Asymmetric Adjustment between Oil Prices and the Consumer Price Index in Malaysia: Evidence from Aggregated and Disaggregated Levels

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Summary: This study examines the asymmetric adjustment of the consumer price index in Malaysia in response to changes in oil prices from January 2005 to December 2022, at both aggregated and disaggregated levels. The findings of momentum threshold autoregressive cointegration tests indicate a cointegrating relationship between oil prices and the consumer price index in Malaysia. The consumer price index and its subcategories demonstrate varying speeds of adjustment back to equilibrium. Specifically, the aggregated consumer price index and the majority of the disaggregated consumer price indexes adjust relatively quickly back to equilibrium when oil prices fall, as opposed to when they rise. This suggests that the pass-through effect of oil prices on consumer prices is heterogeneous, with significant variations in the speed of adjustment across different consumer price subcategories. Consequently, these adjustment speeds should not be overlooked when considering the direction of monetary policy.

Keywords: Asymmetric adjustment, Oil prices, Consumer price index, Momentum threshold autoregressive cointegration, Malaysia

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Oil price changes are often cited as a key cause of inflation, affecting economic activity through various channels. The supply channel, in particular, is significantly impacted by oil prices due to the economy's heavy reliance on oil for transportation fuel. When input costs, such as fuel costs, increase in the supply channel, producers may pass them on to consumers by raising the prices of end goods and services (Salisu et al. 2017). Consequently, there has been considerable empirical research on the oil price-inflation pass-through effect (Lacheheb and Sirag 2019; Mien 2022; Tiwari et al. 2019; Salisu et al. 2017; Asghar and Naveed 2015; Koh, Lim, and Sek 2020; Sek 2019). These studies, however, have analysed only the aggregated level of the consumer price index (CPI), leaving a crucial need to study how each component of the CPI responds to fuel price shocks at the disaggregated level (Kpodar and Liu 2022).

In fact, the effects of oil prices have been reported to vary across CPI subcategories in different regions, such as Malaysia (Ibrahim and Said 2012; Sek 2017; Xuan and Chin 2015), Ghana (Ibrahim Anyars and Adabor 2023), India (Pradeep 2022), Southeast Asia (i.e., Indonesia, Malaysia, and Thailand) (Husaini and Lean 2021), Europe (i.e., France, Germany, Italy, and Spain) (Castro et al. 2017), and Kpodar and Liu's (2022) sample of 122 countries. Nevertheless, these studies limited their analysis to just a few subcategories of CPI rather than all possible categories. Additionally, researchers often overlook intrinsic asymmetric adjustment when examining the oil price-inflation nexus, leading to model misspecification and inappropriate policy decisions (Paleologou 2013). The rise and fall of oil prices have dissimilar impacts on economic performance (Sek 2017) and asymmetrical effects on product prices (Ibrahim and Said 2012), making asymmetric adjustment crucial to bridge the supplier-consumer gap and achieve overall price stability. As such, identifying the heterogeneous effect of oil prices on consumer prices is particularly important for policy actions aimed at addressing the overall inflationary pressure from oil price shocks. To do so, it is imperative to assume that the CPI and its subcategories adjust to their long-run equilibrium at different speeds in response to positive and negative oil price shocks.

Given the aforementioned research paucities, this study complements existing literature on both aggregated and disaggregated CPI. Using a CPI dataset from the January 2005 to December 2022 period, we aimed to analyse the asymmetric adjustment of overall CPI and CPI subcategories in response to oil prices fluctuations in Malaysia. The momentum threshold autoregressive (MTAR) models proposed by Enders and Granger (1998) and Enders and Siklos (2001) were employed for this purpose, providing a clearer picture of the asymmetric adjustment phenomenon to add theoretical value and inform key policy decisions.

1. The Malaysian Context

Malaysia is considered the second-largest producer of oil and natural gas in Southeast Asia (EIA 2021). In 2021, the country produced approximately 508 thousand barrels of crude oil per day and exported approximately 209 thousand barrels of crude oil per day, recording a slight reduction from 280 thousand barrels exported per day the previous year (OECD 2023). Meanwhile, crude oil imports totaled about 131 thousand barrels per day in 2021, a notable drop from 248 thousand barrels per day in 2020

(OECD 2023). Although these statistics position Malaysia as a net exporter of crude oil, the nation has been predicted to become a net oil importer in the near future (Prambudia and Nakano 2012; Xuan and Chin 2015). This challenge is exacerbated by oil prices changes, which have varying impacts on a country's economic inflation depending on whether it is an oil exporter or importer (Sek 2017; Koh, Lim, and Sek 2020; Lacheheb and Sirag 2019). Therefore, despite its historical performance, Malaysia's economy remains a point of concern.

In line with this study's objective to examine the effect of oil prices on aggregated and disaggregated CPI in Malaysia, we focused on the costs of purchasing associated with overall CPI as well as all 12 subcategories of CPI: Food and Non-Alcoholic Beverages (CFOOD), Alcoholic Beverages and Tobacco (CALCO), Clothing and Footwear (CCLO), Housing, Water, Electricity, Gas and Other Fuels (CHOU), Furnishings, Household Equipment and Routine (CFUR), Health (CHEA), Transport (CTRAN), Communication (CCOM), Recreation Services and Culture (CREC), Education (CEDU), Restaurant and Hotels (CRES), and Miscellaneous Goods and Services (CMIS). Figure 1 displays the oil price and aggregated inflation for overall CPI, while Figures 2(a)-2(c) present the oil price and disaggregated inflation for the 12 subcategories in Malaysia from 2006 to 2022.

Between 1991 and 1999, international oil prices were remarkably stable, averaging about $20 per barrel. However, since 2000, oil prices have experienced significant fluctuations. In 2008, the world oil price surged to US$97.33 per barrel, contributing to inflation reaching its highest level of 5.4%. The rise in inflation was primarily attributed to the CFOOD (8.9%) and CTRAN (8.9%) subcategories, followed by CALCO (7.3%) and CREC (6.6%). In contrast, CCLO and CCOM recorded the lowest inflation rates in 2008, both at -0.6%. Subsequently, the 2008 financial crisis and resulting drop in global demand caused oil prices to fall sharply to a low of $61.58 in 2009. Correspondingly, aggregate inflation inched down to 0.6% in 2009 and to 1.7% in 2010. Among the major subgroups that experienced notable drops in 2009 were CFOOD, CALCO, CTRANS, and CRES, at 4.1%, 6.1%, -9.4%, and 2.9%, respectively.

Similarly, the dramatic rise in oil prices from 2011 to 2013, the collapse in oil prices from 2014 to 2016, the 2020 oil price drop, and the COVID-19 pandemic had varying impacts on inflation across subgroups. For instance, the decline in international energy and commodity prices was the main cause of lower headline inflation in Malaysia in 2015 (Bank Negara Malaysia, 2015), primarily attributed to the CTRAN and CHOU categories. More recently, inflation was registered at 3.4% in 2022, a slight increase from the preceding year's 2.5%. This inflationary pressure was again driven by sustained rises in global oil prices. Overall, changes in oil prices are associated with disruptions in Malaysia's aggregate CPI, which may trigger uneven prices hikes across different goods and services.

