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The Impact of RON95 Petrol Prices on Inflation in Malaysia: A Vector Autoregressive (VAR) Approach

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RESEARCH ARTICLE

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Abstract

The Consumer Price Index (CPI) is a key measure of inflation, and in Malaysia, petrol prices are included as a fixed component within the CPI basket. Amid the global oil price volatility and geopolitical tensions, understanding the impact of fuel price shocks on inflation has become increasingly relevant. During two distinct periods, from November 2014 to January 2018 and from March 2020 to February 2021, the price of RON95 petrol, Malaysia's primary fuel, was determined by market forces rather than government regulation. These periods offer a natural setting to examine how RON95 price fluctuations influence domestic inflation. This study examines the relationship between Malaysia's Consumer Price Index (CPI) and RON95 petrol prices using monthly data from November 2014 to June 2021, employing a Vector Autoregressive (VAR) model to explain the dynamic relationship between the two variables. The results indicate that the short-term relationship between the CPI and RON95 petrol prices varies across lags, exhibiting both positive and negative effects, with a mixed correlation. Impulse response analysis reveals that changes in RON95 prices generate a positive response in CPI in both the short and long term. Variance decomposition confirms the predictive relevance of RON95 prices for CPI variation. The variance decomposition results further support this pattern, showing that the share of CPI forecast error variance attributed to RON95 shocks increases from 31.07% in the first period to approximately 63.47% by the tenth period, while inflation accounts for 31.97% in the fourth period to approximately 28.45% by the tenth period. These findings provide empirical evidence that can inform proactive economic measures, such as supporting Bank Negara Malaysia to adjust its monetary policy in response to fuel price fluctuations and may contribute to improved inflation forecasting in future applications.

Keywords: Consumer Price Index; RON95 petrol; fuel prices; time series analysis; VAR model

1. Introduction

The global crude oil price is primarily influenced by the interplay of supply, demand, and market competition (Caltex, 2021). Fluctuations in crude oil prices are a global phenomenon with significant implications for the economies of countries worldwide. Developing countries such as Malaysia can be susceptible to these changes due to their limited financial resilience and heightened sensitivity to external shocks. One of the most notable macroeconomic effects of oil price fluctuations is on the inflation rate, more formally referred to as price volatility. Changes in the inflation rate or general price levels may subsequently lead to broader economic fluctuations, thereby influencing overall economic performance (Bekhet & Yusep, 2009; Vatsa, 2025). Consequently, inflation is widely regarded as a key indicator of macroeconomic stability.

In Malaysia, inflation is measured by the Consumer Price Index (CPI), which tracks the percentage change over time in the cost of purchasing a fixed basket of goods and services that reflects the average consumption habits of a specific population group (DOSM, 2021). The CPI not only serves as a measure of inflation but is also closely linked to changes in the cost of living. It provides insights into consumer price trends and is the most widely used indicator for inflation analysis. An increasing CPI signifies a rise in the cost of living, which diminishes the purchasing power of money. Central banks, such as Bank Negara Malaysia, along with other global financial institutions, closely monitor the CPI to assess economic conditions and formulate monetary policy, especially in setting interest rates (OECD, 2021). This monitoring is crucial for assessing the effectiveness of government economic policies and informing sound fiscal and monetary decisions.

In the Malaysian context, retail fuel prices are regulated through the Automatic Pricing Mechanism (APM) (NST, 2021), a framework designed to protect consumers from significant fluctuations in RON95 prices. The APM operates by applying a sales tax when international oil prices fall below a certain threshold and providing targeted subsidies when prices increase sharply. This mechanism maintains a degree of price stability at the pump, supporting household purchasing power and economic predictability. However, adjustments to the retail price are triggered when the gap between global market prices and the regulated price exceeds the amount that can be absorbed through either taxation or subsidies. As such, the APM reflects Malaysia's broader policy aim of balancing fiscal discipline with social protection, particularly during periods of economic volatility.

This study analyses the period from November 2014 to June 2021 because it covers a complete and transformative phase in Malaysia's fuel pricing policy evolution. The timeframe starts with the shift from broad government subsidies to a market-based managed float system. It ends with the introduction of a price ceiling during the COVID-19 pandemic, which acted as an economic shock testing the policy's resilience and adaptability. Focusing specifically on RON95 petrol rather than RON97 is justified because RON95 is the main fuel used by most Malaysian consumers and is the primary focus of government subsidy and price control measures (Chee, 2025). In contrast, RON97 operates on a fully market-driven float and is generally used by a smaller group of higher-income motorists. Therefore, RON95 offers a more policy-relevant and socially important indicator to analyse government intervention strategies. The historical trend of RON95 prices over this period is shown in Figure 1.

