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Malaysia's Development Expenditure Effects on Gross Domestic Product by Using VECM Approach

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Abstract

The provision of public goods and services to citizens is a significant responsibility of the government. The products include schools, hospitals, roads, and other infrastructure. This investment is essential to stimulate economic growth, create job opportunities, and improve living standards. The effect of development spending on economic growth has been shown in a significant amount of existing literature. However, there are still various opinions on the impact level of development spending on economic growth. Therefore, the goal of our research is to investigate the link between Malaysia's Gross Domestic Product (GDP) and Development Expenditure (DE) based on the long-run and short-run vector error correction model (VECM) approach. The findings show that the long-term impact of GDP on development spending is positive, according to the results of the Johansen co-integration test. The long-run VECM also shows a positive correlation between GDP and government spending on development. Development spending and lag one GDP are negatively correlated. The short-run VECM shows a positive correlation between GDP and GDP lag. Unrestricted Vector Autoregressive (VAR) demonstrates that government spending on development has no discernible impact on GDP. According to the impulse response function (IRF) study, a GDP shock first has a negative effect on development spending before having a positive reaction. Although GDP might not be a strong indicator of DE in the near run, it becomes increasingly apparent over longer time frames, emphasizing the intricate relationship between macroeconomic factors and fiscal policy.

Keywords: Development expenditure, GDP; Long-run vector error correction model (VECM); Short-run VECM; Unrestricted VAR; Impulse response function (IRF) analysis; Variance decomposition (VD) analysis.

1. Introduction

Development expenditure (DE) or investment in development is essential to stimulate economic growth. According to Mulugeta (2023), economic growth could help explain how the government public spending or investing. Among the areas invested are infrastructure, education, healthcare, and technology. Infrastructure projects like roads, bridges, and public transportation systems can improve economic activity and productivity (Srinivasu & Rao, 2013). Invest can be made in all economic sectors, which cover infrastructure, manufacturing, and services. In education, this investment can lead to an improvement in human capital. Investments also create job opportunities. An increase in job opportunities will lead to a decrease in unemployment rates and an improvement in living standards (Appiah, 2017).

Zulkifli et al. (2022) conducted research on the influence of government spending on economic development in Malaysia, using the Co-integration Test and the Long Run Estimation Test. According to the study's findings, development spending has a positive significant impact on Malaysia's economic growth, whereas gross fixed capital creation, healthcare, and education have negative significant effects. Other researchers, Sidek and Asutay (2020), investigated the link between government spending and institutions that generate growth in established and emerging economies. Their findings suggest that to promote economic growth, the government should prioritize funding for development and reduce funding for non-development. The authors contend that this is untrue, pointing out that more government consumer spending and higher-quality institutions promote growth by reducing political risk, corruption, and promoting good governance.

Amusa and Oyinlala (2019) evaluated the impact of government spending on economic development in Botswana using an auto-regressive distributed lag (ARDL) bounds testing technique. According to the empirical findings, aggregate expenditure had a negative short-run and a favorable long-run influence on economic growth. When expenditure is split down, both categories have a favorable short-term impact on economic growth, but only recurrent expenditure has a positive long-run impact. According to the report, limited resources should be prioritized on productive recurring and development investment to increase productivity. Dahliah and Nur (2021) did research to examine the effects of unemployment, the Human Development Index (HDI), and GDP on poverty levels in East Luwu. The study concluded that in order to successfully alleviate poverty, the government should prioritize raising HDI, notably in education and healthcare, while simultaneously targeting greater and more equitable GDP development. The relationship between agricultural GDP and other economic indicators, such non-performing assets (NPAs), in India's agricultural sector from 1961 to 2019 is investigated by Jethwani et al. (2021) using multiple linear regression. Before creating a multi-linear prediction model to forecast the economic performance of the agricultural sector, this study uses feature engineering to examine a number of factors impacting agriculture GDP.

Real GDP forecasting is a challenging but vital task for understanding economic trends and guiding policy decisions. This challenge has been addressed utilizing a range of statistical and machine learning methods. Eissa (2020) used yearly time series data and the ARIMA model to forecast GDP per capita in Saudi Arabia and Egypt. According to the study, the best-fitting models for estimating GDP trends over the next decade were ARIMA(1,1,2) for Egypt and ARIMA(1,1,1) for Saudi Arabia. Dritsaki and Dritsaki (2021) used the ARIMA model and the Holt-Winters exponential smoothing technique to anticipate GDP per capita for five Balkan EU countries. Hamiane et al. (2024) used 75 years of quarterly GDP data to evaluate three GDP forecasting models: ARIMA, LSTM, and an ARIMA-LSTM hybrid.

