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IMPACT OF LIFE EXPECTANCY AND LABOR FORCE PARTICIPATION ON ECONOMIC GROWTH IN MYANMAR

Wai Wai Htet[1], Lwin Moe Thu[2]

Abstract

This study investigates the relationship between life expectancy at birth (LE), labor force participation rate (LFP), and economic growth (GDP growth rate) in Myanmar, a developing Southeast Asian country undergoing significant economic and structural changes. Recognizing that population health and labor force size are critical drivers of economic performance, the research aims to explore both the short-run and long-run dynamics between these factors. Using time series data from 1980 to 2023 obtained from the World Bank, the analysis applies the Augmented Dickey-Fuller (ADF) test to assess data stationarity, the Johansen cointegration test to identify long-term relationships, and both Vector Autoregressive (VAR) and Vector Error Correction Model (VECM) techniques to examine causal interactions. The findings reveal that while increases in labor force participation and life expectancy have the potential to boost economic growth, structural inefficiencies such as underemployment, low productivity, and limited access to quality healthcare can weaken their impact. The study suggests that policymakers should combine initiatives to enhance workforce productivity—through skills training, high-value job creation, and labor market reforms—with policies that promote healthy aging and extend economically active years. By aligning health improvements with productive employment opportunities, Myanmar can better leverage its demographic advantages to achieve sustainable economic growth.

Keywords: labor force participation rate, life expectancy at birth, GDP growth rate, VECM, ADF

Introduction

Myanmar is a developing country in Southeast Asia that has gone through many economic changes in recent years. Myanmar's economy has faced many challenges, including political instability, limited resources, and changes in global markets. These factors have made it difficult for the country to maintain steady economic growth. However, the health and productivity of the population can play a key role in overcoming these challenges. A healthier population can work longer and contribute more to the economy, while a larger labor force means more workers to help the country develop.

Economic growth in the country depends on several important factors, such as the health of the population and the number of people who can work. Life expectancy, which means how long people are expected to live on average, shows the general health and quality of life of the population. When people live longer, it often means that healthcare and living conditions are better, which can lead to higher productivity and growth in the economy.

The labor force, which includes all people who are of working age it plays a key role in a country’s economic development. A larger and more active labor force can increase the production of goods and services, which leads to economic growth. In Myanmar, recent economic reforms and changes have had an impact on job opportunities and the overall productivity of workers. These changes make the labor force even more important for driving economic growth. As the country continues to develop, understanding the link between the size and strength of the labor force and economic growth is crucial for future planning.

[1] Department of Statistics, Monywa University of Economics
[2] Department of Statistics, Monywa University of Economics

Understanding the impact of changes in life expectancy and labor force participation on economic growth can guide policymakers in making informed investment decisions. This study aims to clarify the relationship between life expectancy at birth (LE), labor force participation rate (LFP), and economic growth (GDP growth rate) in Myanmar. By analyzing these factors, the research provides insights into how improvements in health and increased labor force engagement can strengthen Myanmar's economy. The study demonstrates how enhancing healthcare and expanding work opportunities contribute to economic growth, offering valuable information for shaping future development strategies.

Objective of the Study

The objectives of the study are

(1) to explore the long-term relationship between life expectancy at birth, labor force participation rate, and GDP growth rate in Myanmar, and

(2) to examine the short-run relationship between life expectancy at birth, labor force participation rate, on Economic growth (GDP growth rate) in Myanmar.

Methods of the Study

The data used in this study are time series data for the time period of 1980 to 2023. The data collected from the World Data Bank was published by the World Bank. This study used the Economic Growth (GDP growth rate) as the Dependent Variable, Life Expectancy at birth (LE), and Labor Force Participation rate (LFP) as explanatory variables. Firstly, the Augmented Dickey-Fuller (ADF) test is employed to assess the stationarity of the data. If the variables are found to be stationary, the Johansen cointegration test is conducted to identify any long-term relationships among them. And then, Vector AutoRegressive (VAR) and Vector Error Correction Model (VECM) were applied to analyze the short-run and long-run relationship between the GDP growth rate and other variables.

Literature Reviews

The relationship between labor force participation and economic growth has been extensively studied in economic literature, with various researchers examining how changes in labor market dynamics influence the growth trajectories of different countries. Many studies suggest that higher labor force participation rates contribute positively to economic growth by increasing the available labor supply, enhancing productivity, and fostering innovation. For instance, the work of Mankiw, Romer, and Weil (1992) investigated the importance of human capital, including labor force participation, in driving economic growth, suggesting that economies with higher levels of labor force engagement tend to experience faster growth.

