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Analysis of Labor Force Participation in Malaysia using Lee-Carter and Cairns-Blake-Dowd Stochastic Models

Analisis Kadar Penyertaan Tenaga Buruh di Malaysia menggunakan Model Stokastik Lee-Carter dan Cairns-Blake-Dowd

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ABSTRACT

The global population is undergoing a significant aging process due to increased life expectancy and declining fertility rates. This demographic shift has altered the age structure of the workforce, with more older individuals continuing to work until retirement. As a result, many countries, including Malaysia, have experienced rising labor force participation rates (LFPR), which in turn impact the pension systems. Despite this, research on LFPR forecasting remains limited, especially studies that account for both age and year effects. This study aims to address this gap through two main objectives. The first is to forecast the LFPR for Malaysian workers aged 50 to 64 by incorporating age and time effects using stochastic models, and the second is to estimate the expected length of retirement (ELR) based on the projected LFPR. The Lee-Carter and Cairns-Blake-Dowd (CBD) stochastic models are suggested, using a generalized linear model (GLM) approach with Poisson and binomial distributions to enhance model accuracy. Labor force data (2001–2021) were sourced from the Department of Statistics Malaysia (DOSM), and population data were obtained from the United Nations database. The results show that the Lee-Carter model outperforms the CBD model in terms of goodness-of-fit. Male LFPR is expected to remain stable from 2018 to 2047, while female LFPR is projected to increase significantly from 41% to 78%. This rise reflects changing social roles and delayed retirement among women. ELR projections also increase for both genders, driven by longer life expectancy and evolving labor force dynamics.

Keywords: Labor market; stochastic model; labor force participation; retirement; older adults

ABSTRAK

Populasi global kini sedang mengalami proses penuaan yang ketara disebabkan oleh peningkatan jangka hayat dan penurunan kadar kesuburan. Perubahan demografi ini telah mengubah struktur umur tenaga kerja, dengan lebih ramai individu yang berusia terus bekerja sehingga umur persaraan. Akibatnya, kebanyakan negara termasuk Malaysia telah menunjukkan peningkatan dalam kadar penyertaan tenaga buruh (LFPR), yang seterusnya memberi kesan kepada sistem pencen. Namun, kajian mengenai peramalan LFPR masih terhad, khususnya kajian yang mengambil kira kedua-dua kesan umur dan tahun. Kajian ini bertujuan untuk menangani jurang tersebut melalui dua objektif utama. Objektif pertama adalah untuk meramal LFPR pekerja Malaysia yang berumur 50 hingga 64 tahun dengan mengambil kira kesan umur dan masa menggunakan model stokastik. Objektif kedua adalah untuk menganggar jangkaan tempoh persaraan (ELR) berdasarkan LFPR yang diramal. Model stokastik Lee-Carter dan Cairns-Blake-Dowd (CBD) dicadangkan dalam kajian ini, menggunakan pendekatan model linear teritlak (GLM) dengan taburan Poisson dan binomial bagi meningkatkan ketepatan model. Data tenaga buruh (2001–2021) diperoleh daripada Jabatan Perangkaan Malaysia (DOSM), manakala data populasi diperoleh daripada pangkalan data Pertubuhan Bangsa-Bangsa Bersatu. Hasil kajian menunjukkan bahawa model Lee-Carter memberikan prestasi yang lebih baik berbanding model CBD dari segi ukuran kebagusan-penyuaian. LFPR lelaki dijangka kekal stabil antara 2018 hingga 2047, manakala LFPR wanita dijangka meningkat secara ketara daripada 41% kepada 78%. Peningkatan ini mencerminkan perubahan peranan sosial dan kelewatan persaraan dalam kalangan wanita. Unjuran ELR juga meningkat bagi kedua-dua jantina, didorong oleh jangka hayat yang lebih panjang dan dinamik tenaga buruh yang berubah.

Kata kunci: Pasaran buruh; model stokastik; penyertaan tenaga buruh; persaraan; warga tua

INTRODUCTION

Malaysia gained independence in 1957 and has since experienced higher labor force participation rate (LFPR) across various age groups and genders due to socioeconomic advancements (Lim Bao Man et al., 2021; Jaapar et al., 2022). This outcome can be attributed to demographic shifts, aging population and policy reforms that promote prolonged employment participation (Goldin & Katz, 2017). Despite these positive developments in labor force participation, early retirement decisions are influenced by increasing number of new entrants into the job market and biased views of productivity regarding older employees (Alcover & Topa, 2018; Buyens et al., 2009; Stynen et al., 2017). Therefore, the complexities and uncertainties in retirement decisions make modern forecasting methods crucial for understanding LFPR outcomes, enabling more accurate predictions of future behavior of labor force (Queiroz & Ferreira, 2021).

The structure of Malaysia's pension system plays a significant role in shaping decisions for labor force participation, particularly among older workers. The coexistence of a defined contribution scheme (Employees Provident Fund, EPF) for private-sector employees and a defined benefit scheme for public servants creates different financial incentives for retirement timing. In the private sector, the ability to withdraw retirement savings at age 55 may encourage early exits from the labor market, potentially reducing LFPR among those aged 55 and above.

The dynamics of Malaysia's pension system and recent policy responses also have significant effects on LFPR, particularly among older workers. During the COVID-19 pandemic in 2020, the EPF allowed partial withdrawals through schemes such as i-Lestari, i-Sinar, i-Citra and 2022 Special Withdrawal, primarily affecting workers in their prime working age which are from 34 to 54 years (Jiton & Ibrahim, 2024). These emergency withdrawals, while offering short-term relief, may affect long-term pension insufficiency, compelling individuals to remain in the workforce longer to rebuild retirement savings.

In response to increased life expectancy and pension adequacy concerns, the government in Malaysia has raised the statutory retirement age from 55 to 60 in 2013. This shift also has a direct impact on the LFPR, particularly by encouraging extended labor force participation among older workers. Previous studies by Ibrahim (2012) and Hashim et al. (2019) highlight how economic factors such as retirement age affect LFPR trends. Their findings suggest that raising the retirement age can support the intergenerational balance of labor force and reduce the fiscal pressure on pension systems. Furthermore, government's focus on the wellbeing and health status of male workers (Ajis et al., 2024) reflects efforts to sustain participation of older workers in the labor market, especially as health outcomes become a determinant of employability at older ages.

In brief, Malaysia has experienced rising LFPR due to socioeconomic progress, demographic shifts and policy reforms. However, factors such as early retirement, pension system design, emergency withdrawals during the COVID-19 pandemic and statutory retirement age continue to influence participation, especially among older workers, highlighting the need for modern forecasting methods in LFPR studies.

In terms of labor force dynamics, considerable attention has been given to gender gaps in the labor market. In Malaysia, gender disparity in the LFPR among the ageing workforce remains an issue. Although there has been a continuous increase in the LFPR across various age groups and genders (Dey, 2006; Kelle, 2020; Lyberaki, 2011; Yamamoto et al., 2017), this upward trend has not closed the participation gap between men and women. These disparities are reflective of broader socioeconomic changes that continue to reshape the structure of Malaysia's labor market (Lim Bao Man et al., 2021; Jaapar et al., 2022). Despite women's progress in educational attainment, their participation in the workforce remains lower than that of men (Akhtar et al., 2020). While recent studies indicate that women's LFPRs are rising due to higher education levels, increased ICT access and reduced reliance on foreign labor (Cherif & Kouadri, 2021; Suhaida et al., 2013), structural barriers persist. In urban areas, many women have become family breadwinners, contributing substantially to household income. This shift coincides with demographic changes, such as delayed marriage and childbearing (Omar & Jaafar, 2024). However, many women still exit the labor market prematurely due to caregiving responsibilities, particularly for elderly family members (Dey, 2006; Kelle, 2020; Lyberaki, 2011; Yamamoto et al., 2017). The increasing need for eldercare further reinforces the reliance on women for informal care, leading to higher risks of burnout and reduced attachment of labor force (Hazira et al., 2025).