In other study related to economic growth, Komain and Brahmasrene (2007) examined relationship between government expenditures and economic growth in Thailand. In this study, they applied Ordinary Least Square (OLS) Estimation. Hasnul, and Al Gifari, (2015) also studied the effect of government expenditure on economic growth in Malaysia where OLS method was applied and found that development expenditure affects the economic growth significantly. Sukma and Anwar (2021) examined how government spending, foreign debt, and foreign investment influenced Indonesia's GDP from 2005 to 2019. The data analysis approach used in this study was multiple regression analysis models with the Eviews software. It concludes that, between 2005 and 2019, government spending, foreign debt, and foreign investment all had a positive and considerable impact on Indonesia's provincial GDP.

Jainuddin et al. (2023) studied how East Kalimantan's GDP and poverty are impacted directly and indirectly by direct spending, indirect spending, domestic direct investment, and foreign direct investment. Data analysis was done using Path Analysis. The study's findings show that there are positive but not statistically significant direct impacts of domestic direct investment, and foreign direct investment, direct spending, and indirect expenditure on domestic direct investment. Poverty is significantly impacted negatively by indirect spending and GDP. Conversely, direct spending influences poverty in a favorable but insignificant way. Poverty is positively and significantly impacted by domestic direct investment. Also, through GDP, indirect spending and Foreign Direct Investment have negative and substantial indirect impacts on poverty, whereas direct spending and domestic direct investment have negative and insignificant indirect effects on poverty. In East Kalimantan, GDP and poverty are significantly impacted by variables related to direct spending, indirect spending, domestic direct investment, and Foreign Direct Investment at the same time.

The initial study of this research found that if government development expenditure increases by 1%, it will result in GDP (at constant price) rising 0.72% (p-value < 1%); Prob. (F-statistic) < 1%; and R-squared 85.7%). However, the initial finding was not valid because stationary test showed the data were stationary at 1st level. Hence, proper procedure was performed to get the correct coefficients. In order to assess the short- and long-term relationships between public expenditure and economic growth in Ethiopia, Mulugeta (2023) used the VECM system. Nwude et al. (2023) also used VECM to examine how government spending on public debt service, pensions and gratuities, health, education, and agriculture affected Nigeria's economic development during a 40-year period. Therefore, to examine the relationship between Malaysia's GDP and DE as well as future composition, the VAR and VECM system will be used in this study.

2. Methodology

Vector Autoregression (VAR) and Vector Error Correction Model (VECM) are essential econometric tools used for understanding the dynamic relationship among multiple time series. VAR models treat all variables in the system as endogenous and can capture the linear interdependencies among them. When the variables are cointegrated, indicating a long-term equilibrium relationship, the VECM is utilized, incorporating both the short-term dynamics and the long-term equilibrium.

The Augmented Dickey-Fuller (ADF) test is conducted to determine the stationarity of the time series data. Stationarity is crucial for VAR modelling as non-stationary data can lead to spurious results. The null hypothesis of the ADF test states that the series has a unit root (i.e., it is non-stationary). If the null hypothesis is rejected, the series is considered stationary. The ADF test equation is as follows:

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

where Δ is the first difference operator, y_t is the time series, α is a constant term, β is the coefficient on the time trend, γ is the coefficient of the lagged level of the time series, δ is the coefficient of the lagged differences, and ϵ_t is the error term.

Choosing the appropriate lag length is critical for the performance of VAR and VECM models. Several criteria are used to determine the optimal lag length:

Akaike Information Criterion (AIC) : $\text{AIC} = -2\ln(L) + 2k$ (2)

Bayesian Information Criterion (BIC) : $\text{BIC} = -2\ln(L) + k\ln(n)$ (3)

Final Prediction Error (FPE) : $$\text{FPE} = \frac{(n+k)}{(n-k)} \cdot \frac{\sum \epsilon_t^2}{n} \tag{4}$$

Hannan-Quinn Criterion (HQC) : $$\text{HQC} = -2\ln(L) + 2k\ln(\ln(n)) \tag{5}$$

where L is the likelihood of the model, k is the number of parameters, and n is the number of observations.

The Johansen cointegration test is applied to determine the number of cointegrating vectors among the non-stationary time series. In addition to Johansen's test treating each test variable as an endogenous variable, the test is able to find several cointegrating vectors (WAiSWA, 2023). This test involves estimating the VECM and examining the rank of the coefficient matrix. The VECM can be written as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{k-1}^{i=1} \Gamma_i \Delta Y_{t-i} + \epsilon_t \tag{6}$$

where Y_t is a vector of non-stationary time series, Π is the long-run impact matrix, and Γ_i are the short-run impact matrices. The rank of Π determines the number of cointegrating relationships, tested using trace and maximum eigenvalue statistics.

