

Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi: 10.13106/jafeb.2016.vol3.no3.79.

Information Arrival between Price Change and Trading Volume in Crude Palm Oil Futures Market: A Non-linear Approach

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Received: April 18, 2016 Revised: June 19, 2016 Accepted: July 18, 2016

Abstract

This paper is the first of its kind using a non-linear approach based on cross-correlation function (CCF) to investigate the information arrival hypothesis in crude palm oil (CPO) futures market. Based on daily data from 1986 to 2010, our empirical results reveal that: First, the volume of volatility is not a proxy of information flow. Second, dependence causality running from current return to future volume in conditional variance exhibit an asymmetric pattern of time span with different signs of correlation between price and volume series. This finding indicates the presence of noise traders' hypothesis of price-volume interaction in CPO futures market. Both findings suggest that this futures market is weak-form inefficiency. In terms of investors' behavior, they tend to change their expectations on current return based on errors made in previous trade in generating abnormal volume in the subsequent period. As implied, it is advisable for the investors devise their future trading strategies according to time span and changes of return.

Keywords: Price Change-Volume Dynamics, AR-GARCH Model, Cross-Correlation Function, Causality-in-Variance, Dependence Causality.

JEL Classification Codes: G12, G13, G14.

1. Introduction

The study of price-volume relationship has always been a subject of interest in futures market.² If indeed there is a relationship between the two, the market participants will find the information extremely useful to predict the next price movement. Besides the issue of market efficiency, which relies on historical price and past information, the price-volume relationship has also been a subject of empirical investigation by researchers to validate the existence of information arrival hypothesis. There are a number of crude palm oil (CPO) futures related studies, the subject of price-volume relationship with respect to

information arrival hypothesis has yet to be examined for Malaysian CPO futures market and has not received adequate attention in the literature. This paper intends to fill the research gap.

The degree of market efficiency depends on how market participants assess new information arrival and make the assumption on market price movement. Despite the existence of non-linear manner, most market participants forecast the movement of a current price in the linear manner which will result in biased prediction. With biased view of the price movement, the risk of trading in CPO futures is relatively high for producers, traders and other participants.

The evidences of the price-volume relationship have been supported by five hypotheses. The first hypothesis is mixture of distribution, where this explanation is supported by Clark (1973), Karpoff (1987), Tauchen and Pitts (1983), and Andersen (1996). The second hypothesis is the sequential arrival of information, which is proposed by Copeland (1976, 1977). In this context, Copeland's work is further supported by Jennings et al. (1981), Fujihara and Mougoue (1997), Malliaris and Urrutia (1998), and Moosa et al. (2003).

The third hypothesis is noise trader, which is supported

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² In this paper, the term "price-volume relationship" indicates relationship between price change and trading volume. It is acceptable in the literature as price change is interpreted as continuously compounded rate of return, where the rate of return is defined as the first difference of natural logarithmic transformation of price.

by Lewellen et al. (1974), Shiller (1984), Campbell and Kyle (1993), and De Long et al. (1990). The fourth hypothesis is tax-related and non tax-related motive trading, which is proposed by Lakonishok and Smidt (1989). The final hypothesis is a dispersion of beliefs, which is proposed by Shalen (1993) for futures market. His hypothesis is further supported by Harris and Raviv (1993) in speculative markets, Daigler and Wiley (1999), and Coval and Shumway (2005) in the Chicago Board of Trade.

Many of recent empirical methodologies have been employed to study information transmission in the futures markets. In studying the price-volume relation, the study of Gallant et al. (1993) is found as the first to examine interrelationship between volume and volatility in the New York Stock Exchange during 1928-1987 using a non-linear time series based on non-parametric approach. With this background, this paper explores the relationship between price change and trading volume in CPO futures contracts using a non-linear approach based on cross-correlation function (CCF) of standardized residuals and their squares (Cheung and Ng, 1996).

There are four reasons we adopt this approach. First, it does not involve simultaneous modeling for both intra- and inter-variables dynamics. Second, it is found to be asymptotically robust to distributional assumptions. Third, it can detect non-linear causality-in-mean and variance between CPO futures price changes and trading volumes.³ Fourth, it can detect non-linear causality in a large number of series with the expected significant causal effect at long lags.⁴

This approach involves univariate and augmented analyses. Univariate analysis is used to examine feedback causality effects. Then, dependence causality effects can be further examined using an augmented analysis. Each analysis requires the two-stage method to test these casualties. First, to estimate time series models that allow for time variation in both conditional mean and variance. Second, to use obtained standardized residuals and standardized squared residuals in the testing null hypothesis of no causality-in-mean and variance, respectively. In this regard, our study emphasizes the augmented analysis to model interaction between price changes and trading volume and discusses the dependence causality-in-variance between both series.

The investigation of non-linear behavior between price and volume series in CPO futures market contributes to three scenarios. First, it establishes evidence of the type of information flow hypothesis and spillover volatility that exist between CPO futures return and trading volume data.

Second, it describes liquidity and efficiency of CPO futures market. Third, it describes a trading behavior among investors in this commodity market.

This paper is organized as follows. This section is followed by a literature review. The subsequent section touches on data and methodology, followed by findings and empirical results. The last section concludes the discussion and suggests the implication of this study.