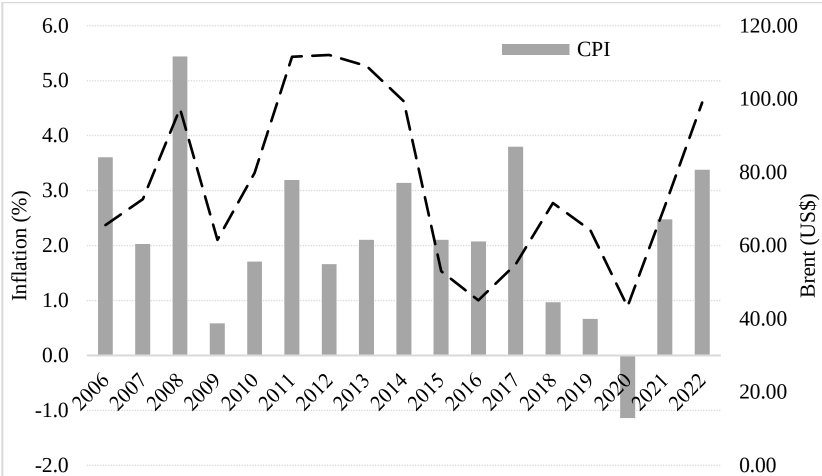
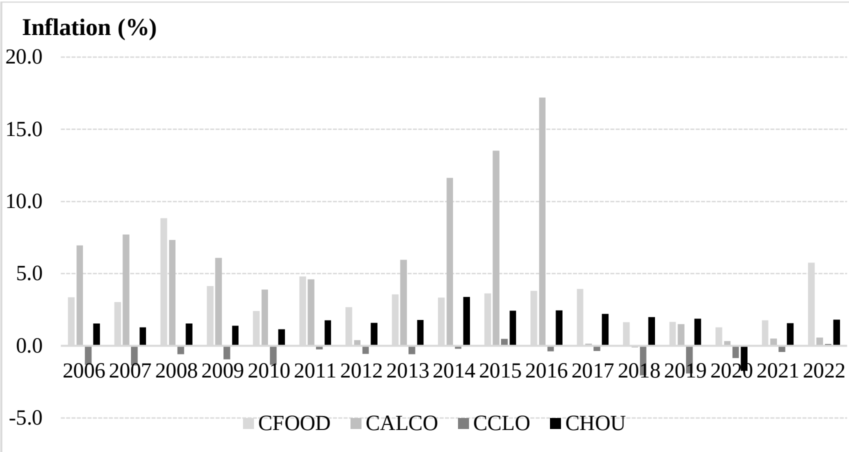
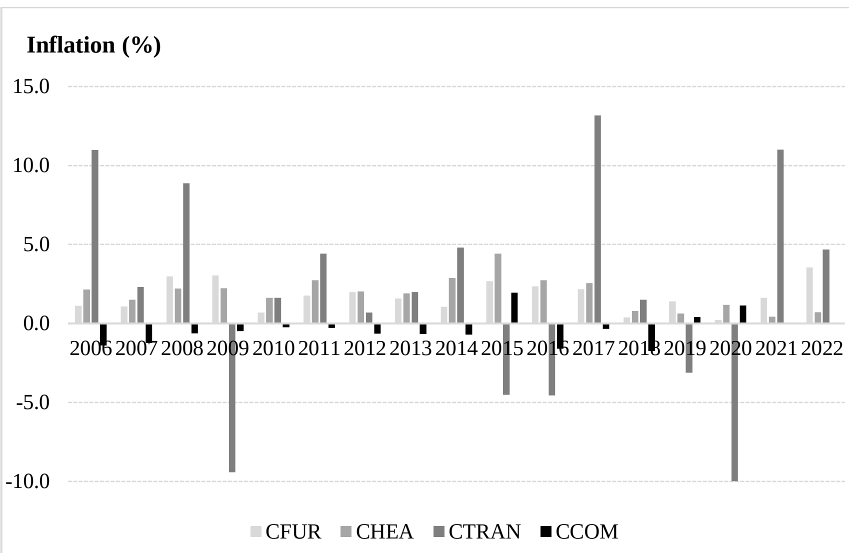


Figure 1 Oil Price and Aggregated Inflation, 2006-2022

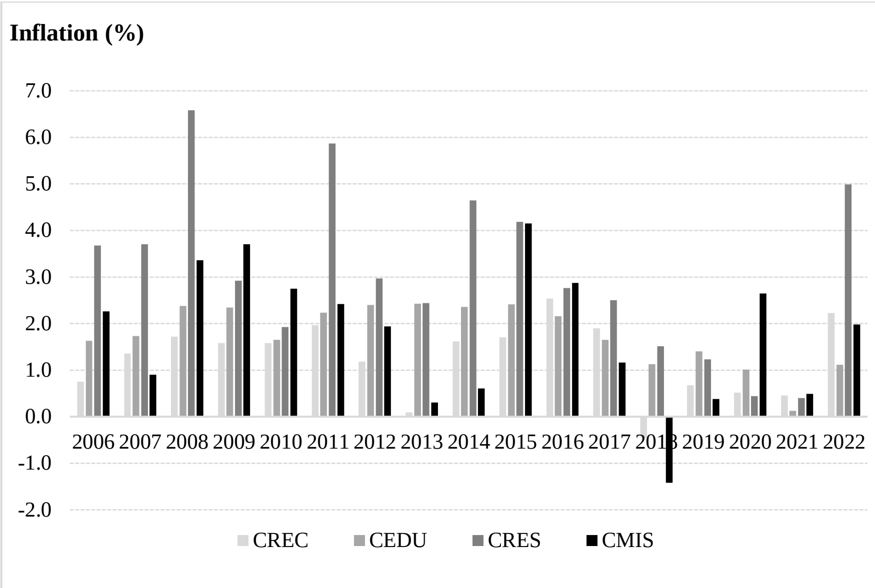
Source: (Bank Negara Malaysia 2023; IMF 2023)



a) Disaggregated inflation for CFOOD, CALCO, CCLO, and CHOU



b) Disaggregated inflation for CFUR, CHEA, CTRAN, and CCOM



c) Disaggregated inflation for CREC, CEDU, CRES, and CMIS

Figure 2 Disaggregated Inflation, 2006-2022

Source: (Bank Negara Malaysia 2023)

2. Literature Review

There has been a growing body of literature exploring the relationship between oil prices and the CPI using various estimation techniques. Some prominent studies have examined this pass-through effect via linear autoregressive distributed lags (ARDL) bounds testing (Asghar and Naveed 2015; Xuan and Chin 2015; Mien 2022; Bala and Chin 2018). For instance, Asghar and Naveed (2015) found that both oil prices and exchange rates significantly affect the inflation rate in the long run in Pakistan. Employing the dynamic ordinary least squares (DOLS) and linear ARDL methods, Mien (2022) showed evidence of a pass-through effect in Cameroon, Chad, and the Republic of Congo, as well as a Dutch disease effect in Equatorial Guinea. Additionally, Xuan and Chin (2015) and Ibrahim and Said (2012) investigated the pass-through effect of oil prices on CPI in Malaysia, with the former differentiating the impacts of actual diesel prices from subsidised retail diesel prices and the latter incorporating both aggregated CPI and disaggregated CPI components (i.e., food, rent, fuel and power, transportation and communication, medical care and health). However, it should be noted that the linear ARDL approach assumes that pass-through effects are symmetric, meaning that increases and decreases in oil prices are presumed to have a similar impact on CPI.