Granger causality tests are performed to identify whether one time series can predict another. The null hypothesis states that the lags of one variable do not Granger-cause the other variable. If null hypothesis is rejected, it implies that past values of one variable contain information that helps predict the other variable. Impulse Response Functions (IRF) trace the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. IRFs are used to analyze the dynamic behavior of the system in response to external shocks, while Forecast Error Variance Decomposition (FEVD) provides information on the proportion of the movements in a variable due to its own shocks versus shocks to other variables in the system. This decomposition helps in understanding the relative importance of each shock in the system.

Diagnostic tests are essential to validate the model's assumptions and ensure the reliability of the results. Common diagnostic tests include autocorrelation test, which check for autocorrelation in the residuals using the Breusch-Godfrey Serial Correlation LM Test, normality test, which assess the normality of residuals using the Jarque-Bera test, and heteroscedasticity test, which detect heteroscedasticity in the residuals using the Breusch-Pagan-Godfrey Heteroskedasticity test.

The Jarque-Bera (JB) test is used to check whether the residuals of a model are normally distributed. It tests the null hypothesis that the residuals are normally distributed against the alternative hypothesis that they are not. The JB test statistic is given by:

$$\text{JB} = n\left(\frac{S^2}{6} + \frac{(K-3)^2}{24}\right) \tag{7}$$

where n is the number of observations, S is the sample skewness, and K is the sample kurtosis. The JB statistic follows a chi-squared distribution with 2 degrees of freedom. If the computed JB statistic is greater than the critical value from the chi-squared distribution, the null hypothesis of normality is rejected.

The Breusch-Godfrey LM test is used to detect the presence of serial correlation in the residuals of a regression model. The null hypothesis is that there is no serial correlation up to order p, against the alternative hypothesis that there is serial correlation. The LM test statistics is given by

$$\text{LM} = nR^2 \tag{8}$$

where n is the number of observations and R^2 is the coefficient of determination from the auxiliary regression. The LM statistic follows a chi-squared distribution with p degrees of freedom. If the LM statistic is greater than the critical value from the Chi-squared distribution, the null hypothesis of no serial correlation is rejected.

The Breusch-Pagan-Godfrey (BPG) test is used to detect heteroskedasticity in the residuals of a regression model. The null hypothesis is that the residuals have constant variance (homoscedasticity), against the alternative hypothesis that the residual variance depends on the explanatory variables (heteroskedasticity). The BPG test statistics is $BPG = \frac{nR^2}{2}$. The BPG statistic follows a Chi-squared distribution with k degrees of freedom, where k is the number of regressors. If the BPG statistic is greater than the critical value from the chi-squared distribution, the null hypothesis of homoscedasticity is rejected.

3. Results and Discussion

The data used in this study consists of Malaysia's government development expenditure (DE) and GDP measured at constant prices, spanning annual data from 1990 to 2022. These data were collected from Department of Statistics Malaysia (DOSM), and throughout the analysis period, these two key indicators were subjected to scrutiny to discern patterns and trends within Malaysia's economic landscape. The graph for GDP and DE is plotted in Figure 1 and Figure 2, respectively. The analysis in this study is run by using Phyton software.

Table 1. ADF test for GDP and DE

ADF Test on GDP		ADF Test on DE	
Test Statistics	: - 5.7009	Test Statistics	: 0.9946
p-value	: 0.0000	*p*-value	: 0.9942
Critical Values (1%)	: - 3.5629	Critical Values (1%)	: - 3.5629
Critical Values (5%)	: - 2.9190	Critical Values (5%)	: - 2.9190

