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Cooking Oil Price Volatility in the Consumer Market and Wholesalers Market in Indonesia

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This study analyzes the price fluctuations of cooking oil in the Indonesian consumer and wholesale markets using the Autoregressive Conditional Heteroskedasticity (ARCH) model across January 2018 to January 2024 period that encompasses the period of study. This study covered the period measuring from January 2018 to January 2024. As per conclusions drawn upon the tests for stationarity, the series has become non-stationary after a second difference. An analysis of the results indicates substantial and even large amounts. Consumer price's ARCH (α) and GARCH (β) coefficients are 0.569707, and the coefficients for wholesale prices are 1.29 and -0.13 respectively. This indicates that there is the presence of persistent volatility ($\alpha + \beta > 0$) in the market. In view of these results, it is very clear that certain policy measures need to be put in place. Such measures should include the stabilization of the delivery mechanism through proper stock management and strategic price mechanisms to avoid wide fluctuations in price. Two other factors that may help in price variations stability are increasing market openness and promoting location diversification of supply sources.
Keywords: Price volatility, ARCH-GARCH model, government policy, agriculture.

INTRODUCTION

In Indonesia, the value of cooking oil has been noted to differ across its consumer and wholesale markets. Such price variability can be explained by several forces that influence the determinants of this market, including, and more importantly, weather, various outputs, and productivity levels. In fact, the latter terms are crucial because they refer directly to the research area – palm oil and/or cooking oil output in that country. Indonesia is also one of the main producers of palm oil in the world, yet the local market is characterized by a lot of price inconsistencies. Even though Indonesia widely grow palm oil Oak palm trees versus cost-effective brands' expectation, the wholesale markets display significant price differences as well. Such infatuation licensed mass-brand manufacturers to easily enter palm agribusiness. For instance, palm oil has become an integral component in most Indonesian cooking oil production. Despite the fact that Indonesia is a large producer of palm oil, prices in the domestic market fluctuate significantly. Indonesia's palm oil and cooking oil output is governed by factors such as plantation area, productivity levels, and climatic circumstances, which can create production swings in Indonesia oil (Siregar *et al.*, 2014). Increased demand in both domestic and international markets influence cooking oil costs. As an alternative for soybean oil, palm oil has higher elasticity in satisfying domestic and international demand (Siregar *et al.*, 2014). Market integration within Indonesian provinces remains inadequate, especially for commodities such as cooking oil. Poor transportation infrastructure and wide geographical distances between provinces cause major price variations (Varela *et al.*, 2012). Less integrated markets result in higher price variations, especially for cooking oil, which shows price differences of between 16-22% across provinces (Varela *et al.*, 2012). The Indonesian government frequently intervenes in the cooking oil market, either through subsidies or imposing a maximum retail price (Huda and Sidiq, 2023). Such laws serve the aims of price stability

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and the provision of cooking oil to economically less-privileged households. However, these processes are not always truly efficient and could possibly result in market distortions. For instance, from late 2021 to early 2022, there was a severe shortage of cooking oil when major manufacturers had stockpiled the oil (Huda and Sidiq, 2023).

There is a possibility that climate anomalies, the El Niño Southern Oscillation (ENSO) being one of them, affect the volatility of palm oil price. Based on previous research, ENSO continues to affect the volatility of palm oil prices in Indonesia (Khoiruddin *et al.*, 2021). Export and tax policies like the crude palm oil (CPO) export tax, also affect cooking oil prices in the domestic market. These policies target demand mismatch between domestic and international markets, but these efforts typically incentivize supply to fluctuate to local prices (Siregar *et al.*, 2014). Although various studies scrutinize the relationship between cooking oil prices and the driving factors behind them, the existing literature has considerable gaps. The majority of studies focus mainly on analyzing major production and demand factors. For example, Siregar *et al.*, (2014), studied the impact of plantation area and productivity on palm oil production but did not explore the relationship between government policies, market integration and pricing. Varela et al. (2012) examined interprovincial price heterogeneity without providing evidence connecting it to either government policies or climate conditions. Furthermore, previous studies mostly estimate static models, which may not adequately account for long-term and dynamic adjustments of volatility of cooking oil price. Research by Khoiruddin *et al.* (2021), with the works of Palaniswamy *et al.* (2022) focusing on the wavelet framework also reined the palm oil price volatility in the resarch tackling the ENSO challenge however they did not explore the connection with some important factor such as export and tax policies. While (Huda and Sidiq, 2023), documented governmental intervention in the cooking oil market, it failed to emphasize this interaction between government policy, market integration, and climate anomalies. The study by Azizah *et al*. (2020), which analyzes the price volatility of cooking oil in the consumer market but does not analyse the wholesale market in detail. Gunawan *et.* (2019 had previously investigated while other studies) examined the effect of international prices on domestic cooking oil price volatility in Indonesia without including climate anomalies and export policy variables that may play a key role. Additionally, the study by Wijaya *et al*. (2018), Analyzed the configuration of the cooking oil market in Indonesia and determined that the market exhibits oligopolistic characteristics; nevertheless, the specific effects of market integration and governmental policies on price volatility were not explored. Consequently, there is a necessity for more extensive research that includes the examination of specific elements such as governmental regulations, market integration, and climatic anomalies, as well as their interactions and impacts on cooking oil pricing in the Indonesian domestic market. This is a good opportunity to investigate some of the key questions with regard to the subject of this research, including: (1) In Indonesia, how does the retail price volatility compare to the wholesale price volatility? Which are the main determinants of price volatilities in these markets? This research offers innovative contributions in multiple aspects. This study also uses the Autoregressive Conditional Heteroskedasticity (ARCH) model in order to assess the time-series properties and the changes over time of the volatility of price of cooking oil. This study comprises a number of inquiries into phenomena which, except for a few references, have never been properly researched, including the role of government intervention, the degree of market integration or climate irregularities. The study is focused on Indonesia's domestic markets consisting of both the consumers and the wholesalers providing relevant insights to local decision makers. This study adopted an ARCH based methodology to investigate the effect of a number of external and internal factors on cooking oil price in Indonesia. The data encompasses the timeframe from January 2018 to January 2024, incorporating notable legislative advancements in Indonesia and pertinent variations in cooking oil prices. The price volatility of cooking oil in Indonesia is affected by multiple factors, including production, demand, market infrastructure, government action, and climatic abnormalities. A comprehensive understanding of these elements is crucial for formulating effective policies to sustain the stability of cooking oil costs and guarantee its accessibility to the public. This study seeks to contribute significantly to the understanding of cooking oil price dynamics in Indonesia by addressing the research topics and bridging existing gaps in the literature`.