2. Literature Review

Theoretically, volatility of stock prices responds to new information arrival. If trading volume links to new information that enters into the market, it acts as the proxy for information flow. As a consequence, the significant relationship exists between stock price changes and volume. Trading volume has been proven to play an important role in the investors' learning process which has led them to come up with effective strategies. For instance, Blume et al. (1994) found that incorporating volume into technical analysis would improve the ability of traders to interpret market information on asset pricing. This indicated that the volume could convey extra information about noisy price movement which could not be obtained from historical price data itself.

In addition, Suominen (2001) found that volume could be used to improve the availability of private information estimation in ensuring accuracy of inferences about their price signal. This could directly assist investors to determine the expected payoff to their trading. There are five information flow hypotheses in the prior research to explain on how information is transmitted between price and volume. These hypotheses are mixture of distribution, sequential information arrival, noise traders, tax-related and non tax-related motives trading and dispersion of beliefs. In this section, we review and synthesize past studies on this relationship with respect to five hypotheses.

2.1. Mixture of distribution hypothesis

The mixture of distribution hypothesis (MDH) was the first hypothesis proposed by Clark (1973) in explaining price-volume relationship. He demonstrated that correlation between variances of return and volume was positive contemporaneous. This implied that volume and return series responded contemporaneously to new information and evolved at constant speed over event time independently with no inter-temporal causality. In the stock market, Epps and Epps (1976) further found that trading volume acted as a mixed variable with the changes of

³ Refer Henry et al. (2007), p.123, para 2.

⁴ Refer Cheung and Ng (1996), p.36, para 2.

logarithmic price to have a mixture of finite variance distribution.

When all traders in the same market were accounted, Tauchen and Pitts (1983) found that number of traders who entered into or exited from speculative market within the trading day could affect the joint distribution between return and volume. The study of Smirlock and Starks (1985) has supported Epps and Epps's hypothesis and further showed that volume increased more higher if increasing price than decreasing price when the new information arrived into the market. In terms of different sign of price changes, Karpoff (1987) found that new simultaneously information arrival on different signs of price movement could lead to sign of contemporaneous correlation to be either positive or negative.

Among 20 actively traded stocks in the CBOE, Lamoureux and Lastrapes (1990) found that ARCH effect in daily return movement has disappeared when trading volume was taken into account. This indicated that the rate of information flow between return and volume exhibited contemporaneous manner. By using generalized method of moments (GMM), Richardson and Smith (1994) found information flow has log-normal distribution among 30 Dow Jones firms from 1982 to 1986 that mildly supported the MDH. In IBM common stock from 1973 to 1991, Andersen (1996) used stylized microstructure framework to examine price changes and volume. This framework indicated the presence of MDH in this stock market. Similar studies also being done in Polish market by Gurgul et al. (2005) and Russian market by Canarella and Pollard (2011). Both studies found that this hypothesis held in both markets.

2.2. Sequential information arrival hypothesis

Copeland (1976, 1977) has proposed sequential information arrival hypothesis (SIAH) and stated that the information arrival was not necessary disseminated instantaneously to all traders, but it disseminated dynamically to a single trader at a time. He made this statement based on his finding of a dynamic positive relationship between absolute of price change and expected value of trading volume in stock market. Such finding was further supported by Jennings et al. (1981) on relationship between price change and volume in the presence of margin requirement in the financial market.

Based on data of 1980-1994 in Korean Stock Exchange, Silvapulle and Choi (1999) found evidence on strong bi-directional linear and non-linear causalities between daily stock returns and volume changes. Their finding did not support the evidence of efficient market hypothesis. This finding implied that the knowledge of current trading volume was important to forecast stock price. Moosa et al.

(2003) observed that causal effect from past negative price changes to current volume changes was stronger than the effect of past positive price changes. They concluded that there was an asymmetry in dynamic causal effect from price changes to volume.

Numerous researchers have also conducted similar studies in various markets such as Greece, Turkey and NASDAQ. For instance, Floros and Vougas (2007), Okan et al. (2009), and Chiang et al. (2010). On the other hand, Garcia et al. (1986) conducted a similar study on corn, wheat, soybeans, soybeans oil and soybeans meal futures markets for the period of 1979-1983. They found that price variability led to volume occurred slightly more frequent than volume led to price variability.

2.3. Noise traders' hypothesis

The noise traders' hypothesis stated that traders made a decision to buy, sell or hold did not based on economic fundamental. There were studies that supported this hypothesis. For instance, Lewellen et al. (1974) found that most investors did not diversify on stocks based on economic fundamental. Shiller (1984) found that noise traders' action in stock market would raise the market price volatility.

De Long et al. (1990) used a simple overlapping generation model. They found that return and trading volume were positively correlated in the short run. This positive causal effect was turned to be a negative causal effect in the long run. They concluded that traders would respond to noise trading instead of fundamental trading.⁵ In order to make them as professional arbitrageurs, noise trading was found to be valuable in futures market as compared to fundamental trading. Bloomfield et al. (2009) found that majority of traders who have pessimistic expectations on stock price would act as noise traders.

In commodity markets such as crude oil futures market, Bhar and Hamori (2005) analyzed the dependence on causality-in-variance between return and trading volume. The application of cross-correlation function function based on standardized residuals and their squares mildly supported the noise traders' hypothesis in the crude oil futures market during 1990-2000.

2.4. A tax-related and non tax-related motives trading

This hypothesis was proposed by Lakonishok and Smidt (1989). Their findings indicated that past price change and current volume trading have negative relationship under a tax-related trading motives and otherwise for non tax-

⁵ Refer to De Long et al. (1990), p. 735.

related motives for stock trading. The reason of negative relationship was most of investors have paid tax on a calendar year basis, so they were able to realize that capital losses before the end of the calendar year. The reason of positive relationship in non tax-related motives for stock trading was investors would sell the stocks since price has risen for their portfolio rebalancing.