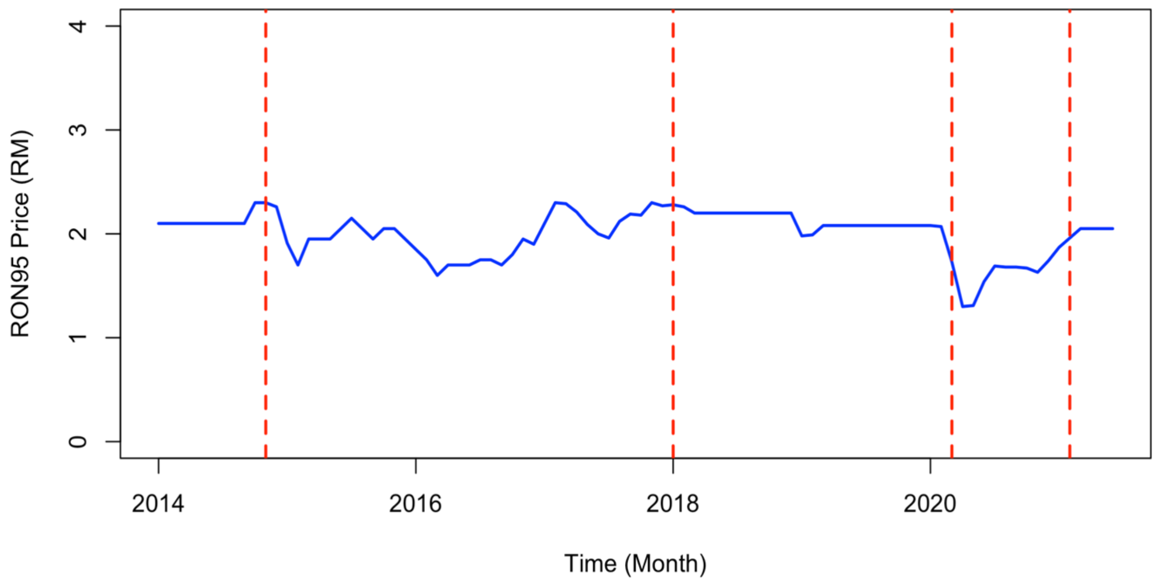

Figure 1. The retail prices of petrol RON95 in Malaysia from November 2014 to June 2021, with dashed red lines indicating deregulated periods of Nov 2014-Jan 2018 and Mar 2020-Feb 2021.

The pattern of Malaysia's RON95 petrol prices from November 2014 to June 2021 in Figure 1 reflects a series of policy transitions shaped by both domestic reforms and global market shocks (Anderl & Caporale, 2024). Initially, fuel prices were determined through a blanket subsidy system, in which the government covered a significant portion of the cost to keep prices artificially low, meaning consumers paid below actual market rates. This changed on December 1, 2014, when a managed float mechanism was introduced, with monthly price revisions based on the average market price of refined oil. During this first deregulated period, from November 2014 to January 2018, the price of RON95 petrol, Malaysia's primary fuel, was determined by market forces rather than government regulation, leading to notable price volatility due to fluctuations in global crude oil prices. This period is indicated by the vertical dashed red lines in Figure 1.

On March 29, 2017, the pricing system evolved into a weekly ceiling price framework, whereby prices were updated every Wednesday and capped to prevent sharp increases. From 2018 to early 2020, the government intervened more actively through targeted subsidies and ceiling controls, stabilising RON95 prices. In early 2019, targeted subsidies were reintroduced to cushion low-income groups when prices surpassed affordability thresholds.

The steepest decline in fuel prices occurred in early 2020, triggered by the COVID-19 pandemic and a collapse in global oil demand. This marked the beginning of the second deregulated phase, from March 2020 to February 2021, when prices again reflected market conditions. In response to renewed volatility, the government imposed a hard price ceiling of RM2.05 per litre in February 2021, stabilising prices through the post-pandemic recovery. This second deregulated period is also indicated by vertical dashed red lines in Figure 1. Together, these two episodes provide a natural experiment for examining how RON95 price fluctuations influence domestic inflation. Figure 1 illustrates this dynamic policy cycle, from a fixed price structure to a managed float system, and ultimately to a tightly controlled ceiling price regime.

A substantial body of literature has applied Vector Autoregressive (VAR) and Structural VAR models to analyse the dynamic relationship between oil prices and inflation. Cologni and Manera (2008) found that oil price shocks significantly affect inflation and monetary policy response in G-7 economies through cost-push and demand channels. Baumeister and Peersman (2013) differentiated between supply-driven and demand-driven oil shocks, revealing that each exerts distinct effects on inflation.

Meanwhile, Kang and Ratti (2013) showed that uncertainty in oil prices can amplify inflationary responses in Asian economies. Recent empirical research by Aharon et al. (2023) employed a Structural VAR to examine the influence of oil price shocks on inflation. It shows that positive oil-specific demand shocks during the COVID-19 period led to a significant increase in price levels across many Asian and ASEAN economies, underscoring the asymmetric effects of oil price shocks during these periods. Further, from a macroeconomic perspective beyond inflation, a study by Shen et al. (2025) reported that oil price shocks may have a substantial indirect effect on output, spending, and price levels, highlighting potential pitfalls of small-scale VAR studies that do not account for broader transmission channels. These studies underscore the importance of VAR frameworks in capturing dynamic interactions between oil prices and inflation, supporting the methodological approach used in this study.

