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ANALYSIS OF AGRICULTURAL SUBSECTORS' CONTRIBUTION TO ECONOMIC GROWTH IN MYANMAR

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Abstract

This study examines the contributions of Myanmar’s key agricultural subsectors—crop production, livestock, fishery, and forestry—to the growth of Gross Domestic Product per Capita based on purchasing power parity (GDPPPP) over a 20-year period. Recognizing agriculture as a cornerstone of the national economy and a primary source of income and employment, the research aims to identify which subsectors play the most significant roles in driving economic growth and how they interact with GDP in both the short and long run. Using a quantitative approach and secondary data from credible sources such as the Central Statistical Organization, the analysis applies econometric techniques including the Augmented Dickey-Fuller (ADF) test, Johansen cointegration, and Vector Autoregressive (VAR) and Vector Error Correction (VECM) models. The findings are expected to provide policymakers and stakeholders with valuable insights for designing targeted strategies, improving resource allocation, and fostering balanced, sustainable growth in Myanmar’s agricultural sector.

Keywords: GDPPPP, Agricultural Sectors, ADF Test, Cointegration, Canonical Cointegration Regression

Introduction

Agriculture plays a crucial role in Myanmar's economy, serving as a primary source of income and employment for a significant portion of the population. The sector is composed of several subsectors, including crop production, livestock, fishery, and forestry, each of which contributes differently to the Gross Domestic Product per Capita (GDPPPP). Analyzing the contributions of these subsectors is essential to understanding their individual and collective impact on the growth rate of the GDPPPP. This study focuses on examining the growth rates of these subsectors and its contributions to the GDP per capita rate in Myanmar.

This study is motivated by the need to enhance the understanding of the factors driving growth in Myanmar's agricultural sector. Agriculture remains the backbone of the national economy, and its performance directly affects the livelihoods of many citizens. However, not all subsectors contribute equally to this growth. By identifying which subsectors are the most influential in driving the agricultural GDP, the study aims to provide valuable insights for policymakers and stakeholders. These insights will help formulate targeted policies and strategic investments that can stimulate balanced growth across the sector. Furthermore, understanding the strengths and weaknesses of each subsector will enable more effective planning and resource allocation, which is essential for improving productivity, sustainability, and long-term economic stability in Myanmar's agriculture.

The agricultural sector is a cornerstone of Myanmar's economy, contributing significantly to national income and providing employment for a large segment of the population. Despite its importance, the sector faces numerous challenges, including variability in productivity across different subsectors, environmental pressures, and fluctuating market conditions. Understanding the contributions of various agricultural subsectors—such as crop production, livestock, fishery, and

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forestry—to the overall GDPPPP is critical for developing strategies that can enhance the sector's performance and resilience.

One key reason for focusing on the contributions of these subsectors is the need to identify which areas are driving growth and which may be lagging. Not all subsectors contribute equally to the GDPPPP, and some may have more potential for growth than others. By conducting a detailed analysis of these contributions, the study seeks to highlight the strengths and weaknesses within the agricultural sector. Another important aspect of this study is its potential to inform future economic planning and development initiatives. As Myanmar continues to integrate into the global economy, the agricultural sector must adapt to changing conditions and increasing competition. By identifying the subsectors that are most critical to GDPPPP, this study can guide efforts to enhance competitiveness and sustainability in the sector.

Objectives of the Study

The objective of this study is

(1) to examine the contributions of key agricultural subsectors, including crop production, livestock, fishery, and forestry, to the overall growth of GDPPPP in Myanmar

(2) to identify the long-run and short-run relationship between agricultural subsectors and GDP growth

Methods of the Study

This study uses a quantitative research approach to analyze the contribution of different agricultural subsectors to the growth of GDP based on purchasing power parity (GDPPPP) in Myanmar. It relies on secondary data obtained from credible sources, including the Central Statistical Organization (CSO) database. The analysis covers 20 years of time series data to identify trends, patterns, and changes in the agricultural subsectors and their effects on GDP growth. To achieve this, the study applies econometric techniques such as the Augmented Dickey-Fuller (ADF) test to check data stationarity, Johansen cointegration to examine long-term relationships, and both the Vector Autoregressive (VAR) and Vector Error Correction (VECM) models to analyze short-term and long-term dynamics between the variables.