2.5. Dispersion of beliefs hypothesis

The dispersion of beliefs hypothesis stated that different types of trader tend to interpret the same information in different ways at the same time. This hypothesis was initially proposed by Shalen (1993) based on his own two-period noisy rational expectations model of futures market. Based on the same information, his results indicated that uninformed traders' dispersion of beliefs tend to increase volatility and create excess volume as compared to informed traders.⁶ Harris and Raviv (1993) developed a model of trading based on different opinions among traders in speculative markets. Their results indicated that traders tend to speculate in the market when their current beliefs were more diffused.

There were some of past studies that supported the dispersion of beliefs hypothesis. For instance, Daigler and Wiley (1999) categorized futures volume into four types of traders, such as local floor traders, clearing members, executing trades and off-the-floor customers. Their finding was consistent with Shalen's finding, where their finding supported traders who without precise information on order flow would provide a strong relationship between volatility and volume. In Treasury bond futures contract at the Chicago Board of Trade, Coval and Shumway (2005) found that futures traders' dispersion of beliefs depended on whether they were holding a daily gain or loss in the morning and afternoon.

3. Data and Methodology

This study uses daily data of closing CPO futures prices (Ringgit Malaysia per metric tonne) and trading volumes (metric tonnes) from January 6, 1986 to October 29, 2010 which consists of 6,074 observations. The data are collected from Thomson DataStream. Daily futures return is calculated by using $P_t = \ln(P_t/P_{t-1})$, where P_t is a daily price at time t and P_{t-1} is a daily price at preceding time t . Daily trading volume in natural logarithmic form is

used in this study and calculated by using $V_t = \ln(\text{Volume}_t)$, where Volume_t is a daily trading volume at time t and \ln is natural logarithm.

Then, we outline the cross-correlation function (CCF) approach developed by Cheung and Ng (1996). This approach produces an adequate model to specify correctly the first moment (mean) and second moment (variance) dynamics, and as well as potential interaction between both series. There are two stages to test null hypothesis of no causality-in-mean and variance between CPO futures return and trading volume in univariate and augmented analyses, respectively.

3.1. Univariate analysis

The first stage for univariate analysis is to estimate an appropriate univariate forecasting model to capture conditional mean and variance across time. The conditional mean for both series is specified as Autoregressive (AR) process, while the conditional variance is modeled as Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process. The number of orders for AR-GARCH univariate model for both stationary series is based on minimum Akaike's (1974) information criterion, AIC. These equations are written as equations (1), (2), (3) and (4). In equations (2) and (4), the estimated parameters should be $w > 0$ and $0 < \alpha_i + \beta_i \leq 1$.

$$R_t = a_0 + \sum_{i=1}^{P1} a_i R_{t-i} + \varepsilon_{R,t}, \quad \varepsilon_{R,t} | \phi_{t-1} \sim N(0, \sigma^2_{R,t}) \quad (1)$$

$$\sigma^2_{R,t} = w + \sum_{i=1}^{P2} \alpha_i \varepsilon^2_{R,t-i} + \varepsilon_{V,t} + \sum_{i=1}^{P3} \beta_i \sigma^2_{R,t-i} \quad (2)$$

$$V_t = a_0 + \sum_{i=1}^{P1} a_i V_{t-i} + \varepsilon_{V,t}, \quad \varepsilon_{V,t} | \phi_{t-1} \sim N(0, \sigma^2_{V,t}) \quad (3)$$

$$\sigma^2_{V,t} = w + \sum_{i=1}^{P2} \alpha_i \varepsilon^2_{V,t-i} + \sum_{i=1}^{P3} \beta_i \sigma^2_{V,t-i} \quad (4)$$

where

R_t = a daily return at time t ;

V_t = a daily trading volume at time t ;

$\sigma^2_{R,t}$ = a conditional variance for return at time t ;

$\sigma^2_{V,t}$ = a conditional variance for trading volume at time t ;

$\varepsilon_{R,t}$ = the unexpected return that cannot be predicted based on all information available up to the preceding period (ϕ_{t-1}); and

$\varepsilon_{V,t}$ = the unexpected trading volume that cannot be predicted based on all information available up

⁶ The excess volatility and excess volume of trade were induced by "noisy" liquidity demand of futures hedgers.

to the preceding period (ϕ_{t-1}).

The second stage is to analyze the cross-correlation of standardized residuals and their squares in order to detect feedback causality-in-mean and variance. Equations (1), (2), (3) and (4) are not simultaneous, so feedback in mean occurs if standardized residuals of return cause standardized residuals of volume and vice versa. Meanwhile, feedback in variance occurs if standardized squared residuals of return cause standardized squared residuals of volume and otherwise.