Lacheheba and Siragca (2019) examined the relationship between oil price fluctuations and inflation in Algeria using the Nonlinear Autoregressive Distributed Lag (NARDL) model. Their findings indicated a significant nonlinear effect of oil price changes on inflation, attributed to the presence of market power in the economy. The NARDL framework is particularly useful in this context, as it captures both short-term dynamics and long-term equilibrium relationships between variables. Similarly, Davari and Kamalian (2018) employed the NARDL approach to investigate the oil price–inflation nexus in Iran. Their study found that declining oil prices contributed to inflationary pressures, while rising oil prices did not demonstrate a statistically significant effect on inflation, suggesting an asymmetric relationship.

Alongside the NARDL approach, several studies have employed the Vector Error Correction Model (VECM), combined with Granger causality and Johansen cointegration tests, to investigate the direction and long-term nature of causal relationships. For example, Bekhet and Yusop (2009) examined the interaction between oil prices, energy consumption, and macroeconomic performance in Malaysia. Their results confirmed a stable long-term relationship among economic growth, oil price fluctuations, employment, and energy consumption, along with evidence of short-term interactions. In the Nigerian context, Musa and Maijama (2021) analysed the causal linkages among domestic oil prices, exchange rates, and inflation. Their findings indicated strong cointegration among these variables, with unidirectional causality flowing from exchange rates to domestic oil prices. Sultan et al. (2020) similarly utilised the VECM framework to study the relationship between oil prices and inflation in India, showing that oil price changes have significant effects on inflation in both the short and long term.

Understanding the relationship between oil prices and inflation is essential, as oil price fluctuations can significantly influence overall economic stability (Elsharif & Elamin, 2025). Due to oil's crucial role in manufacturing and transportation, rises in oil prices often increase input costs, which are then passed on to consumers as higher prices, adding to inflationary pressures. This relationship between oil prices and inflation requires detailed empirical analysis. Such insights are valuable for policymakers, especially central banks, which may need to adjust interest rates in response to oil price changes to keep inflation within target levels. Additionally, understanding this connection aids in more accurate forecasts of consumer behaviour, since inflation affects consumption and saving habits. It also helps investors and financial analysts because movements in oil prices impact the profitability of energy firms and can influence stock and bond markets. A solid understanding of the oil price–inflation relationship is therefore vital for effective macroeconomic policy and financial decision-making (Toni, 2024).

Despite the increasing amount of research exploring the relationship between oil prices and inflation, few empirical studies have concentrated specifically on Malaysia, especially concerning RON95 petrol prices and their influence on consumer inflation. Furthermore, current research often neglects the difference between refined petrol pricing methods and crude oil benchmarks. This gap highlights the need for a focused investigation that considers Malaysia's distinctive fuel pricing system. Addressing this is vital for guiding effective monetary and fiscal policies amid oil price fluctuations.

Therefore, this study aims to firstly, explore the long- and short-term relationships between RON95 petrol prices and inflation; and secondly, evaluate the effects of petrol price shocks on inflation. A VAR approach is used to thoroughly examine the interaction between petrol prices and inflation in Malaysia. In particular, the VAR framework treats both variables as influencing each other and shows how a change in one affects the other over time. By incorporating impulse response functions and variance decomposition, the analysis measures the direction, magnitude, and persistence of petrol price shocks, providing clearer insight into their contribution to inflation dynamics over time.

2. Materials and Methods

This study employs the VAR model to analyse the dynamic relationship between RON95 petrol prices and inflation in Malaysia. The model is particularly suitable for this analysis because it considers all variables as endogenous, enabling the investigation of bidirectional causality and interdependencies without relying on prior structural assumptions. This is significant in the context of petrol prices and inflation, which are likely to influence each other over time. Furthermore, VAR models effectively captured both short-term dynamics and long-term equilibrium relationships in multivariate time series data. The modelling process includes several key steps, as shown in Figure 2.

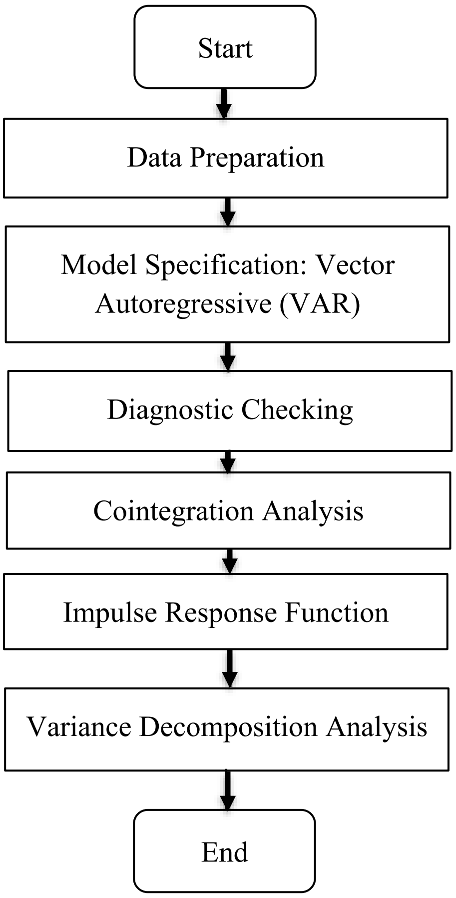

Figure 2. Study framework.

