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LABOUR FORCE PARTICIPATION RATE AND UNEMPLOYMENT RATE: A MALAYSIAN PERSPECTIVE

Aqila Nawwara Ahmad Fauzi[1], Siti Nur Najiha Razali[2] and Nurul Nisa' Khairol Azmi[3,*]
[1,2,3]College of Computing, Informatics and Mathematics, Teknologi MARA Negeri Sembilan
Seremban Campus, 70300 Negeri Sembilan
*nurulnisa@uitm.edu.my

Abstract

During the COVID-19 outbreak in early 2020, Malaysia's unemployment rate increased from 3.26 per cent in 2019 to 4.54 per cent in 2020. This study aims to forecast the unemployment rate for the next four quarters. Additionally, to determine the impact of the labour force participation rate on the unemployment rate. Data for this study were collected quarterly from the Department of Statistics Malaysia (DOSM) covering the period from 2015 to 2023. The methodologies employed include vector autoregressive (VAR) and impulse response function (IRF) analyses. The findings reveal that the unemployment rate was forecasted for four quarters ahead and the IRF analysis indicates that economic shocks have a significant and lasting impact on the unemployment rate.

Keywords: Vector Autoregressive, Impulse Response Function, unemployment rate, labour force participation rate.

1. Introduction

Despite broad terms in economic development, youth unemployment remains a serious issue in Malaysia. According to Kit (2024), 76 per cent of Malaysians between the ages of 15 and 24 are unemployed, or 10.6 per cent of the country's total unemployment population. An increase in recent graduates joining a declining labour market contributes to this problem. Instability is brought on by high unemployment rates, which have an impact not just on individuals but also on the economy and society across the country, (Rohaimi et al., 2022). In order to predict and tackle these issues, policymakers utilise forecasting models.

The COVID-19 pandemic hit Malaysia hard in March 2020, causing businesses to implement unpaid leave and staff reductions to survive financially. Malaysia's economy shrank by 5.6 per cent in 2020, worse than the 4.4 per cent decline the year before. Moreover, the unemployment has serious social consequences, including increased poverty and family strain. Thus, research is needed to understand how the pandemic has affected the overall employment trends. Government actions and economic stimulus efforts are crucial in helping Malaysia recover and create new job opportunities.

This research tackles two primary objectives. Firstly, it aims to forecast the unemployment rate for the next four quarters. Second, the study delves into how the labour force participation rate influences the unemployment rate. Employers and HR departments will find these insights useful as they offer evidence-based solutions to properly handle future unemployment issues in Malaysia. Hence, this research focuses on examining the relationship between unemployment rate and the labor force participation rate and applied Vector Autoregressive (VAR) and Impulse Response Function (IRF) methodologies using data from the Department of Statistics Malaysia (DOSM).

2. Literature Review

The labour force is an important economic statistic for forecasting future trends, formulating policy, and maintaining competitiveness. By examining significant variables and their relationships, previous research has investigated the relationship between the unemployment rate and labour force participation rate. The percentage of the labour force that is actively looking for work is represented by the unemployment rate, which is an important economic indicator. It acts as an indicator of the state of the economy; large numbers denote trouble in the economy, while low numbers show health (Jamaludin et al., 2021).

According to the Ma'in et al. (2021), persistent difficulties, especially for recent graduates, highlight the need for focused interventions to minimise long-term unemployment risks despite efforts to reduce unemployment through different programmes. The percentage of working-age people who are actively employed or looking for employment in an economy is measured by the labour force participation rate, or LFPR. Future labour market conditions can be predicted with the help of LFPR insights, which also impact policy decisions on labor-related matters (Yusuf et al., 2020).

Aaronson et al. (2006) outlined the percentage of people over 15 to 65 who are not in institutions and who report being either employed or actively seeking for employment is known as the labour participation rate. Ahn and Hamilton (2022) said that the bias in the labour force participation rate has grown over time and that the typical figures understate both the unemployment rate and the rate of participation by an average of almost two percentage points. Malaysia has undergone a significant shift in the composition of its labour force, with an increase in the proportion of female workers. In spite of this development, women's labour market participation rates are still comparatively low, at around 46 per cent (Qinfen, 2017).

In conclusion, the LFPR is a crucial metric that indicates the percentage of working-age individuals who are either employed or actively seeking employment. It provides valuable insights into economic health, labour trends, policy decisions, productivity and social impacts. Understanding the LRPF helps in predicting future labour market shortages or surpluses and supports informed decision-making regarding labour market issues.