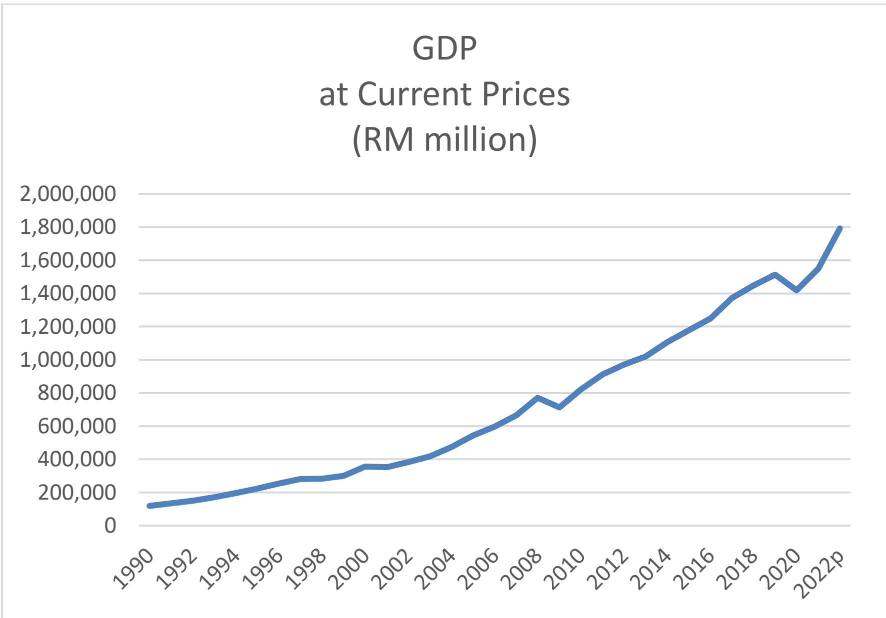

Figure 1. GDP plot at current price (in RM million)

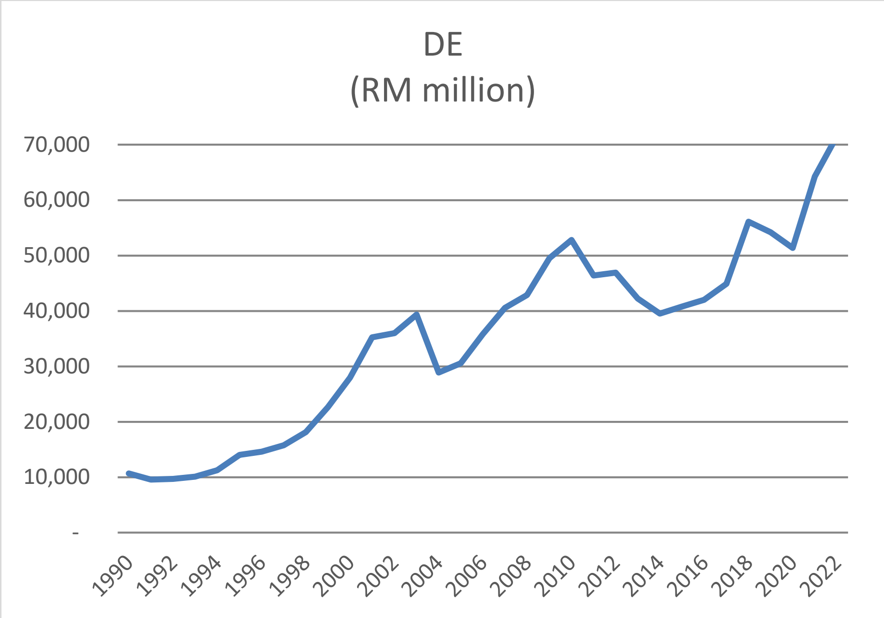

Figure 2. DE plot (in RM million)

Based on Table 1, the test statistics for GDP is -5.7009, which is lower than critical values of 1% and 5%, and the *p*-value is low, suggesting that we can reject the null hypothesis, indicating that the GDP series is stationary. While for DE, the test statistics is 0.9946, which is higher than the critical values, suggesting that the null hypothesis is unable to be rejected. The *p*-value (0.9942) supports the non-rejection of the null hypothesis, indicating that the DE series is non-stationary. The ADF test is analysed for differenced data of DE series and the result is shown in Table 2. The test statistics is -5.8163, lower that the critical values of 1% and 5%, suggesting strong evidence against the null hypothesis. The *p*-value of 0.0000 indicates that the null hypothesis of non-stationarity for the differenced of DE series is rejected and the series is now stationary. Hence, the GDP exhibited stationary at level and DE exhibited stationarity at the first difference.

Table 2. ADF Test for differenced DE

ADF Test on differenced DE	
Test Statistics	: - 5.8163
p-value	: 0.0000
Critical Values (1%)	: - 3.5656
Critical Values (5%)	: - 2.9201

Next is to identify the optimal lag length for the VAR model. The results of the lag order selection for the VAR model are summarized in Table 3 which includes several information criterions, including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Final Prediction Error (FPE) and Hannan-Quinn Information Criterion (HQIC).