This study utilises monthly time series data on RON95 petrol prices and inflation in Malaysia to investigate their dynamic relationship. To ensure the validity of the analysis, the stationarity of each variable is tested using the Augmented Dickey-Fuller (ADF) test (Mansor et al., 2015). This step confirms that both series are integrated of the same order, a prerequisite for VAR modelling. Once stationarity is confirmed, the VAR model is estimated, with the optimal lag length selected based on established information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC). Diagnostic tests are then performed to assess the adequacy of the model, including tests for serial correlation, heteroscedasticity, and the normality of residuals (Mansor et al., 2023; Mansor et al., 2025).

Next, the Johansen cointegration approach is employed to examine the existence of any long-run equilibrium relationship between petrol prices and inflation. Both the Trace and Maximum Eigenvalue tests are conducted using EViews to determine the number of cointegrating vectors. Finally, to evaluate the dynamic interactions between the variables, impulse response functions (IRFs) are generated to trace the effects of shocks in petrol prices on inflation over time. This is complemented by variance decomposition (VD) analysis, which quantifies the proportion of forecast error variance in each variable that is attributable to its own innovations and to innovations in the other variable. Together, these techniques provide a comprehensive understanding of the short and long-term interdependencies between oil prices and inflation in the Malaysian context.

2.1 Stationarity Checking

In this study, a unit root test was performed, specifically the Augmented Dickey-Fuller (ADF) test. This test aims to determine whether the time-series data are stationary. The ADF test identifies the presence of unit roots, which signify non-stationarity in the data. The concept of the unit root in time series data was first introduced by Dickey and Fuller (1979). The general form of the regression equation used in the ADF test is:

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \sum_{i=1}^{k} \alpha_i \, \Delta y_{t-i} + \varepsilon_t \tag{1}$$

where y_t is the value of a variable at time *t*, Δy_t is the difference between y_t and y_{t-1}, β_0 is a constant, β_1 is the coefficient of the lagged series of y, α_i are the coefficients of the lagged differenced series of y for $i = 1, \dots, k$, and ε_t is the error term at time *t*.

The null hypothesis of the ADF test is that the time series contains a unit root ($\beta_1 = 0$), indicating non-stationary. The alternative hypothesis is that the time series is stationary, meaning it has no unit root ($\beta_1 < 0$). The ADF test statistic is calculated as:

$$ADF\ statistic = \frac{\widehat{\beta_1}}{s.e(\widehat{\beta_1})} \tag{2}$$

If the test statistic is less than the critical value from the Dickey-Fuller distribution (or if the p-value is small, typically less than 0.05), the null hypothesis of a unit root can be rejected, suggesting that the series is stationary. If stationarity at the level form is not confirmed, then first differencing is performed. The variable is said to be integrated of order one if it achieves stationarity after first differencing.

2.2 Johansen Cointegration

Once the time series data is stationary, the next step is to perform a cointegration test. In this study, we employed Johansen's cointegration test to examine the presence of a long-term relationship between Oil Prices and Inflation in Malaysia. This analysis provides a comprehensive framework for identifying and modelling long-term equilibria among variables, which is essential for understanding complex economic and financial relationships between oil prices and inflation. The test was developed by Johansen (1988) within a VAR framework to test the null hypothesis of no cointegration against the alternative hypothesis that cointegration exists among the variables.

2.3 The Trace test

The trace test is performed to determine the number of cointegrating relationships among the variables, and the test is calculated using the following equation (3).

$$Trace\ statistic = -T \sum_{i=r+1}^{n} ln\,(1 - \hat{\lambda}_i) \tag{3}$$

where T is the number of observations, $\hat{\lambda}_i$ are the estimated eigenvalues, and n is the number of time series being tested.

This test starts with the assumption of no cointegration vector ($r = 0$) and tests sequentially for $r = 1, \dots, n-1$. A significant test statistic implies rejecting the null in favour of the alternative hypothesis that there are more than r cointegrating relationships. The Maximum Eigenvalue test examines the null hypothesis of r cointegrating vectors against the alternative of $r + 1$ cointegrating vectors. The test statistic is written as equation (4).

$$Eigenvalue\ statistic = -T\ ln\ ln\left(1 - \hat{\lambda}_{r+1}\right) \tag{4}$$

This test considers each eigenvalue individually, providing a more focused test on the addition of each potential cointegrating relationship. A significant test statistic suggests that the null hypothesis of cointegrating vectors should be rejected in favour of *r+1*.

2.4 Vector Autoregressive (VAR) Model

The model was first introduced by Sims (1980), who proposed an autoregressive representation to provide a more data-driven approach in modelling macroeconomic relationships. The mathematical representation of the VAR model for the oil prices (OP_t) and inflation (Inf_t) series is presented in equations (5) and (6).

$$OP_t = \alpha_1 + \sum_{i=1}^{k} \phi_{11,i}\, OP_{t-i} + \sum_{i=1}^{k} \phi_{12,i}\, Inf_{t-i} + \varepsilon_{1t} \tag{5}$$

$$Inf_t = \alpha_2 + \sum_{i=1}^{k} \phi_{21,i} Inf_{t-i} + \sum_{i=1}^{k} \phi_{22,i} OP_{t-i} + \varepsilon_{2t} \tag{6}$$

,where $\phi_{11,i}, \phi_{12,i}, \phi_{21,i}, \phi_{22,i}$ are the parameters of the i^{th} lag of oil prices and inflation variables in the equations. These equations model each variable as a function of its own lagged values and those of the other variable, capturing the dynamic interrelationships between oil prices and inflation over time.