Literature Review

The agricultural sector plays a pivotal role in the economies of many developing countries, including Myanmar. Numerous studies have explored the relationship between agricultural growth and overall economic development, emphasizing the importance of various subsectors such as crop production, livestock, fishery, and forestry. This literature review examines existing research on the contributions of these subsectors to GDPPPP, the factors influencing performance, and the implications for economic policy and sustainability.

Subsequent studies have supported this view, highlighting the role of agriculture in poverty reduction and employment generation. For instance, Timmer (1988) emphasizes that agricultural growth is crucial for creating employment opportunities, particularly in rural areas, where the majority of the population in developing countries resides. The link between agricultural growth and poverty reduction is further explored by Nchuchuwe & Adejuwon (2012), who find that higher agricultural productivity leads to significant poverty alleviation in India.

The contributions of different agricultural subsectors to overall GDPPPP have been a focus of much research. Crop production, as the largest subsector in many developing countries, often receives the most attention. According to Giller et.al. (2021), crop production is typically the dominant contributor to GDPPPP due to its extensive land use and the large share of the rural labor force involved in farming. However, it is also noted that the growth potential of crop production is often constrained by factors such as land availability, soil fertility, and access to modern inputs.

Livestock, fisheries, and forestry are also significant contributors to agricultural GDP, though the roles vary depending on the country's economic structure and natural resource endowments. Herrero et al. (2013) argue that the livestock subsector has the potential to drive agricultural growth, particularly in regions where crop production is limited by environmental factors. The importance of livestock for income diversification and food security is highlighted, noting that it can provide a steady income stream and contribute to dietary diversity.

The fishery subsector is another important area, particularly in coastal and riverine regions. According to Allison (2011), fisheries contribute to many developing countries' food security, employment, and foreign exchange earnings. The emphasis is placed on the sustainable management of fishery resources, which is essential to maintaining its contribution to economic growth, as overfishing and environmental degradation pose significant threats to the sector.

Forestry, while often overlooked in discussions of agricultural growth, also plays a critical role in many countries. Awono et.al. (2016) note that forestry contributes to GDP through the provision of timber, non-timber forest products, and ecosystem services. It is argued that sustainable forestry practices can enhance the long-term productivity of forests and provide income for rural communities, thereby supporting overall agricultural growth.

Pervez et al. (2024) conducted a study titled *Agricultural Output and Economic Growth Nexus: A VECM Approach on Bangladesh* to investigate the relationship between agricultural output and GDP growth. Using the Vector Error Correction Model (VECM), Johansen cointegration, and impulse response functions, the study analyzed annual time-series data for Bangladesh. The findings revealed a stable long-run relationship between agricultural output and GDP, with an error correction term indicating that 66.4% of disequilibrium was corrected each year. The impulse response and variance decomposition results showed that agricultural output had a stronger positive effect on economic growth compared to industrial output. Based on these results, the authors emphasized that agriculture continues to be a vital driver of Bangladesh’s economy and recommended that policymakers prioritize investment in the sector to sustain long-term growth.

Nyamekye et al. (2021) examined the contribution of agriculture to economic development in Ghana in their study *Analysis on the Contribution of the Agricultural Sector to the Economic Development of Ghana*. The study applied Johansen cointegration and VECM methods to annual time-series data from 1984 to 2018 to assess long-run and short-run dynamics between agricultural, industrial, and service sectors with GDP. The results indicated that agricultural output significantly and positively affected GDP growth, though the cointegration test did not confirm a stable equilibrium with GDP in the long run. The VECM analysis demonstrated that short-run changes in agriculture influenced economic output. The authors concluded that agriculture plays a crucial role in Ghana’s economy and recommended policies to increase value-added agricultural exports and improve productivity through government support and investment.

