INFORMATIONAL EFFICIENCY AND HEDGING EFFECTIVENESS IN MALAYSIAN CRUDE PALM OIL MARKETS

GO YOU HOW

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ABSTRACT

Crude palm oil (CPO) is one of the important commodities of Malaysian economy. According to the Malaysian Palm Oil Board, Malaysia is the second largest producer of CPO with 39 per cent of world production and 44 per cent of world exports in 2014. Nonetheless, as a commodity, it suffers from price fluctuation due to factors such as climate change and flood that affect the supply and demand of palm oil. Hence, there lies the issue of volatility in CPO prices which has a negative impact on food security. There are three objectives in this research. **The first objective** is to examine price-volume relation in CPO futures market during the pre-crisis, crisis and post-crisis periods, respectively. Based on daily data from 2000 to 2012, cross-correlation function shows volatility spillovers between return and trading volume in pre-crisis and post-crisis produce different degree of correlations in different time spans, supporting the "heterogeneity of traders" hypothesis. The inconsistent time span observed in cross-correlation function also supports the noise traders' hypothesis. It is observed that in the post-crisis period, market participants have become more risk averse. As a result, there has been an increase in volatility persistence which has reduced the level of informational efficiency. **The second objective** is to examine the hypothesis of Tilton et al. (2011) that asserts investor demand affects commodity prices when spot and futures prices are closely correlated during strong contango. After taking into account market efficiency as measured by variance ratio, our result based on the period of 2000-2014 indicates that higher degrees of efficiency are linked to the high correlations between spot and futures returns during weak contango period and vice versa. During backwardation, bi-directional

causality-in-mean happens between spot and futures returns. Notably, it takes a longer period for the former to Granger cause the latter, indicating a change in the spot return is a long-lived phenomenon. In contrast, it takes a shorter period for futures return to Granger cause spot return, indicating it is a short-lived phenomenon. During weak contango, futures volatility Granger causes spot volatility. During strong contango period, there is no causality-in-mean and variance. Hence, we extend the hypothesis that the preference of holding a long position in the futures market is due to the anticipation of insufficient supply of inventories in the short run for CPO as it is susceptible to seasonality and climate change. **The third objective** is to evaluate the effectiveness of eight hedging models with different mean and variance-covariance specifications for the period of 1986-2013. From the perspective of economic modeling, incorporating the basis term in modeling the joint dynamics of spot and futures returns during the crises provide better results. High dynamic hedge ratios during the Asian financial crisis contribute to the support for CCC-GARCH model. During the global financial crisis, BEKK-GARCH model appears to provide more risk reduction as compared to others. Overall, these findings add to the stylized fact on the dynamic relationship between CPO spot and futures markets under different market conditions.

ABSTRAK

Minyak sawit mentah (MSM) adalah salah satu komoditi yang penting dalam ekonomi Malaysia. Menurut Lembaga Minyak Sawit Malaysia, Malaysia merupakan pengeluar minyak sawit kedua terbesar dengan 39 peratus daripada pengeluaran dunia dan 44 peratus daripada eksport dunia pada tahun 2014. Namun begitu, sebagai komoditi, MSM mengalami turun naik harga kerana faktor-faktor seperti perubahan iklim dan banjir akan memberi kesan ke atas penggunaan minyak sawit dalam penghasilan bekalan makanan. Oleh itu, kajian ini telah mengemukakan tiga objektif yang utama. **Objektif yang pertama** adalah untuk mengkaji perhubungan antara harga dan jumlah dagangan dalam pasaran MSM masa hadapan untuk tempoh krisis, semasa krisis dan selepas krisis. Berdasarkan data dari tahun 2000 hingga 2012, fungsi silang korelasi menunjukkan limpahan turun naik antara harga pulangan dan jumlah dagangan sebelum dan selepas krisis menghasilkan tahap korelasi yang berbeza dalam berlainan jangka masa. Hasil kajian tersebut telah menyokong hipotesis untuk "heterogeneity of traders". Jangka masa tidak konsisten dedapati melalui fungsi silang korelasi juga telah menyokong hipotesis mengenai "noise traders". Selepas krisis, peserta pasaran didapti sanggup mengambil risiko. Ini mengakibatkan peningkatan ketegaran dalam turn naik harga. Seterusny, ia akan menyebabkan pengurangkan tahap kecekapan maklumat dalam pasaran tersebut. **Objektif yang kedua** adalah mengkaji hipotesis daripada Tilton et al. (2011) yang menegaskan permintaan pelabur akan menjejaskan harga komoditi apabila harga spot dan harga hadapan mempunyai hubungan yang rapat dalam tempoh lebihan bekalan (contango yang kuat). Selepas mengambil kira kecekapan di dalam pasaran yang diukur

melalui nisbah varians, hasil kajian kami berdasarkan tempoh 2000-2014 telah menunjukkan kecekapan yang tinggi dapat dikaitkan dengan korelasi yang tinggi antara harga pulangan spot dan harga pulangan masa hadapan dalam tempoh contango yang lemah dan sebaliknya. Dalam tempoh kurang bekalan (backwardation), hasil kajian telah menunjukkan perubahan harga spot adalah "long-lived phenomenon". Manakala, perubahan harga masa hadapan adalah "short-lived phenomenon". Dalam tempoh contango yang lemah, varain dalam harga pulangan masa hadapan didapati akan menyebabkan perubahan varain dalam harga pulangan spot. Dalam tempoh contango yang kuat, sebab-akibat dalam min dan varians didapati tidak berlaku. Oleh itu, kami menyumbangkan satu penyataaan untuk hipotesis tersebut dengan mengemukakan bahawa keutamaan untuk membeli bekalan MSM melalui pasaran masa hadapan adalah disebabkan oleh jangkaan bekalan yang tidak mencukupi dalam jangka masa pendek. Ini kerana hasil-hasil daripada MSM adalah mudah terdedah kepada musim dan perubahan iklim. **Objektif yang ketiga** adalah untuk menilai keberkesanan lapan jenis model perlindungan nilai yang mempunyai spesifikasi yang berbeza dari segi min dan varians-kovarians untuk tempoh 1986-2013. Dari segi pemodelan untuk ekonomi, pembezaan antara harga spot dan harga masa hadapan yang diambil kira semasa krisis dapat memberikan hasil strategik yang lebih baik. Dinamik nisbah lindung nilai yang tinggi dalam tempoh krisis kewangan Asia telah memberi sokongan ke atas model CCC-GARCH. Semasa krisis kewangan global, model BEKK-GARCH didapti dapat memberi pengurangan risiko yang tinggi jika berbanding dengan lain-lain model. Secara keseluruhan, hasil-hasil kajian tersebut menegaskan bahawa perhubungan dinamik antara harga spot dan harga masa hadapan untuk MSM adalah berbeza-beza di dalam keadaan pasaran yang berlainan.

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For Chapter Six entitled "Evaluating the Hedging Effectiveness in Crude Palm Oil Market during Financial Crises" of which was accepted for publication in the Journal of Asset Management. In improving the early version of the draft for this chapter, I would like to take this opportunity to express my gratitude for participants from the International Conference on Economic and Financial Challenges and Issues in the Asia-Pacific Countries" in Chengdu, China, June 29- July 1, 2012 and the 22nd Annual Conference on Pacific Basin Finance, Economics, Accounting, and Management, Aichi University, Nagoya, Japan, September 4 - September 5, 2014 for their comment and suggestion to improve the work.

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It has been a rewarding journey for my personal growth both intellectually and academically as I quest along the journey of completing the studies. It has been a right decision to undertake this journey which I treasure every moment of it.

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December 2016

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LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller
AFC	Asian Financial Crisis
APT	Arbitrage Pricing Theory
BEKK-GARCH	Baba, Engle, Kraft and Kroner-Generalized Autoregressive Conditional Heteroskedasticity
BGARCH	Bivariate Generalized Autoregressive Conditional Heteroskedasticity
BMD	Bursa Malaysia Derivative Berhad
CCC-GARCH	Constant Conditional Correlation -Generalized Autoregressive Conditional Heteroskedasticity
CCFs	Cross-Correlation Functions
COMMEX	Commodity and Monetary Exchange of Malaysia
CPO	Crude Palm Oil
EMH	Efficient Market Hypothesis
FCPO	Crude Palm Oil Futures
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GFC	Global Financial Crisis
KLCE	Kuala Lumpur Commodity Exchange
KLOFFE	Kuala Lumpur Options and Financial Futures Exchange
LOP	Law of One Price
MDH	Mixture of Distribution Hypothesis
MPOB	Malaysian Palm Oil Board
MDEX	Malaysia Derivative Exchange
MME	Malaysian Momentary Exchange
MVHR	Minimum-Variance Hedge Ratio
OHR	Optimal Hedge Ratio
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
PP	Phillips and Perron
SIAH	Sequential Information Arrival Hypothesis
VAR	Vector Autoregressive
VECM	Vector Error Correction Model

CHAPTER 1: INTRODUCTION

1.1 Background of Study

As one of the main crops of Malaysian agriculture, crude palm oil (CPO) contributes significantly to the Malaysian economy. For example, in 2014, palm oil industry has accounted for 6 per cent of Malaysian gross domestic product. The industry has contributed to higher exports of palm oil products over the last few years. Its total export has increased from 25.07 million tonnes in 2014 to 25.37 million tonnes in 2015 by 1.2 per cent. However, lower export price has led to declining total export revenue from RM63.62 billion in 2014 to RM60.17 billion in 2015 by 5.4 per cent. Due to this, export revenue for palm oil has declined from RM44.50 billion in 2014 to RM41.26 billion in 2015 by 7.3 per cent (Malaysian Palm Oil Board (MPOB), 2015).

As indicated in Table 1.1, palm oil is recorded to have the highest world consumption as compared to other major types of vegetable oil. According to the MPOB (2015), the estimated 90 per cent of total production from palm oil is allocated for the purpose of food consumption, whereas the remaining 10 per cent is for industrial consumption such as material in cosmetic products or fuel and diesel.

Table 1.1: Consumption of vegetable oil worldwide by oil types (in million metric tonnes), 2006-2016

	2006/07	2007/08	2008/09	2009/10	2010/11	2011/12	2012/13	2013/14	2014/15	2015/16
Palm oil	**37.7**	**39.4**	**42.1**	**44.5**	**47.63**	**50.16**	**54.98**	**57.31**	**60.73**	**61.57**
Soybean oil	35.6	37.5	36	38.3	40.74	42.22	42.59	45.35	46.79	51.2
Canola oil	17.6	18.3	20.1	22.4	23.27	23.68	23.72	25.63	27	27.09
Sunflower seed oil	10.3	9.4	10.6	11.4	11.75	12.96	13.21	14.57	15.18	14.14
Other	20	20.5	20.9	21.2	21.95	22.78	23.19	23.48	23.57	22.95

Source: Statista (2016), http://www.statista.com/statistics/263937/vegetable-oils-global-consumption/ (accessed on 5 June 2016).

Given the prominence of this commodity to the economy, Malaysian CPO futures market has been in existence in the Kuala Lumpur Commodity Exchange (KLCE) since October 1980. It continues to be one of the active futures markets for CPO related derivative products in the world under the platform of Bursa Malaysia Derivative Berhad (BMDB) in 2003. The BMDB is a futures exchange that provides a market place for CPO futures contracts and price discovery. As compared to other matured futures markets such as the soybean oil futures market in the Chicago Board of Trade (CBOT), CPO futures trading volume is seven times the world production of soybean oil. Therefore, CPO futures market has been expected to have the potential for further growth in the future.

When CPO futures prices are arrived at in an open and competitive trading environment, they are continually updated to reflect the situation of demand and supply on palm oil at any particular in time. Subsequently, these prices are disseminated to market users worldwide through the exchange's real-time price reporting system. With the CPO futures contract, CPO could be physically delivered and traded in Malaysian Ringgits.

The following Figure 1.1 shows that daily CPO spot and futures prices from the beginning of 1986 until to end of 2014 which have increased trend and high variation. Both CPO spot and futures movements are found to be sensitive toward to surrounding different exogenous shocks during outlook of economic activities.

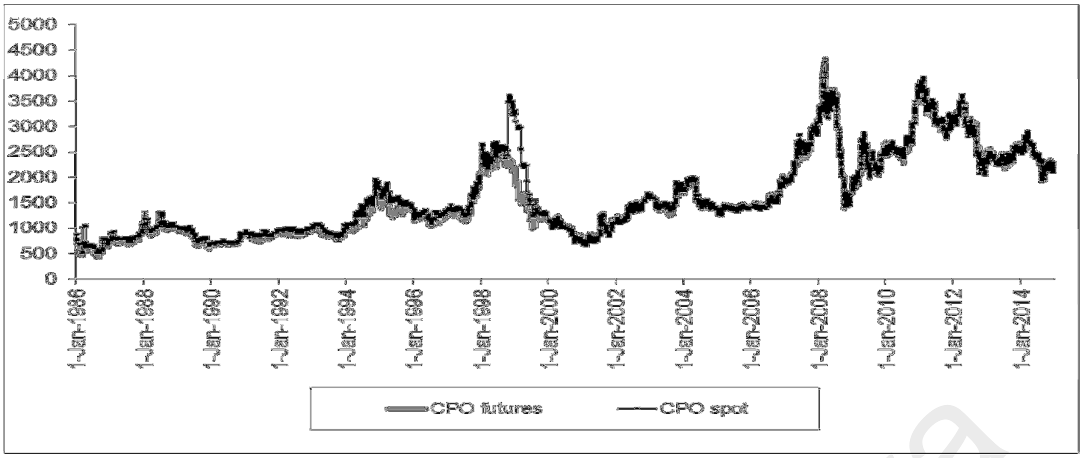

Figure 1.1: Daily CPO spot and futures prices (per metric tonne), 1986-2014
Source: Malaysia Palm Oil Board and Bursa Malaysia Derivative Berhad (2015).

Based on Figure 1.1, CPO futures price has an upward movement from 1998 to 1999. The restructure of the Malaysian derivative market to form COMMEX in responding depreciation of Ringgit In November 1998 has traded CPO futures contracts at RM2,700 per metric tonne, making palm oil the top foreign exchange earner.