Conversely, nonlinear autoregressive distributed lags (NARDL) bounds testing relaxes the assumption of symmetry by decomposing the variable (oil price) into positive and negative partial sums. This approach has enabled the analysis of CPI's asymmetric reaction to oil price changes in various contexts, including selected net oil-exporting and net oil-importing countries (Salisu et al. 2017), Indonesia, Malaysia, and Thailand (Husaini and Lean 2021), India (Pradeep 2022), and Algeria (Lacheheb and Sirag 2019). Salisu et al. (2017), for example, used the panel NARDL technique to prove that oil prices have a larger impact on inflation in net oil-importing nations than in net oil-exporting ones in the long run, although net exporters exhibit a relatively higher speed of adjustment compared to net importers.

Lacheheb and Sirag (2019) utilised time series NARDL to reveal the long-run and short-run asymmetrical effect of oil prices on the CPI in Algeria, concluding that an increase in oil prices raises inflation while a decrease does not influence inflation. Likewise, according to Husaini and Lean (2021), oil price hikes have a greater impact on the Producer Price Index (PPI) than the CPI in Indonesia, Malaysia, and Thailand, whereas oil price reductions significantly affect both the CPI and PPI in Thailand. In Turkey, Altunöz (2022) also found evidence that the effects of crude oil price volatility on the CPI and PPI are asymmetrical in the long run. Alternatively, Sek (2017) observed both symmetric and asymmetric effects of oil prices on domestic prices across sectors in Malaysia. Employing ARDL and NARDL techniques, the study reported that in the long run, oil prices do not directly induce higher consumer prices across sectors; rather, they exert pass-through effects on the CPI via increased import prices and production costs.

In Ghana, Ibrahim Anyars and Adabor (2023) established the asymmetrical influence of oil prices fluctuations on both aggregated and disaggregated inflation from 2000 to 2021. Particularly, the asymmetrical impact was significantly greater on the transport subcategory of the CPI than the energy, food, and core subcategories. Similarly, Adeosun, Tabash, and Anagreh (2023) explored the role of global geopolitical risk in the link between oil prices and domestic food prices from 1995 to 2021 in Nigeria. They applied ARDL and NARDL techniques to demonstrate that in the long run, both positive and negative oil price shocks directly impact food prices; however, in the short run, the effect of oil price shocks vary based on global geopolitical risk.

Apart from ARDL and NARDL approaches, studies have incorporated vector autoregressive (VAR) techniques to detect the pass-through effects of oil price changes (Gao et al. 2014; Kpodar and Liu 2022; Rafei et al. 2022; Yilmazkuday 2021). Kpodar and Liu (2022), using a sample of 122 countries, examined CPI behaviour in response to changes in domestic fuel prices, focusing on different categories of the CPI. Their findings indicated that the inflation response to gasoline price shocks is smaller, more persistent, and broader in developing countries compared to developed ones, suggesting that the distributional impact of fuel price increases is progressive. In Iran, Rafei et al. (2022) employed a time-varying parameter VAR model to analyse data from 1993 to 2018, demonstrating that the pass-through effect of oil price shocks on inflation is time-varying. Indeed, they revealed that the positive effect of rising oil prices on inflation was significantly more pronounced during the country's sanction period relative to other time horizons. Additionally, Yilmazkuday (2021) decomposed the direct and indirect oil price pass-through impact on CPI in the U.S. They found that, in the long run, oil prices influence consumer prices predominantly via ex-gasoline consumer prices. Dedeoğlu and Kaya (2014) investigated this relationship in Turkey using a recursive VAR model on rolling windows. Their analysis noted an increasing trend in the pass-through mechanism of oil prices to domestic prices, with the impact on PPI being nearly twice as high as that on CPI.

Among the numerous studies that have tested oil price changes' symmetrical and asymmetrical effects on domestic prices via ARDL or NARDL models, most appear to be biased in favour of symmetric adjustment. However, economic variables often display unequal adjustment patterns, suggesting that the movement toward long-run equilibrium is best characterised as an asymmetric process (Enders and Granger 1998). In this regard, threshold cointegration is significantly advantageous in adjusting positive and negative shocks to long-term equilibrium at different speeds.

Scholars have utilised TAR and MTAR techniques to reveal how asymmetric adjustment can influence the complete pass-through effect of oil prices on other macroeconomic variables (Koh, Lim, and Sek 2020; Bala, Lee, and Maijama'a 2021; Chen, Lee, and Goh 2013; Rafailidis and Katrakilidis 2014). For example, Koh et al. (2020) explored the oil price pass-through impact on CPI and PPI in oil-importing and oil-exporting economies. Their threshold adjustment analysis found that oil prices have a greater impact on PPI inflation than on CPI inflation, with the effect on CPI inflation being particularly weaker in oil-importing countries. Applying a similar estimation technique, Bala et al. (2021) noted the asymmetric adjustment behaviour between oil prices and economic growth in Malaysia. Chen et al. (2013) also found asymmetric cointegration between oil prices and exchange rates in the Philippines using the TAR approach. Overall, oil prices evidently exert an asymmetric impact on macroeconomic activities.

In summary, the majority of previous studies have adopted NARDL techniques to demonstrate that the CPI reacts asymmetrically to increases and decreases in oil prices. However, these studies have seemingly overlooked potential asymmetries in the adjustment toward long-run equilibrium, which may lead to model misspecification and misguided policy decisions (Paleologou 2013). This gap is crucial as economic variables often display unequal adjustment patterns, suggesting that the movement toward equilibrium is inherently an asymmetric process (Enders and Granger 1998). Other scholars have used threshold cointegration analysis to explore the asymmetric cointegration between oil prices and macroeconomic variables (see Bala et al. 2021; Chen et al. 2013; Koh et al. 2020; Rafailidis and Katrakilidis 2014), focusing mainly on the pass-through effects on aggregated CPI. Conversely, the analysis of CPI subcategories remains limited, particularly via MTAR models, despite recent reports of disaggregated CPI behaviour in response to oil price changes. Therefore, this study fills this gap by positing that positive and negative oil price shocks affect the CPI and its subcategories at different adjustment speeds toward long-run equilibrium.

3. Data and Methodology

3.1 Data

As mentioned in Section 1, the Malaysian CPI dataset can be divided into aggregated CPI and disaggregated CPI, the latter of which encompasses 12 subcategories: CFOOD, CALCO, CCLO, CHOU, CFUR, CHEA, CTRAN, CCOM, CREC, CEDU, CRES, and CMIS. The complete set of CPI categories, which can be obtained from Bank Negara Malaysia, is only available after 2005. Consequently, to ensure consistency, we reassigned the CPI data to the same base year (2005=100) and set January 2005 to December 2022 as the study period. The independent variable, oil price, was proxied by the Brent crude oil price (OP) in US dollars per barrel. OP data is a widely used benchmark for global oil pricing (Wang, Wu, and Yang 2014), obtainable from the International Monetary Fund (IMF 2023). All variables were expressed as natural logarithms.