Ogbonna, Nkemdirim, Udenta, and Nkwagu (2024) explored the role of agricultural value chains in Nigeria's economic growth in their study *Agricultural Sector Value Chain Contributions and Nigeria's Economic Growth*. Using unit root and cointegration tests, VECM, and Granger causality analysis on time-series data from 1981 to 2019, the study evaluated the contributions of the crop, livestock, and fishery subsectors to GDP. The findings showed that all three subsectors had significant positive effects on GDP growth. The analysis also revealed both long-run and short-run relationships between agricultural value chains and the economy. The authors recommended the implementation of supportive policies to expand commercial agriculture, attract private sector participation, and improve the efficiency of agricultural production systems.

The reviewed studies collectively demonstrate that agricultural subsectors are key contributors to economic growth in developing countries. The use of VAR and VECM methods across different contexts, including Bangladesh, Ghana, and Nigeria, consistently revealed significant long-run relationships between agricultural production and GDP growth, as well as short-term dynamics that influence economic performance. In all cases, subsectors such as crops, livestock, and fisheries played essential roles in stabilizing and boosting economic output. These findings suggest that similar econometric modeling could be applied to analyze Myanmar's agricultural subsectors, enabling the identification of the most influential areas within agriculture. Such insights could guide policymakers in prioritizing investments and implementing targeted strategies to enhance the sector's contribution to national economic development.

Data and Methods

Data from the Central Statistical Organization and Government Website (MMSIS) of the data of Gross Domestic Product per Capita (GDPPPP), the export of Agricultural Products (in million kyats), Live Stocks and Fisheries (in million kyats), and Forestry Export (in million kyats). To test the stationarity of the above variable, an augmented Dickey-Fuller test is employed. To test the long-run equilibrium Johansen cointegration test is used, and to test the short-term relationship, the Vector Error Correction Model analysis is used.

Augmented Dickey-Fuller (ADF)

The Augmented Dickey-Fuller (ADF) test, developed by Dickey and Fuller (1979), is a widely used statistical method for determining whether a time series dataset is stationary or non-stationary. This test extends the basic Dickey-Fuller test by incorporating lagged values of the dependent variable to address autocorrelation issues, making it more robust for complex models. The fundamental concept behind the ADF test is to examine whether a unit root exists within a time series. The presence of a unit root indicates non-stationarity, while its absence confirms stationarity. However, caution should be exercised when using this test, as it has a relatively high probability of Type I error, which means it may sometimes incorrectly reject the null hypothesis.

The ADF test has three main variations, each designed to test for a unit root under different conditions. The first version tests for a unit root without additional components, expressed as:

$$\Delta y_t = \phi^* y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + u_t \tag{1}$$

The second variation includes a drift term to account for potential trends in the data:

$$\Delta y_t = \beta_0 + \phi^* y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + u_t \quad (2)$$

The third and most comprehensive version incorporates both a drift term and a deterministic time trend, which is suitable for data exhibiting an increasing or decreasing trend over time:

$$\Delta y_t = \beta_0 + \phi^* y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + \beta_1 t + u_t \quad (3)$$

In these equations, $\Delta y_t = y_t - y_{t-1}$ represents the first difference of the variable, β_0 is the drift term, t is the linear time trend, and u_t is the error term. The null hypothesis ($H_0: \phi^* = 0$) suggests that the series contains a unit root and is non-stationary, while the alternative hypothesis ($H_1: \phi^* < 0$) indicates stationarity.