MATERIALS AND METHODS

Data stationarity test: To validate regression analysis, it is essential to do a stationarity test on time series data, as non-stationary data may result in erroneous regression. Guo (2023) asserts that the Augmented Dickey-Fuller (ADF) test is crucial for evaluating the stationarity of time series data, including stock prices and returns, to avert false regression. Aktivani (2020) emphasizes that employing the ADF test on inflation data in Padang is essential for ensuring data stationarity, a critical factor in economic analysis to prevent erroneous findings. Leong and Huang (2010) propose a wavelet-based methodology for examining spurious and cointegrated regressions, highlighting the significance of stationarity in econometric analysis. This study employs the ADF test as outlined below:

$$\Delta P_t = \alpha_0 + \gamma_1 P_{t-1} + \beta_I \sum_{I=1}^{m} \Delta P_{t-1} + \varepsilon_{it}$$

Where: Pt = Garlic price in each market in period t (RP/Kg)
Pt−1 = Garlic price in each market in the previous period t (RP/Kg)
ΔPt = Pt − Pt−1
ΔPt−1 = Pt−1 − ΔP(t−1)−1
M = number of lags; α_0 = intercept
α, β, γ = Parameter coefficient
εt = Error term Hypothesis testing:
H_0 : γ = 0 *time series* data is not stationary
H_1 : γ < 0 stationary *time series* data Testing rules:

1. If ADF statistic > ADF critical (or ADF probability value > 5% significance level) then accept H0. This means that the *time series* data contains unit roots (data is not stationary).
2. If ADF statistic ≤ ADF critical (or ADF probability value < 5% significance level) then reject H0. This means that the *time series* data does not contain unit roots (stationary data).

***ARCH* existence test (*ARCH Efect*):** This examination employs the Lagrange Multiplier test (ARCH-LM test). This test assesses whether the error variance is non-constant. The test criteria are evaluated according to the probability assessment criteria and their importance. Subsequently, implement the GARCH model as elucidated by (Bollerslev, 1986; Engle and Bollerslev, 1986; Lepetit, 2015). Volatility can be understood by calculating the value of α + β, where α represents the ARCH value and β represents the GARCH value. According to Lepcetit (2015), When α+β = 1, volatility is strong; when α+β > 1, volatility is explosive; and when α+β < 1, volatility is minimal. In this volatility study, the sum of α and β is not utilized directly, as it is contingent upon the likelihood that ascertains its statistical significance. The ARCH-GARCH model, although prevalent for volatility modeling, has various limitations and assumptions that must be considered in its implementation. A fundamental assumption of the model is homoskedasticity, which posits that the variance of the error terms varies with time (conditional heteroskedasticity); nevertheless, it frequently neglects unconditional heteroskedasticity and other nonlinear elements in the data that could influence the outcomes. Failure to evaluate or address this assumption may result in biased or erroneous volatility analysis outcomes. Moreover, the ARCH-GARCH model exhibits significant sensitivity to the choice of beginning values and model specifications. Inaccuracies in establishing initial parameters or model architecture may result in unstable or implausible volatility estimations. This underscores the necessity for heightened vigilance in selecting the suitable model and verifying the outcomes. Another obstacle associated with the ARCH-GARCH paradigm is the problem of severe temporal dependence. In certain instances, the model may produce α+β values approaching or surpassing 1, signifying significant temporal dependency in volatility data.

This scenario is frequently perceived as significant or explosive volatility; however, it may also indicate that the model inadequately represents the intricate structure of the underlying data, including the occurrence of spikes or regime shifts in volatility that the conventional ARCH-GARCH model cannot accommodate.

