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Article

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Dynamic Effects of Malaysia's Government Spending on Environment Quality: Bridging STIRPAT and EKC Hypothesis

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ABSTRACT

This paper investigates how government spending (GSE) affects the environmental quality proxy by CO_2 emissions in Malaysia over the 1978–2020 period. For that purpose, the STIRPAT model in the EKC framework are applied. The F-bounds test is applied to assess the cointegration relationship's existence. The ARDL model is used to measure the short-run and long-run environmental elasticities, and the VECM Granger causality is used to estimate the direction of the causality relationship. Empirical results show a cointegration relationship among environmental quality, GDP, population, and Malaysia's GSE. The findings provide strong support for Malaysia's EKC presence, and the GSE significantly contributes to reducing environmental sustainability. The results show the short-run unidirectional Granger causality running from CO_2 emissions, GDP, and population to GSE at the 1 percent significance levels. Also, this study reveals the long-run unidirectional Granger causality running from CO_2 emissions and population to GSE and GDP at least at 10 percent significance level; and the bidirectional causality between GSE and GDP at least at 10 percent significance level as well. The result implies that the increasing demand for regulatory and protective functions represented by GSE are needed to sustain the increasing level of economic wealth, environment, and communities.

Keywords: Environmental Sustainability, EKC, Government Spending, Dynamic Relationship, Causality, Malaysia
JEL Classifications: O1, O2, Q5

1. INTRODUCTION

Since the early 1990s, economists and environmentalists have extensively investigated economic growth and environmental quality. Several studies (Zhang et al., 2021; Sharif et al., 2020; Suki et al., 2020; Balsalobre-Lorente et al., 2019; Wang et al., 2016; Dogan and Turkekul, 2016; Ozturk and Al-Mulali et al., 2015) reported most of the country's economic growth achievements lead to the cost of environmental pollution. The Intergovernmental Panel on Climate Change (IPCC) indicates the necessary steps to reduce the amount of Greenhouse Gas (GHG) emissions, particularly CO_2 emissions, by 40–70% compared to a decade ago. At the end of the 21st century, IPCC aimed to reduce GHG emissions to zero percent. The failure to achieve this goal will destroy earth biodiversity and socio-economic systems. Consequently, the world will face various risks (such as heatwaves, droughts, floods, food crises, and damages to human, social and economic systems), making this world far from sustainable[1]. Countries in the early stages of development and demonstrating high economic growth rates are often associated with environmental degradation (Chen and Taylor, 2020). For the Malaysian scenario, the time trend of Malaysia's economic activities and the status of environmental quality represented by CO_2 emissions are pictured in Figure 1.

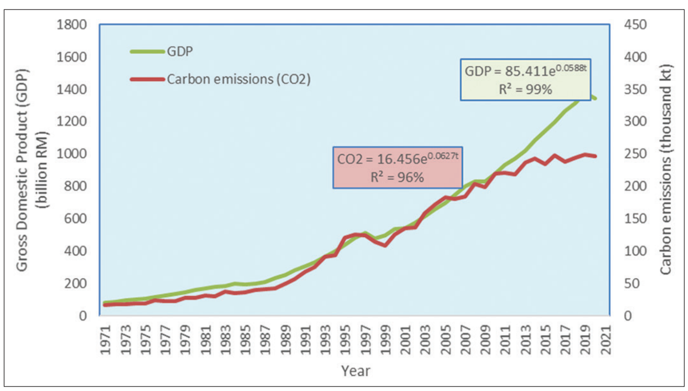
Figure 1 clearly shows the GDP and CO_2 emissions growth by 5.9 % and 6.3 %, respectively, for the 1971–2020 period. For

1 Sustainable development thinking and planning since the late-1980s has assumed an inverse relationship between the level of economic development and the depth of environmental impacts (Chen and Taylor, 2020).

instance, the escalation of GDP is paired with the disruption of environmental pollution represented by CO_2 emissions sequentially becoming a burden to environmental sustainability. Many studies investigated the relationship between GDP and environmental pollution. For example, Bekhet et al. (2020), Begum et al. (2015), Al-Mulali et al. (2015), Ozturk and Al-Mulali (2015) investigate the trade-off between carbon dioxide emissions and GDP in the Environmental Kuznets Curve (EKC) framework. Other studies investigated the role of urbanization in determining the interaction between carbon emission and GDP (Sadorsky, 2014; Martinez-Zarzosa and Maruotti, 2011; He et al., 2017; Ozturk and Al-Mulali, 2015; Bekhet and Othman, 2017). Moreover, Shahzad et al. (2017), Mrabet and Alsamara (2017), Dogan and Ozturk (2017) considered the role of energy consumption and many more.

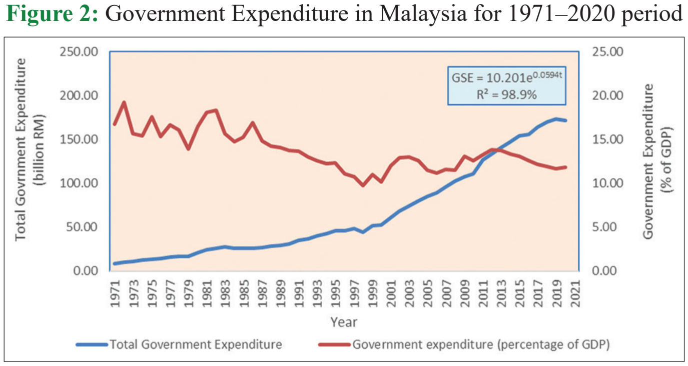
On the other hand, fiscal policy plays a crucial role in the accumulation and allocation of an economy's resources (López et al., 2010). In Malaysia, government spending (GSE) comprises 11%–20% of the GDP (Figure 2). The GSE includes all current government expenditures for the purchase of goods and services (including employee compensation), education, R and D, and national defense and security (Ministry of Finance, 2020). The GSE may affect environmental quality in several ways (Hua et al., 2018; Islam and Lopez, 2013; Lopez et al., 2011). First, spending on education tends to raise the share of cleaner human capital. Second, the GSE on research and development (R and D) can result in a higher adoption rate of cleaner technology. Third, the increase in GSE for operating services such as compensation and salary of civil servants could lead to higher demand for environmental

Figure 1: The trend of GDP and Carbon Dioxide Emission for the 1971–2020 period



Source: World Development Indicator (2021)

Figure 2: Government Expenditure in Malaysia for 1971–2020 period



Source: World Development Indicator (2021)

products and services. The government has recently pump-up their allocation on GSE (RM20 billion stimulus package) to stabilize the economic activities and support society's welfare due to the COVID-19 pandemic[2] (ISIS, 2020). Many studies successfully verified the function of GSE on GDP (economic activities), but the function of GSE to improve the environmental quality is still limited, mainly for cases in Malaysia. Against this backdrop, this study fills this gap in this area by linking the effect of GSE on environmental quality in Malaysia.