Additionally, wage gaps and limited advancement opportunities for women further discourage long-term participation in the labor force (Kouam et al., 2023). These factors not only widen the gender gap in LFPR but may also reduce economic efficiency, as reflected in the lower GDP per capita, especially when female workers exit the labor force before reaching the statutory retirement age (Manansala et al., 2022). Although education remains a key driver of rising female participation (Abu Bakar & Abdullah, 2010), many women still face obstacles such as lack of job skills and unequal access to career progression. Such inequalities contribute to imbalances in the labor market, highlighting the need for policy reforms aligned with Sustainable Development Goal (SDG) 5, which is Gender Equality (Saha & Singh, 2025).

In short, gender disparities in Malaysia remain a key concern in LFPR studies, as women continue to face structural barriers such as caregiving responsibilities, wage gaps and limited career advancement despite higher educational attainment and increased participation. These inequalities affect overall LFPR trends, particularly among older women.

Recent studies have highlighted the trends and challenges in LFPR among older populations, particularly in Malaysia. For example, Chung et al. (2024) observed that Malaysia's LFPR tends to decline near the statutory retirement age but later rises as some retirees re-enter the workforce. Financial strain remains a major factor compelling older individuals to return to work (Elhadary & Ahmed, 2024). Despite this trend, government policies frequently overlook age-related health and disability conditions, leading to discrimination and restrictions in task allocation for older workers (Roehrig et al., 2013). In contrast, such financial pressures are less pronounced in OECD countries, where early retirement is often driven by government support and tax incentives favoring capital over labor (Beck & Park, 2018).

To understand and anticipate these dynamics, several LFPR studies have suggested statistical models to project future conditions of labor market. For instance, Fallick & Pingle (2007) used cohort-based central moving averages, while Queiroz and Ferreira (2021) applied the Lee-Carter mortality model to the Brazilian LFPR data. Other approaches include ordinary least squares (OLS) regression with random walk forecasting (Higgins et al., 2019), parametric and non-parametric methods (Kumar, 2006), and principal component analysis with bootstrapped confidence intervals (Fuchs et al., 2018). These studies reflect a growing interest in statistical forecasting of LFPR as a tool for labor market planning.

Besides forecasting, LFPR studies have explored how demographic and economic factors influence policy outcomes. For examples, Wang et al. (2019) and Zhao et al. (2018) examined the sustainability of pension systems by linking LFPR to several economic measures such as GDP, dependency ratio and birth rate. Rahim and Yusoff (2024) measured Malaysia's replacement ratio to assess adequacy of savings retirement. In other studies, rising dependency ratio have prompted discussions on adjustment of statutory retirement age to ensure economic stability and adequate pension (Chomik et al., 2016; Felstead, 2010; Louria, 2005). Similarly, Yang et al. (2022) emphasized that dependency ratio is critical for refining pension policies and improving job prospects for older workers.

In response to these complexities, our study proposes the Lee-Carter and Cairns-Blake-Dowd (CBD) stochastic models, originally developed for mortality forecasting, to project LFPR in three decades ahead. The Lee-Carter model, with its clear interpretation of age- and year-specific components, is effective in capturing LFPR trends. The CBD model extends the Lee-Carter model, focusing on older populations by incorporating age and year effects, making it particularly suitable for analyzing LFPR in ageing workers. Applying these demographic models to LFPR studies enables more accurate age-specific projections.

Based on the literature, the Lee-Carter and CBD models have been used to forecast mortality improvements in recent years. Hence, these models can also be used to predict the LFPR in aging populations in Malaysia. Although predicting the LFPR poses challenges (Berstein & Morales, 2021; Bozikas & Pitselis, 2019; Fuchs et al., 2018; Queiroz & Ferreira, 2021; Tuzemen & Van Zandweghe, 2018), stochastic forecasting techniques and region-specific adjustments can be used to address these issues (Blau & Kahn, 2017; Higgins et al., 2019).

The Lee-Carter model is recognized for its simplicity and robustness in forecasting age-specific mortality rates, and it has become a foundational tool in demographic and actuarial studies. Numerous researchers have proposed modifications to enhance its predictive accuracy and flexibility (Atance et al., 2020; Fajar & Fajariyanto, 2022; Liu et al., 2019; Odhiambo, 2023). The model has also been compared to neural networks (Schnürch & Korn, 2022) and ARIMA models (Shelleng et al., 2022), often outperforming them in terms of interpretability and stability. Comparative studies have also evaluated the Lee-Carter model alongside several stochastic models for explaining mortality improvements in populations in England, Wales and the United States (Cairns et al., 2011; Maccheroni & Nocito, 2017; Odhiambo, 2023; Renshaw & Haberman, 2006).

An extension of the Lee-Carter model is the CBD model, which introduces age and year effects to better capture mortality patterns at older ages. The CBD model has shown better performance, especially in elderly age groups, when applied to mortality data in England and Wales (Cairns et al., 2011). Other studies have also confirmed the suitability of CBD model for older-age mortality modelling (Maccheroni & Nocito, 2017; Odhiambo et al., 2021).

In the context of LFPR studies, Queiroz and Ferreira (2021) applied a singular value decomposition (SVD) approach in the Lee-Carter model to the LFPR data in Brazil. While SVD can efficiently capture LFPR patterns, it assumes homoscedastic error terms and is less effective at detecting outlier, limiting its ability to capture irregularities (Odhiambo et al., 2021). In response, Lee and Miller (2001) and Booth et al. (2002) proposed the Lee-Carter model using a Poisson GLM framework, which improves parameter estimation and model's prediction. Renshaw and Haberman (2006) further improved the model by incorporating cohort effects, while Hyndman and Ullah (2007) extended the framework by including migration variables.

In conclusion, while the Lee-Carter and CBD models have been used in mortality forecasting, and although preliminary efforts such as those by Queiroz and Ferreira (2021) have explored LFPR using the SVD approach, there is a lack of empirical studies that apply the Lee-Carter and CBD models specifically to LFPR data, especially for age- and year-specific projections. Therefore, further analysis is needed to adapt these models for LFPR forecasting, to account for labor market complexities such as retirement timing, re-entry of older workers and demographic shifts.

The remainder of this study is outlined as follows: Section 2 describe the methodology, while Section 3 provides the results. The conclusions are provided in Section 4.

METHODOLOGY

DATA PREPARATION

Our study suggests the Lee-Carter and CBD stochastic models to forecast LFPR in 2018 until 2047 for both male and female workers in Malaysia. Both models have been applied in actuarial science area for forecasting mortality rates. Therefore, several modifications are required to forecast the LFPR.

The data for this study is a secondary data obtained from official sources. The labor data is obtained from the Department of Statistics Malaysia (DOSM), while the population data is retrieved from the United Nations database. Further details on the dataset are available on websites (DOSM, 2021; United Nations, 2022).

The data consists of labor counts and exposure (population), originally grouped into five-year-age groups (50-54, 55-59, 60-64 years). This data is then transformed into a year-age matrix that serves as a model input. The cubic spline approximation is applied to produce a one-year-age data (Adejumo et al., 2019; Hou & Liu, 2013; Kim et al., 2015; Liggett & Salmon, 1981). The data is then divided into two datasets, training data (2001–2017) and testing data (2018–2021). The training data is used for fitting procedure to obtain parameter estimates, while the testing data is used for measuring the prediction error. We use the root mean squared error (RMSE) and the mean absolute percentage error (MAPE) for calculating the prediction error.