The choice of p is crucial and is based on information criteria such as the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC). The VAR is used because it extends the autoregressive framework, unlike univariate time series models, to capture the simultaneous interactions between oil prices and inflation, thereby providing a more comprehensive understanding of their combined dynamics.

2.5 Impulse Response Function (IRF) Analysis

Impulse response analysis and variance decomposition were introduced by Sims (1980) as part of the VAR framework to evaluate dynamic interactions and the propagation of shocks among variables. Thus, in this study, we employed the Impulse Response Function (IRF) analysis to assess the impact of shocks to oil prices on inflation and vice versa. This analysis offers a dynamic perspective on the interaction between oil prices and inflation over time, providing valuable insights into their interconnectedness within a VAR model. The IRF framework for both oil prices and inflation, derived from a VAR (1) model, is presented in equation (7).

$$\begin{bmatrix} OP_t \\ Inf_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \begin{bmatrix} OP_{t-1} \\ Inf_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{7}$$

The IRFs illustrate how shocks to ε_{1t} or ε_{2t} affects both oil prices, OP_t and inflation, Inf_t over time. The analysis show the response of oil prices and inflation to these shocks at various periods.

2.6 Variance Decomposition (VD)

The next analysis is Variance Decomposition (VD), which breaks down the error variances of oil prices and inflation over time into components attributable to shocks in ε_{1t} and ε_{2t}. This decomposition helps quantify the relative importance of shocks to oil prices and inflation in explaining the variability of each variable over different time horizon, h. To estimate the error variance of OP_t and Inf_t at horizon h, the decomposition can be written as equations (8) and (9), respectively.

$$Var\big(OP_t(h)\big) = \sigma^2_{OP,\varepsilon_1}(h) + \sigma^2_{OP,\varepsilon_2}(h) \tag{8}$$

$$Var\big(Inf_t(h)\big) = \sigma^2_{Inf,\varepsilon_1}(h) + \sigma^2_{Inf,\varepsilon_2}(h) \tag{9}$$

where $\sigma^2_{OP,\varepsilon_1}(h)$ is component of the variance of OP_t forecast errors due to shocks in ε_{1t}, and $\sigma^2_{OP,\varepsilon_2}(h)$ is component of the variance of OP_t forecast errors due to shocks in ε_{2t}. The same applies for inflation, where $\sigma^2_{Inf,\varepsilon_1}(h)$ is component of the variance of Inf_t forecast errors due to shocks in ε_{1t}, and $\sigma^2_{Inf,\varepsilon_2}(h)$ is component of the variance of Inf_t forecast errors due to shocks in ε_{2t}.

3. Results and Discussion

Based on the methodology outlined earlier, this study examined two time series variables of RON95 petrol prices and Malaysia's CPI, covering the period from November 2014 to June 2021. Model specification, diagnostic checks, and subsequent analyses were conducted accordingly.

3.1 Unit Root Tests

Table 1. Augmented Dickey-Fuller (ADF) Unit Root Test.

Variables	Original series, I(0)		First order differencing, I(1)	
	ADF statistic	*p*-value	ADF statistic	*p*-value
RON95 prices	-2.2463	0.4748	-4.8658	< 0.01
CPI series	-1.6347	0.7266	-4.7612	< 0.01

The Augmented Dickey–Fuller (ADF) test results shown in Table 1 indicate that both the RON95 petrol price series and the CPI series are non-stationary in levels. This is supported by the high p-values, which exceed the 5% significance level, meaning the null hypothesis of a unit root cannot be rejected. After applying first-order differencing, the p-values drop below 0.05 for both variables, allowing rejection of the null hypothesis of a unit root. The differenced series are therefore stationary. As a result, RON95 prices and CPI are classified as integrated of order one, I(1), which means each becomes stationary only after a single differencing process. This finding is important for subsequent modelling, including cointegration analysis or vector error correction modelling, which require variables to be I(1).

3.2 VAR Lag Length Selection

Before performing a cointegration analysis, a VAR model was first fitted to identify the optimal lag length. Table 2 shows the selection criteria based on the Log-Likelihood (LogL), Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan–Quinn Criterion (HQ) for lag orders 0 to 4.

Table 2. VAR Optimal Lag Length Selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	137.3296	NA	1.22e-05	-5.6387	-5.5608	-5.6093
1	272.6564	253.7378	5.13e-08	-11.1107	-10.8768	-11.0222
2	283.5876	19.5850	3.85e-08	-11.3995	-11.0097	-11.2522
3	291.8787	14.1640	3.22e-08	-11.5783	-11.0325*	-11.3720*
4	293.8908	3.2696	3.52e-08	-11.4955	-10.7938	-11.2303

According to both the Schwarz Criterion (SC) and Hannan-Quinn (HQ) criterion, the optimal lag length is 3, as indicated by the asterisks in Table 2. Therefore, a VAR (3) model is employed in the subsequent cointegration analysis.