3. Methodology

This study aims to explore the relationships among various labor force attributes. Data for this study were sourced from the Department of Statistics Malaysia (DOSM) February 2023 Malaysia Labour Force Statistics Report and quarterly data spanning from 2015 to 2023. The variables covered include unemployment rate and the labor force participation rate.

3.1. *Vector Autoregressive (VAR)*

The linear interdependencies between several time series are captured by the VAR model. It offers a framework for examining dynamic impacts by highlighting the ways in which each variable influences others and itself over time. In a VAR model, each variable has an equation that describes how it has changed over time based on both its own lags and the lags of all other variables and treating them equally. The VAR model describes the evolution of a set of k variables measured over the same sample period, denoted as $VAR(p)$.

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \epsilon_t \tag{1}$$

where,
x is the intercept.
A_i is the square matrix.
ϵ_t are the error terms satisfying the conditions.
c is constant.

The VAR model involves seven steps before forecasts can be made as depicted in Figure 1. The VAR model involves identifying and defining relevant variables, ensuring the time series data is stationary and differencing will be done if the data is nonstationary. Selecting the appropriate lag length (p) based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), another name for BIC is Schwarz Criterion (SC). The model uses the lowest values of AIC and BIC to ensure the best fit.

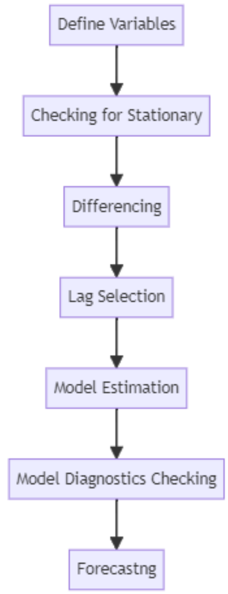

Figure 1: The Flowchart of Steps in VAR

3.2. *Impulse Response Function (IRF)*

The impulse response function (IRF) is a tool used in signal processing, engineering, and economics to analyze how a system responds dynamically to sudden inputs or shocks. It examines how shocks affect variables within the system, aiding in understanding dynamics, forecasting, and evaluating models. By showing the long-term effects of a shock on variables, particularly its impact on unemployment, the IRF helps uncover the dynamics and direction of their influence.

When the shock is observed, the estimation of IRF is defined as:

$$zt = \Phi zt - 1 + ut \quad \text{for } t = \ldots, 0, 1, 2, \ldots, T \tag{2}$$

where Φ is an nxn matrix of coefficients and ut is an $nx1$ vector of reduced form shocks, which is partitioned as

$$ut = r\epsilon t + \zeta t \tag{3}$$

where ϵt denotes the observed shock of interest which is uncorrelated with ζt, where Φ is an nxn matrix of coefficients and ut is an $nx1$ vector of reduced from shocks, which is partitioned as $ut = r\epsilon t + \zeta t$, where ϵt denotes the observed shock of interest which is uncorrelated with ζt (Choi and Chudik, 2019).

4. Result and Discussion

4.1. *Stationary*

In time series analysis, 'stationary' refers to a statistical property of a time series where its mean, variance and autocorrelation is fluctuating around constant number. Figure 2 and Figure 3 depict the result of ACF of the unemployment rate and labour force participation rate respectively. Both figures, which is Figure 2 and Figure 3, show a gradual decline in the ACF, indicating that both time series are non-stationary. Since the time series is found to be non-stationary, differencing technique was used to transform it into a stationary series.

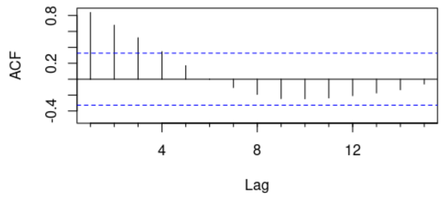

Figure 2: ACF of Unemployment Rate

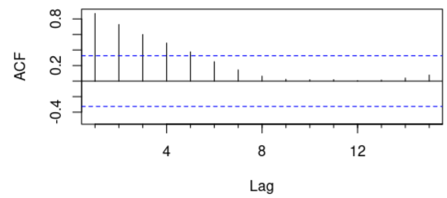

Figure 3: ACF of Labour Force Participation Rate

Figure 4 shows that from 2015 to early 2020, the labor force participation rate and unemployment rate were stable. However, both rates sharply increased starting in early 2020 due to the economic effects of the COVID-19 pandemic. The red line shows a sudden spike in the unemployment rate, and the turquoise line shows significant shifts in the labor force participation rate. These findings highlight the significant impact of the pandemic and economic changes on employment trends and recovery efforts.