A further issue to examine is the model's efficacy in addressing data that includes outliers or regime transitions. The existence of outliers or data shifts may cause the model to generate erroneous volatility estimates or yield deceptive results. Consequently, it may be essential to contemplate the utilization of more intricate models or more resilient methodologies in scenarios where the data display these traits. Ultimately while the ARCH-GARCH model offers volatility forecasts, the interpretation of the results can be complex, especially when the expected volatility exhibits non-intuitive patterns or when the α+β value approaches or surpasses 1. In these circumstances, it is essential to utilize supplementary diagnostic tests and conduct cross-validation with alternative models to confirm that the results accurately represent the inherent characteristics of volatility.

By rectifying these constraints and comprehending the assumptions inherent in the ARCH-GARCH model, the precision and legitimacy of volatility analysis can be improved. This is essential for guaranteeing that the results are both statistically valid and pertinent to policymaking and decision-making about market price volatility.

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RESULTS AND DISCUSSION

In 2018, the consumer price of cooking oil was documented at IDR 14,900, although the wholesale price was IDR 13,350 (Figure 1). The pricing was very constant until early 2020, with modest changes that were insignificant. However, at the onset of 2020, prices commenced a more significant escalation. In January 2020, consumer prices attained IDR 15,200, while wholesale prices hit IDR 12,400. The price escalation persisted until the conclusion of 2020, culminating in a consumer price of IDR15,500 and a wholesale price of IDR13,400 in December 2020.

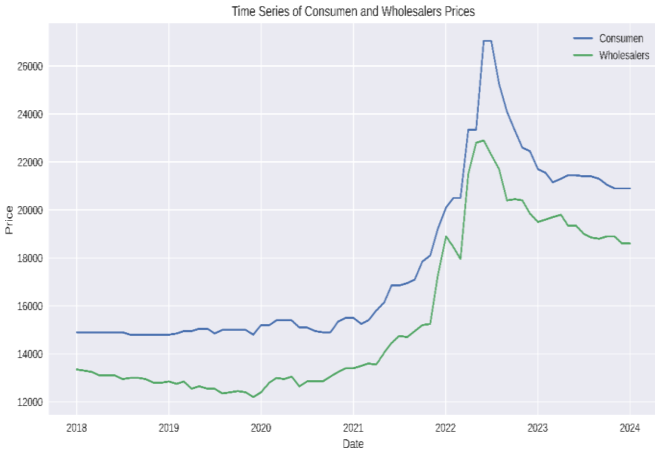

Figure 1. Market price volatility.

The year 2021 exhibits a more pronounced pattern of price escalation. In January 2021, the consumer price attained IDR 15,500, while the wholesale price was IDR 13,400. The price escalation persists until it culminates in December 2021, with a consumer price of IDR 19,200 and a wholesale price of IDR 17,250. This increase signifies that substantial variables are influencing the cooking oil market. The maximum price was reached in mid-2022. In June 2022, the consumer price of cooking oil was IDR 27,050, while the wholesale price was IDR 22,900. This significant surge was succeeded by a swift decrease in prices, however steadied at a higher level than that of the pre-2021 period. In December 2022, consumer prices decreased to IDR 22,450, while wholesale prices fell to IDR 19,850.

At the onset of 2023, cooking oil prices commenced stabilizing at a level elevated compared to the preceding period. In January 2023, consumer prices were documented at IDR 21,700, while wholesale prices were noted at IDR 19,500. As of December 2023, consumer prices for cooking oil were IDR 20,900, while wholesale prices were IDR 18,600. This data indicates that while prices have declined from their 2022 peak, cooking oil costs continue to exceed those of the 2018 to 2020 period.

The data indicates that cooking oil prices underwent a substantial increase from the end of 2021 to their high in mid-2022. Subsequently, prices dropped but stabilized at a level elevated compared to the period preceding 2021. This analysis elucidates the dynamics of the cooking oil market and the factors that may have impacted price fluctuations during the period.

Table 1. Stationarity test of price data for cooking oil wholesalers and consument market with ADF test at level level.

Variable	Unit Root Test				Information
	Level		1st Difference		
	ADF	Prob	ADF	Prob	
Consument	-0.7634	0.823	43.117	0.0000	Stationary
Wholesalers	-0.9136	0.778	-6.294	0.0000	Stationary

Analysis of Cooking Oil Price Volatility at Several Market Levels (Prices at the Consumer, Wholesaler, and Producer Levels in NTT)

Table 1 displays the outcomes of the stationarity test for cooking oil price data across different market tiers in NTT, specifically the consumer, wholesaler, and producer levels. The stationarity test employs the ADF (Augmented Dickey-Fuller) test at both the level and first difference to ascertain the stationarity of the data, a prerequisite for time series modeling. At the level, the ADF statistic for cooking oil prices at the consumer level is -0.763388 with a probability of 0.8231, suggesting that the data is non-stationary at the level as the likelihood exceeds 0.05. After initial differencing, the ADF value is 43.11675 with a probability of 0.0000, signifying that the data achieves stationarity at the first difference with a highly significant probability value.