3.3 Johansen Cointegration Test

The Johansen cointegration test was performed to assess the existence of a long-term equilibrium relationship between oil prices and inflation in Malaysia. The results, as shown in Table 3, include both the Trace and Maximum Eigenvalue statistics.

Table 3. Johansen Cointegration Test.

Null Hypothesis	Alternative Hypothesis	Trace Statistic	Critical Value	p-value
$H_0: r = 0$	$H_1: r \geq 1$	14.766	15.4947	0.0642
$H_0: r \leq 1$	$H_1: r \geq 2$	5.8978	3.8415	0.0152
Null Hypothesis	**Alternative Hypothesis**	**Max-Eigen Statistic**	**Critical Value**	**p-value**
$H_0: r = 0$	$H_1: r \geq 1$	8.8690	14.2646	0.2972
$H_0: r \leq 1$	$H_1: r \geq 2$	5.8978	3.8415	0.0152

For the Trace test, the null hypothesis of no cointegration ($r = 0$) could not be rejected, as the test statistic (14.766) was less than the 5% critical value (15.4947), and the associated p-value (0.0642) exceeded the 0.05 significance level. This indicates there is insufficient evidence to support the existence of at least one cointegrating vector. However, when testing the null hypothesis of at most one cointegrating relationship ($r \leq 1$), the Trace statistic (5.8978) exceeded the critical value (3.8415), with a p-value of 0.0152. This result suggests the null hypothesis should be rejected and indicates the presence of at least one additional cointegrating relationship.

Similarly, the Maximum Eigenvalue test results showed that the null hypothesis of no cointegration ($r = 0$) could not be rejected, as the test statistic (8.8690) was less than the critical value (14.2646), and the p-value (0.2972) was greater than 0.05. However, the test for at most one cointegrating relationship ($r \leq 1$) yielded a test statistic (5.8978) that exceeded the critical value (3.8415), with a p-value of 0.0152, leading to the rejection of the null hypothesis. Although one of the tests ($r \leq 1$) suggests the presence of a cointegrating relationship, the failure to reject the null hypothesis of no cointegration ($r = 0$) in both the Trace and Maximum Eigenvalue tests imply that the overall evidence of cointegration is not strong or consistent. Therefore, it is reasonable to conclude that no robust long-term equilibrium relationship exists between oil prices and inflation in Malaysia.

Consequently, a Vector Error Correction Model (VECM), which requires strong evidence of cointegration, was not utilised. Instead, the study employed a VAR model in first differences to examine short-term dynamics between the two variables. Before estimating the VAR model, the optimal lag length was identified using standard lag selection criteria. Based on the information criteria, a lag length of three was chosen. The VAR model was then estimated using the first differenced series of Malaysia's CPI and RON95 prices. This approach is suitable given the non-stationarity of the original level series and the absence of conclusive evidence supporting a long-term cointegrating relationship.

3.4 Unrestricted VAR Results

Following the findings in Section 3.3, where the Johansen cointegration test did not provide consistent evidence of a long-term equilibrium relationship between oil prices and inflation in Malaysia, an unrestricted VAR model was estimated. This model used the first differences of the variables in their original levels. This approach is suitable for capturing the short-term dynamics between oil prices and consumer price inflation, given the absence of a robust cointegrating relationship. The optimal lag length was determined using standard lag order selection criteria, resulting in a lag length of three.

Table 4. Unrestricted VAR Coefficients.

	Coefficient	Std. Error	t-Statistic	Prob.
C(3)	0.9382	0.0240	39.03	0.0000
C(4)	0.0849	0.0065	13.14	0.0000
C(6)	-0.0809	0.0063	-12.90	0.0000
C(7)	0.2979	0.1144	2.603	0.0122

The estimated coefficients of the unrestricted VAR model, shown in Table 4, reveal statistically significant effects of several lagged variables on the change in the CPI. Specifically, the coefficient for the third lag of CPI (C(3)) indicates that a one-unit increase in the CPI difference three periods prior is associated with an approximately 0.94 unit increase in the current change of CPI. Similarly, the coefficient for the first lag of petrol RON95 prices (C(4)) suggests that a one-unit increase in the petrol price difference from the previous period corresponds to an increase of about 0.08 units in the current CPI difference. These findings demonstrate that inflation exhibits persistence and that short-term fluctuations in petrol prices have an influence on consumer prices.

In contrast, the coefficient for the third lag of petrol RON95 prices (C(6)) is negative and significant, implying that a one-unit decrease in the petrol price difference three periods earlier is associated with an increase of approximately 0.08 units in the current change of CPI. This result suggests complex dynamics in price transmission that may include delayed or nonlinear effects. The positive and statistically significant constant term (C(7)) aligns with theoretical expectations of a positive intercept in aggregate demand. Overall, the model explains roughly 97% of the variation in changes in Malaysia's CPI, indicating high explanatory power.

These results are consistent with findings in previous studies. For instance, Lacheheba and Siragca (2019) and Musa and Maijama (2021) reported significant associations between rising oil prices and inflation. However, Davari and Kamalian (2018) found a significant relationship only during periods of declining oil prices, while Musa and Maijama (2021) observed no long-term causal relationship between inflation and domestic oil prices based on Granger causality tests. Contrarily, Sultan et al. (2020) identified that oil prices affect inflation in India in both the short and long term. These mixed findings suggest that the impact of oil prices on inflation may vary across countries and over time.