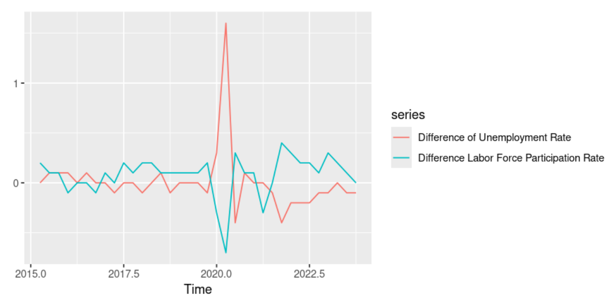

Figure 4: Plot Differencing Labour Force Participation Rate

4.2. *Differencing*

Differencing is a technique used in time series analysis to transform a non-stationary series into a stationary one. Figure 5 and Figure 6 demonstrate that both time series are now stationary as the ACF for both time series show no significant spike. ACF of unemployment rate and labour force participation rate after the first differencing show no significant spike indicate that both of time series are now stationary.

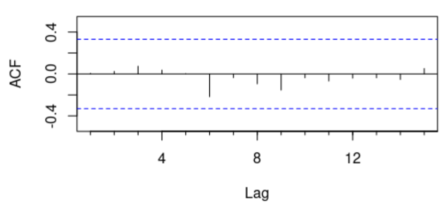

Figure 5: ACF of Unemployment Rate (After First Differencing)

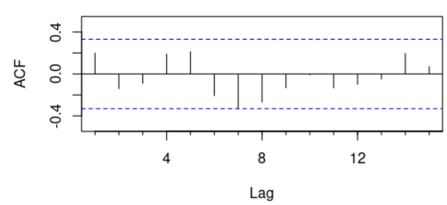

Figure 6: ACF of Labour Force Participation Rate (After First Differencing)

4.3. *Lag Selection*

The value of AIC and SC were observed to determine the lag length. AIC refers to Akaike Information Criterion while SC means Schwarz Criterion. The lower value of both AIC and SC, indicates that the model is better (Fanchette et al., 2020). Table 1 shows that lag 1 has been selected by both AIC and SC.

Table 1: Model Selection Criteria

AIC(n)	HQ(n)	SC(n)	FPE(n)
1	1	1	1

4.4. *Model Estimation*

Model estimation refers to the process of determining the values of parameters within a statistical or economic model. Model estimation was interpreted in this study to understand the relationship between unemployment rate and labour force participation rate. The output of the model is as depicted in Table 2.

Table 2: Estimation Results for Equation: Unemployment Rate

	Estimate	Std. Error	t value	Pr($>|t|$)
Unemployment Rate	0.848	0.091	9.343	1.17×10^{-10} ***
Labour Force Participation Rate	0.004	0.072	0.056	0.956

From the Table 2, the equation can be written and expanded as follows :

$$\begin{aligned}
\Delta y_t &= 0.287 + 0.848\Delta y_t + 0.004\Delta x_{t-1} \\
y_t - y_{t-1} &= 0.848(y - y_{t-1}) + 0.004(x - x_{t-1}) \\
y_t - 0.848y_t &= y_{t-1} - 0.848y_{t-1} + 0.04(x_t - x_{t-1}) \\
0.152y_t &= 0.152y_{t-1} + 0.004x_t - 0.004x_{t-1} \\
y_t &= y_{t-1} + 0.0026x_t - 0.0026x_{t-1} \qquad (4)
\end{aligned}$$

According to the Equation (4), it can be concluded that unemployment rate for today is based on unemployment rate on 1 period before, adjusted by 0.26% of labour force participation rate.

4.5. *Forecast*

The Table 3 represent the estimated unemployment rates for each quarter of 2024 through the employing of point predictions. Therefore, the estimate for first quarter 2024 is 3.37, and it increases progressively every quarter until it reaches 3.53 in fourth quarter 2024.