3.2 Unit Root Tests

A prerequisite procedure for implementing cointegration analysis is to determine the integration properties of the variables studied. To do so, we performed the Augmented Dickey-Fuller (ADF) (Dickey and Fuller 1979; 1981) and Phillips-Perron (PP) (Phillips and Perron 1988) tests, which most empirical studies use to detect the presence or absence of a unit root.

3.3 Engle-Granger Two-Stage Approach

If the prerequisite tests reveal that both the CPI and oil price are integrations of the same order, the Engle-Granger two-stage approach would be used to examine the existence of cointegration between the two variables (Engle and Granger 1987). Following Koh et al. (2020) and Xuan and Chin (2015), we formulated the long-run relationship between oil price and CPI in Malaysia as follows:

$$CPI_t = \delta_0 + \delta_1 OP_t + u_t \tag{1}$$

$$\Delta u_t = \rho u_{t-1} + \sum_{i=1}^{q} \varphi_i \, \Delta u_{t-1} + \ e_t \tag{2}$$

where δ_0 and δ_1 are parameter estimates. Equation (1) was estimated separately for the aggregated CPI and the 12 disaggregated CPIs (2005=100). Residuals from Equation (1) were used to test for stationarity using the ADF unit root test. However, this standard cointegration test suffers from a number of pitfalls. First, it may exhibit low power in the presence of asymmetric adjustment (Enders and Siklos 2001). Second, Equation (2) indicates that the cointegration among variables is symmetric (Haughton and Iglesias 2012). Lastly, the test assumes that the adjustment speed towards long-run equilibrium remains constant in each time period (Esteve and Tamarit 2012). As such, Equation (2) would be misspecified if asymmetric adjustment exists.

3.4 Enders and Siklos' MTAR Cointegration

To address the limitations mentioned above, we employed MTAR models, which are designed to test asymmetric cointegration among variables (Enders and Siklos 2001). The MTAR specification has more robust power and size properties compared to symmetry adjustment (Enders and Siklos 2001). It is particularly useful and relevant when the adjustment shows more momentum in one direction than the other (Thompson 2006; Yuksel 2016; Payne and Waters 2005). The MTAR model can be specified in the following form:

$$\Delta u_t = M_t \rho_1 u_{t-1} + (1 - M_t)\rho_2 u_{t-1} + \sum_{i=1}^{p} \vartheta_i \,\Delta u_{t-i} + e_t \tag{3}$$

$$M_t = \begin{Bmatrix} 1 \; if \; \Delta u_{t-1} \geq \tau \\ 0 \; if \; \Delta u_{t-1} < \tau \end{Bmatrix} \tag{4}$$

where $e_t \sim$ I.I.D $(0, \sigma^2)$; τ is the threshold value; and M_t is the Heaviside indicator function that allows the adjustment to depend on the previous period's change in u_{t-1}. In the MTAR model, if Δu_{t-1} is above the threshold, the adjustment is $\rho_1 u_{t-1}$; if Δu_{t-1} is below the threshold, the adjustment is $\rho_2 u_{t-1}$. Following Payne (2007), we infer that $\Delta u_{t-1} \geq \tau$ corresponds to a decrease in oil prices relative to the CPI. On the other hand, $\Delta u_{t-1} < \tau$ reflects a rise in oil prices relative to the CPI.

Based on Enders and Siklos (2001), we determined the threshold endogenously by identifying its consistent estimate (Chan 1993). In line with MTAR models, the joint *F*-test (*F*-joint) was employed to test the null hypothesis of no cointegration while symmetry adjustment was tested using the standard *F*-test (F-equality) with the null hypothesis of $\rho_1 = \rho_2$.

3.5 Asymmetric and Symmetric Error-Correction Models

We further estimated error-correction models to capture the short-run and long-run dynamics of the MTAR's cointegrating relationship. If there is asymmetric adjustment, Equations (5a) and (5b) would be applied by replacing the single symmetric error-correction term with two asymmetric error-correction terms (Thompson 2006), as shown below:

$$\Delta CPI_t = \emptyset_c + M_t \rho_1 u_{t-1} + (1 - M_t)\rho_2 u_{t-1} + \sum_{i=1}^{q} \alpha_{ci} \,\Delta CPI_{t-i} + \sum_{i=1}^{q} \beta_{ci} \,\Delta OP_{t-i} + v_{ct} \tag{5a}$$

$$\Delta OP_t = \emptyset_p + M_t \rho_1 u_{t-1} + (1 - M_t)\rho_2 u_{t-1} + \sum_{i=1}^{q} \alpha_{pi} \,\Delta CPI_{t-i} + \sum_{i=1}^{q} \beta_{pi} \,\Delta OP_{t-i} + v_{pt} \tag{5b}$$

where ρ_1 and ρ_2 are two asymmetric adjustment coefficients measuring the adjustment speeds of deviations from the long-run equilibrium.

Alternatively, if the cointegration shows symmetric adjustment, the symmetric error correction equations would be specified as follows:

$$\Delta CPI_t = \emptyset_c + \rho u_{t-1} + \sum_{i=1}^{q} \alpha_{ci}\, \Delta CPI_{t-i} + \sum_{i=1}^{q} \beta_{ci}\, \Delta OP_{t-i} + v_{ct} \tag{6a}$$

$$\Delta OP_t = \emptyset_p + \rho u_{t-1} + \sum_{i=1}^{q} \alpha_{pi}\, \Delta CPI_{t-i} + \sum_{i=1}^{q} \beta_{pi}\, \Delta OP_{t-i} + v_{pt} \tag{6b}$$

where ρ is the single symmetric adjustment coefficient.

Based on the asymmetric (symmetric) error-correction models, the long-run causal relationship between these variables was evaluated using the statistical significance of the coefficient of the lagged error-correction term (u_{t-1}). On a similar note, short-run causality was assessed via the statistical significance of the Wald test's F-statistic, which computes the lagged differences of independent variables from the asymmetric (symmetric) error-correction models.

Taking the example of Equations (5a) and (6a), the null hypothesis "H_0: $\beta_{c1}=\ldots=\beta_{cq}=0$" implies that oil price does not Granger-cause aggregated CPI or disaggregated CPI, respectively. For Equations (5b) and (6b), the null hypothesis "H_0: $\alpha_{p1}=\ldots=\alpha_{pq}=0$" shows that aggregated CPI and disaggregated CPI, respectively, do not Granger-cause the oil price.

4. Results and Discussion

4.1 Descriptive Statistics

Table 1 presents the summary of descriptive statistics for all the variables over the study period of 2005 to 2022. The aggregated CPI ranged from 98.6 to 115.5, averaging 111.9 with a moderate standard deviation of 4.3. Among the disaggregated CPIs, CALCO exhibited the highest average of 130.5, followed by CFOOD (119.6), CMIS (119.3), CRES (117.0), and CTRAN (113.3). Both CALCO and CMIS displayed significant variation from their mean, recording standard deviations of 11.7 and 11.0, respectively. For the regressor, the average price of OP stood at US$75.9 per barrel, with a range of US$26.8 to US$133.6 per barrel.