This study inclines to clarify to what extent the GSE influences environmental quality. Also, it contributes to the growing literature on fiscal policy and environmental quality, mainly for cases in Malaysia. The results have significant practical policy implications precisely at the time Malaysia aimed for a sustainable development goal.

The remaining study is structured as follows: Section 2 presents the review of the related theory, earlier empirical work on the nexus between environmental quality and government spending, and hypotheses development; Section 3 explains the formulation of the model, a method used in the study and provides details about the data sources; Section 4 analyzes and discusses the results, and Section 5 concludes the study with policy implications.

2. THEORETICAL BACKGROUND, PAST STUDIES, AND HYPOTHESES

2.1. Theoretical Background

Generally, the Malaysia GSE was allocated for two significant purposes: operation purposes and development purposes (Bekhet and Othman, 2012). The rationale behind this policy was to upgrade and improve productivity and impede long-term economic growth potential. In the 2020 budget, a total of RM297 billion (18.4% of GDP) was allocated, of which RM241 billion (81.1%) for operating expenditure while the balance RM56 billion for development expenditure (Ministry of Finance, 2020). The largest components of operating expenditure are payments, subsidies, supplies, and services. The factor contributing to higher allocation for payments is due to annual salary increments. Supply and services are the second top operation expenditure due to higher outlays for repairs and maintenance and an allocation for professional services. On the other hand, the development expenditure was channeled to promote economic development, upgrade necessary rural infrastructure, and enhance living standards.

Theoretically, government expenditure can affect environmental quality in several ways (Lopez et al., 2011; Lopez and Islam, 2008). The first is through scale effect. The scale effect is when the increase in government spending generates more economic activities and creates more pollution. The second is through the

2 The COVID-19's intensely damaging effects of the Malaysia macroeconomy and economic welfare of the societies. The government of Malaysia imposed the PRIHATIN package purposely to support income during the moving control order (MCO) and to kick-start the economy after the restrictions are lifted (ISIS, 2020).

composition effect. The composition effect is the consequences of better education level and skill that raise the share of cleaner human capital-intensive activities relative to the share of dirtier physical capital-intensive activities. Third, more fiscal spending on R and D can result in a higher adoption rate of cleaner technology by firms, reducing the pollution-output ratio (a technique effect). Finally, private income raised by public-good expenditures leads to higher demand for a cleaner environment and more stringent regulations (an income effect).

2.2. Past Studies

Existing empirical studies on the effect of GSE on environmental quality/pollution are still limited. Lopez and Palacios (2010) examine whether GSE makes the environmental quality cleaner in Europe. The results conclude that total government expenditure has a negative relationship with air pollution. Whereas Lopez et al. (2011) specify the purpose of GSE, which is the reallocation of GSE towards social and public goods, and revealed both allocations significantly reduce the sulfur dioxide (SO_2) emissions. However, increasing the total government size without changing its orientation has a non-positive impact on environmental quality. Halkos and Paizanos (2013) investigated how GSE affected a different kind of pollution and revealed that GSE negatively affects SO_2 and a non-linear relationship between government expenditure and CO_2 emissions. Precisely, at the low-income level, the increase in GSE scales down the CO_2 emissions and scales up at a high-income level. Similar to Halkos and Paizanos (2013), Zhang et al. (2017) investigate the impact of GSE on emissions of three typical pollutants in China. They found that the total effect of GSE on SO_2, soot, and chemical oxygen demand (COD) are different. The effect on SO_2 is negative, while soot and COD are inverted U-shaped and U-shaped, respectively. Also, the proportion of GSE does not have a significant effect on pollution emissions. Huang (2018) pays attention to SO2 emissions and measures the change in these emissions due to the changes in China's government spending. This study's main findings are that SO_2 emissions can be effectively reduced by government spending on environmental protection. Xie and Wang (2019) evaluated the efficacy of government spending on air pollution control in Beijing, China, and found that government expenditure has a noticeable influence on the improvement of air quality. Based on the above review, this study can conclude that the interaction between GSE is different according to pollution types.

Furthermore, Adewuyi (2016) examined the impact of GSE on aggregate and sectoral CO_2 emissions in world economies during the 1990–2015 period and found the rise in GSE raised the CO_2 emission. Halkos and Paizanos (2016) analyzed the effect of fiscal policy on CO_2 emissions in the USA and discovered the GSE increase reduces emissions from production and consumption. Hua et al. (2018) investigated if education spending affects air pollution in China. The regional analysis demonstrates that the effects of education spending are relatively pervasive, while the effects of R and D spending are scarcely identified. The environmental return of education spending appears to be the highest in the eastern cities and diminishes as we move towards the inland area. Insofar, most of the studies mentioned above were tested in China, Europe, and the USA. While in Malaysia, the relationship study between these two variables is still at the infant stage. This study intends to contribute to the existing literature by first investigating the existence of a dynamic relationship between CO_2 emissions (proxy to environment quality) and GSE. This study's uniqueness holds due to dynamic analysis by assuming that the effect of GSE on environmental quality is not instantaneous. So, it needs time lags to influence CO_2 emissions. Instead of that, the current study is the author's first attempt to verify the role and the strength of GSE to represent technology (with technological effect).

Based on the background theory, past studies, and to get to the bottom of this study aim, the following hypotheses are formulated:

- H_1: Significant dynamic relationship exists between environmental quality and its determinants in Malaysia
- H_2: Environmental quality has a significant inverted U-shaped relationship with economic activities
- H_3: Environmental quality has a significant relationship with GSE in Malaysia
- H_4: Significant long-run causality exists between environmental quality and GSE in Malaysia
- H_5: Significant short-run causality exists between environmental quality and GSE in Malaysia.