To reduce dependency on fossil fuels as well as to stabilize and boost palm oil prices through export, research and development activities, the National Biofuel Policy was implemented on March 21, 2006 in Malaysia to promote the use of biodiesel derived from palm oil as environmentally friendly and sustainable energy source (Gain Report, 2014). With this policy, the existence of bio-fuel for non-food uses in 2006 has provided the most efficient pricing of CPO in BMD. Consequently, as observed in Figure 1.1, CPO spot and futures prices have dramatically increased from 2006 to 2008.

From March 2008 to October 2008, both CPO spot and futures prices have dropped to RM1,418 per metric tonne and RM1,390 per metric tonne, respectively. Such scenario illustrated that the global financial crisis 2008/09 has translated into a higher volatility in CPO price. This high volatility made both spot and futures markets to be more uncertain over time. After the global financial crisis, its considerable effect on many commodity prices globally has caused palm oil stocks rise and demand slumps in Indonesia and Malaysia. Subsequently, both palm oil prices have decreased RM2,400 per metric tonne in 2012.

In January 2012, the Environmental Protection Agency in the United States rejected palm-oil based biodiesel for the Renewable Fuels Program. The reason was it failed to meet a requirement in reducing emissions relative to conventional gasoline by 20 per cent. This led to CPO spot and futures prices to decrease by the end of 2012. Next, both CPO spot and futures prices are found to have an upward trend during the period of 2013-2014. This price competitiveness of palm oil and usage of palm oil as the feedstock in the production of biodiesel have increased the export volume of palm oil to the Europe Union from 2.34 million tonnes in 2013 to 2.41 million tonnes in 2014 (MPOB, 2014).

1.2 Problem Overview

Palm oil industry inherently has many challenges. The first challenge is from the perspective of health issue in the 1970s and 80s. The second challenge is the environmental issue in the 1990s, and finally, in recent times, sustainability takes the centre stage in palm oil production. Such production process directly affects the movement of palm oil price over time.

Under normal condition, spot and futures prices for commodities are expected to be almost identically influenced by market forces. However, the issue of fluctuation in agricultural commodity prices due to seasonal production, lower prices during harvest season, changing economic environment, and changing demand and supply positions becomes a significant and persistent in the literature of agricultural economics. The fluctuation of consumption demand or production leads to high spot price volatility that acts as a proxy for general volatility in the spot market. In order for an agricultural economy to compete internationally, the futures market is required to provide the wider role in stabilizing price movement and improving the profitability of trading among market participants.

In fact, volatility in prices is one salient feature for agricultural commodities that have an impact on food security especially for edible oils and fats (Food and Agricultural Organization of the United Nations, 2011).[1] The reason is the inefficiency of commodity markets leads to price fluctuation. This phenomenon gives a risk to producers in making their decisions in allocating how many of inputs should be used for production with low costs. This uncertainty consequently increases the cost of conducting business to manufacturers. Then, it thereby passes high food prices to consumers. As volatility is a highly persistent and variable, volatility clustering remains a major concern among market participants over long horizons (Ding, Granger & Engle, 1993).

Since the volatility of palm oil has a negative impact on food security, this study further defines this problem into three issues. First, the impact of crisis on information transmission between CPO futures price changes and trading volume. The reason is the recent global financial crisis provokes an interest in using CPO futures contracts to generate a positive payoff in which market volatility soars. Second, the impact of

[1] This statement is based on the report "Food price volatility and the right to food". This report is retrieved from http://www.fao.org/fileadmin/templates/righttofood/documents/RTF_publications/EN/issuesbrief_PRICEvolatility_EN.pdf on 18 June 2016.

transition of CPO spot-futures relation on speculative pressures is focused. Third, this study focuses on such relation in evaluating hedging effectiveness of CPO futures contract across different high volatile sub-periods.

1.2.1 The issue of an unsustainable CPO futures trading volume

The first issue is a futures price change does not conform to a normal distribution, but is highly leptokurtic. Such distribution explains that the existence of heterogeneous outlook among market participants towards the arrival of new information. A structural change in variance contributes to the spurious result of information transmission since it affects both statistical tools and interpretation of results. The structural change in market price movement not only reflects information based on its own past movement, but it is also based on the fundamental economic problem and financial factors. Apart from that, the following authoritative opinion is noted below:

> "*Today's methods to control and price risk are still based on the neoclassical assumptions of normal distributions and Brownian motions. This is probably one of the reasons that explain the failure of risk management systems in times of crisis*"
>
> Chittedi (2014, p. 3)

The volatility change of CPO futures prices considerably across periods. As documented by Anderson and Danthine (1983), the pattern of information flow into the futures market contributes to the phenomenon of leptokurtosis. This phenomenon is due to unexpected changes in the development of economy and financial institutions especially during the period of 2008/09 global financial crisis, causing different market participants' interpretation on the arrival of new information in the market. Subsequently, the arrival of information is not available to them at random rate. This leads to the process acquiring information is turned to be costly.

Trading volume is generally thought to be a proxy for the rate of daily information arrival in reflecting the stock return. However, the ability of trading volume to sustain its role in transmitting information over the time is subject to volatility persistence in the market. For example, the arrival of new information presents in the market where the presence of trading volume reduces the volatility persistence of return. This suggests that the volume reflects the noise movement of return by absorbing the volatility persistence of return in the conditional variance process.

The 2008/09 global financial crisis leads to a renewed interest in efficient market hypothesis from two perspectives, indicating that informational efficiency does not mean market participants are uncertain about the future price. The first perspective is the anomaly pertaining to market inefficiency during such crisis which causes them to incur the cost of acquiring the valuable information in trading. The second perspective is the liquidity in capturing "inefficiencies" in testing the abnormal returns. For the case of CPO, the incidents of asymmetric information transmission between price and trading volume is still not covered in the literature.

1.2.2 The issue of violation to CPO spot-futures parity

The uncertainty demand-supply conditions cause large changes in expected spot price in the future and directly lead to superfluous price movement in the current spot market. This causality immediately flows into the futures market, but it does not directly affect futures price movement. Apart from that, the futures price is no longer as a simple manifestation of the spot price. This informational inefficiency could lead to violation in the spot-futures parity due to the existence of cost-of-carry phenomenon. The non-parallelism in movement between spot and futures prices which departs from steady state conditions, providing that speculative activity causes the price fluctuation in CPO markets, especially when the market transition from backwardation to contango. This market transition subsequently dilutes trading activities and causes the occurrence of non-standard operation and non-transparent trading.

However, rather surprisingly, the reflection of production costs considerably influences wage costs and plays a crucial role to link between wage costs and normal price. If wage costs are expected to be changed, the normal price of a commodity which acts as a reference point in both spot and futures markets to price the same commodity towards actual price is also expected to become unstable (Kaldor, 1939; Davidson, 1978). As a consequence, the current price highly deviates from normal price, providing that current price level is uncertainty to be higher than, lower than, or equal to the level warranted. This causes traders encounter difficulty in deciding whether production should be implemented or not.

Since the quality of spot price forecasts based on futures prices has been a contentious issue for many years, this study focuses on the viability of using futures prices to forecast spot prices under different market conditions, namely strong contango, weak contango and backwardation. However, the futures cannot provide better forecast about the expected spot price changes if variance of the expected spot price changes is a large fraction of the variance of the actual spot price changes. The small variation in the expected price changes relative to the variation in the actual price changes leads to forecasts that reflect all the available information may be hidden by the unexpected price changes (French, 1986: p. 50).

The seasonal price pattern will be observed if the convenience yield is high at low inventory levels and the physical storage cost is high at high inventory levels. As a result, production seasonal leads to anticipated changes in the CPO supply and spot price. For example, one might expect CPO futures prices to predict correctly a drop in the CPO spot price during the harvest period when the supply increase, though futures is expected to predict correctly an increase in the CPO spot price between harvest periods. Since the producers of CPO have higher perceived risk than consumers, they tend to respond highly to the change in current price as compared to the change in the expected price.

However, the sensitivity of marginal storage cost function to changes in the inventory is also affected by the seasonal variation. If the marginal storage cost is relatively large, CPO spot price in one period is insulated from shocks in another period. In this case, CPO supply and demand shocks subsequently generate largely expected price changes. This consequently leads to changes in futures price which are able to generate predictable spot price changes if market participants are not spread evenly across all time periods. If changes in the inventory weakly affect the marginal storage cost, supply and demand shocks are freely transmitted from one period to another. As a result, there is no large expected change for CPO futures prices in predicting CPO spot prices. For example, a sudden increase in the demand for CPO will enable the producers to predict current and expected future spot prices.

1.2.3 The issue of basis risk in CPO futures hedging

The third issue is to deal with hedging effectiveness. In the early stage of hedging theory in commodity markets, hedger is a dealer who avoids or reduces risk in the spot market by using futures contracts to take opposite positions in the futures market. Since the influential paper of Bollerslev, Engle and Wooldridge (1988) on the Bivariate-Generalized Autoregressive Conditional Heteroskedasticity (BGARCH) model in capturing changes of spot-futures relation over time, the Constant Conditional Correlation (CCC) (Bollerslev, 1990) is used to capture the interaction of time-varying volatility of spot and futures returns and measure the Minimum-Variance Optimal Hedge Ratio (MVOHR).

This model with the CCC specification that consists of seven parameters in the conditional variance-covariance provides simple computation in the conditional variance-covariance matrix (Kroner & Sultan, 1993; Ng & Pirrong, 1994; and Lien et al. 2002) over the eleven parameters in the conditional variance-covariance structure for the model of Engle and Kroner (1995). However, different model specifications in examining the hedging effectiveness are those of storable commodities such as crude oil, copper, metal and others. There is a lack of studies on non-storable commodities. Nevertheless, there are very few studies incorporate the effect of basis (spot-futures price spread) into conditional mean and variance-covariance structures in examining the effectiveness of hedging for the case of non-storable commodities such as CPO.

Unlike storable commodities, CPO price is determined by available inventories and expected demand. Apart from that, a basis is expected to vary with different demand and supply conditions. In the short run, the current demand is assumed to be same with expected demand. As studied by Ng and Pirrong (1994), large inventories tend to put downward pressure on prices and lead to relatively low volatility for metal. This supports that inventory condition is a proxy of basis in supporting the theory of storage. By taking this inventory effect into account, Kogan et al. (2005) further find that relationship between variance and basis in commodity markets exhibits a "V-shape" pattern. Therefore, the intertemporal basis of a commodity is concluded to deal with the supply of storage and time dimension.

The financial crises reduce the hedging effectiveness for CPO futures market because they cause the collapse of international trade for the physical inventories. However, past studies do not focus on the sensitivity of hedging effectiveness with respect to model specification during crisis periods. Based on selected model specification, if the decision to hedge is taken, it still remains an interesting issue whether market participants use the selected model able to hedge the full position in the spot market.

To determine the size of the position on the hedging instrument that is used to hedge a spot position, there is the problem of whether the hedge ratio should be estimated from level as opposed to a first-difference model or a first-difference model as opposed to an error correction model. There is no single superior hedge ratio, depending on various objective functions. After several decades, many studies have not yet to reach a consensus about whether or not the use of the same model specification will make any difference in hedging effectiveness across high volatile periods.

1.3 Research Questions

In line with the issue of volatility of CPO prices which is stated in the previous section, the research questions are classified into three aspects:

(1) The relationship between CPO futures price changes and trading volume

(a) How does trading volume sustain its role as the proxy of information flow to predict price changes in the CPO futures market across the economic downturn?

(2) The relationship between CPO spot and futures price changes

(a) How does the efficiency of CPO futures price changes influence its correlation with CPO spot price changes when both markets stay in strong contango, weak contango and backwardation?

(b) How does CPO spot price changes cause CPO futures price changes in both mean and variance or vice versa during weak contango, strong contango and backwardation periods?

(3) The hedging effectiveness of CPO futures contracts

(a) How does the basis term sustain its superiority during highly volatile periods in generating the best hedge ratios and performance in the case of the Malaysian CPO futures market?

1.4 Research Objectives

This study sets the following objectives to answer each research question.

(1) The relationship between CPO futures price changes and trading volume

(a) To examine the impact of incorporated trading volume on volatility persistence of CPO futures return during the pre-crisis, crisis and post-crisis periods.

(2) The relationship between CPO spot and futures price changes

(a) To examine whether the efficiency of CPO futures price changes is related to its degree of correlation with spot price changes during weak contango, strong contango and backwardation periods, respectively.

(b) To examine the causal relationship between CPO spot and futures price changes in mean and variance during weak contango, strong contango and backwardation periods, respectively.

(3) The hedging effectiveness of CPO futures contracts

(a) To evaluate the effectiveness of different hedging models based on the minimum variance reduction during the world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/09, respectively.

To ensure different the scopes of the analysis are consistent with the above research questions, the following list of chapters is arranged systematically for this thesis:

Research Question 1(a) is discussed in Chapter Three.

Research Question 2(a) is discussed in Chapter Four.

Research Question 2(b) is discussed in Chapter Five.

Research Question 3(a) is discussed in Chapter Six.

1.5 Organization of the Thesis

Chapter Two intends to view and discuss past researchers' findings of the informational efficiency with two ways: price-volume and spot-futures relations. Since Fama's (1970) influential survey article entitled "Efficient Capital Markets: A Review of Theory and Empirical Work", informational efficiency remains as a cornerstone of financial economics for decades. Based on a massive growth of literature on market efficiency, this chapter provides various definitions of informational efficiency. Then, it is followed by explanations on the linkages between informational efficiency, spot-futures and price-volume relations by presenting research theoretical framework.

This chapter further provides a systematic review of commodity futures markets to link how does informational efficiency influence hedging effectiveness towards the price discovery mechanism. This chapter synthesizes hedging literature based on several aspects. For example, it summarizes the measurements of effective hedge ratios based on various objectives (the minimum-variance hedge ratio and maximum-expected utility hedge ratio), various econometric models, and asymmetric effects and basis terms. Finally, this chapter undertakes to discuss the past findings of the process of futures markets in stimulating price discovery function.