Table 3. Information criterion for lag length

VAR Order Selection (* highlights the minimums)

	AIC	BIC	FPE	HQIC
0	19.59	**19.68***	**3.218e+08***	**19.62***
1	19.67	19.93	3.490e+08	19.76

2	19.76	20.19	3.822e+08	19.91
3	19.94	20.55	4.598e+08	20.15
4	20.12	20.90	5.580e+08	20.40
5	20.22	21.17	6.250e+08	20.55
6	20.15	21.29	6.022e+08	20.55
7	20.31	21.61	7.276e+08	20.77
8	20.35	21.83	7.977e+08	20.87
9	20.32	21.98	8.299e+08	20.90
10	20.16	21.99	7.765e+08	20.81
11	20.18	22.19	8.898e+08	20.89
12	19.93	22.11	8.087e+08	20.70
13	19.56	21.92	6.940e+08	20.39
14	19.55	22.07	9.130e+08	20.44
15	**19.05***	21.75	8.420e+08	20.00

Based on Table 3, the minimum value of AIC is at lag 15, and for BIC, FPE, and HQIC, the minimum number of lags is at lag 0. The output suggests using 15 lags based on the AIC criterion, which seems excessively high given the total number of observations (about 53 years). Using such a high number of lags would overparameterize the model due to our limited data points. Typically, lower lag lengths like those recommended by BIC, FPE, and HQIC (which suggest 0 lags) might be more realistic. For practical purposes, and to avoid overfitting, a more conservative approach for the VAR model is used. The VAR model with 1 to 3 lags is fitted and checked for the model's stability and performance (as shown in Table 4).

Table 4. Stability testing

No of lags	Stability
1	True
2	True
3	True

All VAR models with 1 to 3 lags are stable. Since all are stable, the model is proceed with the smallest lag that still maintains stability to avoid overfitting. VAR model with 1 lag is used for further analysis.

Results for equation GDP

	coefficient	std. error	t-stat	prob
const	8.607127	1.822822	4.722	0.000
L1.GDP	0.082865	0.145750	0.569	0.570
L1.DE	0.000062	0.000139	0.443	0.658

Results for equation DE

	coefficient	std. error	t-stat	prob
const	2682.732215	1952.574844	1.374	0.169
L1.GDP	-216.651828	156.124931	-1.388	0.165
L1.DE	1.134310	0.149122	7.607	0.000

```
===========================================================================

Correlation matrix of residuals
            GDP        DE
GDP    1.000000 -0.028403
DE    -0.028403  1.000000
```

Figure 3. Results for VAR(1) model

Based on the findings in Figure 3, the GDP equation indicates a statistically significant constant term, and the average growth rate of GDP is around 8.60%, while the differenced DE has a significant average increase, suggesting changes over time. The residuals between GDP and differenced DE show a very low negative correlation (-0.028403) indicating almost no linear relationship in the residuals of the two series. Based on the VAR model results (in Figure 3), Johansen co-integration checking can be considered to see whether a VECM model might be applicable.

```
           Trace Statistic        5% Critical        1% Critical
r=0            27.50767965           15.4943            19.9349
r<=1            0.40891661            3.8415             6.6349

        Max Eigen Statistic   Max 5% Critical    Max 1% Critical
r=0            27.09876304            14.2639            18.5200
r<=1            0.40891661             3.8415             6.6349
```

Figure 4. Johansen Co-integration Test

The Johansen co-integration test results in Figure 4 include two statistics: the trace statistics and Max Eigen statistics. The value in trace statistic for the first hypothesis ($r=0$ against $r>0$) is 27.5077 is greater than both critical values, suggesting a rejection of the null hypothesis of no co-integration in favor of at least one cointegrating relationship. While for the maximum Eigenvalue statistic, the value is 27.0988, also greater than the critical values, supporting the existence of at least one cointegrating relationship. Both tests indicate that there is at least one cointegrating relationship between GDP and DE, suggesting a long-term equilibrium relationship between these variables.

Given the presence of co-integration, it is appropriate to model the short-term dynamics through a Vector Error Correction Model. This will allow us to capture both the short-term dynamics and the adjustment towards long-term equilibrium. However, before proceeding with VECM model, Granger causality test is conducted to explore the causal relationship between GDP and DE.

```
Granger Causality
number of lags (no zero) 1
F test:         F=5.2229  , p=0.0267
chi2 test:   chi2=5.5426  , p=0.0186

number of lags (no zero) 2
F test:         F=3.8224  , p=0.0291
chi2 test:   chi2=8.4758  , p=0.0144

number of lags (no zero) 3
F test:         F=2.3120  , p=0.0895
chi2 test:   chi2=8.0650  , p=0.0447
```

Figure 5. Granger Causality test

Granger causality test is able to understand if past values of one variable are useful in predicting the future values of another (refer to Figure 5). For lag 1, the *p*-value for F-test is 0.0267, and Chi-squared test is 0.0186, which suggests a significant Granger causal relationship at the 5% significance level, indicating that one series can help predict the other at lag 1. Similarly, at lag 2, the results indicate a significant causal relationship, where the *p*-value for *F*-test and Chi-squared test is 0.0291 and 0.0144, respectively, reinforcing the findings from lag 1. However, at lag 3, the *F*-test is not significant at the 5% level (*p*-value = 0.0895), but the Chi-squared test is marginally significant at the 5% level (*p*-value = 0.0447). These results generally suggest that there is evidence of causality between the series, particularly at lags 1 and 2. This indicates that past values of GDP and DE can help in forecasting future values of each other.