4.2 Unit Root Tests

The ADF and PP unit root tests were conducted as the first step of our cointegration analysis. The results at level and first difference for trend terms are presented in Table 2. Both the ADF and PP tests suggest that the null hypothesis of a unit root could not be rejected in most cases, implying that all the variables (except CCLO, CTRAN, CCOM, and OP) were non-stationary at levels. When the variables were tested in the first difference, we observed strong evidence in favour of stationary processes. Therefore, the results strongly indicate that the variables under consideration were integrated at the order of one, $I(1)$. These findings enabled us to proceed to examine potential cointegration relationships among the variables.

4.3 Estimation Results

In the absence of cointegration, Chan's (1993) method is typically used to endogenously search for a consistent threshold estimate (τ). This is achieved by arranging the values $\{\Delta u_t\}$ of the MTAR model in ascending order while excluding the smallest and largest 15%. The value resulting in the lowest residual sum of squares is then considered the τ. The empirical results of our MTAR-consistent cointegration tests are reported in Table 3. For most of the MTAR-consistent models, the Ljung-Box test failed to reject the null hypothesis of no residual autocorrelation for up to four and eight lags. However, serial correlation was confirmed for Models 3 and 5 only when higher lag orders of eight were used. Thus, there was convincing evidence of serial independence in the MTAR-consistent models.

Moreover, the MTAR-consistent models rejected the null hypothesis of no cointegration ($\rho_1=\rho_2=0$) for the aggregated CPI and almost all the disaggregated CPI pair models, except for Model 3 (ALCO), Model 6 (CFUR), Model 10 (CREC), and Model 13 (CMIS). These results suggest that there was indeed a cointegrating relationship between the CPI subcategories and oil prices in Malaysia over the study period.

Given that the two variables were cointegrated, we proceeded to examine the possibility of asymmetric adjustment. Based on the standard F-statistic (F-equal) results, the null hypothesis of symmetric adjustment ($\rho_1=\rho_2$) was rejected for Model 1 (CPI), Model 2 (CFOOD), Model 4 (CCLO), Model 5 (CHOU), Model 9 (CCOM), Model 11 (CEDU), and Model 12 (CRES). Meanwhile, we failed to reject the null hypothesis of symmetric adjustment for Model 7 (CHEA) and Model 8 (CTRAN), favouring symmetric adjustment towards the long-run equilibrium for CHEA-OP and CTRAN-OP.

Clearly, $|\rho_1| > |\rho_2|$ indicates that while the adjustment process towards long-run equilibrium is slower for rises in oil prices, it is more rapid for oil price decreases in relation to the aggregated CPI (Model 1), CFOOD (Model 2), CCLO (Model 4), CEDU (Model 11), and CRES (Model 12). On the other hand, $|\rho_1| < |\rho_2|$ reflects that the reversion process towards long-run equilibrium is relatively quicker when oil prices are rising in relation to CHOU (Model 5) and CCOM (Model 9), whereas the adjustment process is slower when oil prices are falling.

Overall, the MTAR-consistent models reveal three major findings. First, there is cointegration between oil prices and CPI, CFOOD, CCLO, CHOU, CHEA, CTRAN, CCOM, CEDU, and CRES, but no cointegration between oil prices and CALCO, CFUR, CREC, and CMIS. Second, the adjustment process towards long-run equilibrium is asymmetric; it is relatively faster when oil prices are falling in relation to CPI, CFOOD, CCLO, CEDU, and CRES, but is only faster when oil prices are rising in relation to CHOU and CCOM. Third, the adjustment towards long-run equilibrium is symmetric for CHEA and oil prices and CTRAN and oil prices.

Table 4 reports the results of the asymmetric error-correction models. The Breusch–Godfrey LM tests confirmed that all models were free of serial correlation in residuals, except for Model 4a and Model 6a. The error-correction terms' coefficients in Equation (5a) were also statistically significant, negative, and within the unit interval range, in line with past empirical studies (Arize, Malindretos, and Ghosh 2015). However, most of the error correction terms in Equation (5b) were statistically insignificant, indicating that oil price is weakly exogenous to the respective CPI categories. The adjustment coefficients (ρ_1 and ρ_2) were noticeably dissimilar as well, confirming the findings of the MTAR-consistent model (Table 3). Specifically, the speed of adjustment ρ_1 was significantly larger in absolute terms relative to the speed of adjustment ρ_2 for Model 1a (CPI), Model 2a (CFOOD), Model 3a (CCLO), Model 6a (CEDU), and Model 7a (CRES). For Model 4a (CHOU) and Model 5a (CCOM), the speed of adjustment (ρ_2) was larger in absolute terms compared to the speed of adjustment (ρ_1).

Based on the asymmetric error-correction model results, the Granger causality Wald tests suggest: (a) bidirectional causation between CEDU and oil prices; (b) unidirectional causality from CPI to oil prices and from CFOOD to oil prices; (c) unidirectional causality from oil prices to CCOM; (d) no Granger causality between CCLO and oil prices, CHOU and oil prices, and CRES and oil prices.

Next, Table 5 presents the results of symmetric error-correction. The Breusch-Godfrey LM tests indicated that only Model 8a suffered from serial correlation. The error-correction coefficients in Model 8a (CHEA) and Model 9a (CTRAN) were highly significant at the 1% level and carried the expected sign. Contrary to this, the error-correction coefficients in the oil price equations (Equation 6(b)) were statistically insignificant, implying that the oil price is weakly exogenous. Moreover, the Granger causality results supported the presence of unidirectional causality from CHEA to oil prices as well as bidirectional causality between CTRAN and oil prices in the short-run.

These findings are consistent with those of Bala et al. (2021) and Xuan and Chin (2015) in Malaysia. According to Bala et al. (2021), economic growth demonstrates asymmetric adjustment in response to oil price changes. Xuan and Chin (2015), furthermore, suggested that actual diesel prices have a pass-through effect on aggregated CPI, CFOOD, CFUR, and CTRAN. They also observed the pass-through effect of subsidised retail diesel prices on aggregated CPI, CFUR, and CCOM. Since CFOOD accounts for almost one-third (i.e., 29.5%) of the overall CPI (Bank Negara Malaysia 2023), oil price rise is likely to exert pressure on this subcategory, especially because oil is utilised in modern agriculture for farm machinery and transportation (Xuan and Chin 2015). In Malaysia, lower income groups tend to experience higher inflation than higher income groups (Bank Negara Malaysia 2015), as they spend more on food and less on transport, healthcare, education, and discretionary expenditure. This makes lower income groups highly vulnerable to changes in prices. Also, if energy demand is inelastic, consumers may reduce their expenditure on non-energy related goods and services when oil prices rise unexpectedly (Edelstein and Kilian 2009).

In summary, the results of the Granger causality tests in Table 4 and Table 5 prove that in the short-run: (a) CEDU and oil prices and CTRAN and oil prices have bidirectional causality; (b) CPI, CFOOD, and CHEA Granger-cause oil prices; (c) oil price Granger-causes CCOM; and (d) there is no Granger causality between CCLO and oil prices, CHOU and oil prices, and CRES and oil prices.