3. EMPIRICAL MODEL, METHODOLOGY, AND SOURCE OF DATA

3.1. Development of a Model

Past studies have widely used the Environmental Impacts of Population, Affluence, and Technology (IPAT) identity developed by Ehrlich and Holdren (1971) to capture the impact of human activities on environmental destruction (Bahera and Dash, 2017; Riti et al., 2017; Wang et al., 2013; York et al., 2003; Stern et al., 1996). IPAT identity can be stated in Equation (1)

$$I = PAT \tag{1}$$

I refer to environmental impact, P, A, T refers to demographic effect (population), economics effect (affluence), and technology effect. However, the model has a generalizability issue as it captures the impartial effect of one factor while keeping other factors constant (Khan et al., 2018; Wang et al., 2013). Dietz and Rosa (1997) addressed the aforementioned econometric issues of the IPAT model. They modified and transformed into a dynamic model known as Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. Equation (2) formalizes the basic STIRPAT model in exponential form.

$$I = \alpha_1 P^{\alpha 2} A^{\alpha 3} T^{\alpha 4} \varepsilon \tag{2}$$

where the α_is [i=1,2,3,4] are coefficients. It transformed into a linear form by applying a logarithm[3] technique (Zhang and Zhao, 2019), as shown in Equation (3).

3 Data is transformed in logarithmic form as it provides efficient, better and consistent results. Instead of that, the logarithmic form of the data does not only make the data smooth but also overcome the heteroskedasticity issue (Ahmad & Du, 2017).

$$\ln I_t = \ln\alpha_1 + \alpha_2 \ln P_t + \alpha_3 \ln A_t + \alpha_4 \ln T_t + \varepsilon \quad (3)$$

Where I denote environmental impacts proxy by CO_2 emissions, P represents the population of a country. A indicates affluence represented by GDP, T shows technology represented by GSE. Theoretically, there are many reasons to use the GSE to represent the technology. Its ability to upgrade and improve productivity, impede long-term growth, enhance the standard of living, change human behavior and mentality to adopt environmentally friendly technology, and reduce the pollution-output ratio. The α_i [i=1,2,3,4] are the elasticities of the explaining variables that also indicate a monotonic positive impact on the CO_2 emissions, vice versa. The larger the elasticity coefficient, the enormous is the impact on CO_2 emissions (Xu et al., 2020). Finally, the ε is the error term of the model, implying the stochastic process.

Equation [3] does not permit the information on EKC relationship between CO_2 emissions and GDP, but is limited to measure the linear relationship via monotonic effect. Thus, Equation (3) has been altered by adding up A^2, as shown in Equation (4), and further enable this study to measure the non-monotonic effect of affluence suggested by EKC on the environment issue (Grossman and Krueger, 1995; Riti et al., 2017).

$$\ln I_t = \ln\alpha_1 + \alpha_2 \ln P_t + \alpha_3 \ln A_t + \alpha_5 \ln A^2_t + \alpha_4 \ln T_t + \varepsilon \quad (4)$$

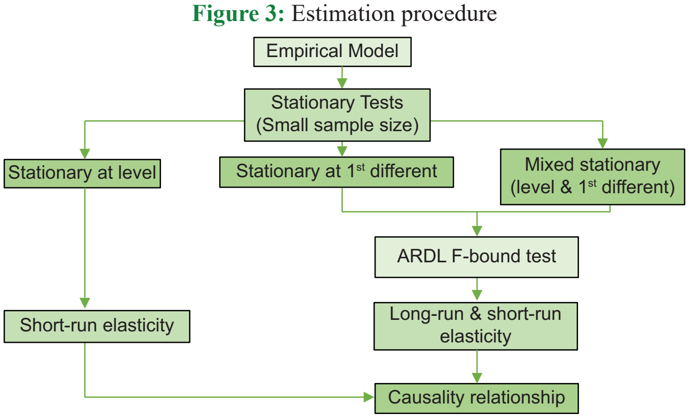
In Equation [4], the EKC hypothesis via the inverted U-shaped relationship between CO_2 emissions and GDP exists if $\alpha_3 > 0$; $\alpha_5 < 0$. On the contrary, if $\alpha_3 < 0$; $\alpha_5 > 0$, a U-shaped relationship between CO_2 emissions and GDP will be applied.

Furthermore, Figure 3 listed the steps of the study's estimation procedure.

3.2. Stationary and Cointegration Tests

Various unit root tests are a prerequisite because simple OLS techniques lead to spurious results via biased estimated parameters (Bloch et al., 2015; Chen et al., 2007). This condition could spoil the research outcome because it makes it difficult to effectively explain the economic reality (Xu and Lin, 2017; Ewing et al., 2007). In this paper, the Ng-Perron test (Ng and Perron, 2001) is utilized to observe each variable's stationarity condition before embarking on OLS. According to Shahbaz et al. (2013), this test is suitable for a small sample size with no structural break. The stationarity test could give the researcher an idea of the adequate model in a future phase and signal a shock or structural break in the time series (Bekhet and Othman, 2017; 2018).

Figure 3: Estimation procedure



Next, the F-bounds test was used to search for a long-term relationship between the study variables. It is consistent with the nature of EKC as a long-run phenomenon, as claimed by Onafowora and Owoye (2014) and Dinda (2004). There are several types of tests to run for this purpose; however, this study believes the F-bounds test is the ideal one due to its capacity to remove the disability of other cointegration techniques (i.e. Engle and Granger, 1987, test, Johansen and Juselius, 1990, test). First, the short- and long-run relationship can be estimated simultaneously; second, the dynamic of the model can solve the problem of autocorrelation and endogeneity and avoid the estimation bias; third, the F-bounds test is fitting for small sample sizes (estimated 30 to 80 observations) and is far superior to multivariate cointegration (Farhani et al., 2014; Narayan, 2005). Thus, for the current study, the dynamic relationship among CO_2 emissions and their determinants can be tested as in Equation (5):

$$\Delta \ln I = \delta_1 + \alpha_1 \ln I_{t-1} + \alpha_2 \ln P_{t-1} + \alpha_3 \ln A_{t-1} + \alpha_4 \ln IA^2_{t-1} + \alpha_5 \ln T_{t-1} + \sum_{m-1}^{k} \Delta,_1 \ln I_{t-j} + \sum_{m-1}^{k} \Delta,_2 \ln P_{t-j} + \sum_{m-1}^{k} \Delta,_3 \ln A_{t-j} + \sum_{m-1}^{k} \Delta,_4 \ln A^2_{t-j} + \sum_{m-1}^{k} \Delta,_5 \ln I_{t-m} + \varepsilon \quad (5)$$

Where Δ is the first difference operator, δ_1 represents the intercept, $\alpha_{1\text{-}5}$ denotes the long-run elasticities of the variables, and $\theta_{1\text{-}5}$ represents the short-run elasticities of the variables. Ɛ represents the error term, k is the maximum lag length, and m indicates the lag's optimal number, and this study uses the Akaike information criterion (AIC). The AIC tends to select the maximum relevant lag length, increase the model's dynamic, and prevent the model from being under-fit (Zhang et al., 2021; Bekhet and Othman, 2017).