LEE-CARTER MODEL

The labor force participation rate (LFPR) is defined as the ratio of labor force to total population within the working-age group, typically between ages 15 until 64. The labor force includes individuals who are currently employed as well as those who are unemployed but actively seeking work. The LFPR at age x in year t refers to the ratio at age x in calendar year t, and can be written as (Queiroz & Ferreira, 2021):

$$m_{xt} = \frac{l_{xt}}{n_{xt}} \tag{1}$$

where m_{xt} is the LFPR, l_{xt} is the number of individuals who are employed or actively seeking employment, and n_{xt} is the total population, all at age x in calendar year t.

The Lee-Carter model assumes that the log-LFPR is represented by three components; the baseline of age-specific LFPR a_x, the time-varying index of LFPR k_t and the sensitivity of each age to changes in the time index B_x. The mathematical expression for the Lee-Carter model is (Lee & Carter, 1992):

$$log(m_{xt}) = a_x + B_x k_t + \varepsilon_{xt} \tag{2}$$

where m_{xt} is the LFPR at age x in year t, a_x represents the average log-LFPR for age x, k_t is the time index, B_x indicates the sensitivity of LFPR to changes in k_t at age x, dan ε_{xt} is the error term.

The parameter estimation of the Lee-Carter model is carried out using the Poisson generalized linear model (Poisson GLM) because the data consists of counts of individuals participating in the labor force, which are discrete in nature. Let l_{xt} be the random variable representing the number of individuals who are employed or actively seeking work. Let n_{xt} be the population, and m_{xt} be the LFPR at age x in calendar year t. The main assumption is that l_{xt} follows a Poisson distribution with expected value $E(l_{xt}) = \lambda_{xt} = n_{xt}.m_{xt}$, where n_{xt} is the exposure (population). Thus, equation (2) can be rewritten as:

$$\lambda_{xt} = n_{xt}.\exp{(a_x + B_x k_t)}. \quad (3)$$

Therefore, the Poisson probability function for the Lee-Carter model is:

$$\Pr(l_{xt}) = \frac{(n_{xt}.\exp{(a_x+B_x k_t)})^{l_{xt}} \exp(-n_{xt}.\exp(a_x+B_x k_t))}{l_{xt}!} \quad (4)$$

and the likelihood function for all ages x and years t is:

$$\mathcal{L} = \prod_{x,t} \frac{(n_{xt}.\exp{(a_x+B_x k_t)})^{l_{xt}} \exp(-n_{xt}.\exp(a_x+B_x k_t))}{l_{xt}!} \quad (5)$$

The log-likelihood function is:

$$\log\mathcal{L} = \sum_{x,t}[l_{xt}(\log\, n_{xt} + a_x + B_x k_t) - n_{xt}\exp(a_x + B_x k_t) - log(l_{xt}!)]. \quad (6)$$

Parameter estimation is carried out using the maximum likelihood method, which involves choosing the parameters (a_x, B_x, k_t) that maximize the log-likelihood in (6). An optimization technique is used to obtain the maximum likelihood estimates. The following constraints are imposed to ensure the uniqueness of the optimization solution: $\sum_t k_t = 0$ dan $\sum_x B_x = 0$. Therefore, the Poisson GLM approach makes the Lee-Carter model suitable for discrete data representing the number of labor force participants.

FORECASTING OF LEE-CARTER MODEL

The projection of LFPR for the next 30 years (2018-2047) requires the forecast of time index k_t. We modelled k_t using ARIMA time series that follows a random walk with drift:

$$k_t = k_{t-1} + \delta + \xi_t \quad (7)$$

where δ is a drift (or trend) term, and ξ_t is normally distributed with error term, $\xi_t \sim N(0, \sigma_\kappa^2)$.

Given the forecast values of k_t, the forecast of LFPR for the next 30 years (2018-2047) can be calculated. Let $\hat{k}_{r+s}$ be the forecast values for the next 30 years, where r is the last year available in the data (in our study $r = 17$) and s is the forecast year (in our study $s = 1,2, \ldots ,30$). The forecast of log-LFPR in year $r + s$ is:

$$ln\ (\widehat{m}_{x,r+s}) = \hat{a}_x + \hat{B}_x \hat{k}_{r+s} \tag{8}$$

where $\hat{a}_x$ and $\hat{B}_x$ are the estimates of a_x and B_x. Therefore, the forecast of LFPR is:

$$\widehat{m}_{x,r+s} = e^{\hat{a}_x + \hat{B}_x \hat{k}_{r+s}} \tag{9}$$

CAIRNS-BLAKE-DOWD (CBD) MODEL

The CBD model is a stochastic model developed to analyze and forecast mortality rates, particularly for older populations. The CBD model is expressed in a logit form (Cairns et al., 2006):

$$log\left(\frac{q_{xt}}{1-q_{xt}}\right) = k_t^{(1)} + (x - \bar{x})k_t^{(2)} \tag{10}$$

where q_{xt} represents the probability of individuals participating in the labor force at age x in calendar year t (LFPR), $k_t^{(1)}$ denotes the baseline level of LFPR in year t, $k_t^{(2)}$ captures how LFPR changes with age in year t, and $\bar{x}$ is the average age. This structure enables the CBD model to separate time trends from age effects, providing a clearer picture of how LFPR evolves across different years and ages.

To enable an equivalent comparison between the Lee-Carter model and the CBD model, the definition of LFPR in each model must be distinguished. For the Lee-Carter model, the LFPR in equation (1) is a central LFPR given by $m_{xt} = \frac{l_{xt}}{n_{xt}}$, where m_{xt} is the central LFPR, l_{xt} is the number of individuals employed or actively seeking employment, and n_{xt} is the population at age x throughout calendar year t.

For the CBD model, LFPR is defined as a probability:

$$q_{xt} = \frac{l_{xt}}{n_{xt}^0} \tag{11}$$

where n_{xt}^0 is the population at age x at the beginning of year t. The main difference is that n_{xt} in the Lee-Carter model represents central exposure throughout year t, while n_{xt}^0 in the CBD model is the exposure at the beginning of the year. Therefore, $n_{xt}^0 > n_{xt}$, and can be approximated as (Villegas et al., 2018):

$$n_{xt}^0 \approx n_{xt} + \frac{1}{2} l_{xt} \tag{12}$$

Parameter estimation for the CBD model is carried out using binomial GLM because the data represent probabilities. For LFPR data, the number of individuals participating in the labor force l_{xt} is assumed to follow a binomial distribution with sample size n_{xt}^0 and probability q_{xt}, that is $l_{xt} \sim binomial(n_{xt}^0, q_{xt})$. Therefore, the binomial probability function for CBD model is:

$$\Pr(l_{xt}) = \binom{n_{xt}^0}{l_{xt}} {q_{xt}}^{l_{xt}} (1 - q_{xt})^{n_{xt}^0 - l_{xt}} \tag{13}$$

and the likelihood function for all ages x and years t is:

$$\mathcal{L} = \prod_{x,t}\left[\binom{n_{xt}^0}{l_{xt}} {q_{xt}}^{l_{xt}}(1-q_{xt})^{n_{xt}^0-l_{xt}}\right]. \quad (14)$$

Next, the simplified log-likelihood function is:

$$\text{Log}\mathcal{L} = \sum_{x,t} l_{xt}\log(q_{xt}) + (n_{xt}^0 - l_{xt})log(1-q_{xt}). \quad (15)$$

Equation q_{xt} can be obtained from equation (10):

$$q_{xt} = \frac{e^{k_t^{(1)}+(x-\bar{x})k_t^{(2)}}}{1+e^{k_t^{(1)}+(x-\bar{x})k_t^{(2)}}}. \quad (16)$$

Therefore, the log-likelihood function, in its simplified form, becomes:

$$\log\mathcal{L} = \sum_{x,t}\left[l_{xt}\left(k_t^{(1)} + (x-\bar{x})k_t^{(2)}\right) - n_{xt}^0 \log\left(1 + e^{k_t^{(1)}+(x-\bar{x})k_t^{(2)}}\right)\right]. \quad (17)$$

The parameter estimation is carried out using the maximum likelihood method, by selecting the parameters $\left(k_t^{(1)}, k_t^{(2)}\right)$ that maximize the log-likelihood in equation (17). Optimization techniques are used to obtain the maximum likelihood estimates.