Table 3: Forecasting of Unemployment Rate

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2024 Q1	3.37	2.98	3.76	2.77	3.97
2024 Q2	3.43	2.92	3.94	2.65	4.21
2024 Q3	3.48	2.90	4.07	2.59	4.38
2024 Q4	3.53	2.90	4.16	2.56	4.49

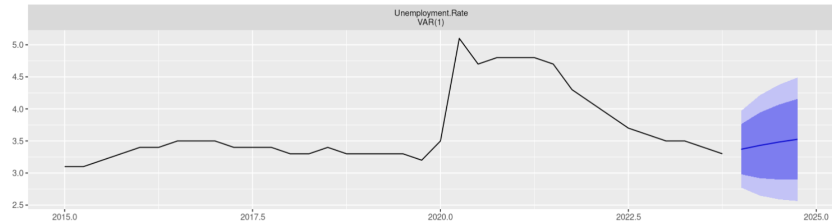

Figure 7: Forecasting Unemployment Rate Based on Labour Force Participation Rate

The shaded regions in Figure 7 show the uncertainty around the point estimates for the confidence intervals. The 80 per cent CI (lighter area) widens from the first to the fourth quarter, indicating increasing forecasting uncertainty. Similarly, the 95 per cent CI (darker area) also expands, highlighting a broader range of possible outcomes as the year progresses. If the labor force participation rate is the main factor considered, the forecast suggests a possible increase in unemployment, with the rate showing a slight upward trend throughout the quarters.

4.6. *Impact towards unemployment rate using Impulse Response Function*

According to the Lu and Xin (2010), the Impulse Response Function (IRF) of the VAR model analyzes the changes in variables after detecting an impulse. The IRF graph determines a variable's behavior in response to a shock by visualizing how the unemployment rate responds to shocks in the labor force participation rate.

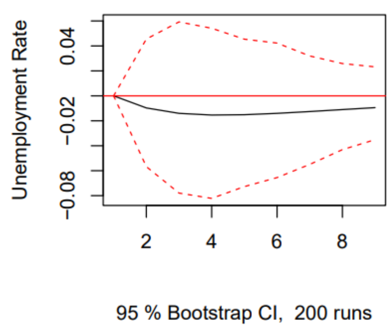

Figure 8: Response of Unemployment Rate to Labour Force Participation Rate Shock

Figure 8 illustrates a significant decrease in the unemployment rate following the initial shock, represented by the black line, which relates to the COVID-19 pandemic. Aaronson et al. (2006) highlighted the importance of understanding labor market dynamics, noting that COVID-19 temporarily reduced the labor force participation rate (LFPR) as individuals exited the workforce for health or family reasons. The black line also shows that the unemployment rate remains below zero for multiple periods, indicating a sustained positive effect. This reflects how the pandemic, company adjustments, government assistance, and economic recovery influenced the labour market. The response is statistically significant and reliable, as the black line stays within the red dashed confidence intervals. This means the effect is not due to chance. Overall, the IRF plot shows a strong and lasting impact of increased job applications during COVID-19 on lowering the unemployment rate.

4.7. *Discussion*

The IRF data shows that an initial shock to the LFPR can briefly increase unemployment as more people enter the labor market, aligning with findings by (Ahn and Hamilton, 2022). The VAR model was used to forecast the unemployment rate for the next four quarters, producing detailed results after ensuring data stationarity. Tables and figures showed the estimated unemployment rates. The IRF analysis also assessed the impact of LFPR, job vacancies, and job applications on unemployment, revealing that shocks to these variables significantly affect the unemployment rate.

5. Conclusions

The purpose of this study was to investigate the connection between Malaysia's unemployment rate and labour force participation. Despite widening confidence intervals indicating long-term uncertainty, the VAR model produced trustworthy insights and stable unemployment projections through 2024. The correctness of the model was demonstrated by its good fit. Economic shocks, particularly during COVID-19, had a major influence on unemployment, according to IRF study. Stable labour markets require constant observation and flexible policy.

6. Recommendations

Advanced analytical techniques are advised in order to comprehend the relationship between Malaysia's unemployment rate and labour force characteristics. Models remain accurate and flexible when methods such as the Bai-Perron test are used to detect weakened structures brought about by changes in the economy or in policy. Additionally, by identifying complex nonlinear correlations between variables, machine learning techniques like Random Forests and Gradient Boosting Machines can increase forecast accuracy. These approaches seek to offer useful perspectives and direct sensible tactics to tackle Malaysia's unemployment issues.

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