Chapter Three discusses the issue of price-volume relation in the CPO futures market. Although many studies on an issue of such relation in commodity markets, but no study has considered the impact of financial crisis on informational efficiency over the relationship between price and trading volume in the CPO futures market. Hence, this chapter bridges the gap of existing empirical studies by examining the relationship between futures price changes and trading volume during the pre-crisis, crisis and post-crisis periods, respectively. Empirical results based on sample cross-correlation functions are presented, interpreted and discussed.

Chapter Four discusses the issue of a link between spot and futures price changes of CPO by testing the hypothesis of Tilton, Humphreys and Radetzki (2011) using analysis of Gulley and Tilton (2014). This chapter intends to provide the discussion on whether the investor demand hypothesis holds in the case of CPO as a non-storable commodity when both markets transited from backwardation to contango or vice versa.

This chapter further explains on how the efficiency of CPO futures price changes is indeed correlated with CPO spot price changes in strong contango instead of weak contango and backwardation.

The correlation coefficient of both price changes does not imply causality. **Chapter Five** subsequently provides the discussion about dynamic causality between CPO spot and futures price changes in both mean and variance during the strong contango, weak contango and backwardation periods. If the causal relationship exists, the non-linear approach based on non-uniform weighting cross-correlations by Hong (2001) is adopted to detect directions of causality-in-mean and variance between spot and futures price changes.

Chapter Six focuses on the issue of hedging effectiveness during highly volatile sub-periods in the case of the Malaysian CPO futures market. It extends the studies by Zainudin and Shaharudin (2011), and Ong, Tan and Teh (2012) by incorporating a basis term (the short-run deviation between CPO spot and futures prices) into conditional variance-covariance structures of Baba-Engle-Kraft-Kroner (BEKK) and Constant Conditional Correlation (CCC) representations. During the world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/09, eight hedging models consist of time-invariant and time-variant models are evaluated based on the percentage of variance reduction. In this chapter, the impact of structural change in estimated minimum-variance hedge ratio and hedging effectiveness with different mean and variance-covariance specifications are also discussed.

Finally, **Chapter Seven** summarizes findings from Chapter Three to Chapter Six. Then, conclusions are drawn from these findings to provide suggested implications for market participants. In addition, the limitations and future directions for research are also provided.

1.6 Significance of Study

This study provides empirical evidence on investors' behaviour in trading CPO from three perspectives as below. In this regard, market participants are able to gauge the behaviour of investors' trading and lead to a better decision making.

1.6.1 Price-volume relation in CPO futures market

In Chapter Three, the distinct feature of price-volume relation across the 2008/09 global financial crisis demonstrates that trading volume does not necessarily play as an indicator of information spillover in the CPO futures market. This finding provides a better signal in the description of a causal relationship between CPO futures price and trading volume in terms their cross-correlations and time span during the pre-crisis, crisis and post-crisis periods, respectively.

If the finding indicates that trading volume acts as a proxy variable for the rate of daily information for CPO prices, market participants who are concerned with market dynamics in the short run can use information about price based on trading volume in a way to deleverage their risk in making decisions at a better market timing. For example, to assess the quality of price in allocating CPO inventories optimal for production, producers can make use of interaction between both series to give an idea about the direction of changes in CPO futures price as an expected output price. They can use information from such relationship so as to detect possible shock in order to limit their uncertainty in trading.

1.6.2 CPO spot-futures relation

In Chapters Four and Five, the proposition of existing investor demand during contango period in the context of CPO is tested. Past studies support that proposition of existing investor demand for copper as a storable commodity when spot and futures prices are closely correlated during the strong contango period. Since the debate on CPO futures prices still remains as a highly controversial issue with respect to implications in curbing excessive speculations and stabilizing prices for non-storable commodities, none of the studies is found to test this proposition in the context of CPO.

The volatility of futures price varies across different market conditions such as backwardation and contango. By taking backwardation and contango into considerations, the finding of such relation which relates to efficiency can provide the suggestion for market participants to adjust their response based on the arrival of new information in making decisions under different market condition.

For investors, if futures market is found to be efficient, they can adjust their decisions in executing inter-temporal arbitrage strategies between spot and futures markets by trading liquid and physical stocks of the commodity. For producers, consumers and intermediate users, both stocks and futures are treated as precautionary instruments. They can relate the efficient futures market to their precautionary behavior towards output and price risks under different market conditions. The efficiency of futures price allows them to adjust their decisions of holding stocks in obtaining convenience yield in the future and using futures contracts as hedging instruments.

1.6.3 Hedging effectiveness of CPO futures

In the context of Malaysian CPO futures, a few studies have been done to examine hedging effectiveness. The financial crises can have a significant impact on hedging effectiveness and even the choice of appropriate hedging strategy. Therefore, in Chapter Six, whether hedging strategies produce asymmetric performance in reducing the variance of portfolio is examined in the context of the world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/09. To resist a large amount of risk in the specific sub-period of unexpected shock, the finding from such way across different regime shifts in volatility movement is expected to assist market participants in making their hedging strategy.

With different model specifications, this study examines whether the success of a hedging strategy depends upon the long-run relationship between CPO spot and futures prices across various high volatile sub-periods. This examination is a pre-requisite for hedgers to design an efficient hedging strategy. If the finding indicates that the success of a CPO futures hedging strategy depends upon such long-run relationship, hedgers are suggested to hedge the price risk contained in their portfolio. If the finding indicates that different high volatile sub-periods disturb the long-run relationship between CPO spot and futures prices, hedgers are suggested to adjust or switch their hedging strategy in an appropriate way. The reason is these sub-periods lead to the existence of time variance in a basis term (spot-futures spread), and thereby affecting the efficiency of a hedging strategy.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a review of literature from two perspectives. The first perspective is informational efficiency. The second perspective is the effectiveness of hedging futures for commodities.

2.1 A Survey of Literature on Informational Efficiency under Price-Volume and Spot-Futures Relations

2.1.1 Introduction

Informational efficiency of financial markets has been the main subject of interest among market participants who place their order to trade on the desired price. The change in movement of market price is associated with the arrival of new information. Numerous studies have emerged to investigate the role of price discovery in mitigating the asymmetric information resulted from different interpretation among market participants. The reason is their different interpretations would lead to asymmetric information in the market. After several decades, many studies have not yet to reach a consensus about the existence of an efficient financial market in terms of "*price is fully reflected*" in explaining information transmission.

To quantify information transmission in the market, which is an important indicator to have a clear understanding about a certain market microstructure, Ross (1989) uses a no-arbitrage model to claim that variance is a proxy for information arrival in the market. In addition, Engle et al. (1990) demonstrate that market participants' actions in processing the market information can influence the variance, where their actions indirectly reveal existing information flow in the market across time. Andersen (1996) further demonstrates that stochastic process and generalized standard autoregressive conditional heteroskedasticity (ARCH) specifications can model information flow which reflects dynamic features in the financial data. From their point of view, the causal effect in volatility is the best representative description of market characteristics.

In recent years, there have been tremendous growths of literature on market efficiency. With the massive growth of studies on market efficiency, review of related literature is not new. For example, since Fama's (1970) influential survey article entitled "Efficient Capital Markets: A Review of Theory and Empirical Work" which indicates that securities markets are extremely efficient in reflecting information about individual stocks and the whole stock market, various aspects of market efficiency are studied. The majority of these studies are found to focus on the price-volume and spot-futures relations in the emerging markets.

Definition of market efficiency by Fama (1970) is widely defined in terms of speed and precision of price adjustment to new information. Although advocates of the efficient market hypothesis (EMH) would deny the use of historical prices in predicting market movement, the relationship of price and volume as well as between spot and futures markets has continued to be a subject of inquiry by many researchers in testing the weak-form EMH.

2.1.2 Definition of informational efficiency

Informational efficiency is the speed and accuracy in which prices reflect the arrival of new information. From this efficiency point of view, investors cannot expose to future price variability based on historical information. Apart from this situation, Samuelson (1965) initially states that informational efficiency happens in the market when prices already incorporated all the information and expectation of market participants. As a consequence, historical price change cannot be used to foresee the subsequent price change.

In the earlier study, Fama (1965) is found as the first one to express the term of "efficient market", where he propounds the efficient market hypothesis (EMH) by indicating that all available information in the market has been fully reflected by security prices. As a consequence, the market will be efficient. He uses a statistical feature of stock prices in focusing the debate between technical and fundamentalist analyses to foresee stock prices. To make this hypothesis to be viable, Fama (1991) adopts the classics categorization of available information by Roberts (1959). Then, he structures the set of available information for market participants by subdividing the EMH into three forms. The first form is the weak-form efficiency, where financial market prices fully reflect all historically available information. It concludes that technical analysis could not be used to obtain excess returns. The second form is the semi-strong form efficiency, where financial market prices fully reflect all publicly available information. Using fundamental analysis, excess returns cannot be achieved. The third form is the strong-form efficiency, where financial market prices contended that market, non-market and inside information which fully reflect all privately available information. Under this perfect market, excess returns are impossible to be achieved consistently.

As listed by Fama (1991), there are four assumptions for market prices in fully reflecting all information. First, there is no transaction cost that associated with trading securities. Second, all market participants can access all information without cost. Third, all market participants have the same reaction towards to current information in affecting the price of a given security. In other words, it is impossible to identify any types of stock price movement, such as cycles, seasonality and trend. Fourth, the price of assets should be equal to their intrinsic values.

Since the early definition of market efficiency is purely based on asset returns without taking the presence of speculative bubbles into consideration, there are different definitions of market efficiency are suggested and proposed by some researchers. For instance, Rubinstein (1975) states that:

> *"An individual will be said to perceive the new information that becomes available to him as fully reflected in revised security prices if and only if he has non-speculative belief".* Rubinstein (1975, p. 815)

By Jensen's (1978) definition of market efficiency:

> *"A market is efficient with respect to information set if it is impossible to make economic profits by trading on the basis of information set".* Jensen (978, p. 98)

Beaver (1981) defines market efficiency in terms of the equality of security prices under two information configurations: with and without universal access to the information system of interest. According to him:

> "*A securities market is efficient with respect to an information system if and only if security prices act as if everyone knows that information system. If this condition holds, prices are said to "fully reflect" the information system".*
>
> Beaver (1981, p. 23)

Black (1986) focuses on "noisy" information for investors, which led to the deviation of asset prices from fundamentals. In this regard, he does not believe that a model with information for trading because traders have different beliefs. He further states that:

"*As the amount of noise trading increases, it will become more profitable for people to trade on information, but only because the price have more noise in them. The increase in the amount of information trading does not mean that prices are more efficient. Not only will more information traders come in, but existing information traders will take bigger positions and will spend more on information. Yet prices will be less efficient. What's needed for a liquid market causes prices to be less efficient*". Black (1986, p. 532)

In addition, he addresses opinion on market efficiency in the American Finance Association as followed:

"*However, we might define an efficient market as one in which price is within a factor of 2 of value, i.e., the price is more than half of value and less than twice the value." The factor of 2 is arbitrary, of course. Intuitively, though, it seems reasonable to me, in the light of sources of uncertainty about value and the strength of the forces tending to cause price to return value. By this definition, I think almost all markets are efficient almost all of the time. "Almost all" means at least 90 %*".

Black (1986, p. 533)

Malkiel (1992) states that:

"*A capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices. Formally, the market is said to be efficient with respect to some information set, if security prices would be unaffected by revealing that information to all participants. Moreover, efficiency with respect to an information set, implied that it is impossible to make economic profits by trading on the basis of information set*".

From a dynamic perspective, Dacorogna et al. (2001) consider that an efficient market should be:

"A market where all market information must be available to the decision makers and where there must be participants with different time scales and heterogeneous expectations trading with each other to ensure a minimum of friction in the transaction costs". Dacorogna et al. (2001, p. 201)

In addition, Timmermann and Granger (2004) state that:

"If the behavior of investors produces efficient markets by their continuous profit seeking, the reverse is that the EMH does not rule out predicting many other variables that, although of general interest, are not the basis for a profit making strategy". Timmermann and Granger (2004, p. 26)

Lastly, Comerton-Forde and Rydge (2006) state that:

"Market efficiency refers to the ability of investors to transact easily at low transaction costs". Comerton-Forde and Rydge (2006, p. 2)

2.1.3 Association between informational efficiency, spot-futures and price-volume relations

Market efficiency relates to the relationship between spot and futures markets. If both markets are perfectly efficient, there is no an arbitrage opportunity. As observed in Figure 2.1, the spot and futures markets provide linkages with the Arbitrage Pricing Theory because the short-run return predictability can be diminished by arbitrage trading in which it is more effective when both markets are liquid. This theory generally explains how various macroeconomic factors or theoretical market indices produce expected return between markets (Ross, 1976). According to Fama (1991), this theory requires the joint hypothesis of market efficiency to avoid difficulties in apportioning anomalous result.

Intuitively, spot and futures prices should be not same due to time difference. This difference of both prices can be induced by lags in information transmission, thin trading, insufficient inventory and seasonal patterns of production and consumption. Consequently, opportunity costs, storage costs and convenience yields provide a sign of basis (spread between spot and futures prices) either a positive or occasionally negative, which can be used as an indicator of surplus of shortage of a physical commodity in the market.

The existence of mispricing in both markets provides the advantage of arbitrage opportunities for market participants, implying that non-constant arbitrage opportunities are possible to be implemented based on spot-futures relationship. For instance, Tilton et al. (2011) state that investor demand for and supply of spot material in explaining the difference between futures and spot prices can provide arbitrage opportunities. For example, they point out that:

> *"A contango that exceeds the cost of storage and interest will induce swap dealer, traders, and other to buy spot and sell futures, to earn from the arbitrage".*
>
> Tilton et al. (2011, p.191)

For weak contango and backwardation, they further state that:

> *"The incentive to buy commodities on the spot market and hold them to cover simultaneous sales on futures markets does not exist when commodity markets are in weak contango or backwardation. Indeed, what market participants would like to do during periods of backwardation is to buy commodities in the futures markets and sell them in the spot market, but future stocks are not physically available for sale today. As a result, the strong link between spot and futures prices exists only during periods of strong contango".* Tilton et al. (2011, p.191)

Östensson (2011) further provides his comment by stating that investors will demand on spot material when the difference between futures and spot prices is larger than the cost of holding stocks. This encourages them to buy on the spot market and sell forward on the futures market during the strong contango period. This inter-temporal arbitrage will continue until this price difference can cover the cost of holding stocks. When this price difference is lower than the cost of holding stocks, investors will supply spot material to the market, which in a weak contango situation by buying futures and selling spot. Since physical stocks in futures markets are not available to be sold, they cannot buy physical stocks on futures markets and sell the stocks immediately on the spot market. As a result, the inter-temporal arbitrage is turned to be unfeasible and reduces the correlation between spot and futures during the period of weak contango and backwardation. However, Fernandez's (2015) finding does not support this augment, where he finds that weak correlation between spot and futures markets for aluminum, copper, lead, nickel, tin, and zinc during the period of contango.