It is important to note that the VAR model was estimated using the first differences of the original level data, not logged variables. Consequently, the estimated coefficients represent the effects of one-unit changes in the differences of the variables on the change in CPI, rather than percentage changes. Interpreting these coefficients as percentage changes would be inappropriate without a logarithmic transformation. This clarification ensures accurate interpretation consistent with the data transformation and supports valid inference from the model results.

3.5 Diagnostic test

Diagnostic testing is fundamental in VAR modelling to evaluate the adequacy of the estimated model and to verify whether the underlying statistical assumptions are satisfied, thereby ensuring valid inference. The key assumptions assessed by diagnostic testing in VAR models include homoscedasticity of residuals, absence of serial correlation, and normality of residuals.

Homoscedasticity requires the variance of residuals to remain constant across observations, ensuring that the model's error terms do not exhibit systematic changes in variability. The absence of serial correlation means residuals are not correlated over time, which is critical for VAR models since they analyse time-dependent data. Residual normality assumes that the residuals follow a normal distribution, which is important for valid hypothesis testing and confidence interval estimation.

To assess these assumptions, three diagnostic tests were employed. The Breusch-Pagan-Godfrey test for heteroscedasticity evaluates whether the residual variance remains constant. The Breusch-Godfrey Serial Correlation LM test detects autocorrelation in residuals across time periods. The Jarque-Bera test examines the normality of residuals. The results of these tests are summarised in Table 5.

Table 5. Diagnostic tests.

	***F*-statistics**	***p*-value**
Heteroscedasticity test: Breusch-Pagan-Godfrey	0.8107	0.4941
Breusch-Godfrey Serial Correlation LM test	1.9283	0.1382
Jarque-Bera	0.0651	0.9680

All *p*-values in Table 5 exceed the 0.05 significance level, indicating that the null hypotheses for each diagnostic test cannot be rejected. Specifically, the Breusch-Pagan-Godfrey test confirms that the residuals exhibit homoscedasticity, meaning the variance of errors remains constant over time, which ensures reliable and efficient parameter estimates. The Breusch-Godfrey Serial Correlation LM test indicates the absence of serial correlation, confirming that the residuals are uncorrelated across time periods, thereby validating the independence assumption. Furthermore, the Jarque-Bera test supports the assumption that the residuals are normally distributed, a condition necessary for valid hypothesis testing and accurate confidence interval estimation. Collectively, the findings demonstrate that the VAR model satisfies the fundamental statistical modelling assumptions, hence establishing a sound basis for statistical inference and short-term forecasting.

3.6 Impulse Response Function (IRF)

This section explores the dynamic interaction between oil prices (Y) and inflation (X) through the Impulse Response Function (IRF) derived from the estimated VAR model. The IRF plots, presented in Figure 3, illustrate the response of each variable to a one standard deviation shock in either itself or the other variable over ten months. The solid lines in the plots represent the estimated impulse responses, while the dashed lines depict the 95% confidence intervals, indicating the statistical significance of the responses.

The response of oil prices to a one-standard-deviation shock, shown in the top-left panel, displays a sharp initial rise followed by a gradual decline, eventually tapering towards zero. This pattern indicates that the shock's effect diminishes over time, aligning with transitory dynamics. The top-right panel illustrates the response of oil prices to a shock in inflation, which initially increases but later falls below zero. This suggests that the effect of inflation on oil prices is positive in the short term, turns negative in the medium term, and ultimately dissipates.

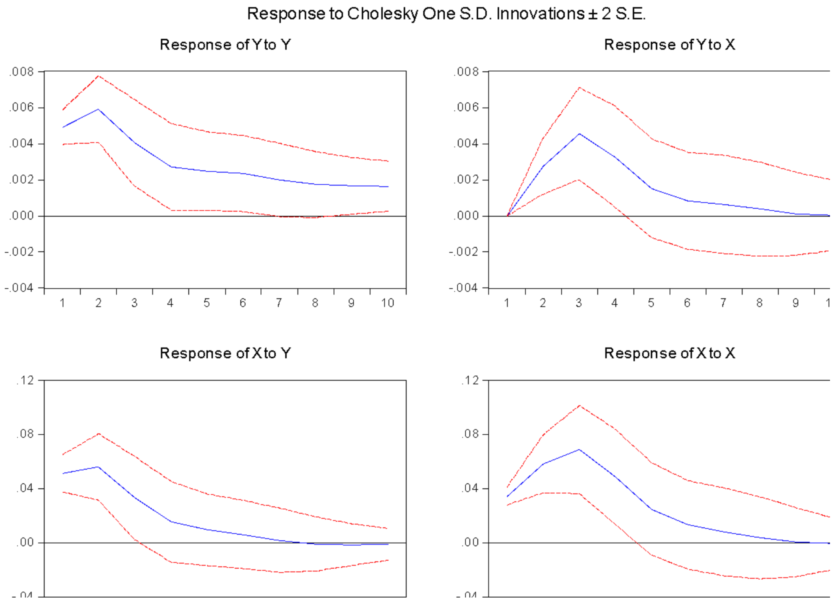

Figure 3. Impulse Response Functions Plots of Oil Prices and Inflation from the VAR Model.