Table 1 Summary Statistics

	CPI	CFOOD	CALCO	CCLO
Mean	111.9	119.6	130.5	95.5
Maximum	115.5	125.5	142.7	100.8
Minimum	98.6	98.6	98.1	93.9
Std. Dev.	4.3	7.8	11.7	1.7
N	216	216	216	216
	CHOU	**CFUR**	**CHEA**	**CTRAN**
Mean	105.9	107.6	108.4	113.3
Maximum	108.0	109.5	111.0	139.4
Minimum	99.4	99.2	98.9	95.7
Std. Dev.	2.2	3.1	3.2	5.0
N	216	216	216	216
	CCOM	**CREC**	**CEDU**	**CRES**
Mean	96.6	105.9	108.4	117.0
Maximum	100.5	107.3	110.4	121.8
Minimum	96.0	99.8	99.7	98.2
Std. Dev.	1.1	2.4	3.2	6.3
N	216	216	216	216
	CMIS	**OP**		
Mean	119.3	75.9		
Maximum	137.3	133.6		
Minimum	99.5	26.8		
Std. Dev.	11.0	24.9		
N	216	216		

Table 2 Unit Root Tests

				ADF				
	CPI		**CFOOD**		**CALCO**		**CCLO**	
L	-3.0472		-2.1279		-2.879		-3.3024	*
FD	-7.9405	***	-13.4474	***	-14.8773	***	-7.776	***
	CHOU		**CFUR**		**CHEA**		**CTRAN**	
L	-3.0716		-2.0915		-3.0229		-4.6304	***
FD	-9.3593	***	-4.5243	***	-9.6691	***	-8.7175	***
	CCOM		**CREC**		**CEDU**		**CRES**	
L	-6.6596	***	-1.4552		-2.9444		-2.8931	
FD	-4.9741	***	-15.6601	***	-6.0143	***	-12.152	***
	CMIS		**OP**					
L	-1.7560		-3.3569	*				
FD	-14.0573	***	-9.0222	***				
				PP				
	CPI		**CFOOD**		**CALCO**		**CCLO**	
L	-2.8124		-2.1299		-2.6681		-5.0738	***
FD	-13.8797	***	-13.4326	***	-19.5587	***	-71.3282	***
	CHOU		**CFUR**		**CHEA**		**CTRAN**	
L	-2.5606		-2.0057		-2.6402		-4.4138	***
FD	-21.4923	***	-14.5588	***	-16.9659	***	-13.1831	***
	CCOM		**CREC**		**CEDU**		**CRES**	
L	-6.8113	***	-1.4272		-2.0038		-2.8032	
FD	-13.0638	***	-15.6519	***	-14.5165	***	-17.648	***
	CMIS		**OP**					
L	-1.7917		-2.6912					
FD	-14.0465	***	-9.2769	***				

Notes: *** and * denote significance at the 1% and 10% levels, respectively. L and FD refer to level and first-difference. ADF and PP unit root tests include trend. The optimal lag lengths for ADF unit root tests are determined by the Akaike information criterion (AIC) with maximum lag order of 8. The bandwidths for PP unit root tests are determined by Newey-West Bartlett kernel.
Source: Source: Authors' calculations.

Table 3 MTAR-Consistent Cointegration Tests

	Model 1 CPI			Model 2 CFOOD			Model 3 CALCO		
	Coeff.	**t-stat.**		**Coeff.**	**t-stat.**		**Coeff.**	**t-stat.**	
ρ_1	-0.0737	-3.4374	***	-0.0346	-3.2259	***	-0.0626	-2.9942	***
ρ_2	-0.0215	-1.6003		-0.0078	-0.6831		-0.0218	-0.7571	
Q(4)	0.2707			1.1035			1.9901		
Q(8)	8.3021			8.0180			37.8750		***
AIC	-7.3172			-6.9277			-4.8001		
SC	-7.2540			-6.8646			-4.7048		
Lags	2			2			4		
τ	0.0035			0.0020			-0.0018		
***F*-equal**	4.2225	**		2.9555	*		1.3040		
***F*-joint**	7.2236	**		5.4292	*		4.7976		
	Model 4 CCLO			**Model 5 CHOU**			**Model 6 CFUR**		
	Coeff.	**t-stat.**		**Coeff.**	**t-stat.**		**Coeff.**	**t-stat.**	
ρ_1	-0.1757	-4.7050	***	0.0090	0.3072		-0.0341	-2.9178	***
ρ_2	-0.0310	-1.1829		-0.0506	-3.2506	***	-0.0085	-1.1867	
Q(4)	1.9245			6.7414			0.9830		
Q(8)	10.8380			37.1910		***	12.6480		
AIC	-7.8345			-8.1404			-9.2950		
SC	-7.7392			-8.0773			-9.1340		
Lags	4			2			8		
τ	0.0054			0.0025			0.0017		
***F*-equal**	10.1784	***		3.2284	*		3.4939	*	
***F*-joint**	11.7037	***		5.3275	*		4.9488		
	Model 7 CHEA			**Model 8 CTRAN**			**Model 9 CCOM**		
	Coeff.	**t-stat.**		**Coeff.**	**t-stat.**		**Coeff.**	**t-stat.**	
ρ_1	-0.0189	-1.3553		-0.1335	-2.7344	***	-0.0199	-2.1111	**
ρ_2	-0.0479	-3.0089	***	-0.3166	-3.3472	***	-0.0466	-4.0276	***
Q(4)	4.3681			0.1467			1.0782		
Q(8)	11.2020			0.7125			8.9874		
AIC	-7.9946			-5.2882			-11.1670		
SC	-7.9315			-5.1272			-11.0391		
Lags	2			8			6		
τ	0.0010			-0.0035			-0.0009		
***F*-equal**	1.8689			2.6726			3.5653	*	
***F*-joint**	5.4441	*		10.7206	***		9.5659	***	

	Model 10 CREC			Model 11 CEDU			Model 12 CRES		
	Coeff.	**t-stat.**		**Coeff.**	**t-stat.**		**Coeff.**	**t-stat.**	
ρ_1	-0.0320	-3.0594	***	-0.0363	-3.2534	***	-0.0738	-3.9670	***
ρ_2	-0.0047	-0.4551		-0.0118	-1.6370		-0.0179	-1.8645	*
Q(4)	3.6674			1.9563			2.1095		
Q(8)	5.0157			6.1675			5.3943		
AIC	-9.2127			-9.0593			-7.1575		
SC	-9.1495			-8.9962			-7.0944		
Lags	2			2			2		
τ	0.0000			0.0011			0.0042		
***F*-equal**	3.4813	*		3.4512	*		7.1634	***	
***F*-joint**	4.7843			6.5741	**		9.5574	***	

	Model 13 CMIS		
	Coeff.	**t-stat.**	
ρ_1	-0.0163	-1.9883	**
ρ_2	-0.0008	-0.1559	
Q(4)	4.8201		
Q(8)	8.2431		
AIC	-7.3598		
SC	-7.2967		
Lags	2		
τ	0.0041		
***F*-equal**	2.4791		
***F*-joint**	1.9889		

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The critical values are obtained from Enders and Siklos (2001). Lags denote the optimal lag length selected by the AIC with a maximum lag order of 8. Q(4) and Q(8) are the Ljung-Box statistics that test if the first four and eight residual autocorrelations are jointly equal to zero. *F*-equal and *F*-joint refer to the null hypotheses $H_0:\rho_1=\rho_2$ and $H_0:\rho_1=\rho_2=0$, respectively. In addition to the MTAR-consistent cointegration tests, this study also performed the Engle-Granger (EG) and MTAR cointegration tests. Both results are not reported in the table to save space.
Source: Authors' calculations.