The examination of market efficiency which solely relies on market price changes cannot be considered as an infallible to reveal market participants' expectation about the subsequent price movement. Trading volume is generally thought to reflect price volatility and accommodate the process governing the arrival rate of new information during given a particular day. For instance, Hiemstra and Jones (1994), Blume, Easley and O'Hara (1994), Suominen (2001), and Le and Zurbruegg (2010) demonstrate that trading volume conveys extra information about noisy price movement which cannot be obtained from the historical price data itself. Therefore, price and trading volume in the same market are required to keep a close watch simultaneously or dynamic. In addition, the impact of volume traded on futures price volatility measured by absolute or squared returns has been empirically confirmed by Clark (1973), Cornell (1981), and Moosa and Silvapulle (2000).

In line with the process of information transmission, several proposed hypotheses are found from past studies in explaining and improving the availability of dependency between price and trading volume. To distinguish the directionality of information flow between both series across time, Figure 2.1 shows that these hypotheses are categorized into the Liquidity-Driven-Trade hypothesis, Information-Driven-Trade hypothesis, Mixture of Distribution hypothesis, Sequential Information Arrival hypothesis, Noise Traders' hypothesis, Tax and Non-Tax-Related Motives hypothesis, Dispersion of Beliefs/Expectation, "Heterogeneity of Traders" hypothesis, Short-Selling Constraint hypothesis. The explanations and discussion of these hypotheses are presented in the next chapter.

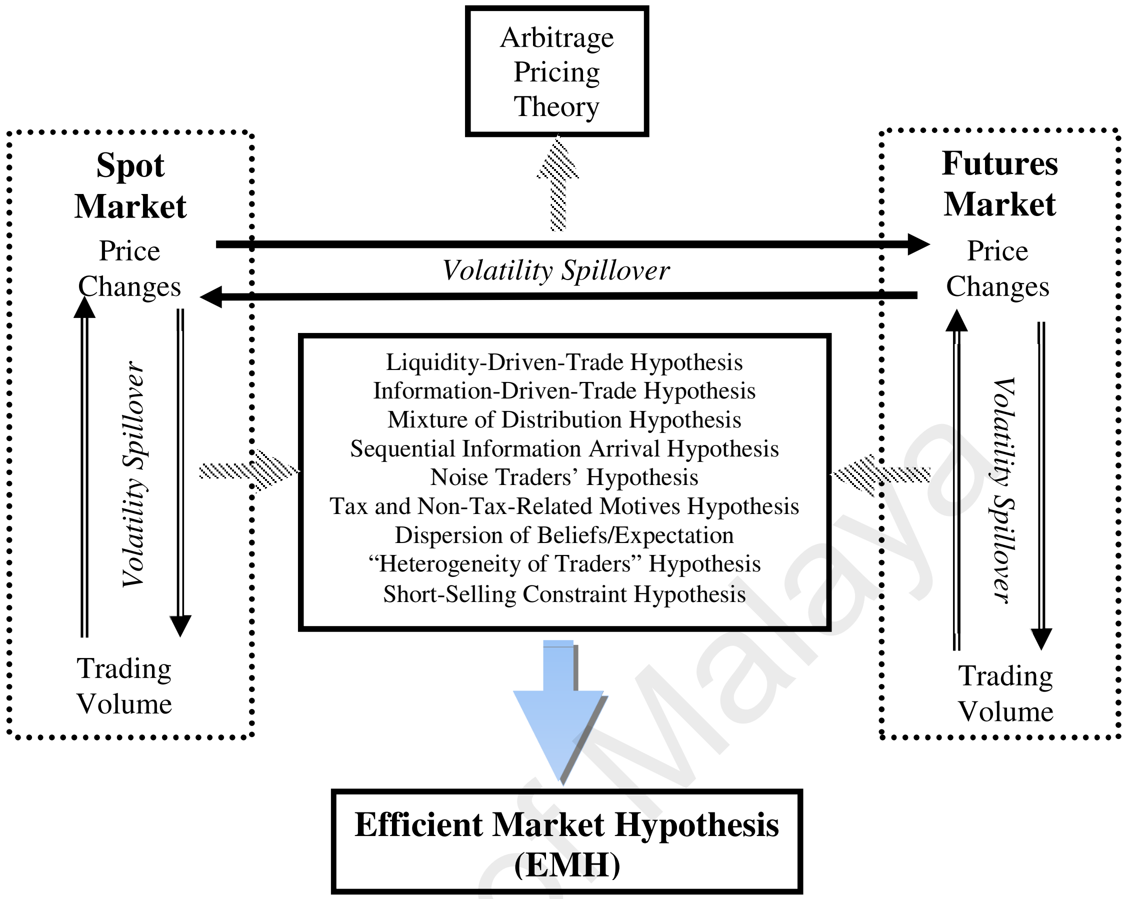

Figure 2.1: Association between informational efficiency, spot-futures and price-volume relations

Source: Author's own sketch.

2.1.4 Challenge of the efficient market hypothesis in the financial markets

Since Fama (1970) provides the most widely accepted definition of informational efficiency, there are two situations should be taken into account in testing the efficient market hypothesis (EMH). First, the identified strategy should be stable across time in order can be used systematically. Second, the strategy should determine systematic abnormal earning, so a normal return can be defined.

Based on the assumptions are discussed above, stock prices are characterized by a random walk (unit root) process, suggesting that they are unpredictable from historical price changes. This hypothesis is satisfied when each investor in the market cannot have the opportunity to obtain systematic abnormal positive returns. However, the EMH has been repeatedly disparaged both empirically and theoretically. For instance, Working (1934), Kendall (1953) and Roberts (1959) fail to explain the use of the Random Walk model in increasing expected gains. Osborne (1959) and Fama (1965) find that daily price changes tend to be followed by larger daily price changes. Their findings are inconsistent with the random walk process.

Subsequently, LeRoy (1976) criticizes that Random Walk and Fair Game Models based on Fama's framework cannot generate testable implications, where both models cannot characterize properly an efficient market because they do not impose any restrictions on the data. Therefore, both models are not stringent enough to test the EMH due existence of anomaly and financial crises.

2.1.4.1 Anomaly

Cootner (1968), Godfrey et al. (1964), Roll (1972), and Singal (2006) find that assumption of the EMH does not always hold because serial correlation frequently happened within daily market prices across time. The reason is the hypothesis ignores the existence of anomaly. These events are characterized by unexplainable in the context of efficient markets, in which case the prices react before and after the date of announcement. For example, these anomalies are the day-of-the-week (DOW), the month-of-the-year (MOY), the turn-of-the-month (TOM) and the Halloween effects. This situation raises the problem in testing the EMH. Due to mispricing or anomalies originated in the cost of information, the cost of trading and the limit of arbitrages lead to inefficient market. Consequently, it leads to rejection of the EMH.

Following to the literature that concludes inappropriate amplitude of prices as a sign of inefficiency, the DOW especially for the Monday effect is firstly documented by Fields (1931). This implies that Monday exhibits significantly negative returns as compared to the other days of a week. Then, many past empirical studies such as French (1980), Gibbons and Hess (1981), Lakonishok and Levi (1982), Rogalski (1984), Smirlock and Starks (1986), and Lakonishok and Smidt (1988) have been done to explain what exactly drives specific and persistence of the Monday effect. For the latest study, Jarrett (2010) finds that the day effects happen among the Pacific-basin stock markets such as in Singapore, Malaysia, Korea and Indonesia, where their price changes have predictable properties during 1985-2000. As a result, the weak form of EMH is not supported because insider trading plays important role in these emerging markets.

Another anomaly which receives much attention in the literature is the MOY. For instance, DeBondt and Thaler (1987) firstly find that the average return in January is significantly higher than those in the other months of the year. This effect is known as the January effect. After that, this effect is demonstrated to exist at the market level. For instance, Stance and Geambasu (2012) confirm this effect happens in the Romanian stock market during 2002-2010.

In addition, the other anomalies which are discussed in the literature are the TOM and Halloween effects. The TOM happens when returns on the turn of the month days are significantly higher than the other trading days. For instance, the study of Kunkel et al. (2003) identify the average return during the TOM period is significantly higher than the average return during the rest of the month. In the subsequent study of Heininen and Puttonen (2008), their finding indicates that the presence of TOM effect in the Romanian stock market. For Halloween effect, Bouman and Jacobsen (2002) state that this effect will lead to the returns during the period of November-April higher than those in the period of May-October.

2.1.4.2 Financial crises

If the markets are truly efficient, participants will have no opportunity to reach systematic abnormal earnings. The efficient market happens when information can be fully reflected without being revealed by prices because all traders are identical (whether they are informed or uniformed). This subsequently causes the average historical returns will be unprofitable in the market. However, Grossman and Stiglitz (1980) find that this is not the true. They extend the noisy rational expectations model by Lucas (1972) to become Constant Absolute Risk-Aversion Model. Their model indicates that the price does not fully reflect the information of informed traders, but only partially reflects because all informed traders in the competitive markets need to pay a higher cost for information.

The EMH in the weak form assumes that all information provided by the past prices already embodied in the present prices. As a result, there is no *deus ex machine* or economic forces ensure stability in the security prices. However, market prices do not only reflect information based on past price movement, but it is also based on the fundamental economics and financial factors. The unexpected changes in the development of the economy and financial institutions lead many market participants to reject the EMH. This criticism even more significantly after the global financial crisis 2008/09 that causesa structural break in the movement of market price.

Apart from that, the validity of EMH is challenged in a number of emerging markets due to three reasons. Firstly, it is unclear whether investors have heterogeneous information or not during the crisis and non-crisis. This is further supported by Wang (1994) and Llorente et al. (2002) who state that ability informed and uninformed investors to assess their financial assets can be variable in time. The second reason is the hypothesis ignores what the market use in determining information under different economic conditions. The third reason is it assumes that constant speed of information to reflect or incorporate into market prices across different periods. As stated by Easton and Kerin (2010), privately held information is not fully incorporated into prices quickly during the global financial crisis. To improve market efficiency on the micro level, quantity, quality and timeliness of information that an investor received should be increased.

The EMH provides misleading inference about efficiency when it ignores structural changes in mean and volatility of coefficient correlations of market prices. To encounter this problem, some studies have taken the impact of crises into account by incorporating dummy variables of a structural break to segregate the period of crisis and non-crisis. For instance, Phengpis (2006) includes two structural breaks such as the European and Asian crises into unit root and cointegration equations in providing evidence of inefficiency in the currency markets such as the British pound, French franc, German Mark and Italian lira. Furthermore, Maslyuk and Smyth (2009) include the structural break of the world oil events during 1991-2004 in testing unit root property of spot and futures prices in the WTI and Brent crude oil markets. They find that both spot and futures prices in crude oil markets follow random walk process and exhibit the weak-form efficiency, implying that it is impossible for investors to make a profit with technical analysis to predict spot or futures prices in the future.

To examine efficiency among 100 firms in the United States during 1998-2008, Liu and Narayan (2011) include two endogenous structural breaks in the dummy form into unit root test and GARCH model. Inferences are drawn from their study mildly support the EMH in the United States firms because 22 out of 100 firms have stationary movement of stock prices. Hwang (2014) includes three dummy variables for the pre-crisis, crisis and post-crisis periods into mean and variance equations to examine spillover effects in the Latin America stock markets. They find evidence of financial contagion during the global financial crisis 2008/09.

Some studies divide time series data into the pre-crisis, crisis and post-crisis instead of adding dummy variables into the estimated models for two reasons. First, adding dummy variables reduces the degree of freedom in the estimated models. Second, the use of dummy variables to capture structural break of crises might distort the results of regression and cointegration test (Ahmad et al., 2012). Most of past studies on market efficiency are found to segregate period based on the 1992 European financial market crisis, 1997 Asian financial crisis and 2008 global financial crisis. For instance, with error-correction model, Aroskar et al. (2004) find a strong evidence of the 1992 European currency crisis that caused market inefficiency for the British pound, Italian lira, German mark and French franc.

On the other hand, Jeon and Seo (2003) examine the impact of 1997 Asian financial crisis on an efficiency of foreign exchange markets among the East Asian countries. They apply the concept of cointegration to test market efficiency across- and within-country. Their result of weaker cointegration between forward rates and corresponding spot rate of the Asian currencies suggests that market efficiency does not last long and becomes weaker immediately in the post-crisis as compared to the pre-crisis. In contrast to their finding, Lim et al. (2008) use the rolling bicorrelation test statistics and indicate that recovery of inefficiency among eight Asian stock markets after the same financial crisis.

Before the global financial crisis 2008/09, Ding and Pu (2012) find that information spilled over from credit derivatives markets to stock market in the United States, while this spillover effect is found to be disappeared during and after the crisis. This suggests that the inefficiency of stock market leads to investor uses its information in facilitating price discovery process across financial markets. Along with two crises, Ahmad et al. (2012) find a sign of inefficiency within the foreign exchange markets in the Asia-Pacific during the 1997 Asian financial crisis more than the 2008 global financial crisis. By using parametric and non-parametric unit root tests, Jain et al. (2013) find that the Indian capital market during the global financial crisis exhibits random walk process. They conclude that this market is informationally efficient in the weak form.