FORECASTING OF CBD MODEL

The forecast of time indices $k_t^{(1)}$ and $k_t^{(2)}$ for CBD model can be obtained using ARIMA time series that follows a bivariate random walk with drift:

$$\boldsymbol{k_t} = \boldsymbol{k_{t-1}} + \boldsymbol{\delta} + \boldsymbol{\xi_t} \quad (18)$$

where $\boldsymbol{k_t} = \begin{pmatrix} k_t^{(1)} \\ k_t^{(2)} \end{pmatrix}$ is the vector of time index parameters, $\boldsymbol{\delta} = \begin{pmatrix} \delta^{(1)} \\ \delta^{(2)} \end{pmatrix}$ is the vector of drift terms, and $\boldsymbol{\xi_t} = \begin{pmatrix} \xi_t^{(1)} \\ \xi_t^{(2)} \end{pmatrix}$ is the vector of error terms that follow a bivariate normal with mean zero and covariance matrix $\boldsymbol{\Sigma}$, $\boldsymbol{\xi_t} \sim N(0, \boldsymbol{\Sigma})$.

Given the forecast values of $k_t^{(1)}$ and $k_t^{(2)}$, the forecast of LFPRs for the next 30 years (2018-2047) can be calculated. Let $\hat{k}_{r+s}^{(1)}$ and $\hat{k}_{r+s}^{(2)}$ be the forecast values for the next 30 years, where r is the last year available in the data (in our study $r = 17$), and s is the forecast year (in our study $s = 1,2, \ldots, 30$). The forecast of logit-LFPR in year $r + s$ is:

$$log\left(\frac{\hat{q}_{x,r+s}}{1-\hat{q}_{x,r+s}}\right) = \hat{k}_{r+s}^{(1)} + (x-\bar{x})\,\hat{k}_{r+s}^{(2)} \quad (19)$$

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Therefore, the forecast of LFPR is:

$$\hat{q}_{x,r+s} = \frac{e^{\hat{k}^{(1)}_{r+s}+(x-\bar{x})\,\hat{k}^{(2)}_{r+s}}}{1+e^{\hat{k}^{(1)}_{r+s}+(x-\bar{x})\,\hat{k}^{(2)}_{r+s}}} \tag{20}$$

EXPECTED LENGTH OF RETIREMENT (ELR)

The ELR refers to the average number of years an individual is expected to spend in retirement, from the retirement year until the death year. It is a key measure in pension planning and actuarial analysis, especially in an ageing population. The ELR can be estimated as the weighted average of life expectancy of a worker at each retirement age (Lee, 2001). Assuming that the earliest working age is at age 20, the ELR is:

$$ELR = \sum_{x=20}^{89} S_x T_x \, \gamma_x [1 - (0.5 \times q_x\,)] \left(\frac{e_x + e_{x+1}}{2}\right) \tag{21}$$

where S_x is the probability of surviving to age x, T_x is the probability of remaining in the labor force until age x, γ_x is the likelihood of retiring at age x if the worker is still employed at age x, q_x is the probability of death in the age interval $(x, x+1)$, and e_x and e_{x+1} are the life expectancies at age x and $x+1$ respectively. The probability of retiring at age x until $x+1$ is $S_x T_x \gamma_x [1 - (0.5 \times q_x)]$. Therefore, the expected length of retirement can be obtained by aggregating $S_x T_x \gamma_x [1 - (0.5 \times q_x)] \frac{(e_x + e_{x+1})}{2}$ at each age.

Equation (21) can be simplified by assuming that the earliest retirement age is 50 (Crafts, 2022). Therefore, the ELR is:

$$ELR = \rho^{20-50} \sum_{x=50}^{89} S_x T_x \, \gamma_x [1 - (0.5 \times q_x\,)] \left(\frac{e_x + e_{x+1}}{2}\right) \tag{22}$$

where ρ^{20-50} is the probability of surviving from age $x = 20$ until age $x = 50$. In our study, (T_x, γ_x) are obtained from the forecasted LFPR, while the survivorship and mortality estimates (S_x, q_x, e_x) are obtained from the projections of the United Nations. Therefore, we need the forecast values for each age and year to calculate the ELR. Figure 1 shows a simple framework to forecast the LFPR and to project the ELR.

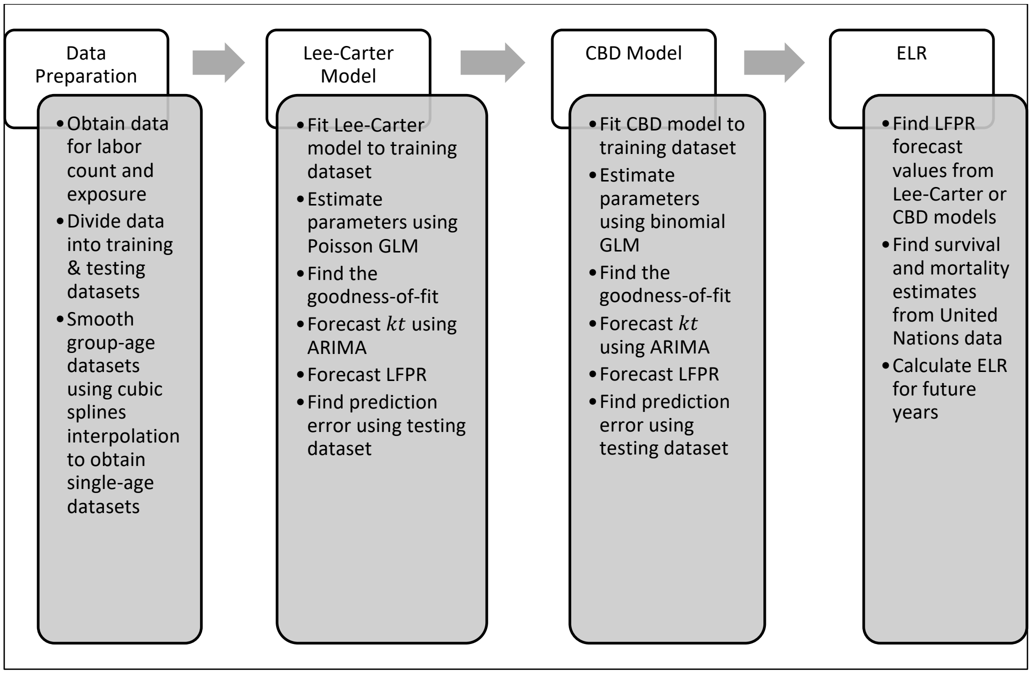
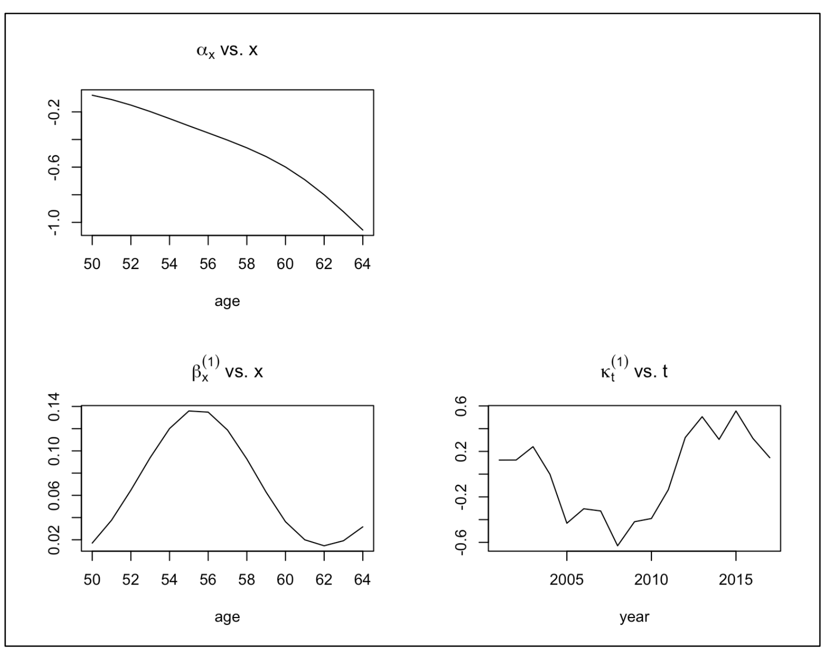