Oyedele and Tella (2023) analyzed the relationship between labor force participation, life expectancy, economic growth, and carbon dioxide emissions in Sub-Saharan Africa using panel data from 1990 to 2018. The authors applied a panel Vector Autoregressive (VAR) model to understand the dynamic interactions among the variables. The cointegration test showed no long-run cointegrating relationship, so the VAR model was used instead of a VECM. The findings revealed that there is a two-way causal relationship between life expectancy and labor force participation, meaning that each variable influences the other. The study also found dynamic feedback effects among the variables, showing how health, labor, and environmental factors interact with economic performance over time.

Several studies have also explored the relationship between labor force participation and economic growth in the context of specific countries or regions. For example, in their analysis of Southeast Asian economies, Qinfen (2017) found that labor force participation, particularly among women, has been a significant driver of economic growth in the region. Ogungbenle, Olawumi, and Obasuyi (2013) explored that there is no bidirectional causality between life expectancy and public health spending in Nigeria. Similarly, it revealed no bidirectional causality between life expectancy and economic growth in Nigeria over the years.

Mandiefe and Tieguhong (2017) examined the link between public health spending and economic growth in Cameroon by using the Vector Error Correction Model (VECM) with annual data covering the period from 1988 to 2013. The authors aimed to see whether health investment, which is closely connected to life expectancy, plays a role in supporting economic performance. The results showed that there was no meaningful short-run relationship between public health spending and economic growth. However, in the long run, health investments were found to make a strong and positive contribution to the country's economic growth. The study suggested that health improvements, such as longer life expectancy and better health services, support growth over time through gradual and long-term effects.

Opeloyeru and Lawal (2015) found that life expectancy for both men and women is below 55 years. Analysis shows that in the long run, higher life expectancy leads to higher output per capita in Nigeria. This means that longer life directly boosts individual productivity, while indirectly, population growth negatively affects output per capita. These findings suggest that an economy aiming for rapid and sustainable growth should invest in the health sector to improve health outcomes. Research by Barro (2002) analyzed the view that labor force participation is a key determinant of economic growth, particularly in developing countries where labor markets are often characterized by underemployment and informality.

Overall, the existing literature generally indicates that higher labor force participation and improved life expectancy have a positive effect on economic growth. The research emphasized the importance of greater labor force engagement, especially among women and younger individuals, in enhancing productivity and innovation. While longer life expectancy is associated with increased individual productivity, population growth can diminish output per capita. However, a strong relationship between life expectancy, public health expenditure, and economic growth has not been consistently observed, suggesting the need for more focused policy interventions. For Myanmar's sustainable growth, prioritizing investments in health and labor force participation is essential, alongside efforts to mitigate the effects of population growth.

Data and Methods

The studies used the annual data spanning from the period of 1980 to 2023 for Myanmar, focusing on GDP growth rate, life expectancy at birth, and labor force participation rate. The data is received from the World Bank. Firstly, the Augmented Dickey-Fuller (ADF) test is applied to check if the data is stationary, meaning the statistical properties of the variables do not change over time. If the variables are stationary, the Johansen cointegration test is used to identify any long-term relationships between GDP growth rate, labor force participation rate, and life expectancy at birth. This test helps determine whether these variables move together in the long run despite short-term changes.

This study applies the Vector Autoregression (VAR) and Vector Error Correction Model (VECM) to examine the dynamic relationship between GDP growth (GDPGR), life expectancy (LE), and labor force participation rate (LFPR) in both the short run and long run. The VAR model is initially employed to determine the optimal lag structure and assess the interdependence among the variables without assuming any long-run equilibrium. Following the identification of a cointegrating relationship among the variables, the VECM is applied to capture both short-term adjustments and long-term equilibrium dynamics. The VECM enables the analysis to account for deviations from the long-run path and how such deviations are corrected over time. By using these models, the study investigates how changes in LE and LFPR influence GDPGR, offering insights into the extent to which demographic and labor factors drive economic performance in both the immediate and sustained periods.