Let U_t and W_t be the standardized residuals for return and trading volume respectively.

$$U_t = \left((R_t - \mu_{R,t}) / \sigma_{R,t} \right) \tag{5}$$

$$W_t = \left((V_t - \mu_{V,t}) / \sigma_{V,t} \right) \tag{6}$$

Let U^2_t and W^2_t be the standardized squared residuals for return and trading volume respectively.

$$U^2_t = \left((R_t - \mu_{R,t})^2 / \sigma^2_{R,t} \right) \tag{7}$$

$$W^2_t = \left((V_t - \mu_{V,t})^2 / \sigma^2_{V,t} \right) \tag{8}$$

In order to ascertain whether there is a causal relationship between return and volume in terms of mean and variance, sample cross-correlation (r) between standardized residuals for both series and r between standardized squared residuals for both series at lag k are computed by using equations (9) and (10).

$$r_{UW}(k) = \frac{C_{UW}(k)}{\sqrt{C_{UU}(0)C_{WW}(0)}} \tag{9}$$

$$r_{U^2W^2}(k) = \frac{C_{U^2W^2}(k)}{\sqrt{C_{U^2U^2}(0)C_{W^2W^2}(0)}} \tag{10}$$

where

$r_{UW}(k)$ = the k th lag sample cross-correlation between standardized residuals for return and trading volume;

$C_{UU}(0)$ = the sample variance of standardized residuals for return;

$C_{WW}(0)$ = the sample variance of standardized residuals for trading volume;

$r_{U^2W^2}(k)$ = the k th lag sample cross-correlation between standardized squared residuals for return and trading volume;

$C_{U^2U^2}(0)$ = the sample variance of standardized

squared residuals for return; and

$C_{W^2W^2}(0)$ = the sample variance of standardized squared residuals for trading volume.

In order to test null hypothesis of no causality at specified lag k , test statistic is computed by using equation (11) and compared to a standard normal distribution. The null hypothesis is rejected if absolute test statistics value greater than a critical value from a standard normal distribution.

$$\text{Test statistic} = (\sqrt{n}) r_{UW}(k) \tag{11}$$

3.2. Augmented analysis

As in the case of causality from equation (1) to equation (4) are too general to be tested empirically. Hence, the augmented equations are required to make the general causality concept applicable and it can be used in practice. For the first stage, we estimate return and trading volume equations respectively by taking interaction of both series in conditional mean and variance into account. The augmented equations for both series are written as below.

$$R_t = a_0 + \sum_{i=1}^{P1} a_i R_{t-i} + \sum_{i=1}^{P2} b_i V_{t-i} + \varepsilon_{R,t} , \tag{12}$$

$$\varepsilon_{R,t} | \phi_{t-1} \sim N(0, \sigma^2_{R,t})$$

$$\sigma^2_{R,t} = w + \sum_{i=1}^{P3} \alpha_i \varepsilon^2_{R,t-i} + \sum_{i=1}^{P4} \beta_i \sigma^2_{R,t-i} + \sum_{i=1}^{P5} V^2_{V-i} \tag{13}$$

$$V_t = a_0 + \sum_{i=1}^{P1} a_i V_{t-i} + \sum_{i=1}^{P2} b_i R_{t-i} + \varepsilon_{V,t} , \tag{14}$$

$$\varepsilon_{V,t} | \phi_{t-1} \sim N(0, \sigma^2_{V,t})$$

$$\sigma^2_{V,t} = w + \sum_{i=1}^{P3} \alpha_i \varepsilon^2_{V,t-i} + \sum_{i=1}^{P4} \beta_i \sigma^2_{V,t-i} + \sum_{i=1}^{P5} R^2_{R-i} \tag{15}$$

The lagged trading volume in level form in equation (12) and the lagged return in level form in equation (14) are used to capture mean spillover. To capture variance spillover, the lagged trading volume in square form is included into equation (13) and the lagged return in square form is included into equation (15).

Then, the following stage is to analyze the cross-correlation of standardized residuals and standardized squared residuals to reveal mean and volatility spillovers. The null hypothesis states that return does not Granger cause volume or volume does not Granger cause return in mean and variance spillovers. This null hypothesis is

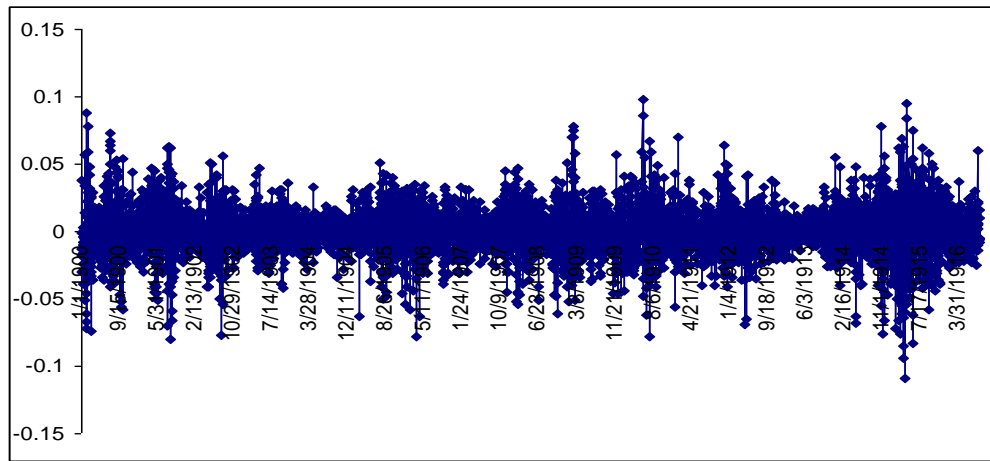
rejected if absolute test statistics value (equation (11)) greater than a critical value from a standard normal distribution. This reveals the existence of information on the lead-lag pattern of interaction between the return and trading volume in this commodity futures market.

