 below summarises their comparative performance for both models.

**Table 11.** Forecasting Performance of Machine Learning Models

| Model | MAE | MSE | RMSE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| Random Forest | 0.2074 | 0.0690 | 0.2626 | 0.0507 | 0.6319 |
| XGBoost | 0.2027 | 0.0672 | 0.2592 | 0.0493 | 0.6414 |

XGBoost outperforms Random Forest across all metrics. It achieves the lowest MAE (0.2027) and RMSE (0.2592) scores for predictive accuracy. Meanwhile, MAPE falls below 5%, which means the model gives reliable short-term forecasts with minimal error in percentage terms. The highest $R^2$ value at 0.6414 also tells us that XGBoost captures more variance in the unemployment rate than all other models we tested.

These results again prove the power of advanced ensemble learning models in economic forecasting and indicate that XGBoost is the strongest pick for modelling complex, non-linear macroeconomic dynamics in this setting.

## 4.4. Performance valuation of models

To evaluate how well each model from this study, namely ARIMA, ARIMAX, Random Forest, and XGBoost, predicted results, we used five measures: MAE, MSE, RMSE, MAPE, and $R^2$. Table 12 presents the results below.

**Table 12.** Comparative Performance of Forecasting Models

| Model Type | MAE | MSE | RMSE | MAPE | $R^2$ |
|---|---|---|---|---|---|
| ARIMA (1,1,1) | 0.3235 | 0.1775 | 0.4213 | 0.0750 | 0.0122 |
| ARIMAX (1,1,1) with GVA | 0.2919 | 0.1391 | 0.3730 | 0.0677 | 0.2257 |
| Random Forest | 0.2074 | 0.0690 | 0.2626 | 0.0507 | 0.6319 |
| XGBoost | 0.2027 | 0.0672 | 0.2592 | 0.0493 | 0.6414 |

Among the models tested, the basic ARIMA(1,1,1) model came out as the worst performing, with the highest values of errors and practically nil $R^2$ (hardly any explanatory strength whatsoever). The same exogenous included in the ARIMAX model greatly improves but only moderately. On the other hand, both machine learning models produce significantly better forecasts. In the end, the XGBoost turned out to be the best across all, with the lowest metrics of errors and the highest $R^2$ (best forecasting ability for the UK unemployment rate).

This result indicates that while the ARIMA and ARIMAX models are based on the dynamics of the unemployment rate, the machine learning approach, particularly XGBoost, is far superior in doing the same. In short, it would have a more practical utility for economic decision-makers, who require accurate forecasts of the labour market.

## 4.5. Discussion

Results from ARIMA, ARIMAX, Random Forest, and XGBoost indicate that while ARIMA captures the short-term, mean-reverting behaviour of the UK unemployment rate, its confidence intervals become much too narrow after 36 months. Thus, long-term forecasting accuracy is greatly limited. In turn, the ARIMAX model incorporating GVA improves the explanatory power of the model but continues to suffer from heteroskedasticity since structural changes are not captured in the model [7, 46]. Results from testing using Zivot–Andrews were inconclusive; hence, to an extent, limiting break-adjusted modelling application [50].

In all accuracy metrics, machine learning models, particularly XGBoost, performed better than classical models. More importantly, they take into consideration complex nonlinear dynamics and interactions.

This essentially reaffirms prior evidence. For example, Ahmad et al. [2] established that global shocks like the COVID-19 pandemic had significant effects on the unemployment pattern in Europe; hence, the need for models that can easily adjust to such crisis situations. The same study is also supported by Edlund and Karlsson [14], who showed that unexpected shocks could tremendously alter the trajectory of unemployment time series data for Sweden. Both these studies argue in favour of adaptive and anticipatory forecasting frameworks.

However, the challenges are associated with applying XGBoost and other machine learning models due to their interpretability constraints for policy focused studies. Unlike machine learning models, which function as non-parametric systems, ARIMA and ARIMAX models estimate transparent parameters directly linked to economic theories. The non-parametric nature of machine learning models, which operate in a complex model, adds to the difficulty for the interpretation of the model outputs to transform the outputs into effective insights for policymakers. Interpretability frameworks like SHAP (SHapley Additive exPlanations) and feature importance analysis that focus on model explanation for each predictor's contribution. Model evaluation using these tools enhances predictive accuracy while simultaneously improving explanatory clarity, thus enhancing the models' practical utility for labor market policy.