The EMH has been proven to be durable and likely to be incorporated into practice. However, based on lessons from the 2008 global financial crisis, Ball (2009, p.12) states that this hypothesis has been just a theory, but not a fact, where it is an abstraction from reality. For example, financial regulators mistakenly rely on the EMH especially in the crisis because it ignores leverage and risk. Since high leverage and risk which are attributable from high returns in a fiercely competitive market, financial regulators will have been exceptionally skeptical about high returns being reported by various financial institutions. Apart from that, financial regulators who believe in efficiency should look more closely at the leverage and risk-taking positions in the market. Second, investors' belief or noise trading behavior in trading will be influenced by economic forces or *deux* *ex machine* especially during the crisis. This leads to the distribution of return evolves over time.

2.1.5 Conclusion and future research direction

There is much discussion on informational efficiency in terms of causality-in-variance because it provides an interesting viewpoint on the assimilation of information between financial or commodity markets. The reviewed literature on price-volume and spot-futures relations are discussed and synthesized in order to give an overview about the informational efficiency of the markets. Since the EMH cannot hold in the short run for various commodity and financial markets due to existing lead-lag relation of spot-futures, the evidence from the survey of literature seems to indicate that the futures contracts act as risk transfer and price discovery to enhance the investors' ability in predicting future spot price movement.

The results from various studies on the price-volume relation are found as mixed. As a result, there is no standard hypothesis to explain the relationship and interaction between price changes and trading volume. The possible reason is can be the effect of different market structures or different period of analyses. Most these findings support sequential over simultaneous information arrival. The sequential information flow that ties between volume and price changes either positive or negative can be traced as the SIAH. The simultaneous changes in both price and trading volume can be interpreted as information flow to support the MDH.

From a perspective of risk management, investors seem to have a general belief that the unexpected shift in the market prices is associated with some disturbing events which relate to the economy, politics and finance. Given the relatively scarce market efficiency literatures from the role of heterogeneous investors during extraordinary events such as financial crises and environmental events, there is a need to undertake related research based on this direction. For example, the quality of spot price forecasts based on futures prices is still a contentious issue. It would be interesting to focus on the viability of using futures prices to forecast spot prices under different market conditions, namely strong contango, weak contango and backwardation.

In addition, Cuny (1993) illustrates a role of liquidity in the futures markets by considering the market design, market structure, a number of traders, and nature of competition between exchanges. Indeed, Chordia et al. (2008) find that a greater liquidity engenders a higher degree of informational efficiency. However, a literature on the relationship between price changes and trading volume in the context of futures markets had been nominal only, especially in explaining an effect of liquidity on informational efficiency.

The existence of a causal effect of volume volatility on price volatility does not prove market inefficiency because the inappropriateness of models used in describing inefficiency. Without taking the speed of adjustment for the arrival of new information into consideration, the concept of EMH has so far failed given the price data from actual markets. To minimize and even avoid such challenge of the EMH, the speed of adjustment for trading volume in reflecting information should be emphasized.

If the trading volume reflects the market information simultaneously, this information transmission is said to be efficient if there is evidence of declining volatility persistence of price due to incorporating trading volume. If past trading volume provides longer time to persist its effect in influencing the subsequent price shocks, this information transmission is said to be inefficient as the volume increases the volatility persistence of price. Therefore, whether trading volume still dominates the role of information flow across changes in variance of the price process during non-event and event periods will be desirable for future research. Therefore, more focus should be given to the comparative investigation of price-volume relationship in futures markets between crisis and non-crisis periods.

2.2 A Review on Hedging Effectiveness in Commodity Futures Markets

2.2.1 Introduction

The futures market serves as a clearing center for information transmission among market participants, providing them the instruments to transfer pricing risk and facilitate price discovery. The futures contract is used as one of the tools to hedge their physical inventories for a specific commodity against the unexpected price fluctuation. The success of such contract depends on the hedging effectiveness (Johnston & McConnell, 1989). This effectiveness is raised from the ability of a futures price in providing information about a spot price at the specified future date, to allow market participants manage their risks in trading effectively.

Commodities provide beneficial to the frontier economies. However, the emphasis of commodity allocation is propelled with an issue of unexpected supply of storage instead of current and expected demands. This leads to commodities normally have higher basis risk (spread between spot and futures prices) than stock indexes. This consequently provides the difficulty in predicting the carrying costs. To guard against future price rises, hedgers are unable to offset higher cost of the physical quantities which need to be purchased. Apart from this, unfavorable movement of basis has been remained puzzled today after for the number of years. Without a proper recognition of which econometric modeling offers high effectiveness of hedging through various futures contracts during different periods, this would enable an inaccurate decision at a specified time of trading.

To recap, there is the tremendous growth of studies on the effectiveness of futures hedging in a substantial way since in the 1960s. There are some literature reviews in this area in the post-1990 period. For instance, Lien (1996) reviews the effect of the cointegration relationship between spot and futures prices on hedging effectiveness. He provides a note to demonstrate that hedger who omits such relationship will provide smaller optimal futures position and lead to poor performance in hedging. To derive optimal hedge ratio (OHR), Satyanarayan (1998) provides a note by demonstrating the second-order condition with less restriction on the ratio of the portfolio excess return to risk. However, Chen et al. (2003) state that there is no single superior OHR. From the reviewed 45 published articles, they further discuss different approaches in estimating futures hedge ratios depend on various objective functions.

In addition, Lien (2004) provides a note to demonstrate that omission of cointegrating relationship between spot and futures prices in estimating the OHR produces a smaller hedge ratio. Such omission leads to loss of hedging effectiveness at the minimal level. Lien (2005) further provides a note to demonstrate that the hedging model with asymmetric stochastic volatility tends to produce a greater average OHR. Such effect of asymmetric responses to good and bad news has no impact on hedging performance. In terms of the minimum riskiness hedge ratio, Ehsani and Lien (2015) provide a note to show that the hedge ratio based on the minimum riskiness index by Aumann and Serrano (2008) tends to be smaller than the hedge ratio based on the conventional minimum variance, while hedge strategy based on the minimum riskiness index by Foster and Hart (2009) does not exist.

Despite the above discussions, there is a lack of attention on the asymmetric effect of basis term in characterizing the dynamics of volatility especially during the period of extraordinary events. If such effect is indeed that important, its ignorance probably misleads informational efficiency and influences effectiveness of futures hedging in stimulating a process of price discovery. In this chapter, we intend to expand a literature by reviewing studies related hedging effectiveness and price discovery in the commodity futures markets.

2.2.2 Futures hedging theories

Generally, the Arbitrage Pricing Theory (APT) and Law of One Price (LOP) are prominent strands of concept in explaining efficiency and degree of integration between spot and futures markets. The APT provides a general explanation about how various macroeconomic factors or theoretical market indices produce an expected return between two markets (Ross, 1976). Meanwhile, the LOP posits that both domestic and foreign prices for a similar product are expressed in a common currency. In spot and futures markets, an identical commodity is traded at the same price by holding the purchasing power parity.

As shown in Figure 2.2, the competing aspect of informational efficiency and hedging effectiveness are discussed based on interconnected between the APT and LOP. Spot and futures prices should be not equal before maturity due to time differences. This price difference can be induced by lags in information transmission, thin trading, insufficient inventory and seasonal pattern of production and consumption.

Consequently, opportunity costs, storage costs and convenience yields provide a sign of basis either positive or occasionally negative that can be used as an indicator of surplus or shortage of a physical commodity in the market.

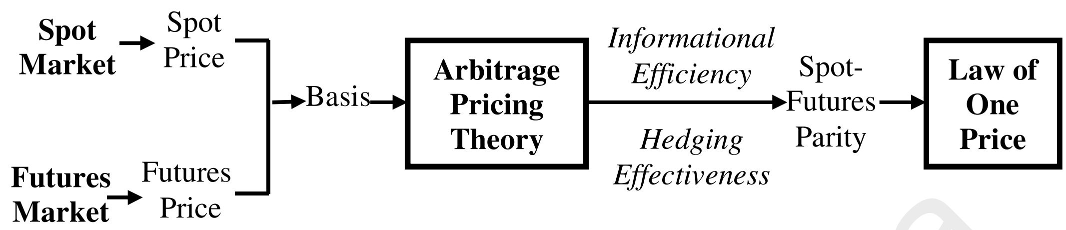

Figure 2.2: Arbitrage Pricing Theory and Law of One Price
Source: Author's own sketch.

Collectively, the existence of mispricing in both spot and futures markets provides the advantage of arbitrage opportunities for market participants, implying that non-constant arbitrage opportunities are possible to be implemented based on spot-futures relation. For example, if the futures price is expected to be higher than the spot price, a Cash and Carry strategy is preferable by long spot and short futures. If the futures price is expected to be lower than the spot price, a Reverse Cash and Carry strategy is preferable by long futures and short spot. Market participants will buy and sell a commodity simultaneously in both markets in order to "lock in" a risk-free profit.

To trade a commodity at the level of efficient price, efficient information flow is required to expect changes in supply and demand of a commodity in the future. It should be noted that information about supply-demand shocks can avoid from asset, maturity and quantity mismatches in designing and implementing an appropriate hedging strategy. One could even argue that the existence of hedging strategies ensures the convergence property at maturity of the futures contract. For instance, Protopapadakis and Stoll (1983) find that the LOP tends to hold in the long run despite the existing short-run deviation between spot and futures prices for silver, copper, tin, lead, zinc, coffee, cocoa, sugar, soybean meal, wheat, rubber and greasy wool.

When futures prices approach its maturity, net carrying costs will be essentially zero and thereby reduce the difference between spot and futures prices. Subsequently, spot-futures parity should be in the existence, which is the essence of LOP in the futures market. Hence, it should not be surprising given that the LOP could be applied to almost exactly in the financial markets because mispricing of both spot and futures can be eliminated through the working of arbitrage.

According to Fama (1991), the efficiency of information flow between mutually substitutable assets must at least of weak form to constitute the long-term purchasing power parity between spot and futures markets. If the spot and futures markets are not the weak-form efficient, the LOP will unlikely to hold. Furthermore, Levy et al. (2006) state that this economic concept assumes integrated markets for similar assets which have same prices can provide approximated zero premium.

To explain the nature of a hedging strategy, the following authoritative definitions of hedging are re-emphasized.

> *"….purchase or sale of futures in conjunction with another commitment, usually in expectation of a favorable change in the relation between spot and futures prices."*
>
> Working (1953, p.326)

> "*Hedging is done for a variety of different purposes and must be defined as the use of futures contracts as a temporary substitute for a merchandising contract, without specifying the purpose.*" Working (1962, p. 244)

Three hedging theories in the futures markets are distinguished from the literature. The first theory suggests that implemented the traditional hedging through futures markets is to emphasize the risk minimization context. Due to this, market participants implement such hedging as one of their risk management programs to mitigate their risk exposure. Furthermore, Working (1953) states that traders who are involved in the futures markets aim for a return maximization motive together with a risk minimization objective.

The second theory suggests that hedging through the futures markets is to anticipate comovement between spot and futures prices. This allows market participants to take a view on the association between spot and futures markets to expect the basis. To trade at a profitable trade, such view will assist them to engage and make a decision on whether the hedging strategy is necessary or not. For instance, Working (1962) states that hedging occurs if participants expect that the basis to fall and they tend to hold the long positions in the spot market, but not if they expect that the basis to rise.

The third theory suggests that risk of price changes in the spot and futures markets are incorporated into hedging to form a portfolio strategy. The spot position is combined with a contrary position taken in the futures market in order to reduce the variation in the spot market position effectively. Most of past studies utilize a portfolio approach to measuring what extent hedged variance of returns on the portfolio can be reduced as compared to the unhedged variance of returns on the portfolio. The effectiveness of hedging based on this theory owns its popularity in most of the studies on the commodity futures markets due to its simplicity to apply and understand the concept.

2.2.3 Optimal hedge ratio (OHR) estimations

The hedge ratio is the number of futures contracts required to minimize the exposure of a unit worth position in the spot market. To implement an effective hedging strategy, OHR should be empirically estimated because both spot and futures prices may not change one for one. As a result, hedge ratio may deviate significantly from one and cannot provide variance reduction (Go & Lau, 2015). To estimate the OHR by corresponding to objective functions, various econometric models with different conditional mean, variance-covariance and correlation specifications have been developed and proposed by several researchers.

Based on a summary of various approaches to estimate the OHR as presented in Table 2.1, there is no single OHR can be found as distinctly superior to the remaining ones because the superior of hedge ratio subjects to which objective function to be optimized. With various approaches, the same estimated hedge ratio as the minimum-variance (MV) hedge ratio can be obtained if the futures price follows a pure martingale process and spot and futures prices are jointly normally distributed. Since the context of minimum variance is concerned with the application of hedging strategies, the MV hedge ratio is found to ignore the expected return. The distribution of both spot and futures prices across time further seems to be contrasted to the conventional assumptions, such as the pure martingale process and normality condition. Due to both reasons, various approaches based on different principles cannot produce a steadily OHR.

To make an objective function to be consistent with the mean-variance analysis and the expected utility maximization principle, there are many assumptions about utility functions and return distributions, leading to different OHRs to be produced. The assumptions on a specific utility function and return distribution are difficult to be imposed. To solve this difficulty, the second-order stochastic dominance principle is applied in making a few assumptions about return distribution and utility function. Based on such principle, the Mean-Gini coefficient-based hedge ratio is derived.

To ensure the maximum utility function is consistent with the mean-variance framework, the optimum mean-variance hedge ratio should depend on the risk aversion parameter of an individual hedger. To be further consistent with the second-order stochastic dominance and expected utility maximization principles, semivariance-based hedge ratio is derived by taking the risk aversion parameter into account. In addition, semivariance-based hedge ratio has some appeal in the sense that it captures perception of risk which is associated with the target return to being consistent with risk-return principle. To further satisfy monotonicity with the respect to stochastic dominance, the minimum riskiness hedge ratio is demonstrated can be obtained based on the riskiness index of AS (Aumann & Serrano, 2008) instead of FH (Foster & Hart, 2009).

The MV hedge ratio cannot be neglected in measuring the performance of hedging due to its simplicity in understanding about the distributions of spot and futures prices. However, hedgers who are found to have different hedging horizons will sometimes implement less hedging strategies and sometimes more. To allow different investment horizons across different periods and markets, the relationship between the MV hedge ratio and the investment horizon is further explored. For example, the optimal multi-period hedge ratio and detrended minimum-variance hedge ratio.