FIGURE 1. Framework to forecast LFPR and to project ELR

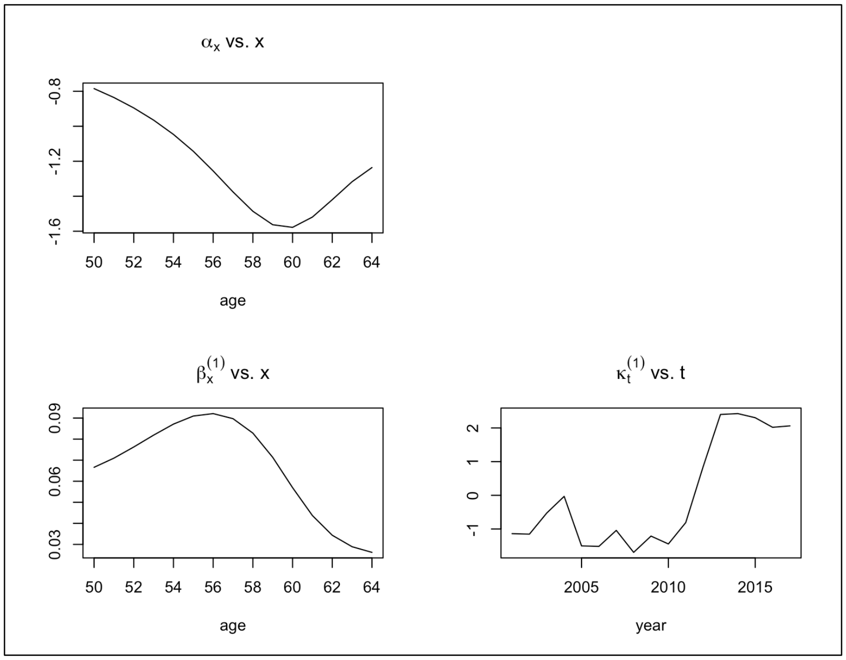
RESULTS AND DISCUSSION

RESULTS FOR LEE-CARTER MODEL

Figure 2 shows the estimated parameters of the Lee-Carter model for male and female LFPR aged 50 to 64, fitted to the training data from 2001 to 2017.



(a)



(b)

FIGURE 2. Parameter estimates of Lee-Carter model (a) male LFPR (b) female LFPR

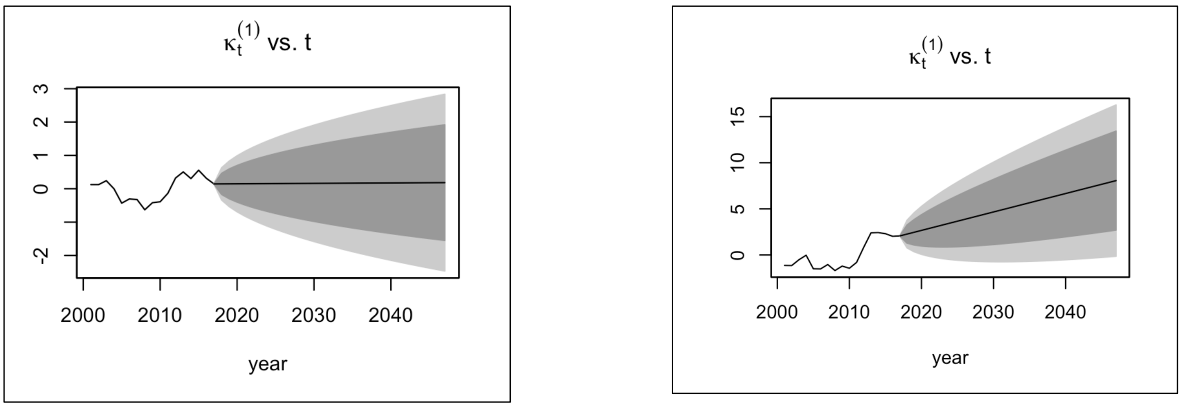
Parameter a_x represents the baseline level of LFPR by age. For male LFPR (Figure 2(a)), the values of a_x gradually decrease from age 50 to 64, indicating that male participations are highest at younger ages and decline with age. For female LFPR (Figure 2(b)), a_x exhibits a U-shaped pattern, declining until age 59 and then rising again after age 60. This suggests that women tend to exit the labor force between ages 50 and 59, possibly due to early retirement or family responsibilities, but some re-enter the workforce after age 60, possibly due to financial constraints or insufficient pension funds.

Parameter k_t reflects changes in the LFPR across all ages over time. For male LFPR, the value of k_t fluctuated slightly but remained around zero between 2000 to 2017, indicating stability in participation rates. In contrast, for female LFPR, there is a sharp increase in k_t after 2011, suggesting a rise in labor force participation, likely due to policy changes, economic necessity or evolving social norms.

Parameter B_x represents the sensitivity of LFPR to changes in k_t across different ages. For males, B_x peaked between ages 55 to 57, indicating that this age group is the most responsive to economic or social policy changes. For females, the pattern is similar but with lower values, suggesting that women are less responsive to temporal changes compared to men across all age groups.

In summary, male workers show a more stable LFPR pattern over time with a gradual decline with age. Female workers, on the other hand, demonstrate more dynamic participation over time, with a significant increase after 2011. This indicates that although male workers still dominate the labor force, female participation is rising and becoming increasingly significant in Malaysia's labor market.

Figure 3 shows the forecast of k_t parameter from the Lee-Carter model for male and female LFPR age 50 to 64 from 2001 to 2047. A comparison of the k_t forecasts between male and female LFPR reveals several differences. For male LFPR (Figure 3(a)), the k_t values remain almost flat after 2020, indicating that the male LFPR is expected to remain relatively unchanged and stable over the next three decades. This may reflect a mature male labor market, the effects of male population aging, or a tendency toward earlier retirement.