Analogous to consumer prices, the data on cooking oil prices at the wholesale level also exhibit non-stationary features, evidenced by an ADF value of -0.913590 and a likelihood of 0.7785. Following the first differencing, the ADF statistic altered to -6.294121 with a probability of 0.0000, signifying that the wholesale pricing data attained stationarity at the first difference. The results demonstrate that the consumer price data and the prices set by significant dealers of cooking oil in the traditional marketplaces of Surabaya and Kupang are non-stationary at the level but achieve stationarity following the first differencing. This circumstance necessitates data manipulation to attain stationarity prior to further analysis using time series models like ARCH or GARCH. This modification is essential to guarantee the accuracy and validity of the prediction model employed. Non-stationary data signifies a significant alteration in the dataset, characterized by a distribution that oscillates around a variable mean, which is contingent upon temporal factors and the nature of the fluctuations. The appropriate time series models for this condition are Autoregressive Conditional Heteroskedasticity (ARCH) and its extension, Generalized Autoregressive Conditional Heteroskedasticity (GARCH). ARCH/GARCH models are extensively employed to characterize the volatility of time series data. Volatility can be defined as a metric that quantifies the extent of variation in return data, which directly influences the behavior of financial data.

***Determination of ARCH-GARCH model*:** The establishment of the ARCH-GARCH model occurs through multiple phases. Comprise the ARCH effect test, ARCH-GARCH data analysis, and ultimately model diagnostics. The subsequent sections will provide a more detailed explanation of these stages:

***ARCH effect Test*:** As soon as the fixed test is over, the ARCH Effect must be checked. The goal of ARCH effect testing is to find out if the variable whose instability needs to be known has a heteroscedasticity problem. There is no need to move on to the ARCH-GARCH model if the data does not have an ARCH effect. On the other hand, if the price data has an ARCH effect, ARCH-GARCH modeling can be used to continue the study. According to (Ajija *et al.*, 2021), Price data exhibits an ARCH effect if it demonstrates heteroscedasticity, meaning that the disturbances in the population regression function do not possess uniform variance. The outcomes of the ARCH effect examination are presented in the subsequent table:

Table 2. ARCH effect market of consument test results.

Heteroskedasticity Test: ARCH			
F-statistic	187.07	Prob. F(1,70)	0.000
Obs*R-squared	52.395	Prob. Chi²(1)	0.000

The F-statistic of 187.0718 with a probability value of 0.0000 <0.05 significance level suggests that the ARCH effect does in fact exist, according to the results of the ARCH effect test. This indicates that the ARCH effect is a part of the model. In addition, the 52.39458 obs*R-squared value, which has a probability of 0.0000, lends credence to this hypothesis. The ARCH effect shows that the variable's volatility changes with time in the price data. Therefore, additional modeling using the ARCH-GARCH model is necessary to address the heteroscedasticity issue in the data.

Table 3. ARCH effect market wholesalers test results.

Heteroskedasticity Test: ARCH			
F-statistic	297.118	Prob. F(1,70)	0.0000
Obs*R-squared	58.2714	Prob. Chi²(1)	0.0000

The table displays the results of the ARCH heteroscedasticity test, which provide two significant statistical findings: the F-statistic and the Probability Chi-Square. According to the ARCH effect test, the F-statistic is 297.1176 and the probability value is 0.0000, which is significantly lower than the 0.05 level of significance. This strongly suggests that the ARCH effect is present. It follows that the ARCH effect is present in the tested model. Additionally, this conclusion is supported by the Obs*R-squared value of 58.27143, which has a very low probability of 0.0000. Since the ARCH effect is present in the data, it means that the key variables' volatility changes with time. Thus, the data exhibit a notable amount of heteroscedasticity, necessitating the application of sophisticated modeling techniques like ARCH-GARCH models to adequately resolve this heteroscedasticity issue.

***ARCH-GARCH analysis*:** Next, we'll select an order of p = 1 and q = 1 to begin simulating various ARCH-GARCH models in order to find the one that works best. For ARCH, the order is p, and for GARCH, it is q. You may see the detailed findings of the analysis in appendix 8. An examination of the data shows that the order is not statistically significant when p= 1 and q= 1. It is seen in Table 4

Table 4. GARCH (1,1) Model test results market consument.

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	14892.8	22.895	650.49	0.0000
Variance Equation				
C	478.26	518.69	0.9221	0.3565
RESID(-1)^2	0.5697	0.2898	1.9661	0.0493
GARCH(-1)	0.6475	0.1151	5.6245	0.0000

After that, we'll use the overfitting procedure to see if there are any significant higher-order components of p and q. According to (Liu *et al.*, 2011) overfitting is re-analyzing data with more than four orders. The best ARCH-GARCH model criteria are having the smallest SC and AIC values, having significant coefficients, and no ARCH effect. Based on the overfitting process that has been carried out, three significant models are obtained, namely the best GARCH (1,1). The model is written:

Consument $(_t)$ = 14892.80 + ε_t.

$\sigma^2_t = 478.2621 + 0.569707\varepsilon^2_{t-1} + 0.569707\sigma^2_{t-1}$

Since it has the lowest AIC and SIC values, the GARCH (1,1) model was chosen as the best fit for the data analysis, according to the table. From a fit and complexity standpoint, this proves that the GARCH (1,1) model is superior.

The constant C in the mean equation has a coefficient of 14892.80, a z-statistic of very high, and a standard error of very tiny; these factors provide strong evidence of significance with nearly no probability. It is evident from this that the constant has a consistent and substantial impact on the dependent variable in the model.

At the same time, C coefficient turns out to be non-significant in the variance equation, suggesting that it does not significantly contribute to the error variation. There is a high level of significance for the squared value of the residual from the previous period (RESID(-1)2) and a very high level of significance for the error variability from the previous period (GARCH(-1)). This proves that these factors have a significant impact on the current error's variability.