With co-integration confirmed and causality established, it's appropriate to proceed with the VECM. This model will allow considering both the long-term equilibrium relationship and the short-term dynamics between GDP and DE.

```
Det. terms outside the coint. relation & lagged endog. parameters for equation
GDP
=============================================================================
                 coef    std err
-----------------------------------------------------------------------------
L1.GDP        -0.2641      0.132
L1.DE          0.0002      0.000

Det. terms outside the coint. relation & lagged endog. parameters for equation
DE
=============================================================================
                 coef    std err
-----------------------------------------------------------------------------
L1.GDP      -154.3669    120.342
L1.DE          0.2381      0.140

                Loading coefficients (alpha) for equation GDP
=============================================================================
                 coef    std err
-----------------------------------------------------------------------------
ec1           -0.2181      0.093

                 Loading coefficients (alpha) for equation DE
=============================================================================
                 coef    std err
-----------------------------------------------------------------------------
ec1           96.8366     85.380

          Co-integration relations for loading-coefficients-column 1
=============================================================================
                 coef    std err
-----------------------------------------------------------------------------
beta.1         1.0000          0
beta.2     -1.743e-05   8.57e-05
```

Figure 6. VECM modelling

The coefficients of the VECM model are presented in Figure 6. For GDP equation, GDP lag 1 (-0.2641) indicates that past GDP is negatively affects current GDP after adjusting for co-integration, while DE lag1 (0.0002) suggesting a weak influence of the past DE towards the current GDP. Additionally, for DE equation, GDP lag 1 (-154.367) implies that past GDP has negative, but not statistically significant, effect on the current DE, while the DE lag 1 (0.2381) indicating a positive effect of past DE on the current DE, marginally significant.

In terms of loading coefficient, these coefficients, which is the error correction term (ECT), represent the speed of adjustment back to the long-run equilibrium after a short-term shock. The coefficient is -0.2181 for GDP equation, suggesting that deviations from long-run equilibrium are corrected by a negative adjustment in GDP. While for DE equation, the coefficient of 96.8366 indicates an adjustment mechanism insignificant. The coefficients in the co-integration relation are normalized on GDP (set to 1.0000 for GDP) and are very small for DE (-0.00001743), which might imply that DE adjustments have a negligible long-term impact on GDP in this model. The VECM indicates that GDP adjusts to maintain long-term equilibrium following shocks, with a statistically significant error correction mechanism. The effects of past values of DE on GDP and vice versa are present but generally weak and not always statistically significant.