To determine the presence of a unit root, the test calculates the test statistic:

$$t = \frac{\phi^*}{\sqrt{\mathrm{var}(\phi^*)}} \quad (4)$$

This test statistic is then compared to critical values at different significance levels. If the calculated value is smaller than the critical value, the null hypothesis is rejected, confirming that the series is stationary.

When conducting the ADF test, it is necessary to decide whether to include a constant, a trend, or neither in the regression model. A visual inspection of the data plot can assist in making this decision. If the data does not start from the origin, a constant should be included. If there is a noticeable upward or downward trend, a trend component should be added.

Additionally, selecting an appropriate lag length is crucial, as too few lags may result in over-rejecting the null hypothesis when it is true, while too many lags can weaken the test's power. Information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) are commonly used to determine the optimal lag length. In this study, the AIC is preferred as it tends to provide a more reliable estimate for selecting the correct lag structure.

Determining the Optimal Lag Length of the Model

Selecting the optimal lag length is crucial for ensuring an accurate and reliable model. The lag length determines how many past observations are included in the model, which affects the overall efficiency of the estimation process. A properly specified model should include Gaussian error terms, which are standard normal error terms free from autocorrelation, non-normality, and heteroskedasticity (Asteriou & Hall, 2011). If the lag length is not correctly chosen, it can lead to omitted variable bias, where important variables affecting short-term behavior are excluded, causing them to become part of the error term.

Choosing too few lags in the Johansen cointegration procedure may result in model specification errors, while selecting too many lags can lead to a loss of statistical power (Maddala et al., 1998). To avoid such issues, it is often more effective to select a smaller lag length that provides a balance between accuracy and efficiency.

A common approach for determining the optimal lag length involves estimating a Vector Autoregressive (VAR) model. The process begins with estimating the model using a large number of lags, then gradually reducing the number by re-estimating the model with one fewer lag each time. This continues until the optimal number of lags is reached. For annual data, using 1 or 2 lags is typically recommended to preserve degrees of freedom.

To select the most suitable lag length, information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) are used. The optimal lag length is determined by choosing the model that minimizes these information criteria. Selecting the correct lag length is essential for producing reliable results and ensuring that the model accurately captures the underlying dynamics of the data.

Vector Autoregressive (VAR) Model

The Vector Autoregressive (VAR) model is widely used to analyze the dynamics and interdependencies of multiple time series variables. It extends the concept of univariate autoregressive models by incorporating multiple variables, making it a combination of simultaneous equation models and time series models. The simplest case of a VAR model is the bivariate VAR, which includes two variables, y_{1t} and y_{2t}. The current values of these variables depend on their past values and error terms, as shown in the following equation:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \beta_{10} \\ \beta_{20} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \alpha_{11} \\ \alpha_{21} & \beta_{21} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix} \tag{5}$$

where u_{it} represents the white noise error term, with expectations $E(u_{it}) = 0$ and $E(u_{1t}, u_{2t}) = 0$. This system can be extended to include multiple variables $y_{1t}, y_{2t}, \ldots, y_{gt}$, where each variable is influenced by the past values of all other variables in the system.

The VAR model is highly flexible and convenient for analyzing multiple time series because it does not require prior specification of endogenous and exogenous variables. However, there are certain limitations. First, it can be difficult to determine which variables significantly influence the dependent variables. Second, all variables in a VAR model must be stationary, but financial and economic time series often exhibit non-stationary behavior. To address this issue, the model can be transformed into a Vector Error Correction Model (VECM), which includes first-difference terms and cointegration relationships, eliminating the requirement for stationarity. Lastly, selecting the appropriate lag length is crucial for accurate model estimation, but this challenge can be managed using various statistical approaches, such as information criteria methods.