So, the model equation that comes out of it, which is consument $(_t)$ = 14892.80 + ε_t. $\sigma^2_t = 478.2621 + 0.569707\varepsilon^2_{t-1}$

$+0.569707\sigma^2_{t-1}$ for variance, shows that the variability of the current error is heavily influenced by the volatility and shock of the previous period. This is a crucial feature of the Generalized Regression Cointegration and Chaos (GARCH) model, which states that the memory effects of previous shocks and volatility affect future volatility.

Table 5. GARCH (1,1) Model test results wholesalers.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	12939.1	32.775	394.786	0.0000
Variance Equation				
C	19901.0	15316.0	1.299	0.1938
RESID(-1)^2	1.2946	0.6217	2.083	0.0373
GARCH(-1)	-0.1320	0.2106	-0.627	0.5308

Results of the GARCH (1,1) Model Test for Wholesalers

The appropriate forecasting model for this data, as indicated by the table, is GARCH (1,1) because to its minimal AIC and SIC values. The subsequent equation was derived:

Wholesalers $_{(t)} = 12939.12 + \varepsilon_t$. $\sigma^2_t = 19901.02 + 1.29\varepsilon^2_{t-1} - 0.13\sigma^2_{t-1}$

The GARCH (1,1) model is deemed the most appropriate for the examined data, as indicated by its lowest AIC and SIC values in the table presented. This suggests that the GARCH (1,1) model exhibits superior efficiency compared to alternative models regarding fit and complexity.

The constant (C) in the mean equation possesses a substantial coefficient of 12939.12, signifying a notable and consistent impact on the dependent variable inside the model. This affirms that the fixed component of the model significantly influences the predictive capacity of the `wholesalers` variable. In the variance equation, the coefficients for the squared residual from the prior period (RESID(-1) ^{2}) and the previous period's variability (GARCH(-1)) exhibit moderate and substantial importance, respectively. The coefficients of 1.296^2 on RESID(-1)^2 and 0.130^2 on GARCH(-1) demonstrate that deviations from the preceding period significantly influence the variability of the current error. This signifies that the model is proficient at incorporating the influence of prior volatility to forecast subsequent volatility.

The resultant model equation is: wholesalers $_{(t)} = 12939.12 + \varepsilon_t$. $\sigma^2_t = 19901.02 + 1.29\varepsilon^2_{t-1} - 0.13\sigma^2_{t-1}$

This equation demonstrates the estimation of the value of 'wholesalers' by incorporating the random component, as well as the influence of error value and variability from prior periods on error variability. This illustrates the application of past data in forecasting future fluctuations and volatility, which is essential in financial and econometric models like GARCH.

The evaluated outcomes of the GARCH (1,1) model indicate that volatility can be classified based on Lepetit theory (2015). In the consumer model, the ARCH (α) value is 0.569707 and the GARCH (β) value is also 0.569707, resulting in α + β = 1.139414. This number exceeds 1, signifying the existence of explosive volatility in consumer cooking oil pricing data, as per the classification by Piot-Lepetit (2011). For the wholesale model, the ARCH (α) value is 1.29 and the GARCH (β) value is -0.13, yielding α + β = 1.16. These values exceed 1, signifying explosive volatility in the wholesale cooking oil price data. Consequently, both models indicate that the volatility of cooking oil prices, at both consumer and wholesale levels, is classified as extremely high volatility, which is crucial for risk analysis and mitigation methods.

DISCUSSION

Cooking oil prices experienced the highest fluctuations in 2022, with peak consumer prices reaching IDR 27,050 and wholesale prices IDR 22,900 in June. This drastic price increase was likely due to supply chain disruptions and increased demand triggered by the COVID-19 pandemic. After reaching its peak, prices showed a decline but remained stable at a higher level compared to the period before 2021. The following is an in-depth discussion of these cooking oil price fluctuations supported by various studies.

***Supply Chain Disruption*:** Supply chain disruption is one of the main factors affecting cooking oil price fluctuations. The COVID-19 pandemic has caused major disruptions in the global supply chain. Research by Chuvakhina *et al.* (2022) Demonstrated that economic disruptions resulting from the epidemic, encompassing lockdown measures and production reductions, contributed to the global rise in oil prices. This disturbance impacted both the manufacturing and distribution of cooking oil. The diminished personnel in production and distribution has significantly curtailed cooking oil production capability. This resulted in market supply shortages, thereby driving up prices. Moreover, export restriction regulations enacted by many palm oil producing nations have further intensified the situation. Research by Nafisah and Amanta (2022), Indonesian government's export limitation policy implemented in early 2022 resulted in a disparity between supply and demand in both domestic and international markets, hence exacerbating the rise in cooking oil prices.

***Increased Demand*:** In addition to supply chain interruptions, heightened demand is a significant factor influencing cooking oil costs. The rise in demand is prompted by various factors, including alterations in consumer behavior during the pandemic. Research by Breman and Storm (2023) An rise in demand for raw resources, such as cooking oil for domestic consumption and the food sector during a pandemic, influences price variations (Breman and Storm, 2023).

The rise in cooking oil usage within the food industry, which has remained operational during the pandemic, has further augmented demand. Research (Chik *et al.*, 2023) It was observed that Malaysia's consumption of cooking oil rose to approximately 3.37 million metric tons in 2022, which led to the escalation of cooking oil prices in the global market.