For testing the existence of a long-run among variables, the hypotheses are formulated as H_0: $\alpha_{1\text{-}5} = 0$ (no long-run relationship) against H_1: $\alpha_{1\text{-}5} \neq 0$ (long-run relationship exist); while for testing the existence of a short-run among variables, the hypotheses are formulated as H_0: $\theta_{1\text{-}5} = 0$ (no short-run relationship) against H_1: $\theta_{1\text{-}5} \neq 0$ (short-run relationship exist). The calculated value of F-statistics decides that cointegration exists among the variables of the study or not. If F-statistics value > I (1) critical value, H_0 for no long-run relationship will be rejected; if F-statistics < I(0) critical value, H_0 for no long-run relationship will be not rejected; if I(0) ≤F-statistics ≤I(1) critical value, the decision is inconclusive (Abassi et al., 2021; Zhang et al., 2021; Bekhet et al., 2017; Pesaran et al., 2001). After validating the dynamic relationship among the variables designated above, the long-run CO_2 elasticity toward the changes in its determinants and EKC hypothesis can be measured (Zhang et al., 2021; Dogan and Turkekul, 2016; Begum et al., 2015).

Later, the ε_{its} terms should be diagnosed, and they typically are distributed with zero mean and constant variance, $\varepsilon_t \sim N(0,\sigma_2)$, homoscedastic, free from autocorrelation problems, and have no multicollinearity. If one of the criteria above is not met, the model could encounter bias in the parameters, become inefficient, and yield an invalid hypothesis. Then the Arch, Breusch–Godfrey, Breusch–Pagan–Godfrey, and RAMSEY tests are employed to ensure that the estimated model is free from the abovementioned problems and is reliable (Abbasi et al., 2021).

Table 1: Variables details

Variables	Proxy	Unit of measurement	Past study
I	CO_2 Emissions	Thousand kt	Cong et al. (2015)
P	Population (aged 15–65)	Million unit	Yeah and Liao (2017)
A	GDP	Billion RM	Lohwasser et al. (2020)
T	Technology	Billion RM	Lopez and Palacios (2010)

Source of data: World Development Indicators.Notes I: Environmental impact, P: Population, A: Affluence, T: Technology

Table 2: Result of a stationary test

Variable	Level	NP statistic	Critical value			Decision
			1%	5%	10%	
lnI	I(0)	0.11	–13.80	–8.10	–5.70	I(1)
	I(1)	–8.99[b]				
lnP	I(0)	–17.54[a]				I(0)
	I(1)	10.60				
lnA	I(0)	1.15				I(1)
	I(1)	–19.74[a]				
lnT	I(0)	–0.87				I(1)
	I(1)	–7.27[b]				

Source: Output of EVIEWS package version 10. a, b, c indicate 1%, 5%, and 10% significant level, respectively. Type of test=N-P statistic

Table 3: Result of F-bounds test

Model	F-Stat.	Critical Value			Decision
		Level (%)	I(0)	I(1)	
lnI/ lnP,lnA,lnA²,lnT	7.073[a]	10	2.427	3.395	Co-integrated
		5	2.893	4.000	
		1	3.967	5.455	

Source: Output of EVIEWS package version 10. a, b, c defined in Table 3

Further, to assess the model's stability, the CUSUM and CUSUMQ tests (Brown et al., 1975) are applied. The model is stable if the CUSUM and CUSUMQ plots are placed inside the 5% significance level (Bekhet and Matar, 2013). If not, there is a possibility of a structural break within the estimation period, or the regression coefficient is not stable (Abid, 2015).

3.3. Causality Relationship

The presence of a long-run relationship is a sign of at least a one-way relationship among the variables. The ARDL approach examines the presence or absence of cointegration between the variables, but it does not test the direction of causality. Remarkably, causality information is essential for policymakers to recognize the variables' causality directions to regulate suitable policies. This study uses the VECM Granger causality approach to examine the causal relations that are a two-step process. Firstly, the estimation of the error correction model to get the causality in the long-run. Secondly, we estimate the Wald statistic to short-run causality between the variables. If there is no dynamic relationship between variables, then the Granger causality test will be vector autoregressive in the first difference form. If there is confirmation for cointegration, then expand the Granger causality test with a single-period lagged error correction term (ECT_{t-1}). This is the foremost step since Engle and Granger (1987) caution that if the series are integrated of order one, VAR estimation's cointegration in first differences will be misleading. Thus, equation [6] is formulated to measure long- and short-run causality among the variables of the current study:

$$\Delta\begin{bmatrix} \ln I \\ \ln P \\ \ln A \\ \ln A^2 \\ \ln T \end{bmatrix}_t = \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \\ \varphi_5 \end{bmatrix} + \sum_{j-1}^{m} \Delta\begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} & \beta_{15} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} & \beta_{25} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} & \beta_{35} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} & \beta_{45} \\ \beta_{51} & \beta_{52} & \beta_{53} & \beta_{54} & \beta_{55} \end{bmatrix}_j \begin{bmatrix} \ln I \\ \ln P \\ \ln A \\ \ln A^2 \\ \ln T \end{bmatrix}_{t-j} + \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \\ \gamma_5 \end{bmatrix} \begin{bmatrix} ECT_1 \\ ECT_2 \\ ECT_3 \\ ECT_4 \\ ECT_5 \end{bmatrix}_{t-1} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix}_t \quad [6]$$