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:

$$\Delta y_{1,t} = \alpha_1(y_{2,t-1} - \beta y_{1,t-1}) + \varepsilon_{1,t} \quad (7)$$

$$\Delta y_{2,t} = \alpha_2(y_{2,t-1} - \beta y_{1,t-1}) + \varepsilon_{2,t} \quad (8)$$

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 Interpretations

The study uses several econometric methods to analyze the contributions of agricultural subsectors to GDPPPP growth in Myanmar. First, the Augmented Dickey-Fuller (ADF) test is applied to check the stationarity of the time series data for crop production, livestock, fishery, forestry, and GDPPPP. Then, a cointegration test assesses the long-term relationship between these subsectors and GDPPPP growth. Finally, Canonical Correlation Analysis (CCA) is employed to identify the main drivers of growth within the subsectors and evaluate their combined and individual impacts on GDPPPP.

Table (1) ADF Unit Root Test

Variables	Level		First Difference	
	t-value	p-value	t-value	p-value
Ln Agriculture	1.0686	0.9966	-4.9236	0.0002
Ln Forestry	0.9184	0.9948	-2.3019	0.0177
Ln Livestock	-1.5042	0.5215	-6.2014	0.0000
Ln GDPPPP	-2.0301	0.2733	-3.0205	0.0417

Source (Own Computation)

The results of the ADF Unit Root Test presented in Table (1) indicate that all the variables—Ln Agriculture, Ln Forestry, Ln Livestock, and Ln GDPPPP—are non-stationary at levels, as evidenced by high p-values, which are greater than the 5% significance level. However, after taking the first differences, the t-values for all variables become significantly negative, and the p-values fall below the 5% threshold. This suggests that the variables are stationary after differencing, implying that all the variables are integrated of order one, I(1). Therefore, these variables require differencing to achieve stationarity before proceeding with further analysis.

Table (2) Johansen Cointegration Test

Hypothesized No of CE	Eigen Value	Trace Statistic	Critical value	p-value
None*	0.6068	67.8518	47.8561	0.0002
At most 1*	0.3439	31.4440	29.7971	0.0320
At most 2*	0.2818	15.0065	15.4947	0.0591
At most 3*	0.0522	2.0921	3.8414	0.1481

Source (Own Computation)

The Johansen Cointegration Test results indicate that there is evidence of long-run equilibrium relationships among the variables in the model. At the "None" level, the trace statistic of 67.8518 exceeds the critical value of 47.8561, with a p-value of 0.0002, suggesting the presence of at least one cointegrating vector at the 5% significance level. Similarly, for "At most 1," the trace statistic of

31.4440 is higher than the critical value of 29.7971, with a p-value of 0.0320, indicating a second cointegrating relationship. For “At most 2,” the trace statistic of 15.0065 is slightly below the critical value of 15.4947, with a p-value of 0.0591, which is marginally above the 5% threshold, implying weaker evidence for a third cointegrating vector. Finally, at “At most 3,” the trace statistic of 2.0921 is lower than the critical value of 3.8414, with a p-value of 0.1481, showing no evidence of further cointegration. Overall, the results confirm at least two cointegrating relationships among the variables, indicating that they move together in the long run despite short-term fluctuations. This supports the theoretical expectation of long-term linkages among the studied variables.

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 3

Table (3) VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	86.8632	NA	0.0000	-4.3612	-4.1889	-4.2999
1	115.2346	49.2762*	0.0000	-5.0123	-4.1505	-4.7056
2	125.8919	16.2665	0.0000	-4.7314	-3.1797	-4.1792
3	133.6524	10.2119	0.0000	-4.2975	-2.0565	-3.5001

* indicates lag order selected by the criteria

Table (3) presents the results of the VAR Lag Order Selection Criteria, which include LogL, LR, FPE, AIC, SC, and HQ. Among the tested lag lengths, lag 1 is selected as the most appropriate based on the Likelihood Ratio (LR) and Akaike Information Criterion (AIC), both of which indicate the best model fit at this lag. The AIC value at lag 1 is the lowest (-5.0123), suggesting it provides the best balance between model complexity and goodness of fit. Although other criteria like SC and HQ suggest different lags, the AIC is widely used in academic research for selecting lag lengths. Therefore, the study uses lag 1 for the VAR model estimation, as it is expected to yield more accurate and reliable results for the analysis.