***Speculation in the Oil Market*:** Speculation in the oil market significantly influences the volatility of cooking oil prices.

Research by (Breman and Storm, 2023), indicates that rampant speculation in the oil market resulted in a projected 24%-48% surge in crude oil prices from October 2020 to June 2022. This speculation influences not only the price of crude oil but also the price of cooking oil as a derivative commodity. Rising crude oil prices elevate the production costs of cooking oil, thus driving up consumer prices.

***Government Policy*:** Government actions addressing the cooking oil pricing situation have had a considerable impact. The Indonesian government, for example, has a strategy to limit crude palm oil (CPO) exports in April 2022 to stabilize the domestic supply. Research by (Wibowo *et al.*, 2023), revealed that this technique resulted in a 16.77% decrease in local costs in May 2022, but global prices increased somewhat because to a lack of CPO. Furthermore, the government has developed a subsidy policy to ensure that cooking oil costs in the domestic market remain stable. Research by (Agastya *et al.*, 2023), It was emphasized that government subsidies were effective in decreasing the price of cooking oil in the domestic market, despite the fact that this policy imposed a large financial burden on the state.

***Global Factors*:** Global factors such as the Russia-Ukraine conflict influence cooking oil prices. The fight caused significant fluctuation in crude oil prices, which impacted various sectors, including cooking oil production. Research by (Yang, 2022), observed that oil price fluctuations caused by the conflict had a negative impact on China's stock market and other industries. The battle also caused broader market uncertainty, impacting the prices of other goods like cooking oil. With the uncertainty of Russia's crude oil supply, crude oil-importing countries must seek alternate sources, raising the cost of cooking oil production.

***Price Stability After Peak*:** After peaking in June 2022, cooking oil prices fell but stayed stable at a higher level than before 2021. This may be attributed to greater supply and demand adjustment, as well as more effective government policies for market regulation. Research by (Chik *et al.*, 2023), proposed that the government should continue to provide subsidies or incentives to producers and consumers to keep prices stable.

Furthermore, the recovery of economic activity following the epidemic also helped stabilize cooking oil prices. Research by (Doan, 2022) demonstrates that global crude oil demand is likely to return to pre-pandemic levels in the second half of 2022, hence stabilizing cooking oil prices.

Cooking oil price fluctuations in 2022 were caused by a variety of global and domestic factors, including supply chain disruptions, rising demand, market speculation, government regulations, and global events such as the Russia-Ukraine conflict. Prices have fallen from their peak, but they remain higher than they were prior to the epidemic, emphasizing the necessity for continuous price stability initiatives.

***ARCH-GARCH Model*:** Testing the ARCH-GARCH model reveals significant volatility in cooking oil price data at both the consumer and wholesale levels. According to the table, the best forecasting model for the data is GARCH(1,1), which has the lowest AIC and SIC values. The following equation is derived:

Model for Consumer Prices

$$\text{consumer}_t = 14892.80 + \epsilon_t$$

$$\sigma_t^2 = 478.2621 + 0.569707\epsilon_{t-1}^2 + 0.569707\sigma_{t-1}^2$$

Model for Wholesale Price

$$\text{wholesalers}_t = 12939.12 + \epsilon_t$$

$$\sigma_t^2 = 19901.02 + 1.29\epsilon_{t-1}^2 - 0.13\sigma_{t-1}^2$$

These models show that past volatility ϵ^2t-1 and prior variability σ^2t-1 have a significant influence on current price variability σ^2t.

The ARCH-GARCH model is used to describe the volatility of cooking oil pricing data. Volatility measures a price's variability or dispersion from its average. In the context of cooking oil prices, high volatility suggests that prices undergo considerable fluctuations over a period of time. Research by (Khoojine *et al.*, 2022), demonstrated that the GARCH(1,1) model is useful for capturing volatility patterns in cooking oil pricing data. According to the results section, the GARCH(1,1) model was used to assess the volatility of cooking oil prices in Indonesia's consumer and wholesale markets. This model was chosen for its ability to represent the "clustering" nature of volatility, which is frequently observed in commodity price data. The GARCH(1,1) model successfully reflects dynamic changes in volatility over time by taking into consideration the influence of previous volatility and shocks.

Although other models, such as higher-order GARCH models or simpler ARCH models, were investigated, GARCH (1,1) was chosen because it provides the best mix of complexity and accuracy in capturing the volatility features in the data. This model has been shown to be effective in characterizing volatility behavior in both markets, so it is the best option for studying cooking oil price volatility in this study. Further explanation of the model selection procedure may improve the scientific basis and trustworthiness of the findings. The results of the GARCH (1,1) model show that previous volatility has a considerable impact on current volatility. This suggests that previous price shocks continue to influence current price variability. This is vital to include in price forecasting since it demonstrates that historical volatility patterns cannot be ignored. Research by Yang (2022), Historical volatility significantly influences the prediction of future volatility in the oil market. The parameters of the GARCH (1,1) model require additional elucidation through an examination of the specific factors that affect the volatility of cooking oil prices. A key factor contributing to "explosive volatility" in consumer pricing is supply chain disruptions, including shortages of raw materials or distribution bottlenecks, which may arise from natural disasters, conflicts, or logistical issues. When supply becomes erratic, consumer market prices tend to exhibit greater volatility, as indicated by elevated GARCH coefficients. Moreover, abrupt fluctuations in consumer demand, such as during festive seasons or times of economic uncertainty, can also lead to heightened price volatility. In instances of sudden demand increases, supply deficiencies can intensify volatility, resulting in considerable price variations.