Augmented Dickey-Fuller (ADF) Test

The ADF test is used to check if the data is stationary. It involves testing whether the time series has a unit root, which means it changes over time and is not stable. The null hypothesis is that the data is non-stationary, while the alternative hypothesis is that it is stationary. The test helps ensure that the data is suitable for further analysis.The ADF test checks for stationarity in time series data. The equation for the ADF test is:

$$\Delta. y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t \quad (1)$$

Where:

- Δy_t is the first difference of the series.
- α is a constant.
- βt is a time trend.
- y_{t-1} is the lagged level of the series.
- δ_i are the coefficients of the lagged differences.
- ϵ_t is the error term.
- The null hypothesis $H_0: \gamma = 0$ (series has a unit root, i.e., it is non-stationary).

Johansen Cointegration Test

When dealing with non-stationary variables, it is essential to conduct a cointegration test to determine whether a long-term equilibrium relationship exists among them. Cointegration analysis helps in understanding the connection between causation and long-run equilibrium in time series data. Since non-stationary time series often exhibit changing means and variances over time, it is crucial to identify whether a set of variables moves together in the long run. Among various cointegration tests, the Johansen Cointegration Test is the most widely used method for detecting the presence of cointegration.

The Johansen test is specifically designed to identify cointegrating relationships between multiple non-stationary time series variables. If cointegration is found, it indicates that the variables share a long-run relationship despite being individually non-stationary. Unlike the Engle-Granger test, which can only detect a single cointegrating relationship, the Johansen test is more flexible as it allows for multiple cointegrating relationships. Additionally, it eliminates the problem of error propagation by testing all variables simultaneously within a system of equations. Another advantage is that it does not require any variables to be pre-normalized (Phillips, 1991).

The Johansen approach includes two main test statistics to determine the number of cointegrating relationships:

(i) Trace Test

The trace test examines the number of cointegrating equations in a dataset by evaluating whether the number of linear combinations among the variables is equal to or greater than a given value. K_0. The hypotheses are formulated as follows:

Null Hypothesis (H_0): $K = K_0$ (There are at most K_0 cointegrating relationships)

Alternative Hypothesis (H_1): $K > K_0$ (There are more than K_0 cointegrating relationships)

To apply the trace test, K_0 is initially set to zero. If the null hypothesis is rejected, it implies that at least one cointegrating relationship exists among the variables. The test continues by incrementing K_0 until the null hypothesis is no longer rejected. The presence of a cointegrating relationship confirms that the variables have a stable long-run association.

(ii) Maximum Eigenvalue Test

The maximum eigenvalue test is another method to determine the number of cointegrating relationships. It focuses on the largest eigenvalue of the estimated cointegration matrix. An eigenvalue is a nonzero vector that, when subjected to a linear transformation, changes only by a scalar factor. The hypotheses for the maximum eigenvalue test are as follows:

Null Hypothesis (H_0): $K = K_0$ (There are at most K_0 cointegrating relationships)

Alternative Hypothesis (H_1): $K = K_0 + 1$ (There is one additional cointegrating relationship)

If the null hypothesis is rejected when $K = K_0$, it suggests that there is only one possible outcome for the variable to form a stationary process. However, if $K_0 = m - 1$ and the null hypothesis is rejected, which means that all variables in the time series are stationary, which is an uncommon scenario unless the dataset exhibits stationarity from the beginning.

Overall, the Johansen cointegration test provides a comprehensive framework for identifying and estimating long-term relationships between non-stationary variables. By using both the trace test and the maximum eigenvalue test, researchers can accurately determine the number of cointegrating relationships within a given dataset.

Vector Error Correction Model (VECM)

The Vector Error Correction Model (VECM) is an extension of the Vector Autoregression (VAR) model, specifically designed to handle non-stationary time series that are cointegrated. Unlike a standard VAR model, which does not account for long-run equilibrium relationships, the VECM incorporates cointegration constraints into its structure. This allows the model to capture both long-term equilibrium relationships and short-term dynamic adjustments.

The key feature of the VECM is the presence of an **error correction term**, which represents the deviation from the long-run equilibrium. This term ensures that any short-run fluctuations in the data are gradually corrected, guiding the variables back toward their equilibrium relationship. The inclusion of this term makes the VECM particularly useful for analyzing economic and financial time series, where variables often exhibit both short-run fluctuations and long-term dependencies.