4. Results and Discussion

<Figure 1> shows the movement of volatility at the end of whole period is slightly higher than at the beginning of the period, while <Figure 2> indicates that volatility in trading volume is increasing throughout time, especially

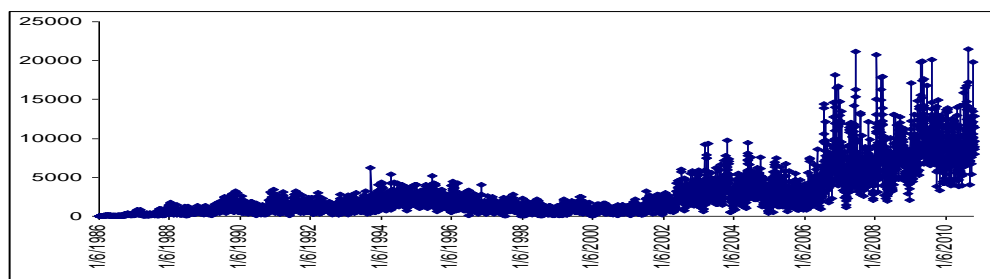
from 2007 to 2010. The high volatility spikes are found clearly on June 13, 2007; January 24, 2008; April 23, 2009; August 19, 2009; and August 25, 2010. As observed, there was volatility clustering in both series.

These spikes were associated with the significance of oil bubble crisis that happened during the period of 2007-2008. It implied that the financial crisis had dampened investors' confidence in the stock market where equity market performance had declined with losses from 2007 to early 2009. Therefore, the investors would attempt to invest in this commodity market as the tangible investment rather than in the stock market.



Source: DataStream

<Figure 1> Daily CPO Return from January 6, 1985 to November 1, 2010



Source: DataStream

<Figure 2> Daily CPO Trading Volume from January 6, 1985 to November 1, 2010

<Table 1> Descriptive Statistics

		V	R
Mean		7.2953	0.0002
Standard Deviation		1.2363	0.0173
Maximum		9.9761	0.0975
Minimum		0.0000	-0.109
Skewness		-0.8667	-0.0345
Kurtosis		5.1314	6.1708
Jarque-Bera		1910.355	2546.119
P- Value		0.0000	0.0000
Observations		6075	6075
Augmented Dickey-Fuller	Drift	-4.2710***	-77.1653***
	Drift and Trend	-6.1055***	-77.1614***
Phillips-Perron	Drift	-23.6840***	-78.4004***
	Drift and Trend	-49.0149***	-78.395***

Notes: $R_t = \ln(P_t / P_{t-1})$ and $V_t = \ln(\text{Volume}_t)$. P-value is the probability value associated with the Jarque-Bera test statistic. *** indicates as the null hypothesis of there exists a unit root is rejected at the 1% level of significance.

<Table 1> shows the descriptive statistics on the daily return and trading volume. It is obvious from Jarque-Bera test statistics and its corresponding p-values demonstrate that the null hypothesis of normal distribution is rejected at the 1% level of significance for both series⁷. This indicates that information arrives at an uneven rate may lead to serial correlation with non-constant variation in both series. The distributions for return and trading volume with negative skewness and kurtosis greater than 3 indicate the both series are leptokurtic. This is consistent with findings from Stulz et al. (1990) and Chan et al. (1991) on futures return distribution⁸. This fat tailed distribution implies that both series exhibit non-linear dependence which relates to the rate of information arrival (Sutcliffe, 1993)⁹

The existence of a unit root is tested using augmented Dickey-Fuller (1979, 1981) and Phillips-Perron (1988) tests. The auxiliary regression model of these unit root tests is specified in two different ways. The first model includes a constant term only (drift). The second model includes a constant term and time trend. By using two auxiliary models, both tests confirm that return and trading volume are stationary at level form.

We begin the analysis with the univariate model by identifying the fit of AR-GARCH model to explain

conditional mean and variance of both series. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) correlograms on squared return and trading volume are used to determine the model specification correctly for conditional mean. The ACF and PACF correlograms on squared residuals are further used to examine the existence of GARCH effects in both series .

Based on the ACF and PACF correlograms for squared return and trading volume, we choose the lag order of the conditional mean is five for return data and six for trading volume data. Meanwhile, ACF and PACF correlograms on squared residuals indicate that the conditional variance of both series is characterized by the GARCH (1,1) process. Therefore, we model the univariate model for return and trading volume using the AR(5)-GARCH (1,1) and AR(6)-GARCH (1,1) models respectively. Both univariate models are written as equations (16), (17), (18) and (19).

$$R_t = a_0 + a_1R_{t-1} + a_2R_{t-2} + \dots + a_5R_{t-5} + \varepsilon_{R,t},$$

$$\varepsilon_{R,t} | \phi_{t-1} \sim N(0, \sigma_{R,t}^2) \tag{16}$$

$$\sigma_{R,t}^2 = w + \alpha_i \varepsilon_{R,t-1}^2 + \beta_i \varepsilon_{R,t-1}^2 \tag{17}$$

$$V_t = a_0 + a_1V_{t-1} + a_2V_{t-2} + \dots + a_6V_{t-6} + \varepsilon_{V,t},$$

$$\varepsilon_{V,t} | \phi_{t-1} \sim N(0, \sigma_{V,t}^2) \tag{18}$$

$$\sigma_{V,t}^2 = w + \alpha_i \varepsilon_{V,t-1}^2 + \beta_i \varepsilon_{V,t-1}^2 \tag{19}$$

The estimated results of fitting these univariate models to the return and trading volume are reported in <Table 2>.