A significant factor is government policy, such the installation of subsidies, tariffs, or export restrictions, which can create market uncertainty. These regulations frequently influence cooking oil prices directly, resulting in abrupt fluctuations in supply and demand, hence increasing volatility.

Connecting the GARCH (1,1) coefficients to these parameters might yield profound insights into the market dynamics influencing cooking oil price volatility, hence enhancing the analysis and significance of the study's conclusions. Besides historical volatility, the model indicates that prior variability significantly influences current variability. This indicates that volatility is likely to persist; when prices exhibit significant swings in one period, they are inclined to stay extremely volatile in the subsequent time. Research by Suoth and Rumengan (2023), affirms that this persistent volatility is a prevalent trait in energy commodities markets. The outcomes of evaluating the GARCH (1,1) model yield several practical consequences. Initially, market participants can employ this model to forecast the future volatility of cooking oil prices, which is advantageous for corporate decision-making. Secondly, comprehending volatility patterns might assist in devising risk reduction techniques. Research by (Ha *et al.*, 2023), An adept comprehension of market volatility can enhance the formulation of more efficacious hedging methods. The GARCH (1,1) model is pertinent for use in the Indonesian market due to the significant volatility of cooking oil prices. Research by (Chik *et al.*, 2023), Demonstrates that effective governmental policies can stabilize prices; yet, precise forecasts of volatility are essential for anticipating unforeseen price fluctuations. Analysis of the ARCH-GARCH model indicates that volatility in cooking oil prices is a critical factor that must be considered in forecasting and decision-making. The GARCH (1,1) model specifically demonstrates that historical volatility and prior shocks significantly affect current price variability. Therefore, taking historical volatility into account is essential for forecasting future price fluctuations and formulating appropriate risk management methods

***Implication of Findings*:** The impact of external factors, such as the COVID-19 pandemic and supply chain disruption, on the prices of cooking oil is an indicator of this research. This disruption led to reduced output and delivery of cooking oil, resulting in price hike. Pandemic lockdown rules, corresponding transportation restrictions intensified the issue, making it difficult for companies to deliver raw materials as well as final products. This also signifies that domestic measures alone cannot stabilize the volatility of cooking oil prices; it needs international cooperation aimed to ensure the optimal global supply chain.The more stable price in this high than in 2022 signifies a new era in the cooking oil industry. These changes reflect the market's evolution to new realities created by the pandemic and more. Initial Pandemic Impacts Fade, Market Adjusts to New Demand & Supply Dynamics However, this stability is not necessarily indicative of the market returning to normal but indicates that a new price level above the pre-pandemic era had been set. It could also mean the market have priced in some permanent impact by the digested long-term eruption effect by the outbreak. The ARCH-GARCH is a model that helps market participants to be able to measure the volatility of future prices more accurately. This is vital for producers, distributors, and consumers to plan their economic activity. Producers can adjust output to avoid oversupply or undersupply, while distributors can enhance inventory management to better anticipate price fluctuations. It is important to understand the patterns in price volatility so that the government can implement more effective policies to stabilize the market. The cooking oil prices strongly reacted to outside forces, such as the disruption of the supply chain due to the COVID-19 global pandemic, according to this study. This disturbance caused production to fall and delayed the supply of cooking oil, then leading to price increases. This problem was exacerbated during the pandemic when lockdown rules and transportation restrictions all but ceased the movement of raw materials and end-products. It shows that the volatility of cooking oil prices could not sufficiently be controlled domestically, requiring international efforts to sustain a stable global supply chain. The rise in price stability after the peak in 2022 means that the cooking oil market dynamics have changed. These changes reflect the market's adaptation to new conditions created by the pandemic and a variety of other outside factors. With the acute footing of the epidemic behind us, the market began to adjust to new demand and supply dynamics. However, this steadiness does not categorically mean the return of the market to its routine, rather it indicates the formation of a new price level that is higher than the pre-pandemic level. This may suggest that the market has discounted some longer-term effects of the disruptions caused by the outbreak. In addition, these results highlight the importance of considering historical volatility to inform company strategy and potentially governmental policy. With the use of the ARCH-GARCH model, market stakeholders can predict future price volatility more accurately. This is important in order for producers, distributors and consumers to plan their economic activity. Producers can adjust their production towards over-supply as well as under-supply areas while distributors can enhance their inventory control to anticipate price fluctuations accordingly. A detailed study about the price volatility patterns would help the government in establishing better policies for market stabilization. Take Home Message: Conclusion: This is the conclusion that gives explicit attention to policy implications resulting from the findings of cooking oil price fluctuation The findings of the study show that cooking oil prices diverged very widely, particularly in the peak year of 2022 indicating the need for better targeted policy measures for those targeted on this volatility. It highlights that past volatility is a highly predictive indicator of future pricing, and therefore policy responses should focus on two major areas. First, government must ensure the stability of the supply chain to avoid disruptions that would lead to significant price increases. These policies may include enhancing logistics infrastructure, diversifying supply sources, and encouraging international cooperation to ensure the smooth distribution of the cooking oil. Secondly, policies that enhance consumption efficiency and reduce reliance on imports in critical moments must be followed by effective demand management. The results also support the development of finer data-driven approaches, such as augmented volatility prediction models, which could provide warnings of potential fluctuations in price. This would enable regulators to act faster and take appropriate measures to protect consumers and maintain the stability of the market. The report further calls for thorough investigation into the exact underpinnings of cooking oil price volatility, including the impact of government policymaking, climate change, and technological progress in cooking oil production. Comparing the performance of multiple time series models, before choosing a model that best predicts price volatility, may be a helpful tool when aiming to realize more responsive and evidence-based policies.