Formulation of the VECM

If two or more variables are found to be cointegrated, an error correction model can be applied to analyze their relationship. The general form of the VECM for two cointegrated variables y_1 and y_2 can be expressed as:

$$\Delta y_{1,t} = \alpha_1(y_{2,t-1} - \beta y_{1,t-1}) + \varepsilon_{1,t} \quad (2)$$

$$\Delta y_{2,t} = \alpha_2(y_{2,t-1} - \beta y_{1,t-1}) + \varepsilon_{2,t} \quad (3)$$

Where:

$\Delta y_{1,t}$ and $\Delta y_{2,t}$ represent the short-run changes in the variables.

$(y_{2,t-1} - \beta y_{1,t-1})$ is the error correction term, which captures deviations from the long-run equilibrium.

α_1 and α_2 are the speed of adjustment coefficients, indicating how quickly each variable returns to equilibrium.

$\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are the error terms, representing unexplained variations.

Interpretation of the Error Correction Term

In the long-run equilibrium, the error correction term is equal to zero, meaning that the variables are perfectly aligned with their cointegrating relationship. However, if the variables deviate from this equilibrium, the error correction term becomes nonzero. This signals a temporary imbalance, prompting the variables to adjust in subsequent periods to restore equilibrium.

The magnitude of the speed of adjustment coefficients (α_1 and α_2) determines how quickly the system corrects itself. If these coefficients are large in absolute value, the adjustment process is rapid. Conversely, if they are small, the return to equilibrium is slow.

Significance of the VECM

Accounts for Long-Term Relationships: The VECM explicitly models the long-run equilibrium, ensuring that the variables do not drift apart indefinitely.

Captures Short-Term Dynamics: By incorporating lagged differences in the variables, the model allows for short-term fluctuations without losing sight of the long-run trends.

Corrects Deviations: The error correction mechanism ensures that temporary deviations from equilibrium are gradually corrected over time.

In summary, the VECM is a powerful tool for analyzing relationships between cointegrated time series variables. It balances short-run flexibility with long-run stability, making it particularly useful in economics, finance, and other fields where variables exhibit persistent trends and interdependencies.

The Wald test is commonly used to examine short-run causality between variables in econometric models. This test calculates a test statistic based on an unrestricted regression. The Wald statistic assesses how closely the unrestricted estimates align with the restrictions imposed by the null hypothesis. If the restrictions are valid, the unrestricted estimates should closely satisfy those restrictions.

Results and Interpretation

In this study, the data analysis involved a multi-step econometric approach to examine the impact of life expectancy at birth and labor force participation rate on economic growth in Myanmar. Initially, the Augmented Dickey-Fuller (ADF) Unit Root Test is applied to confirm the stationarity of the time series data, ensuring that the variables become stable after first differencing. Subsequently, the Johansen Cointegration Test is used to detect any long-term equilibrium relationships among the variables, establishing the presence of cointegrating vectors that indicate persistent interconnections over time.

Table (1) ADF Unit Root Test

Variables	Level		First Difference	
	t-value	p-value	t-value	p-value
LFP	-1.6031	0.7745	-6.1109	0.0000
Life Expectancy at birth	0.5749	0.8366	-9.1740	0.0000
GDP growth rate	-0.4380	0.8932	-5.8387	0.0267

Source; Own Computation

Table 1 shows the results of the Augmented Dickey-Fuller (ADF) unit root test for the study variables. The findings reveal that Labor Force Participation, Life Expectancy at Birth, and GDP Growth Rate are not stationary at their level forms because their p-values are greater than 0.05. However, after taking the first difference, all three variables become stationary, as their p-values fall below the 5% significance level. Stationarity in the data is crucial for conducting further time series analysis, as it ensures that the statistical properties of the variables are stable over time and meet the conditions required for advanced econometric modeling.

Table (2) Johansen Cointegration Test

Hypothesized No of CE	Eigen Value	Trace Statistic	Critical value	p-value
None*	0.3506	39.3322	35.0109	0.0215
At most 1*	0.2000	24.5987	18.3977	0.0489
At most 2*	0.0426	1.8284	3.8415	0.1763

Source: Own Computation

Table 2 presents the results of the Johansen Cointegration Test, which examines the long-run relationship among the study variables. The trace statistic shows that the null hypothesis of no cointegration is rejected at the 5% level, since the trace value of 39.3322 is higher than the critical value of 35.0109 with a p-value of 0.0215. This indicates that there is at least one cointegration equation among the variables. Similarly, the test for “at most one” cointegration relationship is also significant, with a trace statistic of 24.5987 compared to the critical value of 18.3977 and a p-value of 0.0489, suggesting the existence of a second cointegration equation. However, the result for “at most two” cointegration equations is not significant, as the trace statistic of 1.8284 is lower than the critical value of 3.8415, and the p-value of 0.1763 exceeds the 5% level. Taken together, the findings suggest that there are two cointegration equations among the variables, confirming that they move together in the long run despite possible short-term fluctuations. This implies that variables such as labor force participation, life expectancy, and GDP growth rate share a stable and long-term equilibrium relationship, which is important for further modeling and policy implications.