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
LNGDPPPP	1.0000		
Ln Agriculture	0.5579	0.7504	0.7435
Ln Forestry	-1.1253	0.8952	-1.2570
Ln Livestock	-0.8825	0.2045	-4.3162
Constant	0.0619		

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

GDP growth rate = Lngdpppp + 0.5579Agriculture – 1.125Forestory-0.883Livestock–+0.0619
Std (0.7504) (0.8952) (0.2045)
t-stat [0.7435] [-1.2570] [-4.3162]

According to Table (4), the long-run cointegration equation in the VECM model examines the relationship between gross domestic product per capita (LNGDPPPP) and the three key sectors: agriculture, forestry, and livestock. The coefficient of agriculture (0.5579) is positive, indicating that in the long run, a rise in agricultural output is associated with an increase in GDP per capita. However, the t-statistic (0.7435) suggests that this relationship is not statistically significant. In contrast, the coefficients of forestry (-1.1253) and livestock (-0.8825) are both negative, implying that increases in these sectors are linked to a decrease in GDP per capita. Among them, the livestock sector shows a statistically significant long-run effect, as its t-statistic (-4.3162) exceeds the critical value, suggesting a strong negative relationship. The constant term is 0.0619. Overall, the results suggest that, in the long run, the livestock sector plays a more significant role in influencing economic output, while the impact of agriculture and forestry appears weaker or statistically insignificant.

Table (5) Short Run in the VECM

Error Correction	D(GDpgrowth)	Standard Error	p-value
ECT	-0.0135	0.0175	-0.07704
D(GDPPPP(-1))	0.0888	0.3339	0.2661
D(Agriculture(-1))	0.0565	0.0311	1.8116
D(Forestry(-1))	0.0008	0.0285	0.0278
D(Livestock(-1))	-0.0118	0.0116	-1.0153
C	-0.0022		

The short-run estimation results from the Vector Error Correction Model (VECM) in Table (5) indicate the immediate effects of changes in the agricultural subsectors on GDP growth. The error correction term (ECT) has a negative sign (-0.0135), suggesting that deviations from the long-run equilibrium are corrected over time; however, the magnitude is very small, implying slow adjustment toward equilibrium in the short run. The coefficient for GDP per capita purchasing power parity in the previous period [D(GDPPPP(-1))] is positive (0.0888), but its p-value (0.2661) indicates that the effect is not statistically significant. Agriculture in the previous period [D(Agriculture(-1))] shows a positive coefficient (0.0565), suggesting that growth in this subsector may contribute to GDP growth in the short run.

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 = 97.4872	0.0000
Residual Portmanteau Tests for Autocorrelation	Q = 71.9572	0.0023
Residual Heteroskedasticity	365.4466	0.0871

The diagnostic tests for the Vector Error Correction Model (VECM) presented in Table 8 assess the validity and reliability of the model. The residual normality test, measured by the Jarque-Bera (JB) statistic, has a value of 97.4872 with a p-value of 0.0000, indicating that the residuals do not follow a normal distribution. The residual Portmanteau test for autocorrelation produces a Q statistic of 71.9572 with a p-value of 0.0023, suggesting the presence of autocorrelation in the residuals, which may affect the model’s efficiency. The residual heteroskedasticity test, with a test statistic of 365.4466 and a p-value of 0.0871, fails to provide strong evidence against the null hypothesis of homoskedasticity, implying that the variance of the residuals is relatively stable.

Conclusion

The findings from the analysis highlight several key points regarding the relationship between agricultural subsectors and GDP growth in Myanmar. First, the model selection process identified lag 1 as the most appropriate for the VAR model, as it provides the best trade-off between model accuracy and complexity based on widely accepted statistical criteria. This choice ensures that the estimation captures short-term dynamics without overfitting the data.