Table 4: Long-run and Short-run Elasticities

Level equation, Case 2: Restricted Constant and No Trend							
Long - Run				Short - Run			
Variables	Coefficient	t-Statistic	Prob.	Variables	Coefficient	t-Statistic	Prob.
lnA	22.666[a]	8.778	0.000	ΔlnA	6.261	0.792	0.435
lnA²	-1.085[a]	-8.257	0.000	$\Delta \ln A_{t-1}$	-21.842[b]	-2.332	0.028
lnT	0.474[b]	2.420	0.023	$\Delta \ln A_{t-2}$	0.623[b]	2.372	0.026
lnP	0.039	0.081	0.935	$\Delta \ln A^2$	–0.255	–0.651	0.521
C	–109.116[a]	–8.170	0.000	$\Delta \ln A^2_{t-1}$	1.098[b]	2.354	0.027
				ΔlnT	0.421[b]	2.296	0.030
				$\Delta \ln T_{t-1}$	0.378[b]	2.124	0.044
				ΔlnP	–3.842	–1.593	0.124
				$\Delta \ln P_{t-1}$	25.861[a]	3.089	0.005
				$\Delta \ln P_{t-2}$	–18.636[b]	–2.478	0.020
				ECT_{t-1}	–1.123[a]	–7.160	0.000

$ECT_{t-1} = \ln I - (22.666*\ln A - 1.085*\ln A^2 + 0.474*\ln T + 0.039*\ln P - 109.116)$
a, b, c defined in Table 3.

Figure 4: CUSUM and CUSOMSQ curves tests.

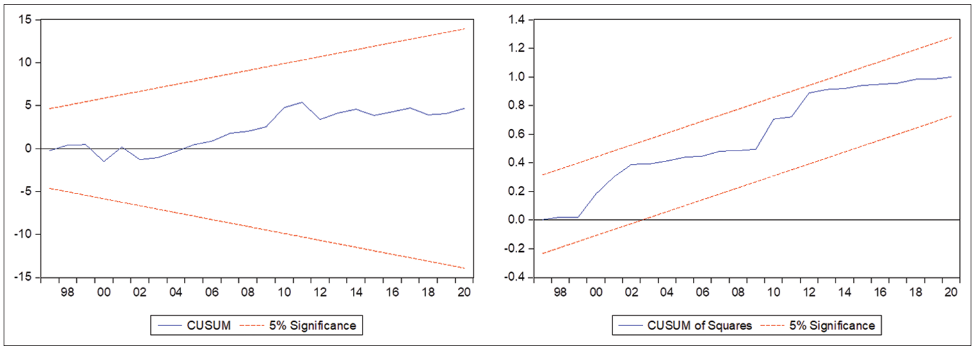


Figure 5: Short-run and long-run causality relationship

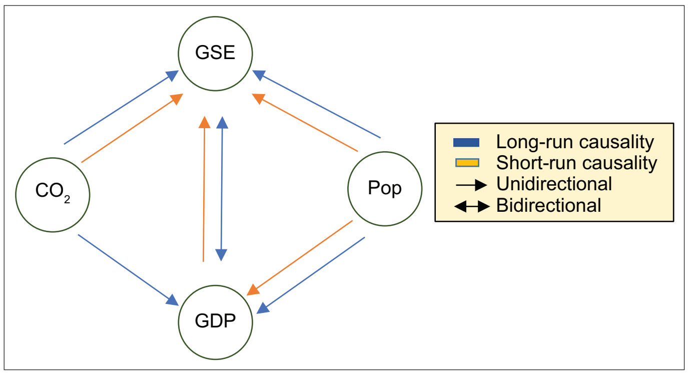


Table 5: Residual diagnostic checking via reliability test

Test	F-Stat/ probability	Decision
Normality test	0.083 (0.958)	H_0: Normal distributed
Breusch-Godfrey Serial Correlation test	2.071 (0.122)	H_0: No serial correlation
ARCH-Heteroscedasticity test	0.097 (0.756)	H_0: No Heteroscedasticity
Ramsey RESET test	2.052 (0.165)	H_0: Model has a correct functional form

The ECT_{t-1} is derived from the long-run relationship. The long-run causality relationship (unidirectional, bidirectional, and neutral) can be identified through coefficient ($_{is}$) of ECT_{t-1} via t-test (Ivy-Yap and Bekhet, 2016). Meanwhile, the short-run causality relationship is exposed by the significance of the coefficients ($\beta_{i,js}$) for each explanatory variable via the Wald F or χ^2 test.

3.4. Data sources and Description of Variables

This study uses data for Malaysia at a yearly frequency over the 1978–2020 period. The variables included in the ARDL model are CO_2 Emissions (I), government expenditure (T), GDP (A), and population (P). All of the variables are shown as natural logarithms[4]. All data are obtained from the World Development Indicator (WDI), issued by the "World Bank." Table 1 presents the details of the variables.

4. RESULT ANALYSIS

To assess the integrated degree of the variables employed, the N-P test is utilized, and the results are presented in Table 2. It shows that all variables are substantially stationary [I(1)] at 1% except for lnP, which is stationary at I(0). These results are consistent with most previous studies that employed financial and macroeconomics variables (Bekhet and Othman, 2011; Othman et al., 2020).

Since the data is relatively stable with the combination of I(0) and I(1) level of stationarity and the sample size being relatively small (n=42), the F-bounds assessment is the most proper method to measure the cointegration relationship. Prior to the F-bounds test, the optimal lag selection is determined by utilizing the "Akaike information criterion (AIC)," and the result shows the best lag extent for this model is 3 (refer to the appendix for details).

Table 3 presents the results of the F-Bounds test. The empirical findings show long-run relationships between all variables at a 1% significant level over the 1978–2020 period and it is consistent with Othman et al. (2020). This is because the calculated F-statistic for each model is higher than the upper bound critical value at a 1% level of significance.

Concerning the above findings, the error correction model has been formulated to confirm the long-run elasticities between CO_2 emissions, GDP, population, and GSE. The results are demonstrated in Table 4. It shows that lnA and quadratic forms of lnA have a significant positive and a negative impact on lnI. It means that the long-run relationship between lnA and lnI is not linear, confirming the EKC theory's existence. This result could be attributed to Grossman and Krueger (1991), where they found a non-linear relation between CO_2 emissions and economic growth, which is an inverted U-shaped relationship. Also, this result is consistent with Suki et al. (2020) and Bekhet et al. (2020).