Table 4 Asymmetric Error-Correction Models

	$\tau=0.0035$						
	Model 1a ΔCPI				**Model 1b ΔOP**		
	Coeff		**t-stat**		**Coeff**		**t-stat**
Constant	0.0011		2.7632	***	0.0043		0.7167
$I_t u_{t-1}$	-0.1057		-4.8957	***	-0.3872		-1.2580
$(1-I_t)u_{t-1}$	-0.0291		-2.0071	**	-0.1606		-0.7998
W_{S1}	5.4542	***			8.0805	***	
W_{S2}	2.3715				17.6386	***	
Adj. R^2	0.1428				0.1754		
AIC	-7.4501				-2.0394		
SC	-7.3378				-1.9441		
LM(2)	0.2597				1.3808		
	$\tau=0.0020$						
	Model 2a ΔCFOOD				**Model 2b ΔOP**		
	Coeff		**t-stat**		**Coeff**		**t-stat**
Constant	0.0015		2.9586	***	0.0054		0.8646
$I_t u_{t-1}$	-0.0476		-4.4249	***	-0.1039		-0.7704
$(1-I_t)u_{t-1}$	-0.0115		-0.9783		-0.0820		-0.5232
W_{S1}	2.8197	*			4.0846	**	
W_{S2}	1.5945				8.2466	***	
Adj. R^2	0.0898				0.1797		
AIC	-7.0861				-2.0191		
SC	-6.9898				-1.8581		
LM(2)	0.4263				1.2754		
	$\tau=0.0054$						
	Model 3a ΔCCLO				**Model 3b ΔOP**		
	Coeff		**t-stat**		**Coeff**		**t-stat**
Constant	-0.0007		-2.3508	**	0.0008		0.1302
$I_t u_{t-1}$	-0.2090		-6.2028	***	0.2488		0.3634
$(1-I_t)u_{t-1}$	-0.0332		-1.2766		-0.2197		-0.4209
W_{S1}	71.3090	***			1.5748		
W_{S2}	2.1152				14.0659	***	
Adj. R^2	0.6657				0.1545		
AIC	-8.0928				-2.0070		
SC	-7.9489				-1.8950		
LM(2)	2.3598				1.3248		

	τ=0.0025					
	Model 4a ΔCHOU			Model 4b ΔOP		
	Coeff	**t-stat**		**Coeff**	**t-stat**	
Constant	0.0010	3.8593	***	0.0031	0.5223	
$I_t u_{t-1}$	-0.0576	-1.8839	*	-1.3569	-2.1664	**
$(1-I_t)u_{t-1}$	-0.0733	-4.6289	***	0.2618	0.7771	
W_{S1}	9.0146	***		1.4810		
W_{S2}	1.8949			19.3010	***	
Adj. R^2	0.2475			0.1674		
AIC	-8.3774			-2.0322		
SC	-8.2003			-1.9372		
LM(2)	34.7809	***		1.2573		
	τ=-0.0009					
	Model 5a ΔCCOM			Model 5b ΔOP		
	Coeff	**t-stat**		**Coeff**	**t-stat**	
Constant	-0.0003	-5.2829	***	-0.0014	-0.2141	
$I_t u_{t-1}$	-0.0505	-5.3204	***	-0.5703	-0.5929	
$(1-I_t)u_{t-1}$	-0.0660	-6.9401	***	0.0715	0.0732	
W_{S1}	9.0672	***		1.6248		
W_{S2}	2.9637	*		19.4621	***	
Adj. R^2	0.3725			0.1450		
AIC	-11.8368			-2.0032		
SC	-11.6597			-1.9079		
LM(2)	0.3524			1.8824		
	τ=0.0011					
	Model 6a ΔCEDU			Model 6b ΔOP		
	Coeff	**t-stat**		**Coeff**	**t-stat**	
Constant	0.0008	4.2752	***	0.0015	0.2338	
$I_t u_{t-1}$	-0.0519	-4.8511	***	0.2062	0.5320	
$(1-I_t)u_{t-1}$	-0.0256	-3.3189	***	-0.1246	-0.4996	
W_{S1}	3.7481	***		2.5153	*	
W_{S2}	3.8642	*		21.0179	***	
Adj. R^2	0.1621			0.1563		
AIC	-9.3315			-2.0144		
SC	-9.1705			-1.9036		
LM(2)	7.7115	**		0.7013		

	τ=0.0042					
	Model 7a ΔCRES			**Model 7b ΔOP**		
	Coeff	**t-stat**		**Coeff**	**t-stat**	
Constant	0.0012	0.2326		0.0027	0.4505	
$I_t u_{t-1}$	-0.1128	-5.9478	***	-0.2460	-0.9845	
$(1-I_t)u_{t-1}$	-0.0273	-2.6724	***	-0.0105	-0.0813	
W_{S1}	3.7139 ***			2.5520		
W_{S2}	0.0065			19.0235 ***		
Adj. R^2	0.1615			0.1513		
AIC	-7.3799			-2.0131		
SC	-7.2350			-1.9181		
LM(2)	3.8573			1.4156		

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% levels. τ is the tau value. LM(2) is the Breusch–Godfrey LM test for serial correlation with two lags. W_{S1} and W_{S2} correspond to the Wald statistic for the joint significance of all lagged values of changes in the CPI and OP, respectively.
Source: Authors' calculations.

Table 5 Symmetric Error-Correction Models

	Model 8a ΔCHEA			**Model 8b ΔOP**	
	Coeff	**t-stat**		**Coeff**	**t-stat**
Constant	0.0022	0.6015		0.0049	0.8019
u_{t-1}	-0.0553	-4.7731	***	-0.1779	-0.8098
W_{S1}	5.3628 ***			3.2323 **	
W_{S2}	0.9932			19.7036 ***	
Adj. R^2	0.1373			0.1645	
AIC	-8.1594			-2.0263	
SC	-7.9823			-1.9309	
LM(2)	15.7482 ***			2.3916	
	Model 9a ΔCTRAN			**Model 9b ΔOP**	
	Coeff	**t-stat**		**Coeff**	**t-stat**
Constant	0.0014	1.2285		0.0035	0.5894
u_{t-1}	-0.1740	-4.8517	***	-0.2644	-1.4449
W_{S1}	5.8361 ***			6.2375 ***	
W_{S2}	2.8869 *			9.0600 ***	
Adj. R^2	0.1824			0.2228	
AIC	-5.3489			-2.0872	
SC	-5.2365			-1.9589	
LM(2)	0.1833			1.1641	

Notes: *** and * denote significance at the 1% and 10% levels, respectively. LM(2) is the Breusch-Godfrey LM test for serial correlation with two lags. W_{S1} and W_{S2} correspond to the Wald statistic for the joint significance of all lagged values of changes in the CPI and OP, respectively.
Source: Authors' calculations.