In the long run, agriculture shows a positive but statistically weak association with GDP per capita, indicating that while the sector may contribute to economic growth, its influence is not strong enough to be significant in the model. Forestry and livestock, on the other hand, show negative long-run relationships with GDP per capita, with livestock having a significant impact. This suggests that expansion in livestock production, under current conditions, may be linked to inefficiencies or structural constraints that limit overall economic benefits.

In the short run, the results show that adjustments toward the long-run equilibrium occur slowly, as indicated by the small and negative error correction term. Agricultural output from the previous period appears to have a positive influence on GDP growth, although not strongly significant. This implies that short-term gains from agricultural activity may contribute to economic performance, but the effect is relatively modest.

The diagnostic tests reveal certain limitations in the model's statistical assumptions. The residuals do not follow a normal distribution, and autocorrelation is present, which could reduce the efficiency of the estimates. However, the absence of strong evidence of heteroskedasticity suggests that the residual variance is relatively stable.

Suggestion

Based on these findings, it is suggested that policymakers place greater emphasis on improving the productivity and efficiency of the livestock and forestry sectors, as their current structure may be constraining long-term economic growth. Efforts to enhance agricultural sector performance in the short term should also be supported through better infrastructure, technology adoption, and market access. Furthermore, improving data quality and addressing statistical issues in future research could strengthen the reliability of economic modeling for policymaking.

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PPENDIX (A)

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.068646	0.9966
Test critical values:	1% level	-3.605593	
	5% level	-2.936942	
	10% level	-2.606857	

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

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.923664	0.0002
Test critical values:	1% level	-3.605593	
	5% level	-2.936942	
	10% level	-2.606857	

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

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.918432	0.9948
Test critical values:	1% level	-3.600987	
	5% level	-2.935001	
	10% level	-2.605836	

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

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.301911	0.0177
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

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

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.504186	0.5215
Test critical values:	1% level	-3.600987	
	5% level	-2.935001	
	10% level	-2.605836	

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

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.201431	0.0000
Test critical values:	1% level	-3.605593	
	5% level	-2.936942	
	10% level	-2.606857	

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

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.030124	0.2733
Test critical values:	1% level	-3.605593	
	5% level	-2.936942	
	10% level	-2.606857	

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

Null Hypothesis: D(LNGDPPPP,2) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.020508	0.0417
Test critical values:	1% level	-3.610453	
	5% level	-2.938987	
	10% level	-2.607932	

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

Date: 08/02/25 Time: 12:33
Sample (adjusted): 1983 2021
Included observations: 39 after adjustments
Trend assumption: Linear deterministic trend
Series: LNGDPPPP LMAGRI_DIF LNFORESTORY_DIF LNLIVESTOCK_DIF
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 *	0.606839	67.85184	47.85613	0.0002
At most 1 *	0.343922	31.44398	29.79707	0.0320
At most 2	0.281894	15.00645	15.49471	0.0591
At most 3	0.052229	2.092070	3.841465	0.1481

Trace test indicates 2 cointegrating eqn(s) 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: LNGDPPPP_DIF LMAGRI_DIF LNFORESTORY_DIF LNL...
Exogenous variables: C
Date: 08/02/25 Time: 12:38
Sample: 1980 2021
Included observations: 38

Lag	LogL	LR	FPE	AIC	SC	HQ
0	86.86342	NA	1.50e-07	-4.361233	-4.188855*	-4.299902
1	115.2346	49.27623*	7.87e-08*	-5.012347*	-4.150459	-4.705694*
2	125.8919	16.26648	1.07e-07	-4.731154	-3.179757	-4.179179
3	133.6524	10.21119	1.79e-07	-4.297497	-2.056590	-3.500199