Furthermore, the GSE is significantly influenced by the GDP and CO_2 emissions relationship in the long-run at 5 percent and consistent with Adewuyi (2016). Simultaneously, the population's role is insignificant in influencing the GDP and CO_2 emissions relationship in the long-run. As regards the short-run scenario, none of the variables has a significant impact on lnI. So, it indicates that EKC does not exist in the short run.

Several diagnostic tests, present in Table 5, are used to check the robustness of the model. It demonstrated that the model has

4 The dynamic approach of ARDL, transformation data, and logarithm could reduce the multicollinearity problem (Gujarati and Porter, 2009). All series were transformed into logarithmic form to eliminate the heteroscedasticity issue (Abassi et al., 2021)

Table 6: Government Expenditure by Sustainable Development Goals (SDG)

Sustainable development goal		2015		2019	
		Rm million	% Total	Rm million	% Total
Goal 1	No Poverty	0.00	0.00	0.00	0.00
Goal 2	Zero Hunger	0.00	0.00	0.00	0.00
Goal 3	Good Health & Well-being	2.03	0.10	0.03	0.00
Goal 4	Quality Education	0.25	0.00	2.86	0.10
Goal 5	Gender Equality	0.00	0.00	0.00	0.00
Goal 6	Clean Water & Sanitation	1,303.45	44.20	1,608.68	50.70
Goal 7	Affordable & Clean Energy	132.20	4.50	411.16	13.00
Goal 8	Decent Work & Economic Growth	0.38	0.00	2.30	0.10
Goal 9	Industry, Innovation & Infrastructure	51.86	1.80	39.89	1.30
Goal 10	Reduced Inequality	0.00	0.00	0.00	0.00
Goal 11	Sustainale Cities & Communities	639.32	23.70	385.50	12.20
Goal 12	Responsible Consumption & Production	29.04	1.00	117.42	3.70
Goal 13	Climate Action	496.55	16.90	441.45	13.90
Goal 14	Life Below Water	35.08	1.20	7.12	0.20
Goal 15	Life on Land	52.20	1.80	87.75	2.80
Goal 16	Peace, Justice & Strong Institutions	12.65	0.40	31.32	1.00
Goal 17	Part6nership for the Institution	133.09	4.50	35.66	1.10
	Total	2,946.08	100.00	3,171.13	100.00

Source: Ministry of Finance (MOF) 2021

the desired econometric properties. Namely, the residuals are normally distributed, serially uncorrelated, homoscedastic, and have a correct functional form (Abbasi et al., 2021; Law, 2008).

Moreover, the cumulative sum (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests are examined to check the model's coefficients' stability. As shown in Figure 4, CUSUM and CUSUMSQ curves remain within the 5% significance level's critical boundaries. These statistics properties specify the stability of both the long-run and short-run coefficients in the error correction model.

Likewise, Figure 5 summarized the multivariate Granger causality test results. It shows evidence of the short-run unidirectional Granger causality running from CO_2 emissions, GDP, and population to GSE at the 1 percent significance levels; and the short-run unidirectional causality running from population to GDP at the 10 percent significance levels. The unidirectional causality between GSE and GDP is consistent with Lahirushan and Gunasekara (2015), who measure a dynamic analysis for ASEAN's case. The short-run causality is meaningful for policymakers to create fruitful policy in Malaysia to achieve sustainable development goals and the 12th Malaysia Plan.

Furthermore, Engle and Granger (1987) argued that long causal directions between these variables must exist if a cointegration relationship exists among the variables (Bekhet et al., 2020). This study reveals the long-run unidirectional Granger causality running from CO_2 emissions and population to GSE and GDP at least 10 percent significance level. The bidirectional causality between GSE and GDP at least at a 10 percent significance level as well. The long-run bidirectional causality between GSE and GDP is not consistent with Zulkofli et al. (2018) because they revealed a unidirectional causality instead of bidirectional causality. The causality relationship to GSE indicates that the increasing demand for regulatory and protective functions represented by GSE are needed to sustain the increasing level of economic wealth, environment, and communities, and it is consistent with Keynesian and Wagner's school of thought (Lahirushan and Gunasekara, 2015).

5. CONCLUSION AND POLICY IMPLICATION

Sustainable development is one of the critical issues highlighted by researchers and policymakers worldwide. This study focused on observing the impact of government expenditures on Malaysia's environmental quality for the 1978–2020 period. So, the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model in the EKC framework are utilized. In terms of methodology, this study employed the F-bounds test, ARDL, and VECM causality to assess the existence of the dynamic relationship, the short-run and long-run environmental elasticities, and the short-run and long-run causality direction, respectively.

Empirical results show a long-run relationship between CO_2 emissions, GDP, and Malaysia's government expenditure (GSE). Furthermore, the results confirmed the significant inverted U-shaped relationship between CO_2 emissions and GDP in the long run with the GSE–CO2 emissions' significant positive elasticity. With the significant EKC relationship, these results highlight the understanding that Malaysia is currently moving towards environmental sustainability, and the GSE is a function of environmental sustainability. Indeed, the government spending on compensation, education, R and D function has functioned well in transferring knowledge, technology know-how, and stimulating productivity.

In terms of causality relationship, the results show a significant unidirectional short-run causality relationship running from CO_2 emissions, GDP, and population to GSE; unidirectional short-run causality running from population to GDP. Furthermore, for the long-run causality, results show unidirectional long-run causality relationship running from CO_2 emissions, GDP, and population to GSE; unidirectional long-run causality running from population to GDP; and bidirectional causality between GDP and GSE. This circumstance indicates how much government spending on Malaysia's development depends on the environmental, economic, and social agenda. These conditions inlined with sustainable development goals 6, 11, and 13 stated in Table 6[5]. The environmental issue is one reason why the government increases their spending, and these spendings are significant to boost the country's income.

This study also indicates that GSE does play a significant role in promoting economic growth. This has happened in Malaysia, where the Malaysian government (GOM) has revised its 2020 total expenditure allocation upwards to RM314.7 billion from the initial budget estimate of RM297 billion with the prolonged COVID-19 pandemic crisis (The Edgemarket, 2020). And this strategy is one of the Malaysian government's positive actions to cushion the impact of the crisis and stimulate GDP growth. Expansionary fiscal policy measures through additional allocation and tax relaxation are crucial to protecting people's livelihood, supporting businesses, and mitigating the fallout of economic activities from the crisis. However, GOM has narrowed down the operating expenditure to RM241.02 billion, down from RM262.26 billion for 2019, and increased the development expenditure to RM56 billion, up from RM53.7 billion in 2019 (Reuters, 2019).