VAR Lag Length Selection

To apply the Cointegration test and Vector Error Correction model, the next important step after knowing that the data is stationary at the first difference is to determine the number of lags. The Vector Auto Regression (VAR) lag order selection method is used to choose the optimal lag length. There are five different criteria used to determine the lag lengths, such as the sequentially modified likelihood ratio (LR) test statistic, the final prediction error criterion (FPE), the Akaike information criterion (AIC), the Schwarz information criterion (SIC), and the Hannan-Quinn information criterion (HQ). These lag specification criteria results are shown in Table 2

Table (3) VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-336.473	NA	3121.527	16.5598	16.6851	16.6053
1	-291.237	81.6460	533.9451*	14.7921*	15.2936*	14.9747*
2	-287.962	5.4321	711.812	15.0713	15.949	15.3901
3	-275.786	18.4123*	621.952	14.9164	16.1702	15.3730

* indicates lag order selected by the criteria

Source: Own Computation

Table 3 shows the results of the VAR Lag Order Selection Criteria, which are used to determine the appropriate lag length for the Vector Autoregression (VAR) model. The table presents the values of different statistical criteria, including the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan–Quinn Criterion (HQ) for different lag lengths. The results indicate that most of the criteria suggest lag order 1 as the most suitable for the model. Specifically, the FPE, AIC, and SC values are minimized at lag 1, and the LR statistic is also significant, which collectively highlight that lag 1 provides the best fit compared to the other lag structures. Although the LR test shows some improvement at lag 3, other criteria, such as FPE and AIC, do not consistently support this, and the values are less efficient compared to lag 1. Therefore, lag order 1 is selected as the optimal lag length, ensuring that the model captures the dynamic relationships among the variables without overfitting. This choice is important because using the correct lag length improves the reliability of the results and ensures that the VAR model properly reflects both the short-term dynamics and the long-term relationships among the variables.

Specification and Estimation of the Vector Error Correction Model

If the variables are cointegrated, it is possible to continue by estimating the Vector Error Correction Model (VECM). Therefore, the long-run and short-run equilibrium can be found with VECM. These findings can determine which health variables have a long-run and short-run relationship with economic growth (GDP per capita). The lags for the VECM are selected based on the optimal lag length defined in Table 3. The results of VECM are shown in Tables 4 and 5.

Table (4) Long Run in the Cointegration Equation (VECM)

Variables	Coefficients	Std.Error	t-statistic
GDP Growth	1.0000		
LFPR	1.6748	0.9344	1.7923
LE	2.0297	0.3056	6.6358
Constant	226.5705		

Source: Own Computation

According to Table 4, the long-run cointegration equation is:

GDP growth rate = Constant +1.6748 Labor Force Participation Rate +2.0297 Life Expectancy

Std (0.9344) (0.3056)

t-stat [1.7923] [6.6358]

Table 4 presents the results of the long-run cointegration equation estimated under the Vector Error Correction Model (VECM). In this model, GDP growth is treated as the normalized dependent variable with its coefficient restricted to 1.0000, while the labor force participation rate (LFPR), life expectancy (LE), and the constant term are included as explanatory variables. The coefficient of LFPR is 1.6748 with a standard error of 0.9344 and a t-statistic of 1.7923. Although this coefficient is positive, the t-statistic shows that the impact of LFPR on GDP growth is only weakly significant in the long run, suggesting that higher labor force participation tends to contribute to economic growth, but the strength of the relationship may not be very strong. In contrast, life expectancy (LE) has a coefficient of 2.0297 with a standard error of 0.3056 and a t-statistic of 6.6358, which is highly significant at conventional levels. This indicates that improvements in life expectancy exert a strong and statistically significant positive influence on GDP growth in the long run. The constant term is 226.5705, representing the intercept of the equation, which reflects other long-run structural factors affecting GDP growth that are not directly captured by LFPR and LE.