(a) (b)

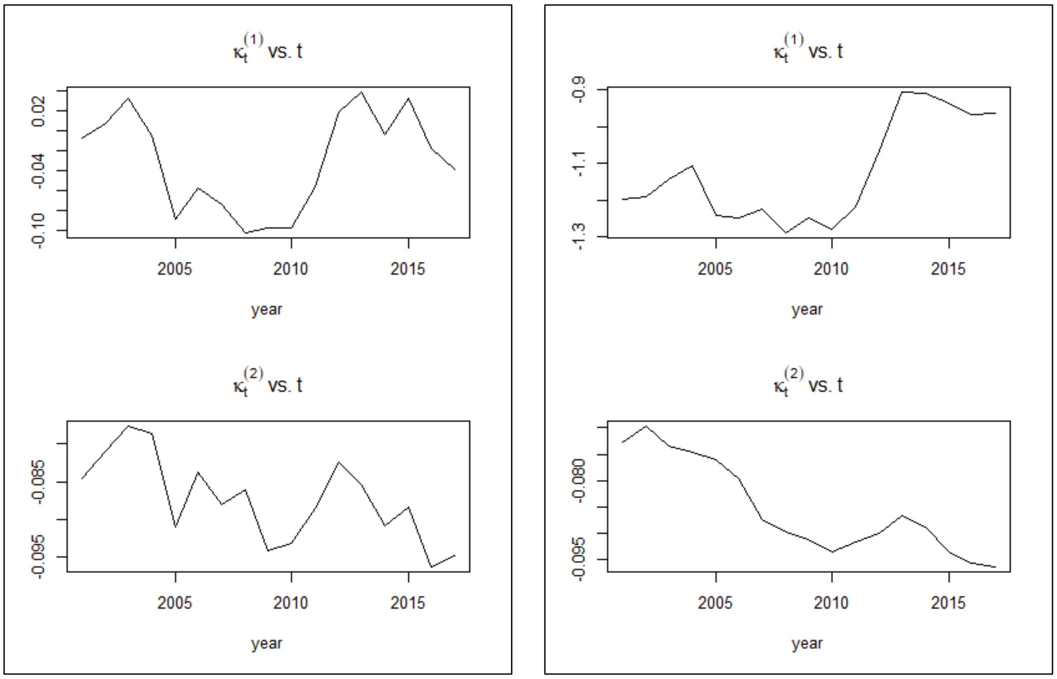
FIGURE 3. Forecasted k_t of Lee-Carter model (a) male LFPR (b) female LFPR

In contrast, for female LFPR (Figure 3(b)), the k_t values increase significantly after 2020 through to 2047. This upward trend reflects the expectation that female labor force participation will continue to grow. Contributing factors may include structural economic changes, rising levels of female education, more women-friendly policies (such as childcare support and flexible work arrangements) and increasing economic demands that encourage women to remain in the workforce. Additionally, the confidence intervals in both male and female k_t graphs show growing uncertainty over time.

Overall, the forecasts suggest that the future of Malaysia's labor market may see a growing contribution from female workers, while male labor force participation remains at current levels. This result also agrees with studies by Queiroz and Ferreira (2021) who found that female participation has increased.

RESULTS FOR CBD MODEL

Figure 4 displays the parameter estimates from the CBD model fitted to LFPR data for ages 50 to 64 from 2001 to 2017, with (a) representing male LFPR and (b) representing female LFPR. The plotted parameters are $k_t^{(1)}$, which represents the overall level of LFPR each year, and $k_t^{(2)}$, which reflects how LFPR varies by age over time.



(a) (b)

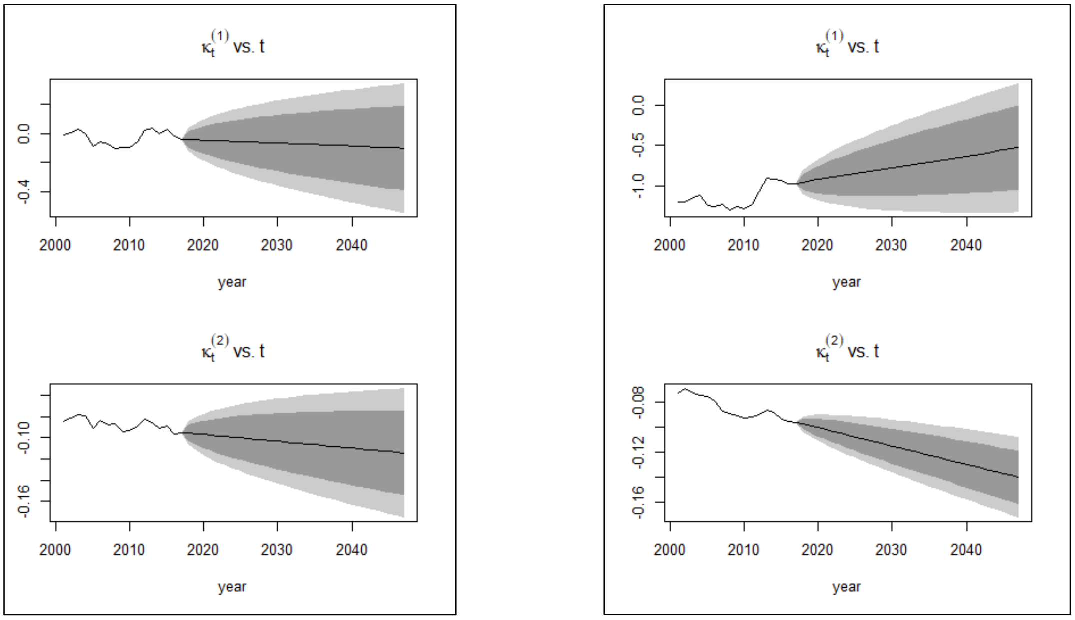
FIGURE 4. Parameter estimates of CBD model (a) male LFPR (b) female LFPR

Figure 4(a), which illustrates male LFPR, shows that the trend of $k_t^{(1)}$ fluctuated moderately between 2001 and 2017, remaining within a narrow range. This indicates that the overall male LFPR remains relatively stable throughout the period. Similarly, the parameter $k_t^{(2)}$ shows minor fluctuations without a clear upward or downward trend, suggesting that age differences in male LFPR remains consistent over time. In summary, male LFPR appears stable in both overall level and age-specific variation, reflecting a persistently high level of engagement among older men in the labor market during the study period.

Figure 4(b) shows a different pattern for female LFPR. The parameter $k_t^{(1)}$ rises sharply after 2010, indicating a clear upward trend in the overall female LFPR. This trend is likely driven by improvements in educational attainment, policy changes that support female employment, and evolving social norms related to women's roles in the workforce. Meanwhile, $k_t^{(2)}$ exhibits a consistent downward trend. In other words, the LFPR gap between younger and older women is narrowing, suggesting that more older women are remaining or returning to the labor force.

Overall, Figure 4 highlights a contrast between male and female LFPR patterns. Male LFPR remains stable across age and time, while female LFPR shows a marked increase, particularly among older age groups. This result also agrees with studies by Queiroz and Ferreira (2021) who observed a constant increase in labor force for women.

Figure 5 shows the forecast values of $k_t^{(1)}$ and $k_t^{(2)}$ for male and female LFPR from CBD model in 2001 until 2047. For male LFPR, the forecast of $k_t^{(1)}$ shows a gradual downward trend after 2020. This suggests that male LFPR is expected to decline slowly over time. However, the projected values remain close to zero, indicating that the anticipated decline is moderate. The parameter $k_t^{(2)}$ also exhibits a slight downward trend, suggesting that the participation gap between younger and older males may slightly widen. This means that older male workers are expected to gradually reduce their involvement in the labor force compared to the younger age groups.



(a) (b)

FIGURE 5. Forecasted k_t of CBD model (a) male LFPR (b) female LFPR

In contrast, the forecast of $k_t^{(1)}$ for female LFPR shows a moderate upward trend, especially after 2020. This indicates an overall increase in female LFPR, consistent with past trends showing rising participation due to changes in education, social roles and economic needs. Although the increase is gradual, the upward trend is clear and reflects the growing involvement of women in the labor market over the long term. The forecast of $k_t^{(2)}$ also shows a continuous downward trend, suggesting that the participation gap between younger and older women is expected to narrow. In other words, more older women are expected to remain in or return to the labor force, possibly due to longer working periods, delayed retirement age or financial necessity.