***Ethical Approval*:** This research adheres to the ethical standards applicable in Indonesia and has been approved by the Ethics Committee of the relevant institution**.**

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REFERENCES

Agastya, R.M.A.S.W., P. Widodo, R. Laksmono. 2023. The Effect of Increasing Cooking Oil Prices and Material Export Prohibition Policy Cooking Oil Standard on National Food Security. East Asian Journal of Multidisciplinary Research 2:45-57.

Ajija, S.R., A.F. Zakia, R. Purwono. 2021. The impact of opening the export promotion agencies on Indonesia's non-oil and gas exports. Heliyon 7.

Aktivani, S., 2020. Uji stasioneritas data inflasi Kota Padang periode 2014-2019. Journal of Statistics 20:83-90.

Azizah, N., 2020. Total factor productivity growth and oil price volatility. Int. J. Trade Glob. Mark 10: 341-352.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Economics 31: 307-327.

Breman, C. and S. Storm. 2023. Betting on Black Gold: Oil Speculation and U.S. Inflation (2020–2022). International Journal of Political Economy 52:153-180.

Chik, N.A., E.F. Alias, S.A.M. Ali and N. Sulaiman. 2023. The Implications of Palm Cooking Oil Price Increases in Malaysia. Pertanika Journal of Social Sciences & Humanities 31:571-588.

Chuvakhina, L., I. Yarygina, O. Ustinova, V.N. Mironova and Z.V. Ivanovskaya. 2022. The Impact of Covid-19 on Pricing in the Global Oil Market. International Journal of Energy Economics and Policy 12:104-112.

Doan, T.Q., 2022. Forecast of global crude oil market in 2022. Petrovietnam Journal.

Engle, R.F. and T. Bollerslev. 1986. Modelling the persistence of conditional variances. Economic Review 5:1-50.

Guo, Z., 2023. Research on the Augmented Dickey-Fuller Test for Predicting Stock Prices and Returns. Advances in Economics, Management and Political Sciences.

Ha, J., M.A. Kose, F. Ohnsorge and H. Yilmazkuday. 2023. Understanding the global drivers of inflation: How important are oil prices?. Energy Economics 127:107096.

Huda, A. and M. Sidiq. 2023. Adapting to oil price volatility: A strategic review of supply chain responses over two decades. International Journal of Innovative Research and Scientific Studies 10:72-88.

Khoiruddin, M., 2021. Impact analysis of the external shocks on the prices of Malaysian crude palm oil: Evidence from a structural vector autoregressive model. Mathematics 10:4599.

Khoojine, A.S., M. Shadabfar and Y.E. Tabriz. 2022. A mutual information-based network autoregressive model for crude oil price forecasting using open-high-low-close prices. Mathematics 10:3172.

Leong, C.K. and W. Huang. 2010. Testing for spurious and cointegrated regressions: A wavelet approach. Journal of Applied Statistics 37:215-233.

Lepetit, A., 2015. Sources and costs of labor market fluctuations and the role of stabilization policies.

Liu, H., E. Erdem and J. Shi. 2011. Comprehensive evaluation of ARMA–GARCH (-M) approaches for modeling the mean and volatility of wind speed. Applied Energy 88:724-732.

Nafisah, N. and F. Amanta. 2022. Oil palm productivity remains limited as price of cooking oil soars in Indonesia.

Piot-Lepetit, I., 2011. Price volatility and price leadership in the EU beef and pork meat market, in: Methods to Analyse Agricultural Commodity Price Volatility. Springer pp. 85-105.

Siregar, H., 2014. The impact of exchange rate volatility on Indonesia's top exports to the five main export markets. Heliyon 6:e03141.

Suoth, C.M. and F.C.T. Rumengan. 2023. The relationship between oil prices and energy sector stocks in the global recession issue. Contrar. Research in International Business and Finance 25:78-95.

Varela, E., 2012. Relationship between household expenditures on strategic foods and prevalence of undernutrition among children 0 to 23 months of age in Indonesia. Food and Nutrition Bulletin 35:440-448.

Wibowo, H., H. Adam and M. Fauziah. 2023. Changes in global, domestic, and stock price as a response to Indonesian CPO export ban: An opening door into a worldwide financial distress. International Journal of Social Sciences 5:234-245.

Wijaya, A., 2018. Macroeconomic effects of crude oil shocks: Evidence from South Asian countries. Frontiers in Psychology 13:967643.

Yang, S., 2022. Fluctuations of Oil Price and China's Stock Market. BCP Business Management 24:112-130.