In conclusion, this study has confirmed the interaction and interdependencies among GSE, GDP, and environmental quality. To achieve Malaysia's sustainable development, this study recommends policymakers formulate the direction of its operation and development expenditure. Instead of supporting the welfare of the societies, it should consider how the allocation of money (e.g. payments, supplies and services, education/training, housing, and health) benefited environment quality, mainly improving Malaysian attitude and behavior awareness on environmental issues.

The suggestion for future study is to investigate the proper strategy on how Malaysia can solve budget deficits. This is because the theory suggests that persistent and large budget deficits lead to a harmful effect on major macroeconomic fundamentals. The failure to solve this problem could harm Malaysia's sustainable development in the long run.

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5 The issue of SDG, mainly climate change issue is one of the reasons why the government allocates a large portion of development expenditure on it. The 2021 Budget will be the base to align its annual budget to the SDGs, beginning with the development expenditure's allocation (Table 6).

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APPENDIX

Appendix 1

VAR lag order selection criteria						
Endogenous variables: LI LEP LA LA2 LGE						
Exogenous variables: C						
Date: 02/25/21 Time: 11:46						
Sample: 1978 2020						
Included observations: 40						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	183.2009	NA	9.29e-11	–8.910043	–8.698933	–8.833712
1	501.5231	541.1477	4.01e-17	–23.57615	–22.30949*	–23.11817*
2	530.0956	41.43017	3.57e-17	–23.75478	–21.43257	–22.91514
3	564.1883	40.91130*	2.67e-17*	–24.20942*	–20.83166	–22.98813

*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

Appendix 2

VECM causality analysis				
Estimation method: Least squares				
Date: 02/25/21 Time: 13:48				
Sample: 1981 2020				
Included observations: 40				
Total system (balanced) observations 200				
	Coefficient	**Std. Error**	**t-Statistic**	**Prob.**
C(1)	0.103746	0.210352	0.493202	0.6226
C(2)	-0.312251	0.233744	–1.335867	0.1838
C(3)	0.076210	0.208985	0.364669	0.7159
C(4)	9.926454	11.44439	0.867364	0.3872
C(5)	–11.25294	13.65233	–0.824251	0.4112
C(6)	0.484009	15.44964	0.031328	0.9751
C(7)	20.21430	14.50499	1.393610	0.1656
C(8)	0.000216	0.767086	0.000282	0.9998
C(9)	–1.021897	0.724489	–1.410507	0.1606
C(10)	0.339207	0.311589	1.088637	0.2782
C(11)	0.228986	0.272177	0.841311	0.4016
C(12)	0.064000	0.176032	0.363573	0.7167
C(13)	–0.014257	0.009735	–1.464616	0.1453
C(14)	0.010923	0.010817	1.009835	0.3143
C(15)	0.009261	0.009671	0.957600	0.3399
C(16)	1.652009	0.529616	3.119259	0.0022
C(17)	–0.080688	0.631793	–0.127712	0.8986
C(18)	–0.668682	0.714968	–0.935262	0.3513
C(19)	–0.295202	0.671252	–0.439778	0.6608
C(20)	0.031907	0.035499	0.898816	0.3703
C(21)	0.014111	0.033527	0.420881	0.6745
C(22)	–0.001938	0.014419	–0.134379	0.8933
C(23)	–0.002692	0.012596	–0.213746	0.8311
C(24)	–0.015594	0.008146	–1.914194	0.0576
okC(25)	0.162568	0.085726	1.896363	0.0600
C(26)	0.090433	0.095260	0.949331	0.3441
C(27)	0.118325	0.085169	1.389290	0.1670
C(28)	–4.175577	4.664022	–0.895274	0.3722
C(29)	–1.709982	5.563843	–0.307338	0.7590

(*Contd...*)

Appendix 2: ***(Continued)***

VECM causality analysis				
Estimation method: Least squares				
Date: 02/25/21 Time: 13:48				
Sample: 1981 2020				
Included observations: 40				
Total system (balanced) observations 200				
	Coefficient	Std. Error	t-Statistic	Prob.
C(30)	9.995979	6.296315	1.587592	0.1146
C(31)	3.520044	5.911336	0.595473	0.5525
C(32)	–0.497693	0.312617	–1.592024	0.1136
C(33)	–0.191424	0.295257	–0.648330	0.5178
C(34)	0.126252	0.126984	0.994235	0.3218
C(35)	0.053485	0.110923	0.482180	0.6304
C(36)	0.178372	0.071740	2.486373	0.0141
C(37)	3.205653	1.734875	1.847772	0.0667
C(38)	1.772623	1.927802	0.919505	0.3594
C(39)	2.428598	1.723598	1.409028	0.1610
C(40)	–86.08919	94.38744	–0.912083	0.3633
C(41)	–31.59080	112.5974	–0.280564	0.7795
C(42)	187.2948	127.4207	1.469893	0.1438
C(43)	69.88466	119.6298	0.584175	0.5600
C(44)	–9.326292	6.326530	–1.474156	0.1427
C(45)	–3.805273	5.975213	–0.636843	0.5253
C(46)	2.453783	2.569824	0.954845	0.3413
C(47)	1.074239	2.244778	0.478550	0.6330
C(48)	3.573308	1.451821	2.461259	0.0151
C(49)	0.506881	0.075964	6.672610	0.0000
okC(50)	–0.259559	0.084412	–3.074906	0.0025
C(51)	0.068352	0.075471	0.905684	0.3667
C(52)	–13.16268	4.132909	–3.184846	0.0018
C(53)	4.684585	4.930264	0.950169	0.3437
C(54)	–6.805587	5.579325	–1.219787	0.2246
C(55)	20.75067	5.238186	3.961423	0.0001
C(56)	0.347078	0.277018	1.252912	0.2123
C(57)	–1.039428	0.261635	–3.972824	0.0001
C(58)	0.117566	0.112524	1.044809	0.2979
C(59)	0.478695	0.098291	4.870165	0.0000
C(60)	0.246241	0.063570	3.873520	0.0002
Determinant residual covariance		2.35E-18		
Equation: D(LI)=C(1)*(LI(–1)+2.94814446087*LEP(–1)–27.5835196223*LA(–1)+1.28817374181*LA2(–1)–1.51756667667*LGE(–1)+93.0417087351)+C(2)*D(LI(–1))+C(3)*D(LI(–2))+C(4)*D(LEP(–1))+C(5)*D(LEP(–2))+C(6)*D(LA(–1))+C(7)*D(LA(–2))+C(8)*D(LA2(–1))+C(9)*D(LA2(–2))+C(10)*D(LGE(–1))+C(11)*D(LGE(–2))+C(12)				
Observations: 40				
R-squared	0.336646	Mean dependent var		0.054005
Adjusted R-squared	0.076043	S.D. dependent var		0.081418
S.E. of regression	0.078261	Sum squared resid		0.171493
Durbin-Watson stat	1.984292			
Equation: D(LEP)=C(13)*(LI(–1)+2.94814446087*LEP(–1)–27.5835196223*LA(–1)+1.28817374181*LA2(–1)–1.51756667667*LGE(–1)+93.0417087351)+C(14)*D(LI(–1))+C(15)*D(LI(–2))+C(16)*D(LEP(–1))+C(17)*D(LEP(–2))+C(18)*D(LA(–1))+C(19)*D(LA(–2))+C(20)*D(LA2(–1))+C(21)*D(LA2(–2))+C(22)*D(LGE(–1))+C(23)*D(LGE(–2))+C(24)				
Observations: 40				
R-squared	0.845418	Mean dependent var		0.025767