* 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

Vector Error Correction Estimates
Date: 08/02/25 Time: 12:40
Sample (adjusted): 1984 2021
Included observations: 38 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LNGDPPPP_DIF(-1)	1.000000
LMAGRI_DIF(-1)	0.557911
	(0.75039)
	[0.74350]
LNFORESTORY_DIF(-1)	-1.125262
	(0.89520)
	[-1.25700]
LNLIVESTOCK_DIF(-1)	-0.882470
	(0.20445)
	[-4.31622]
C	0.061922

Error Correction:	D(LNGDPP...	D(LMAGRI...	D(LNFORE...	D(LNLIVES...
CointEq1	-0.013507	0.231833	0.015019	1.294817
	(0.01753)	(0.26706)	(0.18854)	(0.35400)
	[-0.77043]	[0.86809]	[0.07966]	[3.65772]
D(LNGDPPPP_DIF(-1))	0.088835	-0.789703	-1.183900	-13.45093
	(0.33391)	(5.08647)	(3.59098)	(6.74226)
	[0.26605]	[-0.15526]	[-0.32969]	[-1.99502]
D(LNGDPPPP_DIF(-2))	-0.037287	0.937279	-0.425537	2.194769
	(0.32766)	(4.99126)	(3.52376)	(6.61605)
	[-0.11380]	[0.18778]	[-0.12076]	[0.33173]
D(LMAGRI_DIF(-1))	0.056464	-1.652618	-0.557625	-0.215660
	(0.03117)	(0.47478)	(0.33519)	(0.62933)
	[1.81163]	[-3.48083]	[-1.66363]	[-0.34268]
D(LMAGRI_DIF(-2))	0.028719	-0.878734	-0.038606	0.513105
	(0.03190)	(0.48595)	(0.34308)	(0.64414)
	[0.90025]	[-1.80827]	[-0.11253]	[0.79657]
D(LNFORESTORY_DI...	0.000791	0.085815	-0.620669	1.619466
	(0.02847)	(0.43368)	(0.30618)	(0.57486)
	[0.02779]	[0.19787]	[-2.02717]	[2.81715]
D(LNFORESTORY_DI...	0.000427	-0.116191	-0.690172	0.019372
	(0.02802)	(0.42677)	(0.30129)	(0.56569)
	[0.01526]	[-0.27226]	[-2.29072]	[0.03424]
D(LNLIVESTOCK_DIF(...	-0.011808	0.115895	0.044467	0.206520
	(0.01163)	(0.17715)	(0.12507)	(0.23482)
	[-1.01534]	[0.65421]	[0.35554]	[0.87949]
D(LNLIVESTOCK_DIF(...	-0.008092	-0.021818	-0.022147	0.166083
	(0.00791)	(0.12052)	(0.08509)	(0.15975)
	[-1.02273]	[-0.18103]	[-0.26029]	[1.03962]
C	-0.002280	0.035247	0.018141	0.005942
	(0.00340)	(0.05180)	(0.03657)	(0.06866)
	[-0.67062]	[0.68045]	[0.49606]	[0.08653]
R-squared	0.173511	0.366797	0.361234	0.672633
Adj. R-squared	-0.092147	0.163268	0.155916	0.567408
Sum sq. resids	0.012234	2.838957	1.414983	4.988107
S.E. equation	0.020903	0.318420	0.224800	0.422074
F-statistic	0.653137	1.802184	1.759387	6.392327
Log likelihood	98.86104	-4.630826	8.599241	-15.33960
Akaike AIC	-4.676897	0.770043	0.073724	1.333663
Schwarz SC	-4.245953	1.200987	0.504668	1.764607
Mean dependent	-0.002669	0.046618	0.027613	-0.000666
S.D. dependent	0.020002	0.348103	0.244683	0.641726

Determinant resid covariance (dof adj.)	6.69E-08
Determinant resid covariance	1.97E-08
Log likelihood	121.4074
Akaike information criterion	-4.074073
Schwarz criterion	-2.177920
Number of coefficients	44