Table (5) Short Run in the VECM

Error Correction	D(GDpgrowth)	Standard Error	p-value
ECT	0.2156	0.1794	1.2023
D(GDPGR(-1))	0.4362	0.2478	1.7601
D(Life Expectancy(-1))	9.9466	0.5897	16.8678
D(Labor Force Participation))	0.2221	0.5861	0.3791
C	0.1819	0.9351	0.1945

Source: Own Computation

Table 5 shows the short-run estimation results from the Vector Error Correction Model (VECM), where changes in GDP growth are explained by the error correction term (ECT), past values of GDP growth, life expectancy, labor force participation, and a constant. The coefficient of the error correction term (ECT) is 0.2156 with a standard error of 0.1794 and a t-statistic of 1.2023. Since this value is not statistically significant, it suggests that deviations from the long-run equilibrium are corrected slowly, and the system does not exhibit a strong tendency to return to equilibrium in the short run. The first lag of GDP growth [D(GDPGR(-1))] has a positive coefficient of 0.4362 with a t-statistic of 1.7601, which indicates a weak but positive short-run effect of past GDP growth on current GDP growth, implying some persistence in economic performance. Life expectancy at its first lag [D(Life Expectancy(-1))] shows a very strong and significant positive coefficient of 9.9466 with a t-statistic of 16.8678, which highlights that improvements in health and longevity have a substantial immediate effect on boosting GDP growth in the short run. On the other hand, the coefficient of labor force participation [D(LFPR)] is 0.2221 with a low t-statistic of 0.3791, suggesting that short-run changes in labor force participation do not significantly influence GDP growth. The constant term (C) is 0.1819 with a very low t-statistic of 0.1945, which shows that unexplained short-run variations in GDP growth are minimal.

Vector Error Correction Model Diagnostic Tests

To ensure the validity of the Vector Error Correction Model, the Residual Autocorrelation test, Jarque-Bera normality test, and White's heteroskedasticity test are performed. Those diagnostic tests check the model for residual autocorrelation, normality, and heteroskedasticity, respectively. The results of those tests are presented in Table 6.

Table (6) Diagnosis Tests of VECM

Diagnosis	Statistics	p-value
Residual Normality Test	JB = 69.854	0.0000
Residual Portmanteau Tests for Autocorrelation	Q = 89.584	0.0046
Residual Heteroskedasticity	254.869	0.0958

Source: Own Computation

Table 6 presents the diagnostic tests used to check the reliability and validity of the VECM results. The residual normality test shows a Jarque-Bera (JB) statistic of 69.854 with a p-value of 0.0000, which is highly significant. This result indicates that the residuals are not normally distributed, meaning the model does not fully meet the assumption of normality. However, in large samples, normality is often less critical due to the central limit theorem, and the results can still be interpreted as reliable. The residual Portmanteau test for autocorrelation reports a Q-statistic of 89.584 with a p-value of 0.0046. Since this p-value is below the 5% significance level, it suggests that autocorrelation exists in the residuals, meaning there is some correlation between error terms across periods. This implies that the model may not have captured all the dynamic relationships in the data, and this limitation should be acknowledged. On the other hand, the residual heteroskedasticity test shows a statistic of 254.869 with a p-value of 0.0958, which is above the 5% significance level. This means that the null hypothesis of homoskedasticity cannot be rejected, and the residuals do not show significant heteroskedasticity.

Conclusions

The findings of the analysis show that the study variables are not stable in their original form but become stable after taking differences, making them suitable for further time series analysis. The results also confirm the existence of long-run relationships among labor force participation, life expectancy, and GDP growth, meaning that these variables move together over time despite short-term changes. The lag order selection suggests that using one lag is the most appropriate for the model, as it captures the dynamic behavior of the variables without overfitting. In the long run, life expectancy shows a strong positive influence on economic growth, while labor force participation also contributes positively but less strongly. In the short run, improvements in life expectancy are found to have an immediate effect on growth, whereas labor force participation has little impact. Finally, diagnostic tests indicate that while the model is generally reliable, some issues, such as non-normality and autocorrelation, remain, which should be considered when interpreting the results.

The study recommends that schools, community organizations, and families should work together to improve awareness of healthy lifestyles, nutrition, and daily habits that can influence overall well-being. Emphasis should be placed on educational programs that help individuals understand the importance of maintaining good health and staying active in the workforce. Furthermore, regular monitoring of these initiatives can help identify areas that need improvement and ensure that interventions are effective in promoting long-term benefits. By fostering a supportive environment and providing guidance on health, nutrition, and labor participation, the community can help strengthen economic growth and enhance the quality of life for individuals.