⁷ Information arrives at an uneven rate means that not all participants can assess to the same information.

⁸ Refer Chan et al. (1991), p. 662.

⁹ Sutcliffe (1993) stated that the difference between risk of margin calls in long and short positions would lead to the skewed distribution. This would directly lead to non-linear movement in futures prices.

For conditional variance equation, the estimated coefficients of ARCH and GARCH are 0.0989 and 0.8929 for return, while the estimated coefficient of ARCH and GARCH are 0.0777 and 0.8844 for trading volume. Both positive coefficients in both series are statistically significant which imply there exists clustering movement of volatility in return and trading volume. We measure the persistence of volatility through the sum of ARCH and GARCH coefficients ($\alpha_1 + \beta_1$). We find that persistence of 0.9918 for return and persistence of 0.9621 for trading volume approximate to unity, implying that both series exhibit stationary movement in volatility and high persistence of shock.

For diagnostic checking, $Q^2(10)$ and $Q^2(30)$ are the Ljung-Box (1978) Q statistics with 10 and 30 lags for the standardized squared residuals. These test statistics indicate that univariate models for both series are free from serial correlation. The ARCH-LM test further indicates that these models are also free from heteroscedasticity problem. This suggests that the selected specification for these univariate models explains the data well.

We obtain the standardized residuals and standardized squared residuals from the respective estimated univariate model in <Table 2>. Then, we use these standardized

residuals and their squares to compute sample cross-correlations. In <Table 3>, the sample cross-correlations between standardized residuals of return and standardized residuals of trading volume under the "Levels" column are used to test causality-in-mean. In the "Squares" column, the sample cross-correlations between standardized squared residuals of return and standardized squared residuals of trading volume are used to test causality-in-variance.

As shown in <Table 3>, the column headings "Lag" refers the number of days for trading volume data lags behind the return data. The significance of these cross-correlations implies that past daily trading volume Granger causes current daily return. The column headings "Lead" refers the number of days for return data lags behind the trading volume data. The significance of cross-correlations in this column implies that current daily return Granger causes future daily trading volume.

As shown at "Levels" column in <Table 3>, correlations of 0.0297 and 0.0278 between standardized residual for past volume and standardized residual for current return at lags 4 and 7. This indicates the mean of daily trading volume movement in 4 and 7 days ago Granger causes current mean of daily return movement.

<Table 2> Empirical Results of Univariate AR-GARCH Model Estimations

Parameters	R		V	
	Coefficient	SE	Coefficient	SE
Conditional mean equation:				
a_0	0.0001	0.0002	0.1552***	0.0373
a_1	0.0124	0.0136	0.4385***	0.0141
a_2	0.0018	0.0135	0.1217***	0.0154
a_3	0.0215*	0.0129	0.1207***	0.016
a_4	0.0109	0.0132	0.0995***	0.0151
a_5	0.032**	0.0132	0.0791***	0.0145
a_6	-	-	0.1193***	0.014
Conditional variance equation:				
ω	3.21×10^{-6} ***	3.65E-07		
α_1	0.0989***	0.0055	0.0086***	0.0009
β_1	0.8929***	0.0055	0.0777***	0.0050
$\alpha_1 + \beta_1$	0.9918	0.9621	0.8844***	0.0076
Log-likelihood	16978.95		-3634.585	
ARCH-LM test statistic	1.0993 (0.2944)		0.1463 (0.7021)	
Q(10)	26.297 (0.003)		105.33 (0.000)	
Q(30)	57.585 (0.002)		123.80 (0.000)	
$Q^2(10)$	9.5863 (0.478)		6.0573 (0.810)	
$Q^2(30)$	29.155 (0.509)		11.664 (0.999)	

Notes:*** and ** indicate as significance level at the 1% and 5%, respectively. P-values are stated in parentheses. Q and Q^2 are denoted as Ljung-Box Q-statistics test for standardized residual and standardized squared residual.

<Table 3> Univariate Cross-Correlation of Standardized and Squared Standardized Residuals

Lag length(k)	Levels		Squares	
	Lag	Lead	Lag	Lead
	V (-k) and R	R and V (+k)	V (-k) and R	R and V (+k)
0	0.0355***		0.083***	
1	-0.0191	0.0217	0.0097	-0.0255**
2	-0.0173	0.0116	-0.0029	-0.019
3	-0.0124	0.0141	-0.021	-0.0051
4	0.0294**	0.0126	-0.0054	-0.0046
5	-0.0057	0.0188	-0.002	0.0005
6	0.0148	0.0183	0.0026	-0.0118
7	0.0278**	-0.0083	0.0105	-0.0069
8	0.0117	-0.0023	-0.0015	-0.0103
9	-0.006	0.0033	0.0008	-0.0055
10	-0.0083	0.0192	-0.005	0.0333***

Note: *** and ** indicate as significance level at the 1% and 5%, respectively.

As observed in “Squares” column in the same table, we find correlations of -0.0255 and 0.0333 are significant at lags 1 and 10, respectively. This implies that movement of current variance for daily return Granger causes movement of variance for daily trading volume after 1 day and 10 days, respectively. For contemporaneous causal relationship, significant correlations of 0.0355 and 0.083 at lag 0 indicate both series have feedback causality-in-mean and variance simultaneously.

Based on the feedback causality-in-mean and variance results in <Table 3>, we build a better AR-GARCH model to describe time-series dynamics of the data by incorporating relevant and significant lagged return and trading volume into the respective univariate model.