4.4 Speed of adjustment

Table 6 summarises the adjustment coefficients based on Table 4 and Table 5. We noted that ρ_1 was significantly larger in absolute terms relative to ρ_2 for CPI, CFOOD, CCLO, CEDU, and CRES. The national CPI was found to adjust rapidly to the long-run equilibrium paths (speed of adjustment is about 10.6% monthly) for a fall in oil prices but converts slowly in response to rising oil prices (about 2.9% a month). For the CPI subcategories, the results reveal that the adjustment speeds of CFOOD, CCLO, CEDU, and CRES are faster when oil prices are falling than when they are rising. The estimated error-correction coefficients further suggest that when oil prices fall, about 4.8%, 20.9%, 5.2%, and 11.3% of CFOOD, CCLO, CEDU, and CRES deviations from their long-run equilibrium are corrected each month; meanwhile, when oil prices rise, the convergence of CEDU and CRES to the long-run equilibrium is adjusted by about 2.6% and 2.7% each month. Conversely, the adjustment process towards long-run equilibrium is relatively faster when oil prices are rising in relation to CHOU (7.3% per month) and CCOM (6.6% per month), while adjustment is slower when oil prices are falling. In other words, CHOU and CCOM take a longer time to converge to long-run equilibrium when oil prices decrease.

Compared to the asymmetric error-correction models, the adjustment process for CHEA and CTRAN as a result of disequilibrium was shown to be symmetric. CHEA and CTRAN adjust towards long-run equilibrium with a speed of about 5.5% and 17.4% per month, respectively. Overall, we conclude that the CPI and its subcategories adjust back to equilibrium at varying speeds, corroborating previous studies. For example, Xuan and Chin (2015) noted that the Malaysian CPI converges to the long-run equilibrium in one year, adjusting by about 22.11% for the actual diesel price and 19.01% for the subsidised retail diesel price. According to Ibrahim and Said (2012), moreover, the adjustment speed for CFOOD is quicker than the CPI in Malaysia, with CFOOD's convergence to long-run equilibrium corrected by about 55% the next year compared to the CPI's 31%. Another study reported the annual adjustment speed of the CPI to range between 36.9% and 56.8% for the ARDL model and between 27.8% and 73.8% for the NARDL model (Sek 2017).

Table 6 Adjustment Coefficients

Model	DV	ρ_1		ρ_2	
Model 1a	ΔCPI	-0.1057	***	-0.0291	**
Model 2a	ΔCFOOD	-0.0476	***	-0.0115	
Model 3a	ΔCCLO	-0.2090	***	-0.0332	
Model 4a	ΔCHOU	-0.0576	*	-0.0733	***
Model 5a	ΔCCOM	-0.0505	***	-0.0660	***
Model 6a	ΔCEDU	-0.0519	***	-0.0256	***
Model 7a	ΔCRES	-0.1128	***	-0.0273	***
Model	**DV**	ρ			
Model 8a	ΔCHEA	-0.0553	***		
Model 9a	ΔCTRAN	-0.1740	***		

Notes: ***, **, and * denote significant at the 1%, 5%, and 10% levels. DV is the dependent variable. ρ, ρ_1, and ρ_2 are the adjustment coefficients.
Source: Authors' calculations

5. Conclusion

This study explored the asymmetric adjustment of the CPI in Malaysia as a result of oil price changes from January 2005 to December 2022. Using MTAR cointegration tests, the CPI was assessed in both aggregated form and disaggregated form containing 12 subcategories. Both the MTAR and MTAR-consistent models yielded quantitatively similar results; however, the MTAR-consistent model was preferred due to its lower Akaike Information Criterion.

The major findings of this study are as follows: First, we confirm the existence of a cointegrating relationship between oil prices and the CPI in Malaysia. For the CPI subcategories, a long-run equilibrium relationship was observed for CFOOD, CCLO, CHOU, CHEA, CTRAN, CCOM, CEDU, and CRES in response to oil prices. However, no long-run equilibrium relationship was found for CALCO, CFUR, CREC, and CMIS when paired with oil prices. Second, the study provides compelling evidence that both aggregated CPI and disaggregated CPI, in relation to oil prices, adjust asymmetrically to the threshold value. The disaggregated CPI categories that undergo asymmetric adjustment are CFOOD, CCLO, CHOU, CCOM, CEDU, and CRES, while symmetric adjustment occurs for the CHEA and CTRAN. Third, the CPI subcategories return to equilibrium at varying speeds. The national CPI and four CPI subcategories (CFOOD, CCLO, CEDU, and CRES) adjust more quickly to their long-run equilibrium when oil prices decrease as opposed to when they increase. Conversely, CHOU and CCOM correct deviations from the equilibrium more rapidly during increases in oil prices instead of decreases. Meanwhile, CHEA and CTRAN converge to the long-run equilibrium at a similar speed.

Overall, there are significant differences in adjustment speeds between aggregated CPI and disaggregated CPI categories in Malaysia. The CPIs swiftly return to their long-run equilibrium when oil prices are decreasing, rather than increasing, and exhibit greater rigidity below the threshold level. This indicates that consumers of disaggregated CPIs respond to oil price changes far more heterogeneously, potential stemming from the CFOOD, CCLO, CHOU, CCOM, CEDU, and CRES categories.

These findings point to the complexity of adopting a monetary policy stance due to the differing adjustment speeds between overall CPI and the CPI subcategories when oil prices fluctuate. Since central banks often use the CPI as a key indicator in policymaking, we assert that considering the CPI’s asymmetric adjustment behaviour in relation to oil prices is crucial for formulating appropriate monetary policies in Malaysia. Notably, a forward-looking approach may be necessary, wherein central banks analyse the factors driving asymmetry and how these effects are likely to unfold over time. This involves assessing pass-through effects, supply chain dynamics, and market structure to gauge potential inflationary pressures and adjust monetary policy pre-emptively. The asymmetric adjustment of crude oil prices to the CPI also underscores the importance of energy policy. Governments may need to develop strategies to mitigate the impact of oil price fluctuations on consumers, such as by promoting energy diversification, investing in renewable energy sources, or implementing mechanisms to stabilise fuel prices.

Additionally, sharp hikes in crude oil prices typically lead to higher transportation and production costs, which can affect various sectors of the economy. In such cases, central banks may respond by raising interest rates to curb inflationary pressures resulting from escalating consumer prices. The pass-through effect, wherein changes in oil prices are reflected in higher prices for goods and services, can vary based on factors such as the intensity of competition in different industries, the flexibility of pricing mechanisms, and the availability of substitutes. In some instances, changes in oil prices may have a limited impact on the CPI if businesses absorb part of the cost increase, particularly in competitive markets. As such, governments might consider fiscal measures to counter the asymmetric effects on the CPI. In times of high oil prices, policymakers could implement targeted subsidies or tax breaks to cushion the impact on consumers. Conversely, during periods of low oil prices, they may need to adjust tax policies to maintain revenue streams and fund essential public services.

Moreover, since oil prices are often denominated in US dollars, fluctuations in exchange rates can influence the asymmetrical adjustment of the CPI. If the local currency depreciates against the US dollar, it can amplify the impact of rising oil prices on imported goods, contributing to higher consumer prices. Conversely, a stronger local currency may mitigate the pass-through effect, particularly for countries that are net oil importers. Lastly, the application of asymmetric adjustment is currently limited to the 12 disaggregated CPIs. Future studies may explore the application of asymmetric adjustment to both the headline and core CPIs in response to oil price changes.

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