Table 2.1: Summary of OHR development

Author(s) (Year)	Objective	Type of OHR	Limitation	Advantage
Johnson (1960)	Minimization of the variance of the hedged portfolio	Minimum variance hedge ratio	It ignores the expected return of the hedged portfolio. It cannot measure the hedge ratio at different time scales.	It is easy to understand and simple to be used.
Howard & D'Antonio (1984)	Maximization of the ratio of the portfolio's excess return to its volatility	Sharpe hedge ratio	It is inconsistent with the expected utility maximization principle. It consists of returns which are often skewed with excess kurtosis. The second-order conditions should be satisfied with some restrictions.	It considers the risk-return tradeoff criteria.
Cecchetti et al. (1988)	Maximization of the expected utility	Maximum expected utility hedge ratio	It does not take the production of a spot commodity, investments (in risky and risk-free assets), borrowing, lending, transaction cost and opportunity cost into account in explaining the return on a diversified portfolio.	It considers with a specific return distribution and the logarithm of terminal wealth in order to be consistent with the expected utility maximization principle.
Cheung et al. (1990)	Minimization of mean extended-Gini coefficient	Minimum mean extended-Gini (MEG) coefficient hedge ratio	It ignores the expected return on the hedged portfolio.	It provides a necessary condition for stochastic dominance regardless of the probability distribution of return.
Kolb & Okunev (1993)	Maximization of the expected utility	Optimum mean-MEG hedge ratio	-	It is consistent with the concept of stochastic dominance by taking an expected return on the hedged portfolio into consideration.
Lien & Luo (1993)	Minimization of the variance of the end-period wealth	The optimal multi-period hedge ratio with minimum variance of the end-period wealth	-	It allows in estimating the hedge ratio with multiperiod instead of within the conventional single time-period framework.
Hsin et al. (1994)	Maximization of the expected utility	Optimum mean-variance hedge ratio	A parameter value of risk aversion in the function of utility is difficult to be determined because different individuals will choose different OHRs.	It consists of risk and returns which are consistent with the mean-variance framework.

Table 2.1: (Continued)

Author(s) (Year)	Objective	Type of OHR	Limitation	Advantage
Kuo & Chen (1995)	Maximization of the ratio of the portfolio's excess return to its volatility	Sharpe hedge ratio	-	It provides the simplification of the second order conditions for the function of Sharpe ratio with less restriction.
Lence (1995)	Maximization of the expected utility	Maximum expected utility hedge ratio	-	It considers the production of a spot commodity, investments (in risky and risk-free assets), borrowing, lending, transaction cost and opportunity cost into account in explaining the return on a diversified portfolio and minimum-variance hedge ratios.
De Jong et al. (1997)	Minimization of generalized semivariances	Minimum generalized semivariance hedge ratio	-	It captures the relationship between the generalized semivariance (GSV) and expected utility. It is consistent with the concept of stochastic dominance.
Chen et al. (2001)	Maximization of the conventional mean-variance based utility function	Optimum mean-generalized semivariance (GSV) hedge ratio	-	It consists of mean return in the function of generalized semivariance (GSV). It is consistent with the risk-return model.
Chen et al. (2014)	Minimization of the riskiness index.	Minimum AS and FH riskiness hedge ratios	-	It satisfies monotonicity with the respect to stochastic dominance. From the derivation of a moment generating function restriction, it has an expected utility interpretation.
Wang et al. (2014)	Minimization of variance of the detrended hedged portfolio	The detrended minimum-variance (D-MV) hedge ratio	-	It measures the hedge ratio at different time scales.

2.2.4 Effectiveness of hedging models with various specifications

By definition based on a portfolio of spot and futures returns, an effectiveness of the futures market is to what extent hedgers are able to reduce their risk in the spot market by using futures contracts. Hedging effectiveness is the degree of risk reduction achievable by a hedger vis-à-vis to non-hedger. Apart from that, the risk minimization context is an important criterion for the success of a hedging strategy through futures contracts. This general definition is found to be consistent with the following definitions:

"*The effectiveness of hedging is measured by considering the gain and loss due to the price changes incurred in an unhedge position relative to that incurred in a hedge position.*" Johnson (1960, p. 144)

"*Percentage reduction attributable to hedging in the ex-ante variance of terminal wealth.*" Lence et al. (1993, p. 131)

In measuring the effectiveness of a specific futures contract by using the JSE method, Ederington (1979) defines that hedging effectiveness is a variance reduction in the spot return portfolio. Due to movement of the OHR exhibits time-variant characteristics and correlations between two returns varies across time, he finds that the R-squared based on a simple regression model is inappropriate in measuring the hedging effectiveness. Howard and D'Antonio (1984) define that the hedging effectiveness is a ratio between excess return per unit of risk in the portfolio of the spot and futures positions to excess return per unit of risk in the portfolio of the spot position.

To hedge against the fluctuation in commodity prices, the effect of risk in trading spot and futures markets as well as the spot-futures spread on a hedging strategy should be specifically categorized into symmetric and asymmetric effects (as shown in Figure 2.3). As a result, the hedging effectiveness is the capacity of a futures contract to reduce the overall risks. Table 2.2 summarizes a literature on the type of superior hedging model based on different objective functions in various commodity markets.

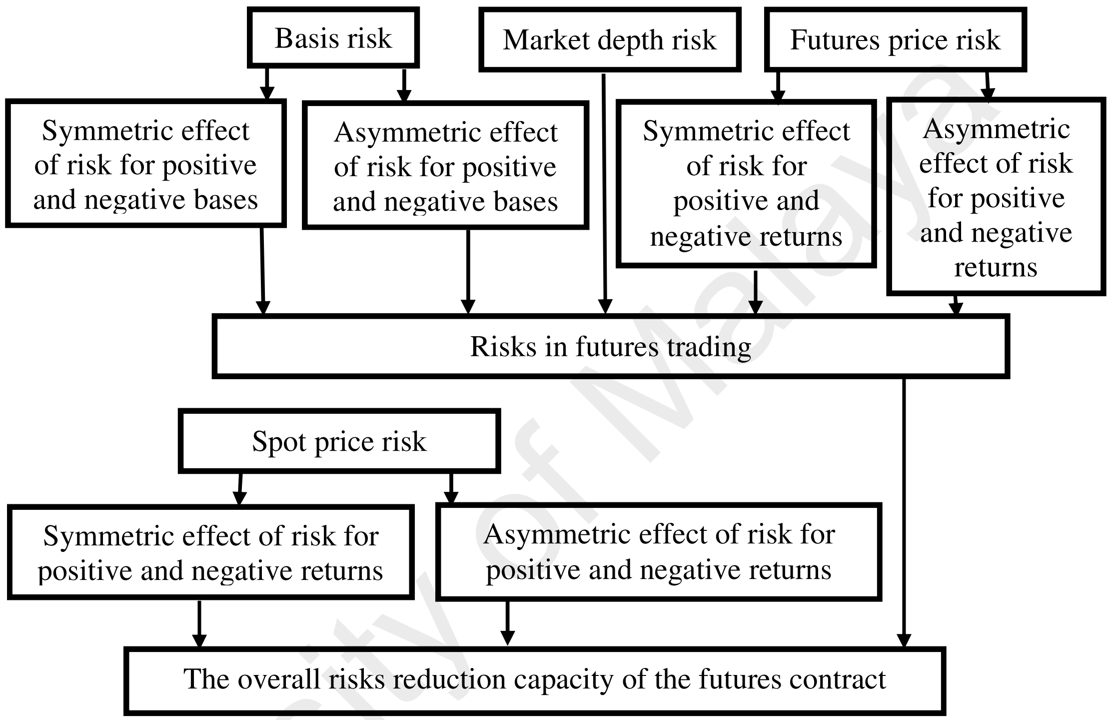

Figure 2.3: Concept of hedging effectiveness
Source: Author's own sketch.

Table 2.2: Summary of hedging effectiveness in the commodity futures markets research

Author(s) (Year)	Journal	Country	Commodity	Period	Criterion	Effective Model
Myers (1991)	Journal of Futures Markets	United States	Wheat	Jun1977-May 1983	Minimum variance of the hedged portfolio	Bivariate GARCH model
Sephton (1993)	Applied Financial Economics	Canada	Feed wheat and canola	1981-1982	Minimum variance of the hedged portfolio	Multivariate GARCH model
Moschini & Myers (2002)	Journal of Empirical Finance	United States	Corn	Jan1976-Jun1997	Comparing between stochastic time-varying and deterministic time-varying hedge ratios	BEKK-GARCH model
Alizadeh et al. (2004)	Applied Economics	Rotterdam, Singapore and Houston	Crude oil and petroleum	Jun 30,1988-Nov 9, 2000	Minimum variance of the hedged portfolio	BEKK-GARCH model
Switzer & El-Khoury (2007)	Journal of Futures Markets	United States	Light sweet crude oil	Jan 1986-Apr 2005	Minimum variance of the hedged portfolio	Asymmetric Bivariate GARCH
Maharaj et al. (2008).	International Journal of Business and Economics	United States	WTI, light, sweet crude oil and soybean	Jun 1989- Oct 2005	Minimum variance of the hedged portfolio	Wavelet analysis based on symmetric model
Lien & Yang (2008, a)	Journal of Banking and Finance	United States	Corn, soybeans, cotton, coffee, pork belly, lean hog, heating oil, crude oil, copper and silver	Jan 1, 1980-Dec 31, 1999	Minimum variance of the hedged portfolio	Asymmetric Bivariate GARCH model
Lien & Yang (2008, b)	Global Finance Journal	China	Copper and aluminum	Jan 1, 1996-Dec 31, 2004	Minimum variance of the hedged portfolio	Asymmetric Bivariate fractionally integrated GARCH model
Park & Jei (2010)	Journal of Futures Markets	United States	Corn and soybeans	Jan 1, 1997-Jan 23,2001	Minimum variance of the hedged portfolio	Asymmetric DCC-Bivariate GARCH model
Ji & Fan (2011)	Energy	United States	WTI crude oil, gasoline and heating oil	Jan 7, 1994- Jul 31,2009	Minimum variance of the hedged portfolio	DCC-ECM-MVGARCH model
Wu et al. (2011)	Journal of Futures Markets	United States	Corn and light sweet crude oil	Jan 2, 1992 -Jun 30, 2009	Minimum variance of the hedged portfolio	Asymmetric BEKK-GARCH model
Zainudin & Shaharudin (2011)	Asian Academy of Management Journal of Accounting and Finance	Malaysia	Crude palm oil	Jan 1996- Aug 2008	Minimum variance of the hedged portfolio Utility-Maximizing Objective	BEKK-GARCH model with mean intercept and BEKK-GARCH model with VAR

Table 2.2: (Continued)

Author(s) (Year)	Journal	Country	Commodity	Period	Criterion	Effective Model
Bekkerman (2011)	Agricultural Finance Review	United States	Wheat	Jul 1, 1998-Dec 29, 2009	Minimum variance of the hedged portfolio	VAR-multivariate DCC-GARCH model
Ong et al. (2012)	World Applied Sciences Journal	Malaysia	Crude palm oil	Jan 2009-Jun 2011	Minimum variance of the hedged portfolio	OLS regression model
Toyoshima et al. (2013)	Applied Financial Economics,	United States	WTI crude oil	Jan 3, 2007-Dec 30, 2011	Minimum variance of the hedged portfolio	Asymmetric DCC-GARCH model
Zainudin (2013)	Investment Management and Financial Innovations	Malaysia	Crude palm oil	Jan 2, 1996-Aug 15, 2008	Minimum variance of the hedged portfolio	BEKK-GARCH with break estimation model
Lau & Bilgin (2013)	Emerging Markets Finance and Trade	China	Aluminum	Dec 1, 1993-Dec 31, 2010	Minimum variance of the hedged portfolio	Symmetric DCC-GARCH model
Carpantier & Samkharadze (2013)	Journal of Futures Markets	United States	All commodities from the S&P GSCI index	Jan 17, 1995-Apr 15, 2010	Minimum variance of the hedged portfolio and optimum mean-variance of the hedged portfolio	Asymmetric BEKK-GARCH model
Pan et al. (2014)	Energy Economics	United States	WTI crude oil, gasoline and heating oil	Jan 2, 1987-Dec 28, 2012	Minimum variance of the hedged portfolio and maximum utility	Regime Switching Asymmetric DCC-GARCH model
Lin et al.(2014)	Economic Modelling	China	Fuel oil	Apr 16, 2010-Apr 15, 2011	Minimum variance of the hedged portfolio	DCC-GARCH model
Tejeda & Feuz (2014)	Agricultural Finance Review	United States	Corn, soybean meal, feeder cattle and live cattle	Dec 1998-Marc 2012	Minimum variance of the hedged portfolio	Parsimonious regime-switching dynamic correlation model
Go & Lau (2015)	Journal of Asset Management	Malaysia	Crude palm oil	Jan 1986-Dec 2013	Minimum variance of the hedged portfolio	CCC-GARCH and BEKK-GARCH models with basis term
Zhang & Choudhry (2015)	The European Journal of Finance	United States	Wheat and soybean	Jan 1, 1980- Jun 23, 2006	Minimum mean absolute error based on the Model Confidence Set	BEKK-GARCH model with a student t distribution
Zhang & Choudhry (2015)	The European Journal of Finance	United States	Live cattle and live hogs	Jan 1, 1980- Jan 14, 2008	Minimum mean absolute error based on the Model Confidence Set	Asymmetric GJR and quadratic GARCH models with a student t distribution

When hedging is undertaken, the assumption of the JSE method should be unrealistic. However, some studies are still found to apply such method. For instance, with the application of estimated hedge ratio with more than one delivery specifications, Kamara and Siegel (1987) evaluate the hedging benefit of the wheat futures market in Chicago under the assumption of equal variances between spot prices for soft and hard wheat. They find higher risk reduction for soft wheat than hard wheat. Four-week hedging is further found to be more effective than two-week hedging. Therefore, they conclude that this optimal hedging strategy of the underlying asset by using commodity futures contracts would be more effective than financial futures contracts.