Overall, Figure 5 indicates that male LFPR is expected to gradually decline in the coming decades, while female LFPR is projected to increase, thereby narrowing the gender gap. In addition, the age-specific pattern is also shifting, with more older women expected to remain in the workforce for a longer period. Therefore, it is important to consider gender-specific health and longevity factors when designing labor market policies, retirement planning and pension systems. This approach helps in better understanding the drivers of LFPR and projecting its future trends (Cairns et al., 2006; Lee & Carter, 1992).

MODEL SELECTION

The training dataset (2001-2017) is used to estimate the parameters, while the testing dataset (2018-2021) is utilized to calculate the prediction errors (RMSE and MAPE). We select the best model by comparing the Akaike Information Criterion (AIC), Bayesian Information Criterion

(BIC), deviance, RMSE and MAPE from both Lee-Carter and CBD models. The AIC, BIC and deviance are obtained from the in-sample results (using the training dataset), whereas the RMSE and MAPE are calculated from the out-of-sample results (using the testing dataset). Table 1 provides the AIC, BIC, deviance, RMSE and MAPE for both male and female LFPRs.

TABLE 1. Summary of in- and out-of-samples measures

Model		Male	Female
Lee-Carter	AIC	14,220	10,749
	BIC	14,380	10,908
	Deviance	10,838	7,579
	RMSE	0.2415	0.3712
	MAPE	0.3407	0.4287
CBD	AIC	39,752	149,261
	BIC	39,873	149,382
	Deviance	36,572	146,205
	RMSE	0.2167	0.3010
	MAPE	1.4183	1.1886

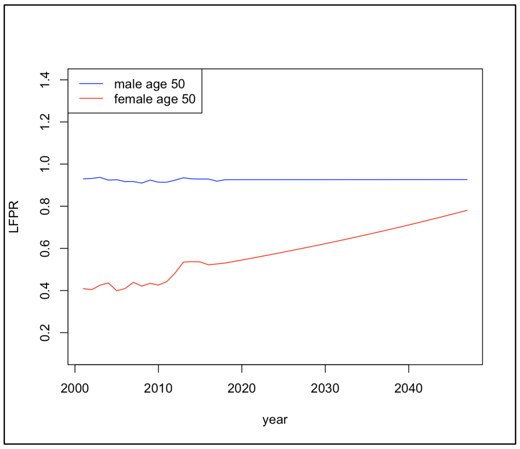
The AIC, BIC and deviance for the Lee-Carter model are generally smaller than those for the CBD model, suggesting a better fit to the data. Additionally, the Lee-Carter has significantly lower MAPE than the CBD model, indicating higher accuracy in the LFPR forecasts. These results suggest that the Lee-Carter model performs better than the CBD model.

LABOR FORCE PARTICIPATION RATE (2001-2047)

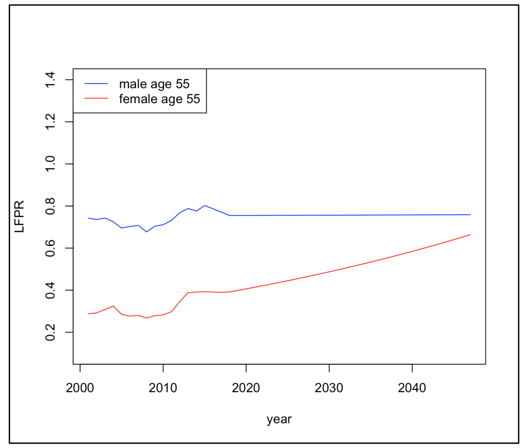
Table 2 and Figure 6 provide the LFPR forecasts from the Lee-Carter model for male and female workers at age 50, 55 and 60 in 2001 until 2047. The male LFPRs remain high and consistent throughout the projection period. In contrast, the female LFPRs show a noticeable rise, indicating that more women are staying in the workforce at ages 50 to 60. This trend may be attributed to societal shifts, economic needs, or government interventions aimed at increasing the female LFPRs.

TABLE 2. LFPR forecasts for male and female workers at age 50, 55 and 60

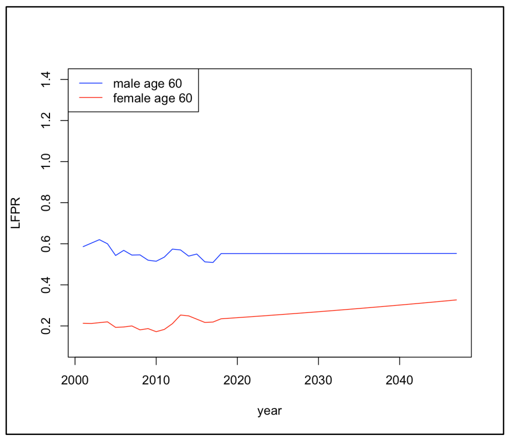
Year	LFPR age 50		LFPR age 55		LFPR age 60	
	Male	Female	Male	Female	Male	Female
2001	0.93	0.41	0.74	0.29	0.59	0.21
2007	0.92	0.44	0.71	0.28	0.54	0.20
2017	0.92	0.53	0.77	0.39	0.51	0.22
2027	0.93	0.60	0.76	0.46	0.55	0.26
2037	0.93	0.68	0.76	0.55	0.55	0.29
2047	0.93	0.78	0.76	0.66	0.55	0.33



(a)



(b)



(c)

FIGURE 6. LFPR forecasts for male and female workers age (a) 50, (b) 55 (c) 60

EXPECTED LENGTH OF RETIREMENT (2001-2047)

The ELR (in years) is projected using equation (22), assuming that the earliest age to work is 20 and the earliest age to retire is 50. Table 3 provides the projected ELR for male and female workers in 2001 until 2047. The results show increasing ELRs for both genders in the projection period. Additionally, male workers are forecasted to have longer retirement durations compared to female workers. However, male ELR increases from 15.19 years in 2001 to 20.05 years in 2047, while the female ELR rises at a much faster rate, starting from 7.65 years in 2001 and reaching 19.35 years in 2047.

TABLE 3. Projected ELR for male and female workers

Year	ELR (years)	
	Male	Female
2001	15.19	7.65
2007	15.76	7.42
2017	16.36	8.95
2027	17.39	12.85
2037	18.67	15.83
2047	20.05	19.37

Since the male LFPR has slower growth than the female LFPR, the higher ELR for male workers may be attributed mainly to the increase in life expectancy. As for female workers, the substantial rise in both LFPR and ELR suggest that the growth in life expectancy surpasses the increase in the LFPR. This outcome suggests a significant shift in the Malaysian women's workforce and their retirement planning.

Life expectancy and ELR are the two main factors that should be considered when planning for employment and retirement. Figure 7 illustrates the projected ELR (black and blue lines) and the forecasted life expectancy at age of 50 (EL50, red and green lines) for both male and female workers in 2001 until 2047.