(*Contd...*)

Appendix 2: ***(Continued)***

VECM causality analysis				
Estimation method: Least squares				
Date: 02/25/21 Time: 13:48				
Sample: 1981 2020				
Included observations: 40				
Total system (balanced) observations 200				
	Coefficient	Std. Error	t-Statistic	Prob.
Adjusted R-squared	0.784690	S.D. dependent var		0.007805
S.E. of regression	0.003622	Sum squared resid		0.000367
Durbin-Watson stat	1.319771			
Equation: D(LA)=C(25)*(LI(–1)+2.94814446087*LEP(–1)–27.5835196223*LA(–1)+1.28817374181*LA2(–1)–1.51756667667*LGE(–1)+93.0417087351)+C(26)*D(LI(–1))+C(27)*D(LI(–2))+C(28)*D(LEP(–1))+C(29)*D(LEP(–2))+C(30)*D(LA(–1))+C(31)*D(LA(–2))+C(32)*D(LA2(–1))+C(33)*D(LA2(–2)) + C(34)*D(LGE(–1))+C(35)*D(LGE(–2))+C(36)				
Observations: 40				
R-squared	0.378959	Mean dependent var		0.032780
Adjusted R-squared	0.134979	S.D. dependent var		0.034293
S.E. of regression	0.031894	Sum squared resid		0.028483
Durbin-Watson stat	2.040950			
Equation: D(LA2)=C(37)*(LI(–1)+2.94814446087*LEP(–1)–27.5835196223*LA(–1)+1.28817374181*LA2(–1)–1.51756667667*LGE(–1)+93.0417087351)+C(38)*D(LI(–1))+C(39)*D(LI(–2))+C(40)*D(LEP(–1))+C(41)*D(LEP(–2))+C(42)*D(LA(–1))+C(43)*D(LA(–2))+C(44)*D(LA2(–1))+C(45)*D(LA2(–2)) C(46)*D(LGE(–1))+C(47)*D(LGE(–2))+C(48)				
Observations: 40				
R-squared	0.360660	Mean dependent var		0.657768
Adjusted R-squared	0.109491	S.D. dependent var		0.683986
S.E. of regression	0.645455	Sum squared resid		11.66516
Durbin-Watson stat	2.034686			
Equation: D(LGE)=C(49)*(LI(–1)+2.94814446087*LEP(–1)–27.5835196223*LA(–1)+1.28817374181*LA2(–1)–1.51756667667*LGE(–1)+93.0417087351)+C(50)*D(LI(–1))+C(51)*D(LI(–2))+C(52)*D(LEP(–1))+C(53)*D(LEP(–2))+C(54)*D(LA(–1))+C(55) *D(LA(–2))+C(56)*D(LA2(–1))+C(57)*D(LA2(–2))+C(58)*D(LGE(–1))+C(59)*D(LGE(–2))+C(60)				
Observations: 40				
R-squared	0.760562	Mean dependent var		0.052091
Adjusted R-squared	0.666497	S.D. dependent var		0.048939
S.E. of regression	0.028262	Sum squared resid		0.022365
Durbin-Watson stat	2.488374			

VEC Granger Causality/Block Exogeneity Wald Tests			
Date: 02/25/21 Time: 12:44			
Sample: 1978 2020			
Included observations: 40			
Dependent variable: D(LI)			
Excluded	**Chi-sq**	**df**	**Prob.**
D(LEP)	0.772017	2	0.6798
D(LA)	2.269767	2	0.3215
D(LA2)	2.295796	2	0.3173
D(LGE)	1.546231	2	0.4616
All	11.46298	8	0.1768
Dependent variable: D(LEP)			
Excluded	**Chi-sq**	**df**	**Prob.**
D(LI)	1.377943	2	0.5021
D(LA)	1.568751	2	0.4564
D(LA2)	1.455884	2	0.4829
D(LGE)	0.053131	2	0.9738
All	2.775398	8	0.9477
Dependent variable: D(LA)			
Excluded	**Chi-sq**	**df**	**Prob.**
D(LI)	2.106859	2	0.3487
D(LEP)	5.686107	2	0.0582
D(LA2)	4.280822	2	0.1176
D(LGE)	1.053160	2	0.5906
All	12.78479	8	0.1195
Dependent variable: D(LA2)			
Excluded	**Chi-sq**	**df**	**Prob.**
D(LI)	2.128965	2	0.3449
D(LEP)	5.607996	2	0.0606
D(LA)	3.587651	2	0.1663
D(LGE)	0.979396	2	0.6128
All	12.19800	8	0.1426
Dependent variable: D(LGE)			
Excluded	**Chi-sq**	**df**	**Prob.**
D(LI)	15.03031	2	0.0005
D(LEP)	23.88427	2	0.0000
D(LA)	15.74295	2	0.0004
D(LA2)	15.82895	2	0.0004
All	40.97361	8	0.0000