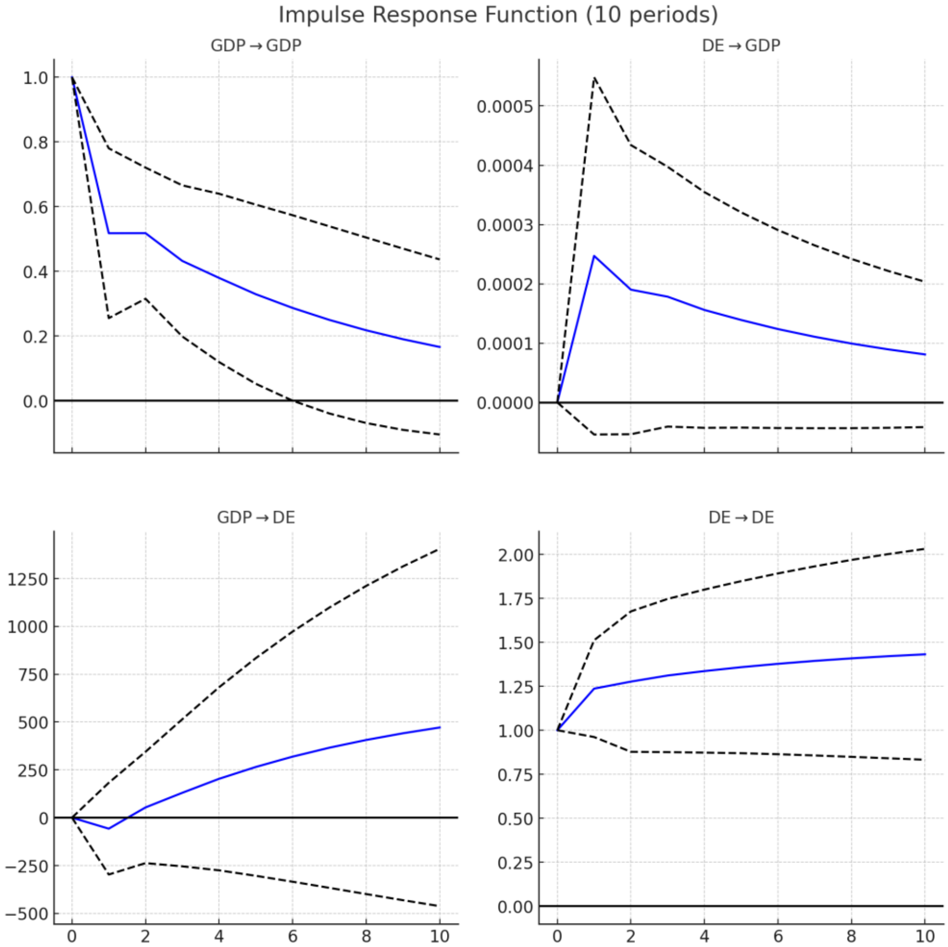

Figure 7. Impulse Response Function on GDP and DE

Impulse Response Function (IRF), as presented in Figure 7, illustrates how a one-unit shock to GDP or DE affects the values of these variables over 10 periods. The dynamic interaction between DE and GDP can be elucidated through the impulse response function. Specifically, in response to a shock to GDP, it has a minor positive effect on the DE initially, which then fades. Conversely, a shock to DE seems to have a negligible impact on GDP. The response is relatively smaller and stabilizes quickly, showing that shocks in development expenditure changes might have a lesser and short-lived impact on GDP. In response of GDP to its own shock, there is a negative immediate response, which stabilizes over time. This suggests that a positive shock in GDP might lead to a short-term decline followed by a stabilization and have a prolonged effect on itself. In response of DE to its own shock, the DE shows a relatively small response to its own shocks, indicating it has a limited self-correcting mechanism. These responses reflect the dynamics and interactions between GDP growth and development expenditure, illustrating their short to medium-term adjustments after experiencing shocks.

Table 5. Variance Decomposition Analysis

Variance Decomposition of DE			
Period	**S.E.**	**DE**	**GDPCT**
1	0.108	100.0	0.000
2	0.163	95.2	4.712
3	0.187	94.3	5.689
4	0.198	94.5	5.402
5	0.202	94.8	5.193
6	0.204	94.5	5.480
7	0.206	93.7	6.282
8	0.208	92.5	7.481
9	0.210	91.0	8.931
10	0.212	89.4	10.506

The variance decomposition analysis, as delineated in Table 5, provides valuable insights into the short- and long-run dynamics of the relationship between DE and GDP. In the short run, particularly in the third month, shocks to DE account for a substantial portion, amounting to 94.3%, of the variation in its own fluctuations (own shock). Conversely, shocks to GDP only contribute to a modest 5.7% fluctuation in DE during this period. However, in the long run, the impact of GDP shocks becomes more pronounced, with a 10.5% contribution to the variance of DE. This observation underscores the weak endogeneity of DE to GDP dynamics, indicating a relatively limited predictive capacity of GDP for government spending patterns. These findings suggest a nuanced relationship between GDP and DE, wherein the latter demonstrates a certain degree of independence from short-term GDP fluctuations but exhibits a higher susceptibility to long-term GDP dynamics.

Although, GDP may not serve as a robust predictor of DE in the short term, its influence becomes more discernible over extended time horizons, highlighting the complex interplay between fiscal policies and macroeconomic variables. Further exploration of these dynamics can provide valuable insights for policymakers seeking to formulate effective strategies to promote sustainable economic growth and development.

Table 6. Diagnostic check (*p*-value) for VAR and VECM model

	VAR(1)	**VECM**
Jarque Bera Normality test	0.550	0.355
Breusch-Godfrey Serial Correlation LM Test	0.476	0.279
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.073	0.084

The VAR(1) and VECM models described above successfully passed all the diagnostic tests, as shown in Table 6, demonstrated by the result of *p*-values exceeding 5%, as indicated by the Residual Normality test, the Breusch-Godfrey Serial Correlation LM Test, and the Heteroskedasticity Test, specifically the Breusch-Pagan-Godfrey examination. These diagnostic assessments affirm the robustness and validity of the model's statistical assumptions and framework, thereby enhancing the reliability of the analytical results derived from it.