In addition, policy focus still requires investment in human capital. Workforce training specific to sectors, in IT and renewable energy, for example, is important to fulfil labour needs in the future [23, 33]. Equally important is supporting small and medium-sized enterprises (SMEs). This, according to the OECD, can be achieved through the provision of tax reliefs, simplification of administrative procedures, and targeted financial aid [32]. These become rather urgent post-Brexit, when there is a pronounced shortage of workers, particularly in low-wage sectors, [43]. Another major strategy is the reform of immigration policy. Orefice [36] has highlighted that skilled migration contributes both to filling the gaps in the workforce and increasing economic productivity. Therefore, easy access to foreign talent will be paramount for the UK in the coming years.

The predictions from the ARIMAX and XGBoost models will also assist in forecasting labour market shocks for such policy institutions as the Bank of England [4], the UK Treasury, and its fiscal watchdog, the Office for Budget Responsibility (OBR) [34]. In this way, reliable unemployment forecasts help measure employment elasticity to output and thus improve interest-rate decision rules and targeting fiscal packages. The integration of such data-driven models into policy planning promotes macroeconomic stability management and advances reaction to cyclical downturns. Also, new policy directions stress green investment and lifelong learning as twin paths for inclusive growth. Pushing SMEs and big firms to use clean-energy tech and digital innovation not only adds new jobs but also backs the UK's Net Zero 2050 aim. At the same time, putting money into reskilling and digital skills programs, as noted by the World Economic Forum (2023) [47], lets workers adjust to automation and AI transformations in the long run, thus reducing structural unemployment.

These policy implications correspond with the theoretical assumption that labor market dynamics have a very close relationship with macroeconomic stability and growth in productivity. In conclusion, fiscal policy should focus on infrastructure and human capital development. Suárez-Cuesta and Latorre [44] provide empirical evidence that such investment can advance employment as well as economic resilience, in other words, help in buffering subsequent downturns.

# 5. Conclusions

The primary aim of this paper is to investigate the forecasting performance of different approaches to modelling the monthly unemployment rate in the United Kingdom, including the classical ARIMA (1,1,1), its exogenous variant (ARIMAX), and two machine learning models, such as Random Forest and XGBoost. The ARIMA model demonstrates strong predictive capabilities for short durations and predicting short-term unemployment when data availability or accuracy is crucial. However, it has difficulties in identifying significant changes, economic disruptions, and intricate patterns that may occur over extended durations. Inconclusive Zivot-Andrews test findings made it impossible to definitively confirm the structural stability.

Adding macroeconomic factors, like gross value added, to the ARIMAX model slightly enhances forecast accuracy compared to the traditional ARIMA model. However, the ARIMAX model still suffers from statistical limitations, particularly under conditions of heteroskedasticity. In contrast, machine learning models, especially XGBoost, demonstrate greater forecasting accuracy and robustness. Their consistently lower values across all performance metrics, including MAE, RMSE, MAPE, and MSE, reflect this improvement. These models are inherently better suited to capture complex, nonlinear, and interaction-driven relationships in the labour market, which traditional time-series models may fail to effectively accommodate. Their adaptability enables them to respond to changing macroeconomic trends without the stringent parametric assumptions necessary for ARIMAX. Regardless, their limits are direct interpretability, which is essential for policy-focused analysis.

Taken together, the findings of this study support the use of ARIMA models as a reliable tool for short-term unemployment forecasting, owing to their transparency and statistical interpretability. For medium- and long-term projections, however, machine learning models, particularly XGBoost, demonstrate superior performance due to their ability to model complex, non-linear dynamics in labour market data. These results highlight the value of hybrid models that integrate classical econometrics with modern machine learning techniques to enhance forecasting's robustness and adaptivity.

This study suggests that combining data-driven and theory-based models may provide a more comprehensive knowledge of labour market dynamics, especially under macroeconomic instability and structural changes. It is confined to forecasting the unemployment rate; hence, caution is advised when applying this understanding to other macroeconomic variables such as GDP, FDI, CPI, and other similar indicators. Future studies should include more exogenous variables, evaluate the temporal stability of results (employing rolling predictions and changepoint detection), investigate ensemble learning techniques, and add SHAP interpretability and feature importance analysis to improve the relevance of findings in practical scenarios.

## Acknowledgement

This research was supported by the VNUHCM-University of Information Technology's Scientific Research Support Fund.