For gold, silver and copper, Varela (1999) uses a simple regression model to regress cash prices to futures prices. His finding indicates that the relationship between near-term (15- and 30-day) for gold futures and realized cash prices regardless the delivery date provides an intercept of zero and a slope of one in the model. The closest to delivery (15-day) for silver futures and all copper futures with realized cash prices deliver on first and middle business day also provides a similar finding. This finding supports an unbiased expectation hypothesis, implying that the short-term parity between gold and silver in the cash market and the copper futures provides a good basis in anticipating futures prices. Based on the last business day of a delivery month (15-day) for silver and copper, the estimated model is found to have an intercept greater than zero and a positive slope coefficient significant less than one. This suggests that the rejection of such hypothesis is due to the absence of trading on that day. The relationship between long term (45- and 60-day) for gold and long term (30-, 45-, and 60-day) for silver also supports such finding, implying that the cash prices less respond than futures prices.

Lien et al. (2002) find that an OLS estimated model is better than a CCC-GARCH model in currency futures, commodity futures and stock index futures during 1988-1998. Their results indicate that an underperformance of the model often generates the too variable forecasted variance. According to them, a time-varying regime-switching model appears to be a better model to improve the accuracy of the model in forecasting. In Malaysian crude palm oil (CPO), Ong et al. (2012) use an OLS method to estimate the hedge ratio in each month for the sample period of 2009-2011. They report that the increasing hedge ratio during January 2009 - June 2011 contributes to 19-53 per cent of the hedging effectiveness. They claim that this low level of hedging performance is due to four events: (1) the rising of petroleum crude oil, (2) recovery of world economy in 2010, (3) weak impact of the tsunami and earthquake in Japan, and (4) debt crisis in Europe causes stable and consistent movement of volatility in the CPO spot market.

An estimation of risk-minimizing hedge ratios with time-variant, the number of scholars demonstrates that a model based on the GARCH framework produces effectiveness of dynamic hedge ratios with respect to the highest variance reduction. For instance, to estimate time-varying hedge ratios for May and December contracts of wheat, Myers (1991) uses a method of moving sample variances and covariances, and GARCH model by assuming constant conditional covariance matrix for spot and futures prices. The author finds that the GARCH model produces a marginally better hedge ratio in terms of variance reduction than either the constant hedge or the moving sample variances and covariances hedge. With a bivariate GARCH (BGARCH) model, Baillie and Myers (1991) demonstrate that such model appears to be an appropriate model in fitting time variation in the conditional covariance matrix since the OHR is found to exhibit non-stationary movement across time in the United States six commodities. As a comparison to a traditional method, Sephton (1993) demonstrates that the multivariate

GARCH model able to reduce conditional variance in wheat and canola markets during 1981-1982.

Moschini and Myers (2002) use the BEKK-GARCH model for hedging of weekly corn prices in the Midwest during 1976-1997. They find that this model is the best, but it cannot be used to explain deterministic seasonality and time-to-maturity effects. Alizadeh et al. (2004) compare hedging effectiveness across Rotterdam, Singapore and Houston during 1988-2000 using such model. They point out that low hedging performance is due to different regional supply and demand of crude oil and petroleum. By using the BEKK-GARCH model with mean specifications comprising the intercept, Vector Autoregressive (VAR) and Vector Error Correction Model (VECM), Zainudin and Shaharudin (2011) claim that different restrictions impose in the conditional mean equation could affect the hedging effectiveness in the Malaysian CPO futures market. Based on the risk minimization within in- and out-of-sample, they find that a parsimonious model such as the BEKK-GARCH models with mean intercept and VAR provides better hedging performance as compared to complicated model such as the BEKK-VECM model. Another measurement of hedging effectiveness is through the maximum-utility hedging function comparison. They find that the difference between the tested models is small in terms of utility maximization.

To link time-varying hedge ratios for wheat markets across six regions, Bekkerman (2011) incorporates market linkages and wheat prices into the hedge ratio estimation process. By using data for the period of 1998-2009, this estimation process is based on the VAR-multivariate DCC-GARCH, bivariate BEKK-GARCH and no hedge models, respectively. Then, the obtained the in-sample and out-of-sample of portfolio variance for the multivariate DCC-GARCH model is further compared to the respective BEKK-

GARCH and no hedge models. As a result, the VAR-multivariate DCC-GARCH is found as the superior model in risk reduction because it better captures price interdependencies, where all relevant information affects linked price variability. This evidence suggests that the multivariate model appropriately synthesize and evaluate information about temporal, spatial and product characteristic related to agricultural commodities.

By using data for the period of 1996-2008, Zainudin (2013) uses the BEKK-GARCH model to incorporate regime shifts dummies to capture four structural breaks in the Malaysian CPO spot and futures returns. As a result, she suggests that these breaks influence the non-biasedness in volatility estimation of parameters in the model. For example, incorporated regime shirts dummies in the variance specification are able to reduce volatility persistence, while these dummies in the mean specification are able to increase volatility persistence. To examine the relevance of modeling structural breaks on the measurement of risk minimization, estimations on both models with and without break are compared within the in-sample and out-of-sample periods. The minimum-variance result indicates that the model with regime shifts produces a steadier estimated hedging ratio and hedging performance as compared to the model without regime shift. This evidence supports that incorporating regime shift into the estimation process provides the better proportion of spot position that needs to be hedged.

By using 5-minute of high frequency data of the Shanghai fuel oil futures and China Security 300 during 2010-2011, Lin et al. (2014) consider market micro-noise to build the models. They analyze and examine the impact of market incompleteness on the optimal hedging performance under bull and bear markets. Their finding indicates that micro-noise and futures return have a negative relationship. By taking this negative relationship together with the dependence of market incompleteness based on market return volatility, the performance of CCC-GARCH, DCC-GARCH, Diagonal BEKK-GARCH, Full BEKK-GARCH and Scalar BEKK-GARCH models in terms of variance portfolios are evaluated. As a result, they find that the DCC-GARCH model as a simple model more likely executes to be a perfect hedge with 1:1 ratio as compared to the other models.

Tejeda and Feuz (2014) apply a parsimonious regime-switching dynamic correlation model to estimate single and multi-product time-varying hedge ratios. Based on in-sample and out-of-sample evaluations for the sample period of 1998-2012, multi-product hedge ratio consists of corn, soybean meal, feeder cattle and live cattle are found to provide a substantial reduction in the operation's margin variance. This substantial reduction in the variance is also found in a single time-varying hedge ratio over the naïve hedging strategy.

2.2.4.1 The asymmetric effect of positive and negative returns on hedging effectiveness

Previous researchers demonstrate that commodities often exhibit the "inverse leverage effect", indicating that responses to past negative and positive shocks of the same magnitude have different effects on the conditional variance. The hedging model which takes the asymmetric response of the conditional variance-covariance matrix into account can deliver a superior measure of OHR and reduce risk. There are some studies take into account asymmetries in their dynamic OHR, applications. For instance, Brooks et al. (2002) find that asymmetric effect of positive and negative returns cannot be neglected from the BEKK parameterization in estimating hedge ratios. This is demonstrated through the GARCH model with the asymmetric effects, providing that the superior hedging performance for in-sample, but its effectiveness is low for out-of-sample.

Lien (2005) provides a stochastic volatility framework by incorporating asymmetric responses to the good and bad news. By using the framework, average OHR is found to increase along with the rising degree of asymmetric stochastic volatility. However, the increasing of this asymmetry is found as no significant in affecting hedging performance. The reason is their framework does not take constant correlation and spillover effects between spot and futures prices into consideration. Consequently, both conditions will become restrictions in his framework. By using Fama's regression approach (1984) and simple random walk model, Switzer and El-Khoury (2007) examine the effectiveness of hedging in the New York Mercantile Exchange Division light sweet crude oil futures market from 1986 to 2005. Based on variance reduction, they present evidence of the superiority of multivariate GARCH model with the asymmetric effect of bad and good news relative to alternative models, including the symmetric bivariate GARCH model.

For the crude oil and soybean markets in the sample period of 1989-2005, Maharaj et al. (2008) use wavelet analysis to estimate hedge ratios. They use a simple regression model to estimate symmetric hedge ratios, while they further use a two-stage regime switching threshold model to estimate asymmetric hedge ratios. The asymmetric model involves econometric sophistication because it includes positive and negative returns on futures contract to account the asymmetric nature of response from spot return to futures return. However, regardless of whether the absence of asymmetry or not, variance ratio test and variance reduction for both models indicate that wavelet analysis with the econometric sophistication does not boost hedging effectiveness.

In examining the effectiveness of corn and soybeans futures during 1997-2001, Park and Jei (2010) incorporate asymmetric individual into conditional variance and correlation specifications for the bivariate DCC-GARCH model. Their estimated model is found to provide a high goodness-of-fit after considering a bivariate skewed-t density distribution and asymmetric effects into both specifications. However, this high goodness-of-fit does not guarantee to be a superior model in hedging performance. According to them, the GARCH models are not guaranteed superior to the unconditional hedge ratio model (OLS) because transaction cost is ignored instead of volatility.

By using daily data of S&P Goldman Sachs Commodity Index for the period of 1995-2010, Carpantier and Samkharadze (2013) find that commodity inventory effect after positive shock increases price volatility more than after negative shock with the same magnitude. Based on the variance minimization framework within the in-sample and out-of-sample forecasts, the BEKK-GARCH model consists of an asymmetric basis term in the variance-covariance structure that captures such effect is found to surprisingly outperform as compared to the symmetric BEKK-GARCH, OLS and naïve models, respectively. Based on the framework of mean-variance optimization, the result confirms that the inventory effect is relevance for consideration. The multivariate model with those that assumes the asymmetric response to past innovations due to inventory effect would be more effective in hedging. Such model has important implications for improving assessment of the widespread Value-at-Risk applications.

Furthermore, Pan et al. (2014) develop a DCC-GARCH model that captures the asymmetry and regime switching correlations between spot and futures prices. They examine the effectiveness of the model in the context of refined product for WTI crude oil, gasoline and heating oil during 1987-2012. In this regard, they compare the hedging performance of BEKK-GARCH, CCC-GARCH and DCC-GARCH models based on variance reduction and utility. As a result, their Regime Switching Asymmetric DCC model is found to display the superior performance.

2.2.4.2 The effect of basis term on hedging effectiveness

The spread between spot and futures prices (basis) for a commodity is attributed to location, quality and timing discrepancies between commodities traded in the spot market and those are delivered on the futures market (Paroush & Wolf, 1989). Such risk is due to time-varying variation in the spot-futures spread. There are three dimensions for the basis effect on hedging effectiveness: intertemporal prices for identical goods (time dimension), quality of delivery goods (grade dimension), and different par delivery locations (spatial dimension).

As suggested by the EMH, the deviation of spot-futures relation can be examined through the short-run adjustment towards the long-run equilibrium relationship between spot and futures prices because both prices contain a stochastic trend. From the literature, the study by Kroner and Sultan (1993) is found as the first one to adopt the GARCH framework with an error-correction term in estimating dynamic hedge ratios. They find that this framework provides the superior hedging performance over conventional hedging measures. Lien (1996) provides a note by stating that omitting the cointegration relationship in modeling the dynamic effect between spot and futures markets will produce a poor hedging performance. If hedgers who misspecify behavior of spot and futures prices, they tend to adopt a futures position which is smaller than optimal position. Lien (2004) further evaluates the effect of omitted the cointegration relationship of both prices on optimal hedge ratio and hedging effectiveness. Based on his three propositions, ignoring the cointegration relationship provides a smaller hedge ratio. This subsequently produces a minimal effect on the hedging effectiveness with less than 20 per cent.

Subsequently, a number of researchers adopt the GARCH model with an error-correction term in their studies. For instance, to evaluate the effectiveness of a multi-product hedging strategy in the WTI crude oil, gasoline and heating oil markets during 1994-2009, Ji and Fan (2011) combine the dynamic conditional correlation with a multivariate GARCH model based on an error-correlation term to obtain the DCC-ECM-MVGARCH model. Based on a criterion of the minimum risk reduction of in-sample and out-of-sample, they find that their model appears to be more sensitive to market fluctuations in trading crude oil related products for refineries. As a result, their model provides better performance as compared to the naïve strategy, traditional OLS model and dynamic BGARCH model.

Go and Lau (2015) evaluate eight hedging models in the CPO futures market with different mean and variance-covariance specifications during high volatility in three distinct periods. These periods correspond to the world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/09. In estimating the time-varying hedge ratios, they find that the models with a basis term produce better performance during the Asian financial crisis and global financial crisis. They suggest that incorporating the basis term in modeling the joint dynamics of spot and futures returns during the crises can provide better results.

2.2.4.3 The asymmetric effect of positive and negative bases on hedging effectiveness

For the study by Lien and Yang (2008 a) in using the bivariate GARCH model to estimate the dynamic minimum-variance (MV) hedge ratio, they separate basis effects into positive and negative effects and include into the conditional variance-covariance and correlation specifications. Their findings indicate that a positive basis has a greater impact than a negative basis for ten commodities in the United States during the sample period of 1980-1999. As a result, the asymmetric model is found to be more superior to the conventional model. Lien and Yang (2008 b) further examine the hedging effectiveness of aluminum and copper futures contract traded on the Shanghai Futures Exchange. Their result of in-sample and out-of-sample indicate that the asymmetric bivariate fractionally integrated GARCH model is the best hedging model because it accounts asymmetric effects in basis on market volatility and behavior.

However, Maharaj et al. (2008) use wavelet analysis to estimate hedge ratios based on symmetric and asymmetric error correction Glosten-Jagannathan-Runkle (GJR)-GARCH models. They find that both sophistication models do not provide an improvement in hedging effectiveness for crude oil, soybeans and S&P 500. During the period of 1992-2009, Wu et al. (2011) use an asymmetric version of the BEKK model to account for a possibly asymmetric effect of volatility. They find evidence of hedging strategy in the corn and crude oil markets to be slightly efficient than traditional strategy in the corn futures alone.