For return, we update equation (16) for the conditional mean by incorporating lag 0 of trading volume into equation (20). This is because the empirical results in <Table 3> show feedback causality-in-mean between return and trading volume occur simultaneously¹⁰. <Table 3> shows feedback causality-in-variance between return and trading volume occurs at lag 0, we incorporate current squared trading volume into equation (17) for conditional variance to become equation (21)

For trading volume, we include lag 0 of the return into equation (18) because <Table 3> shows both series exhibit contemporaneous causal effect in mean. Equation (22) with augmented current return has a better description on conditional mean. Since <Table 3> reveals causality-in-variance from return to trading volume at lags 0 and 1, we

incorporate current and lag 1 of squared returns into equation (19) to become equation (23) in order to account variance spillover between both series¹¹. Based on feedback causality-in-mean and variance, we propose the augmented equations for return and trading volume data as equations (20), (21), (22) and (23).

$$R_t = a_0 + a_1R_{t-1} + a_2R_{t-2} + \dots + a_5R_{t-5} + \gamma_1V_t + \varepsilon_t, \quad \varepsilon_{R,t} | \phi_{t-1} \sim N(0, \sigma_{R,t}^2) \quad (20)$$

$$\sigma_{R,t}^2 = w + \alpha_i \varepsilon_{R,t-1}^2 + \beta_1 \sigma_{R,t-1}^2 + \theta_1 V_t^2 \quad (21)$$

$$V_t = a_0 + a_1V_{t-1} + a_2V_{t-2} + \dots + a_6V_{t-6} + \gamma_1R + \varepsilon_t, \quad \varepsilon_{t} | \phi_{t-1} \sim N(0, \sigma_{V,t}^2) \quad (22)$$

$$\sigma_{V,t}^2 = w + \alpha_i \varepsilon_{V,t-1}^2 + \beta_1 \sigma_{V,t-1}^2 + \theta_1 R_t^2 + \theta_2 R_{t-1}^2 \quad (23)$$

<Table 4> shows the results of estimated augmented models which are from equation (20) to equation (23). After we compare log-likelihood in <Tables 2> and <Table 4>, we find the log-likelihood increases from 16978.95 (in <Table 2>) to 16982.35 (in <Table 4>) for return equation, and from -3634.585 (in <Table 2>) to -3605.607 (in <Table 4>) for trading volume. This reflects the increase of explanatory power in augmented AR-GARCH model when it allows the interaction effect between return and trading volume. The diagnostic tests such as Ljung-Box Q and ARCH-LM tests conclude both augmented AR-GARCH models can fit well to the data.

¹⁰ The lags 4 and 7 of trading volume are not included into equation (20) because these lagged trading volumes are insignificant even at the 10% level.

¹¹ The lag 10 of squared return is not included into equation (23) because it is insignificant even at the 10% level.

As seen in <Table 4>, after lag 0 of squared trading volume is included, ARCH and GARCH coefficients in return equation (21) are still positive and statistically significant. The small decline in persistence for volatility of return from 0.9918 to 0.9909 indicates that small degree of persistence is absorbed by the contemporaneous value of the squared trading volume. Furthermore, a coefficient of 3.46×10^{-8} in equation (21) indicates contemporaneous trading volume has a small size of impact on conditional variance of return. Both evidences indicate volume contains little information about the variance of return process that weakly supports the mixture of distribution hypothesis. This implies that volume is not the proxy variable for information flow.

Once the augmented AR-GARCH models (shown from equation (20) to equation (23)) are estimated by taking interaction effect into account, the cross-correlations computed from standardized residuals and their squares of these models are analyzed further to detect the pattern of information flow and the results are presented in <Table 5>. Our study emphasizes the empirical results in “Squares”

column because it reports about dependence on conditional variance that is used as the proxy for information arrival and processing.

After we compare the empirical results in <Tables 3> and <Table 5>, we find the results are robust because univariate and augmented models provide slightly different results. Although causality pattern in mean from past trading volume to current return still exists, causality pattern in mean at lag 0 as seen in <Table 3> has already absent in <Table 5>. When model captures the interactive effect, a dynamic causality-in-variance from current return to future trading volume slightly changes from lag 1 to lag 2.

From the “Squares” column in <Table 5>, significant correlation of 0.0594 at lag 0 indicates variance spillover between return and trading volume happens simultaneously. At column headings “Lead”, significant correlation of -0.0186 at lag 2 indicates movement of current variance for daily return has negatively dependence causal effect on variance of daily trading volume movement after 2 days. Meanwhile, significant correlation of 0.0333 at lag 10 indicates this dependence causal