## References

[1] Adu, W. K., Appiahene, P., and Afrifa, S. VAR, ARIMAX and ARIMA models for nowcasting unemployment rate in Ghana using Google trends. *Journal of Electrical Systems and Information Technology 10*, 1 (2023), 12.

[2] Ahmad, M., Khan, Y. A., Jiang, C., Kazmi, S. J. H., and Abbas, S. Z. The impact of COVID-19 on unemployment rate: An intelligent based unemployment rate prediction in selected countries of Europe. *International Journal of Finance and Economics 28*, 1 (2023), 528–543.

[3] Akaike, H. A new look at the statistical model identification. *IEEE Transactions on Automatic Control 19*, 6 (1974), 716–723.

[4] Bank of England (2025). Monetary policy report: August 2025 (accessed on 18 October 2025).

[5] Box, G. E. P., and Jenkins, G. M. *Time Series Analysis: Forecasting and Control*. Holden-Day, 1976.

[6] Breiman, L. Random forests. *Machine Learning 45*, 1 (2001), 5–32.

[7] Breusch, T. S., and Pagan, A. R. A simple test for heteroscedasticity and random coefficient variation. *Econometrica 47*, 5 (1979), 1287–1294.

[8] Celbiş, M. G. Unemployment in rural Europe: A machine learning perspective. *Applied Spatial Analysis and Policy 16*, 3 (2023), 1071–1095.

[9] Chakraborty, T., Chakraborty, A. K., Biswas, M., Banerjee, S., and Bhattacharya, S. Unemployment rate forecasting: A hybrid approach. *Computational Economics 57*, 1 (2021), 183–201.

[10] Chen, T., and Guestrin, C. XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (New York, 2016), B. Krishnapuram, M. Shah, A. J. Smola, C. C. Aggarwal, D. Shen and R. Rastogi, Eds., ACM, pp. 785–794.

[11] Corea, F. (2017). *Essays on Machine Learning for Economics and Finance*. PhD thesis, LUISS Guido Carli University, Italy, (accessed on 15 April 2024).

[12] Dickey, D. A., and Fuller, W. A. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association 74*, 366a (1979), 427–431.

[13] Dongdong, W. The consumer price index forecast based on ARIMA model. In *Proceedings - 2010 WASE International Conference on Information Engineering, ICIE 2010* (Beidai, China, 2010), vol. 1, IEEE, pp. 307–310.

[14] Edlund, P.-O., and Karlsson, S. Forecasting the Swedish unemployment rate VAR vs. transfer function modelling. *International Journal of Forecasting 9*, 1 (1993), 61–76.

[15] Funke, M. Time-series forecasting of the German unemployment rate. *Journal of Forecasting 11*, 2 (1992), 111–125.

[16] Gogas, P., Papadimitriou, T., and Sofianos, E. Forecasting unemployment in the Euro area with machine learning. *Journal of Forecasting 41*, 3 (2022), 551–566.

[17] Goldfeld, S. M., and Quandt, R. E. Some tests for homoscedasticity. *Journal of the American Statistical Association 60*, 310 (1965), 539–547.

[18] Guerrero, V. M. ARIMA forecasts with restrictions derived from a structural change. *International Journal of Forecasting 7*, 3 (1991), 339–347.

[19] Gupta, R., Pierdzioch, C., and Salisu, A. A. Oil-price uncertainty and the U.K. unemployment rate: A forecasting experiment with random forests using 150 years of data. *Resources Policy 77* (2022), 102662.

[20] Hill, P. *Working Hard or Hardly Working? Evaluating New Labour's Active Labour Market Policy*. PhD thesis, The University of Warwick, UK, 2016.

[21] Huwart, J.-Y., and Verdier, L. *Economic Globalisation: Origins and Consequences*. OECD Insights. OECD Publishing, 2013.

[22] Jarque, C. M., and Bera, A. K. A test for normality of observations and regression residuals. *International Statistical Review 55*, 2 (1987), 163–172.

[23] Kalejaiye, P. O. Addressing shortage of skilled technical workers in the USA: A glimpse for training service providers. *Future Business Journal 9*, 1 (2023), 50.

[24] Katris, C. Prediction of unemployment rates with time series and machine learning techniques. *Computational Economics 55*, 2 (2020), 673–706.

[25] Khan Jaffur, Z. R., Sookia, N.-U.-H., Nunkoo Gonpot, P., and Seetanah, B. Out-of-sample forecasting of the Canadian unemployment rates using univariate models. *Applied Economics Letters 24*, 15 (2017), 1097–1101.