The bottom-left panel presents the response of inflation to a shock in oil prices. Inflation initially declines, but the magnitude of this negative effect diminishes over time, approaching zero. This implies that the impact of oil price shocks on inflation weakens as time progresses. In the bottom-right panel, the response of inflation to a shock in inflation is initially strong and positive, followed by a gradual decline, indicating mean-reverting behaviour where the initial effect is substantial but temporary.

It is noteworthy that, during certain periods, the confidence intervals include zero, indicating that the responses may not be statistically significant across the entire horizon. Nevertheless, the IRF analysis offers valuable insights into the dynamic relationships between oil prices and inflation. It shows that while shocks to both variables produce immediate responses, the effects are typically short-lived. Such findings are important for policymakers, emphasising the temporary nature of economic shocks and supporting more responsive and time-sensitive policy actions in the context of oil price and inflation volatility (Mansor et al., 2018).

3.7 Variance Decomposition

Table 6 presents the results of the variance decomposition (VD) analysis based on the VAR model. In the VD analysis, Periods 1 to 10 represent the forecast horizons used in the VAR model, indicating the number of periods ahead for which the forecast error variance is calculated. Period 1 corresponds to the one-step-ahead forecast, where the forecast error variance of each variable is driven solely by its own immediate shock as the model has not yet incorporated any effects from other variables. As the horizons extend from Period 2 to 10, the model increasingly incorporates lagged interaction between oil prices and inflation, allowing shocks in one variable to gradually influence the other.

Based on Table 6, at the initial horizon (Period 1), 100% of the forecast error variance in oil prices (Y) is attributed solely to its own innovations. This is consistent with expectations, as the VAR model does not incorporate the contemporaneous or lagged influence of other variables in the first period. As the forecast horizon extends, the proportion of oil price variance explained by shocks to inflation (X) gradually increases. This indicates that inflation exerts a growing influence on oil price dynamics over time. For example, in later periods, a non-negligible share of oil price variability is attributed to innovations in inflation, reflecting the dynamic interactions captured by the model.

Table 6. Variance Decompositions of Oil Prices (Y) and Inflation (X).

Variance Decomposition of Y				Variance Decomposition of X			
Period	**S.E.**	**Y**	**X**	**Period**	**S.E.**	**Y**	**X**
1	0.0049	100.00	0.00	1	0.0617	68.93	31.07
2	0.0082	88.63	11.37	2	0.1015	55.76	44.24
3	0.0102	72.69	27.31	3	0.1270	42.32	57.68
4	0.0111	68.03	31.97	4	0.1368	37.75	62.25
5	0.0114	68.34	31.66	5	0.1393	36.85	63.15
6	0.0117	69.25	30.75	6	0.1401	36.65	63.35
7	0.0119	69.91	30.09	7	0.1403	36.54	63.46
8	0.0120	70.47	29.53	8	0.1403	36.52	63.48
9	0.0121	71.02	28.80	9	0.1404	36.53	63.47
10	0.0122	71.55	28.45	10	0.1404	36.53	63.47

A comparable trend is observed for inflation (X). In Period 1, approximately 68.93% of its forecast error variance is explained by its own innovations, while 31.07% is accounted for by shocks to oil prices. By Period 10, the contribution of oil price shocks rises to approximately 63.47%, indicating an increasing influence of oil prices on inflation as the horizon extends. These findings underscore the evolving nature of the relationship between oil prices and inflation. The variance decomposition analysis illustrates how shocks to one variable progressively affect the other across forecast horizons, highlighting the transmission mechanisms inherent in the VAR model.

4. Conclusion

This study investigated the dynamic relationship between Malaysia's CPI and RON95 petrol prices using a VAR model, with particular emphasis on two deregulated pricing periods from November 2014 to January 2018 and March 2020 to February 2021, during which market mechanisms rather than administrative controls determined RON95 prices. These periods offered a relevant context for evaluating the transmission of RON95 price shocks to domestic inflation.

The empirical analysis shows that in the short term, the effects of RON95 price on the CPI are mixed, alternating between positive and negative across lags. For instance, the first lag of RON95 has a positive effect of 0.0849 on CPI, while the third lag is negative at 0.0809, indicating variability in the short-run pass-through effect. Over longer forecast horizons, the impulse response functions show that a one-standard-deviation shock to RON95 produces an initial CPI response of about 0.02 before gradually converging toward zero. The variance decomposition results further support this pattern, showing that the share of CPI forecast error variance attributed to RON95 shocks increases from 31.07% in the first period to approximately 63.47% by the tenth period, signalling a growing influence as the forecast horizon extends.

These findings have important policy implications. Given the sustained and intensifying influence of fuel price shocks on inflation, it is essential for policymakers, particularly Bank Negara Malaysia, to closely monitor RON95 price developments and implement timely monetary policy interventions to mitigate inflationary pressures. Furthermore, the results underscore the importance of establishing fuel price stabilisation mechanisms and promoting diversification of energy sources to enhance the macroeconomic resilience against external oil market volatility. The findings may also inform improvements in inflation forecasting models and the formulation of effective macroeconomic policy strategies in Malaysia.

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