<Table 4> Empirical Results of Augmented AR-GARCH Model Estimations

Parameters	R		V	
	Coefficient	SE	Coefficient	SE
Conditional mean equation:				
a_0	-0.0022**	0.0010	0.1597***	0.0364
a_1	0.0116	0.0137	0.4429***	0.0140
a_2	0.0003	0.0135	0.1202***	0.01540
a_3	0.0203	0.0130	0.1190***	0.0159
a_4	0.0101	0.0133	0.0990***	0.0153
a_5	0.0307**	0.0132	0.0772***	0.0144
a_6	-	-	0.1183***	0.0141
γ_1	0.0003**	0.0001	0.9501***	0.3459
Conditional variance equation:				
ω	1.57×10^{-6}	1×10^{-6}	0.0103***	0.0011
α_1	0.1004***	0.0055	0.0764***	0.0054
β_1	0.8905***	0.0056	0.8749***	0.0087
θ_1	$3.46 \times 10^{-8*}$	1.88×10^{-8}	38.0101***	5.4166
θ_2	-	-	-37.3611***	4.8830
$\alpha_1 + \beta_1$	0.9909		0.9513	
Log-likelihood	16982.35		-3605.607	
ARCH-LM test statistic	1.0710 (0.3007)		0.2480 (0.6185)	
Q (10)	26.110 (0.004)		104.55 (0.000)	
Q (30)	56.084 (0.003)		123.29 (0.000)	
Q^2 (10)	9.1343 (0.519)		6.7310 (0.751)	
Q^2 (30)	29.229 (0.506)		12.056 (0.999)	

Notes: *** and ** indicate as significance level at the 1% and 5%, respectively. P-values are stated in parentheses. Q and Q^2 are denoted as Ljung-Box Q-statistics test for standardized residual and standardized squared residual.

<Table 5> Augmented Cross-Correlation of Standardized and Squared Standardized Residuals

Lag length(k)	Levels		Squares	
	Lag	Lead	Lag	Lead
	V (-k) and R	R and V (+k)	V (-k) and R	R and V (+k)
0	-0.0095		0.0594***	
1	-0.0229	0.0226	0.0107	-0.0254
2	-0.0191	0.014	-0.0023	-0.0186**
3	-0.0135	0.0133	-0.0216	-0.0047
4	0.0262**	0.0118	-0.0054	-0.0029
5	-0.0081	0.0185	-0.0019	0.0015
6	0.0122	0.0179	0.0039	-0.0109
7	0.0258**	-0.0083	0.0106	-0.0065
8	0.0091	-0.0049	-0.0019	-0.0095
9	-0.008	0.0034	0.002	-0.0053
10	-0.0103	0.019	-0.0038	0.0333***

Note: *** and ** indicate as significance level at the 1% and 5%, respectively.

effect in variance is turned to be a positive after 10 days. This evidence is an indication of noise traders' behavior of return-volume interaction since the time span of the dynamic effect of variance of return to cause the variance of trading volume does not exhibit a systematic pattern

Our results do not fully support findings from study of Bhar and Hamori (2005), where their findings mildly support for noise traders' hypothesis in the crude oil futures market¹². From the perspective of investors' behavior, one-way causality from return to volume in the second moments at lags 2 and 10 implies that investors change their expectations about current returns based on errors made in previous trading. This makes them to generate abnormal trading volume in the subsequent period.

5. Conclusions

This study adopts a non-linear approach that does not require a simultaneous modeling to examine information arrival between price changes and trading volume in Malaysian CPO futures market. The reason is a linear approach based on simultaneous modeling cannot longer be viewed as an adequate approach if non-linearity exists in financial time series data.¹³ Based on AR-GARCH models with relevant lagged variables in the conditional mean and/or variance equations, this study demonstrates that incorporating interaction between return and trading volume

is essential to define the information dependency between both series concerned. The standardized squared residuals from these augmented models are then analyzed using cross-correlation functions in order to discover dependence causality-in-variance of both series.¹⁴ This causality acts as a proxy of information flow between both series.

Our empirical results provide two findings. First, volatility of volume is not proxy for information flow which is not consistent with most prior research, example Blume et al. (1994) and Suominen (2001). This can be indicted by including current contemporaneous trading volume in square form into the conditional variance of return equation (GARCH) leads to persistence for returns slightly declines from 0.9918 to 0.9909. This implies a mixture of distribution hypothesis in the CPO futures market is not evident because contemporaneous trading volume conveys little of additional information about volatility movement in return.

Second, one-way dependence causality from current return to the subsequent volume in the second moments is found to occur at lags 2 and 10, respectively. At the same time, significant correlation of -0.0186 between standardized squared residuals for return and trading volume at lag 2 is turned to be a significant correlation of 0.0333 at lag 10. The time span of this dynamic effect is found to exhibit not systematic pattern and different signs of correlation at lags 2 and 10. This is an indicative of noise traders' behavior of return-volume interaction in this commodity futures market.

Our study highlights the price volatility is a determinant of the unexpected volume changes in CPO futures market, where our finding is consistent with Garcia et al. (1986),

¹² From their results of dependence causality-in-variance are reported in <Table 6> (p. 536), we observe the causation patterns from the rate of return to volume exhibit systematic pattern. For example, every 6 lags, this causal effect from the rate of return to volume is found to happen at lags 3, 9 and 15, respectively.

¹³ Refer Hinich & Patterson (1985), p.69.

¹⁴ Bhar & Hamori (2004) state that information arrival between a change of price and trading volume can be captured by dependence causal-in-variance which is also known as interactions in second moment or volatility spillover.

Kocagil and Shachmurove (1998), and Bhar and Hamori (2005) in commodity futures markets. Since changes of return and trading volume exhibit unidirectional causal effect, this finding suggests: First, this futures market has low liquidity, low responsive and weak-form inefficiency where this market restricts traders to enter and exit as needed. Second, investors tend to change their expectations about current returns based on errors made in previous trading in order to generate abnormal trading volume in the future.

Any changes in return volatility at the different time spans may result either a negative movement or a positive movement in volatility of future volume. This study implicates that time span is important for investors to expect changes in return in order to devise their strategies in generating profits consistently through abnormal trading.

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