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Null Hypothesis: GDPGR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.603072	0.7745
Test critical values:	1% level	-4.198503	
	5% level	-3.523623	
	10% level	-3.192902	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(GDPGR) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.110987	0.0000
Test critical values:	1% level	-3.600987	
	5% level	-2.935001	
	10% level	-2.605836	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LE has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.574883	0.8366
Test critical values:	1% level	-2.619851	
	5% level	-1.948686	
	10% level	-1.612036	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.173950	0.0000
Test critical values:	1% level	-3.596616	
	5% level	-2.933158	
	10% level	-2.604867	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: LFPR has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.437991	0.8932
Test critical values:	1% level	-3.592462	
	5% level	-2.931404	
	10% level	-2.603944	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: D(LFPR) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.838623	0.0000
Test critical values:	1% level	-3.596616	
	5% level	-2.933158	
	10% level	-2.604867	

*MacKinnon (1996) one-sided p-values.

Date: 08/19/25 Time: 06:34
Sample (adjusted): 1982 2023
Included observations: 42 after adjustments

Series: GDPGR LE LFPR
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.350593	39.33215	35.01090	0.0215
At most 1	0.200009	24.59871	18.39771	0.0489
At most 2	0.042600	1.828449	3.841465	0.1763

Trace test indicates at least one cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

VAR Lag Order Selection Criteria
Endogenous variables: GDPGR LE LFPR
Exogenous variables: C
Date: 08/19/25 Time: 06:38
Sample: 1980 2023
Included observations: 41

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-336.4734	NA	3121.527	16.55968	16.68506	16.60534
1	-291.2372	81.64597	533.9451*	14.79206*	15.29359*	14.97469*
2	-287.9619	5.432071	711.8120	15.07131	15.94900	15.39092
3	-275.7861	18.41230*	621.9518	14.91639	16.17023	15.37297

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

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Vector Error Correction Estimates
Date: 08/19/25 Time: 06:39
Sample (adjusted): 1983 2023
Included observations: 41 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
GDPGR(-1)	1.000000		
LE(-1)	2.029724 (0.30564)` [6.63579]		
LFPR(-1)	1.674728 (0.93440) [1.79230]		
C	226.5705		
Error Correction:	**D(GDPGR)**	**D(LE)**	**D(LFPR)**
CointEq1	0.21567 (0.17939) [1.20232]	0.103988 (0.06827) [1.52323]	0.20256 (0.05755) [3.53622]
D(GDPGR(-1))	0.43615 (0.24780) [1.76010]	0.17616 (0.09430) [1.86811]	0.328957 (0.07950) [4.13761]
D(GDPGR(-2))	0.47330 (0.37320) [1.26823]	-0.289006 (0.14203) [-2.03486]	0.480322 (0.11974) [4.01140]
D(LE(-1))	9.94664 (0.58974) [16.8678]	-0.660574 (0.22443) [-2.94330]	0.329738 (0.18921) [1.74268]
D(LE(-2))	-0.196015 (0.44442) [-0.44106]	-0.143242 (0.16913) [-0.84694]	0.083889 (0.14259) [0.58833]
D(LFPR(-1))	0.222157 (0.58605) [0.37908]	-0.297913 (0.22303) [-1.33577]	0.022951 (0.18803) [0.12206]
D(LFPR(-2))	0.141366 (0.52832) [0.26758]	-0.015241 (0.20106) [-0.07580]	0.006520 (0.16951) [0.03846]
C	0.181888 (0.93509) [0.19451]	-0.022853 (0.35586) [-0.06422]	-0.099234 (0.30001) [-0.33076]
R-squared	0.875411	0.276403	0.381844
Adj. R-squared	0.745211	0.122913	0.250720
Sum sq. resids	1120.521	162.2821	115.3450
S.E. equation	5.827107	2.217575	1.869573
F-statistic	2.414732	1.800788	2.912087
Log likelihood	-125.9900	-86.37965	-79.38077
Akaike AIC	6.536098	4.603885	4.262477
Schwarz SC	6.870453	4.938241	4.596832
Mean dependent	0.205136	0.090439	-0.262463
S.D. dependent	6.508590	2.367866	2.159835