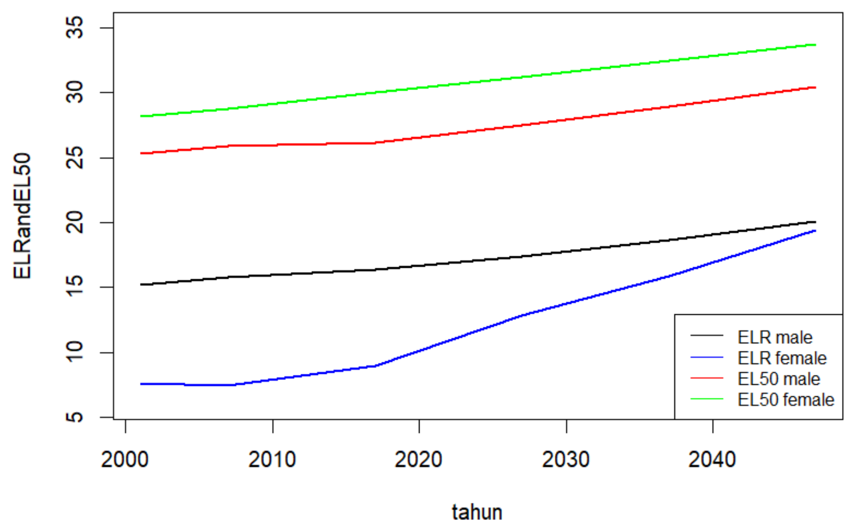


FIGURE 7. Life expectancy at age 50 (EL50) and ELR

Several key observations can be made. Firstly, the life expectancy at age 50 (EL50) for both males (red line) and females (green line) increases steadily over time. Secondly, the ELR for both genders show a steady increase over time. Notably, the ELR for female workers (blue line) rises more sharply than males (black line), suggesting that women will spend a growing portion of their post-50 years in retirement. This trend may be driven by improvements in life expectancy and rising LFPR.

RESIDUAL ANALYSIS

Figure 8 displays a residual heatmap showing the goodness-of-fit of the Lee-Carter and CBD models by varying colour intensity. The colour intensity represents residual values, with red and blue shades indicating over- and under-estimation respectively, and lighter colours indicating smaller residuals (better fit).

The residuals for Lee-Carter male in Figure 8(a) are generally lighter and more evenly distributed compared to the CBD model in Figure 8(c), indicating a better overall fit. Minor underestimations occur around certain ages. The Lee-Carter female residuals in Figure 8(b) also performs better than the CBD in Figure 8(d), with smoother residual patterns and fewer deviations. A noticeable pattern of underestimation is also visible in several age groups.

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In summary, the Lee-Carter model demonstrates a more stable and consistent fit for both male and female LFPR data across age and time. The heatmaps visually support the conclusion that the Lee-Carter model has better goodness-of-fit for the Malaysian LFPR data during the study period.

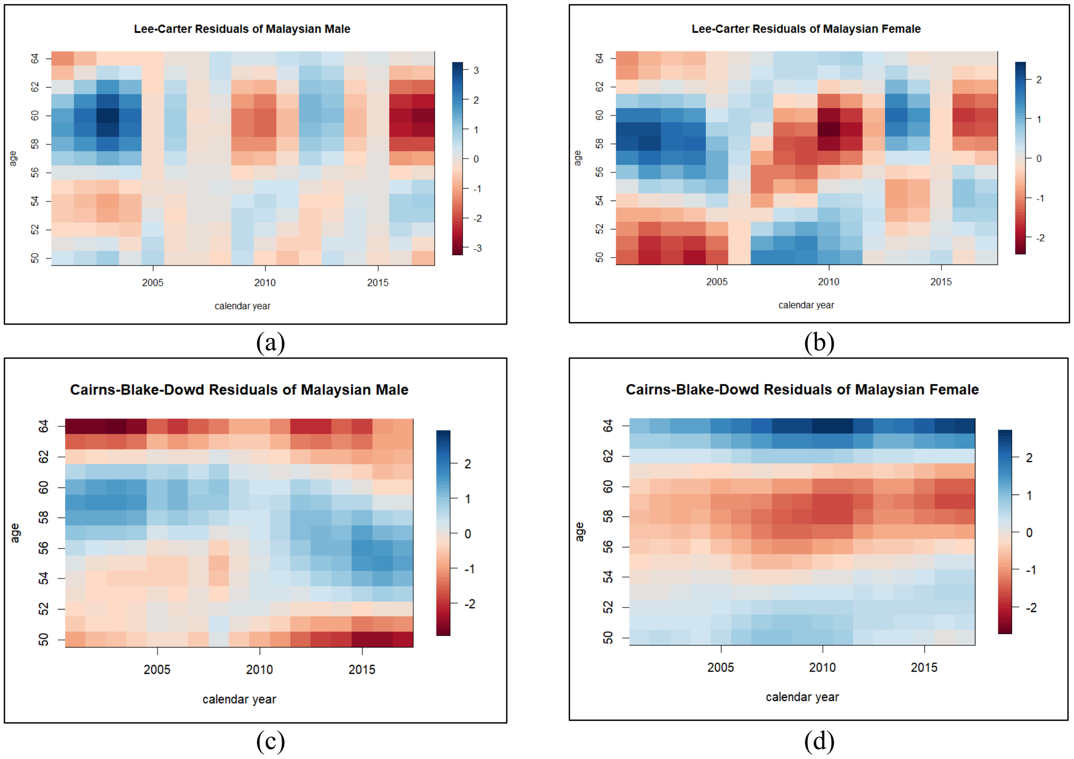

FIGURE 8. Residual heatmap for fitted LFPR (a) Lee-Carter male (b) Lee-Carter female (c) CBD male (d) CBD female

CONCLUSION

This study suggested stochastic modeling to forecast the LFPR of older workers in Malaysia, specifically focusing on the age group 50 to 64. Using the Lee-Carter and CBD models within a GLM framework, our study integrated Poisson and binomial distributions to account for the discrete and probabilistic nature of LFPR data. These models, traditionally used for mortality forecasting, are adapted to capture age-specific and time-related dynamics in labor market participation. The labor force data is obtained from the Department of Statistics Malaysia (DOSM) and population are sourced from the United Nations database, covering the years 2001 until 2021.

The results show that the parameter estimates from the LC model reveal notable age and gender-specific patterns. For male workers, the age-specific parameter declines steadily with age, indicating reduced participation as age increases. In contrast, the female LFPR shows a U-shaped pattern, suggesting that many women exit the workforce in their 50s, possibly due to caregiving or early retirement, and some re-enter the labor force post-60, potentially due to financial necessity. The time-varying parameter illustrates stable trends for men from 2001 to 2017, reflecting steady male participation. However, for women, the parameter increases significantly after 2011, indicating rising LFPR likely driven by socioeconomic shifts, policy reforms and changing gender roles. The sensitivity parameter suggests that males aged 55–57 are most responsive to temporal changes, while females are less responsive but follow similar age patterns.

Forecasting results for 2018 until 2047 indicate that male LFPRs are expected to remain stable, whereas female LFPRs are projected to rise significantly, from 41% to 78%, highlighting a narrowing gender gap in labor market participation. This trend reflects increasing female integration into the workforce, influenced by delayed retirement, improved education and evolving family roles.

In terms of model performance, the residual diagnostics confirm that the LC model offers a better fit than the CBD model for both men and women, affirming its suitability for modeling age-specific LFPR. Additionally, projections of ELR reveal a growing retirement duration for both genders, driven by increasing life expectancy and shifts in labor force dynamics. These findings emphasize the importance of accounting for demographic and gender-based differences in labor market forecasts and suggest the need for adaptive pension policies to ensure long-term sustainability.

Despite these results, several limitations merit discussion. First, while the models account for age and period effects, cohort effects are not explicitly modelled, potentially limiting the ability to capture generational influences on labor participation behavior. Second, the study focuses solely on Malaysia, thus, generalization to other demographic or institutional contexts is limited.

Future research could extend this work by incorporating additional covariates, such as health status, education and employment trends, into the forecasting framework. Moreover, hybrid models that combine stochastic approaches with machine learning techniques may enhance predictive performance and capture nonlinear dynamics. Comparative studies across countries with varying pension systems and demographic profiles would also be valuable in assessing the model robustness and comparing the LFPR forecasts.

In summary, this study highlights the used of stochastic mortality models in labor market forecasting and the importance of gender and age in managing the effects of an aging workforce. These insights are vital for ensuring the sustainability of pension systems and aligning labor market strategies with demographic realities.

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