4. Conclusion

In conclusion, this research explores the intricate relationship between GDP and government development expenditure through various econometric analyses, including Johansen co-integration tests, Vector Error Correction Models (VECM), and Impulse Response Function (IRF) analyses. The findings reveal that while government development expenditure does not significantly explain GDP fluctuations in the short term, GDP has a long-term positive impact on government spending patterns. The analysis indicates a low negative correlation between the residuals of GDP and government expenditure changes, suggesting almost no linear relationship. The co-integration tests confirm a long-term equilibrium relationship, where GDP adjusts to maintain equilibrium following shocks, with a significant error correction mechanism. IRF analysis shows that GDP shocks initially negatively impact government expenditure but have a subsequent positive effect, whereas shocks in government spending have minimal influence on GDP. Variance decomposition analysis highlights that GDP is not a strong predictor of government expenditure in the short run, but its influence grows over time, demonstrating the complex interplay between economic growth and fiscal policies. These findings offer critical insights for policymakers in designing strategies to foster sustainable economic growth and development. While GDP might not be a strong indicator of DE in the near run, it does have a noticeable impact over longer time frames, indicating the intricate relationship between macroeconomic factors such as gross domestic product, inflation, economic growth, and unemployment figures and fiscal policy. All these dynamics factors can be considered for further investigation. More methodologies from previous studies discussed in Introduction part can be applied such as ARDL, OLS, Path Analysis and many other to study the impact on DE.

5. References

Amusa, K., & Oyinlola, M. A. (2019). The effectiveness of government expenditure on economic growth in Botswana. *African Journal of Economic and Management Studies*, 10(3), 368-384.

Appiah, E. N. (2017). The effect of education expenditure on per capita GDP in developing countries. *International Journal of Economics and Finance,* 9(10), 136-144.

Dahliah, D., & Nur, A. N. (2021). The influence of unemployment, human development index and gross domestic product on poverty level. *Golden Ratio of Social Science and Education*, *1*(2), 95-108.

Dritsaki, M., & Dritsaki, C. (2021). Comparison of the Holt-Winters exponential smoothing method with ARIMA models: Forecasting of GDP per capita in five Balkan countries members of European Union (EU) post COVID. *Modern Economy*, *12*(12), 1972-1998.

Eissa, N. (2020). *Forecasting the GDP per Capita for Egypt and Saudi Arabia Using ARIMA Models. Research in World Economy, 11 (1), 247-258*.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 251-276.

Hasnul, & Al Gifari (2015): "*The effect of Government Expenditure on Economic Growth: the case of Malaysia"*. Munich Personal RePEc Archive Paper No. 71254.

Hamiane, S., Ghanou, Y., Khalifi, H., & Telmem, M. (2024). Comparative analysis of LSTM, ARIMA, and hybrid models for forecasting future GDP. *Journal homepage: http://iieta. org/journals/isi*, *29*(3), 853-861.

Jainuddin, J., Amalia, S., & Awaluddin, M. (2023). The Effect Of Government Expenditure And Investment On Gross Regional Domestic Product And Poverty In East Kalimantan Province. *International Journal of Economics, Business and Accounting Research (IJEBAR)*, 7(2), 821-829.

Jethwani, B., Dave, D., Ali, T., Phansalkar, S., & Ahhirao, S. (2021). Indian agriculture GDP and non performing assets: A regression model. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1042, No. 1, p. 012007). IOP Publishing.

Komain, J., & Brahmasrene, T. (2007). The relationship between government expenditures and economic growth in Thailand. *Journal of Economics and Economic Education Research*, 8(1), 93-102.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

Mulugeta Emeru, G. (2023). Effect of public expenditure on economic growth in the case of Ethiopia. *The Scientific World Journal*, 2023.

Nwude, C., Nwaeze, C., & Nwude, C. A. (2023). Government expenditure and economic growth: evidence from the critical sectors in an emerging economy. *Qeios* ID: CBTRTL· https://doi. org/10.32388/CBTRTL.

Sidek, N. Z. M., & Asutay, M. (2021). Do government expenditures and institutions drive growth? Evidence from developed and developing economies. *Studies in Economics and Finance*, 38(2), 400-440.

Srinivasu, B., & Rao, P. S. (2013). Infrastructure development and economic growth: Prospects and perspective. *Journal of business management and social sciences research*, 2(1), 81-91.

Sukma, I., & Anwar, K. (2021). The Effect Of Foreign Investment, Government External Debt, And Government Expenditure On Gross Domestic Product In Indonesia. *Journal of Malikussaleh Public Economics*, 4(1), 20-29.

Tsay, R. S. (2005). *Analysis of financial time series*. John wiley & sons.

WAİSWA, D. (2023). Role of macroeconomic indicators in Uganda’s food price inflation: a VECM approach. *Equinox Journal of Economics Business and Political Studies*, 10(2), 111-127.

Zulkifli, S. A. M., Effendi, N. A., & Shafai, N. A. (2022). The Impact of Government Expenditure on Economic Growth in Malaysia. *Advances In Business Research International Journal*, 8(1), 21-32.