[26] Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., and Matsopoulos, G. K. A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks. *Future Internet 15*, 8 (2023), 255.

[27] Ljung, G. M., and Box, G. E. P. On a measure of lack of fit in time series models. *Biometrika 65*, 2 (1978), 297–303.

[28] Milas, C., and Rothman, P. Out-of-sample forecasting of unemployment rates with pooled STVECM forecasts. *International Journal of Forecasting 24*, 1 (2008), 101–121.

[29] Mohamed, A. O. Modeling and forecasting Somali economic growth using ARIMA models. *Forecasting 4*, 4 (2022), 1038–1050.

[30] Mohammed, E. A., Naugler C., and Far, B. H. Emerging business intelligence framework for a clinical laboratory through big data analytics. In *Emerging Trends in Computational Biology, Bioinformatics, and Systems Biology: Algorithms and*

*Software Tools* (2015), A. R. Hamid and Q. N. Tran, Eds., Morgan Kaufmann Publishers Inc., pp. 577–602.

[31] NAO (National Audit Office) (2006). *Report – value for money: The closure of MG Rover* (accessed on 25 June 2024).

[32] OECD. *Aid for Trade at a Glance 2015: Reducing Trade Costs for Inclusive, Sustainable Growth*. OECD Publishing, Paris, 2015.

[33] OECD. *OECD Economic Surveys: Slovak Republic 2017*. OECD Publishing, Paris, 2017.

[34] Office for Budget Responsibility (15 March 2023). *Economic and fiscal outlook: March 2023* (accessed on 18 October 2025).

[35] ONS (2024). *Unemployment rate (aged 16 and over, seasonally adjusted): %* (accessed on 31 May, 2025).

[36] Orefice, G. Skilled migration and economic performances: Evidence from OECD countries. *Swiss Journal of Economics and Statistics 146*, 4 (2010), 781–820.

[37] Paparoditis, E., and Politis, D. N. The asymptotic size and power of the augmented Dickey–Fuller test for a unit root. *Econometric Reviews 37*, 9 (2018), 955–973.

[38] Phillips, P. C. B., and Perron, P. Testing for a unit root in time series regression. *Biometrika 75*, 2 (1988), 335–346.

[39] Sa'adah, S., and Wibowo, M. S. Prediction of gross domestic product (GDP) in Indonesia using deep learning algorithm. In *2020 3rd International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)* (Yogyakarta, Indonesia, 2020), IEEE, pp. 32–36.

[40] Schwarz, G. Estimating the dimension of a model. *The Annals of Statistics 6*, 2 (1978), 361–364.

[41] Segnon, M., Gupta, R., Bekiros, S., and Wohar, M. E. Forecasting US GNP growth: The role of uncertainty. *Journal of Forecasting 37*, 5 (2018), 541–559.

[42] Sofianos, E., Alexakis, C., Gogas, P., and Papadimitriou T. Machine learning forecasting in the macroeconomic environment: the case of the US output gap. *Economic Change and Restructuring 58*, 1 (2025), 9.

[43] Sumption, M., Forde, C., Alberti, G., and Walsh, P. W. (15 Aug 2022). *How is the End of Free Movement Affecting the Low-wage Labour Force in the UK?* The Migration Observatory report (accessed on 25 May 2024).

[44] Suárez-Cuesta, D., and Latorre, M. C. Modeling the impact of public infrastructure investments in the U.S.: A CGE analysis. *International Advances in Economic Research 29*, 3 (2023), 165–176.

[45] Vicente, M. R., López-Menéndez, A. J., and Pérez, R. Forecasting unemployment with internet search data: Does it help to improve predictions when job destruction is skyrocketing? *Technological Forecasting and Social Change 92* (2015), 132–139.

[46] White, H. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica 48*, 4 (1980), 817–838.

[47] World Economic Forum (May 2023). *The Future of Jobs Report 2023* (accessed on 18 October 2025).

[48] Yamacli, D. S., and Yamacli, S. Estimation of the unemployment rate in Turkey: A comparison of the ARIMA and machine learning models including Covid-19 pandemic periods. *Heliyon 9*, 1 (2023), e12796.

[49] Zhang, Y., Shang, W., Zhang, N., Pan, X., and Huang, B. Quarterly GDP forecast based on coupled economic and energy feature WA-LSTM model. *Frontiers in Energy Research 11* (2023), 1329376.

[50] Zivot, E., and Andrews, D. W. K. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics 10*, 3 (1992), 251–270.