By taking the global financial crisis into consideration in examining the effectiveness of WTI futures contracts, Toyoshima et al. (2013) choose the sample period of 2007-2011 to compare the performance of the asymmetric-DCC-GARCH model against the DCC-GARCH and Diagonal-BEKK-GARCH models. They find that an asymmetric-DCC-GARCH model provides the highest variance reduction. Then, it is followed by the DCC-GARCH and Diagonal-BEKK-GARCH models. On the contrary, Lau and Bilgin (2013) find that consideration of a structural change of volatility spillover and asymmetric basis effects are not important to improve the hedging performance of aluminum futures contracts in China during 1993-2010. The reason is a magnitude of return and volatility between the London futures and Shanghai futures markets does not greatly affect the effectiveness of the aluminum futures contract in China. Finally, the in-sample and out-of-sample evaluations support that the symmetric DCC-GARCH model is the best.

2.2.5 Price discovery in futures markets

The process of price discovery in the futures markets can be stimulated through hedging activities. This process is important for market participant to determine their profitable transaction by minimizing variation between agreement price and price discovery. In doing so, information about price volatility should be utilized efficiently to facilitate their transaction. There is detected in a number of studies to indicate that the futures market stimulates the process of price discovery. For instance, Black (1976) is the first to find that the commodity futures markets facilitate informed production, storage and processing decisions in providing price discovery mechanism. Under the EMH, Garbade and Silber (1983), Oellermann et al. (1989), and Schroeder and Goodwin (1991) suggest that the futures price plays a vital role in stimulating the process of price discovery for the underlying spot market.

To test the unbiasedness hypothesis in the United States rice futures market for the sample period of 1986-1999, McKenzie et al. (2002) use the standard OLS regression model to examine whether the futures price can be used to provide a long-run unbiased forecast of the subsequent cash prices at contract maturity. Across different contract months, the result of OLS regression model supports that the futures market has the weak-form efficiency. Then, they pool data of futures prices with different contract months and test the long-run unbiasedness hypothesis by using the Johansen cointegration procedure. Their result provides the rejection of such hypothesis. Based on the error-correlation model, their result shows that there is non-rejection on the short-run unbiasedness and market efficiency, suggesting that this long-grain rough rice futures market is efficient.

On the way to facilitate the process of price discovery, price limits are used as a substitution for margin requirement. For instance, Veld-Merkoulova (2003) finds that a hypothesis of price limits in the commodity futures market can delay the price discovery process instead of facilitating it. Subsequently, the delaying price discovery reduces the market liquidity. However, no evidence is found to support the price limits can reduce volatility because its impact on volatility and price exhibits a non-linear form.

To investigate whether the price of the Baltic International Freight Futures Exchange (BIFFEX) contract dominates the process of price discovery, Kavussanos and Nomikos (2003) use causality test, generalized impulse response analysis and forecasting evaluation to detect causality between futures and spot prices. Based on the sample period of 1988-1998, their result provides three findings: First, spot and futures prices are cointegrated; Second, causality test and generalized impulse response analyses indicate that futures price able to discover and reveal information more rapidly as compared to the spot price; and Third, causality from the futures price to spot price is found to be stronger than causality from the opposite way. These findings suggest that the information content of futures prices can be used as an indicator in generating a forecast of the spot prices but not the other way round.

In the subsequent study, Wu and McCallum (2005) report that futures-based forecast models have a lower mean squared prediction error than a random walk model of spot prices. This suggests that the futures-based forecast models such as Hotelling's futures and futures-spot spread models produce an unbiased predictor of the spot price of oil during 1987-2005. As compared to the random walk model, Coppola (2008) finds that improvement of forecast accuracy for the futures-based forecast models only can be achieved at the 1-month horizon, but not at longer horizons. This empirical finding is observed to explain on a lead-lag relationship from the futures to the underlying spot market.

In the United States and China, Liu and An (2011) use the multivariate GARCH and information share frameworks to investigate information transmission and price discovery between the copper and soybean markets. They find that a stronger effect of the New York Mercantile Exchange (NYMEX) and Chicago Board of Trade (CBOT) to the Chinese markets. To eliminate the disparity between spot and futures markets, they find that the Chinese copper market adjusts more quickly than the NYMEX copper market. From this finding, they highlight that the NYMEX and CBOT futures markets are the main forces driving the process of price discovery in the Chinese markets.

2.2.6 Conclusion

Drawing from the great extent of studies about the performance of futures contracts through hedging mechanism, it is important to view a linkage between informational efficiency and hedging effectiveness as prescribed by the APT and LOP. The systematic review of 95 articles reveals three most common subjects concern by researchers. The first subject is the OHR by corresponding to various objective functions. Then, it is followed by the effectiveness of hedging models with different conditional mean, variance-covariance and correlation specifications. Finally, it touches on the role of futures markets in discovering efficient information on pricing.

From the majority of articles, futures prices over the contract life are found to be a biased prediction of spot prices in which the existence of asymmetric information. Market participants who are risk averse tend to provide risk premium. To mitigate such asymmetry, there are few studies on the expected utility maximizing the hedge ratio as most researchers prefer to use the MV hedge ratio because its simplicity in understanding and using econometric modeling. Apart from that, the context of risk minimization is considered to be more relevant to the success of a futures contract.

Furthermore, the choice of different sample time periods provides inconsistent evidence on the superiority of incorporating the symmetric or asymmetric effect of return and basis in the model development process. This suggests that the time dimension of the basis is the important determinant of hedging performance. To design an efficient hedging strategy, the success of a hedging strategy depends on the long-run relationship between CPO spot and futures prices across high volatile sub-periods. However, such dimension for the period of extraordinary events that contribute to other persuasive proof of informational inefficiencies such as irrational traders, tax effects, transaction costs and misinterpretation of information are less catered.

The continued research is necessary in light of the long-term implication on futures markets by obtaining sensible hedging effectiveness with respect to model specification during crisis periods. Therefore, a comparison is done on two aspects: First, the performance of futures contracts is examined in a comparative setting between storable and non-storable commodities. Second, such comparison is further applied to different period of extraordinary events. To obtain a better result from both comparisons, parsimonious models with various specifications should be developed in a way that positive and negative bases have the different effect on spot and futures volatilities.

CHAPTER 3: THE IMPACT OF GLOBAL FINANCIAL CRISIS ON INFORMATIONAL EFFICIENCY: EVIDENCE FROM PRICE-VOLUME RELATION IN CPO FUTURES MARKET

3.1 Introduction

The relationship between price changes and trading volume in the futures markets has been a long-standing debate in the field of finance, to provide market participants useful information content about return distribution that would improve market volatility forecasts, with a purpose of reducing risk to their investment and trading on commodity derivative related products in the future. The reason is trading volume conveys additional information of the price volatility of which cannot be obtained from historical price data itself (Hiemstra and Jones, 1994; Blume et al., 1994; Suominen, 2001; Le and Zurbruegg, 2010). Since many empirical studies on the price-volume relation, there is still no general consensus about what actually drives such relation in the futures markets especially during the period of extraordinary events.

As shown in Figure 3.1, the heterogeneous reaction among investors through hedging strategy contributes to large swing of volatility in Malaysian crude palm oil (CPO) futures market from July 1, 2008 to December 31, 2008. This testifies that movement of daily futures prices for CPO is uncertain during the period of 2008/09 global financial crisis (GFC). Apart from that, the question is addressed: **how does trading volume sustain its role as the proxy of information flow to predict price changes in the CPO futures market across the economic downturn?** In this regard, this study attempts to examine and compare the influence of volatility persistence on the causal direction in variance between return and trading volume during pre-crisis, crisis and post-crisis periods, respectively.

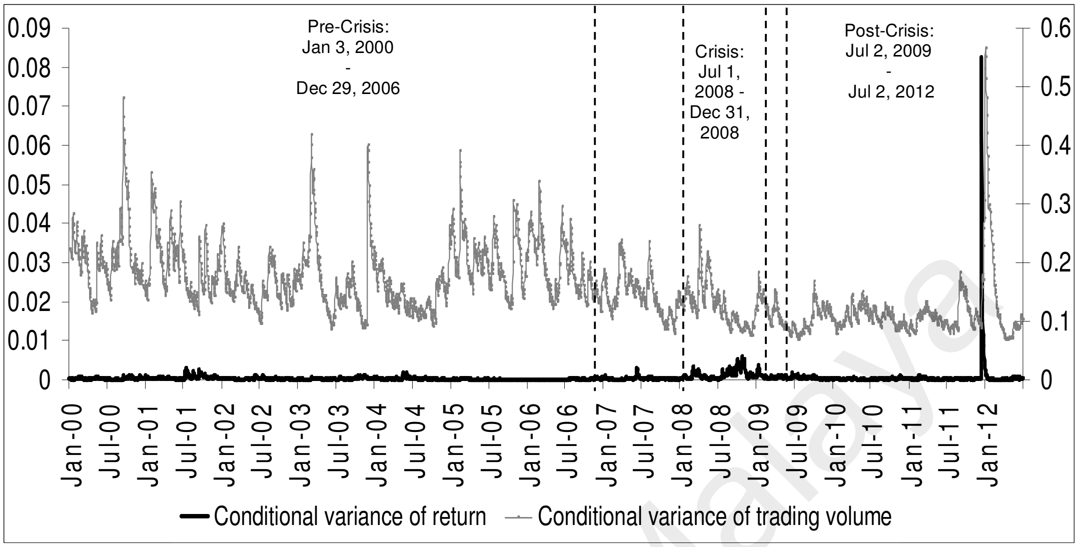

Figure 3.1: Univariate conditional variance of Malaysian FCPO return and volume, 2000-2012

Source: Authors' estimation based on Threshold-GARCH model of daily price changes and volumes in the futures market of CPO.

In order to capture the effect of global financial crisis on information transmission of both series, this study uses the period of July 1, 2008 - December 31, 2008 as the crisis period because the movement of variance during this sub-period highly fluctuated. To avoid some volatile movement at the end of pre-crisis period, the starting and ending periods of pre-crisis are chosen to be on January 3, 2000 and December 29, 2006, respectively. However, the persistence of volatile movement for a series still exists after on December 31, 2008. To avoid such volatility persistence after on December 31, 2008, the starting period of post-crisis is chosen to be on July 2, 2009.

The examination of such relationship across pre-crisis (January 3, 2000 - December 29, 2006), crisis (July 1, 2008 - December 31, 2008) and post-crisis (July 2, 2009 - July 2, 2012) is motivated by the following literature. First, Wang (1994) and Llorente et al. (2002) state that ability of informed and uninformed investors could be variable across time in assessing their financial assets. From their behavior point of view, it is ambiguity to indicate whether they have heterogeneous information or not during the period of crisis and non-crisis. Second, based on lessons from the GFC, Ball (2009) states that investors can easily identify the occurrence of unexpected events in the future after the fact by using their hindsight instead of prediction. They would behave asymmetrically in executing their trading strategies based on their expectation about the market crash.

Third, Easton and Kerin (2010) state that private information cannot be fully and quickly incorporated into price during the GFC. Hence, increasing the quantity, quality and timeliness of information should be required to improve trading efficiency at the micro level during the crisis period. Consequently, the assumption of constant speed of incorporating information into prices does not hold across different periods. Fourth, Easton and Kerin (2010) state that the GFC reinforces information to be not fully incorporated into prices quickly. However, their statement is found as anecdotal because it does not really provide any additional useful evidence on market efficiency.

Across the period of financial crisis, price changes exhibit fat-tailed distribution which is one of the well-known characteristics of market behavior. It is worth nothing that the behavior of traders here is different from the dispersion of beliefs proposed by several researchers. For instance, Daigler and Wiley (1999) state that futures traders who without precise information on order flow would cause a stronger relationship between volatility and volume at the same time. Coval and Shumway (2005) find that futures traders' dispersion of beliefs depends on whether they are holding a daily gain or loss in the morning and afternoon.

Theoretically, market participants may interpret information during financial crisis differently. This would make them behave asymmetrically on their trading strategies due to sentiment, reaction to market trends, and different costs of short-selling activities (Epps, 1975; Jennings et al., 1981; Karpoff, 1987; Go and Lau, 2014). In addition, their asymmetric behavior is also due to the market illiquidity in non-mature financial markets such as emerging markets that cause a small amount of trading to trigger a large price change (Gennotte and Leland, 1990). Furthermore, an unobservable directing process during the period of high volume causes noisiness of volume to become more severe as compared to the normal period (Marsh and Wagner, 2004). In confronting heterogeneous information and high opportunity cost, their reaction towards the arrival of new information might exhibit different delays (Tersvirta, 1998). This causes dissemination of information among them is turned to be uneven and contributes to the occurrence of asymmetric information. As a consequence, a linkage between trading volume and new information may also break down in the tail, where one of the series becomes noisier.

There are four reasons for choosing the Malaysian CPO futures market in examining such relation across the GFC. The first reason is variations in agricultural commodity prices provide the impact on food consumption especially for types of edible oil and fat. The reason is the inefficiency of commodity markets leads to price fluctuation and reflects economic conditions such as inflation, interest rates, production costs, income, economic growth, and market confidence. The second reason is whether the price-volume relation can be generalized to the case of commodity futures markets, especially for vegetable commodities such as CPO since most of the studies pertain to the stock markets. The third reason is a CPO futures contract still remains as active and liquid trading CPO derivative related products in the world. As a result, information from the futures market can be transmitted more effectively as compared to its underlying market. With this market structure, participants can dominate function of price discovery and this will directly reflect the relationship between price and trading volume.

The fourth reason is how investors behave in trading CPO may change during the period of financial crisis due to this commodity may have desirable characteristics. For example, declining income levels during the GFC period in some developing countries led users to reduce their food consumption on "luxuries" like fats and edible oils related products. According to Oil World (2010), consumption growth of palm oil has decreased from 9.8 per cent in 2007/08 to 8.5 per cent in 2008/09, and 4.5 per cent in 2009/10. The sharp decline in consumption from 2007 to 2010 concurs with Fry and Fitton (2010) that palm oil products generally have a high income elasticity of demand. With this high income elasticity of demand for the commodity, the price-volume relation is expected to attenuate across the crisis period.

To test whether past trading volume in the CPO futures market across the 2008 economic turmoil can be exploited to obtain additional information about the subsequent movement of price changes, cross-correlation functions of standardized residuals and their squares developed by Cheung and Ng (1996) is used to capture the non-linear causal effect of both series (Henry et al., 2007: 123). There are three reasons for application of this non-linear approach. The first reason is a significant fraction of macroeconomic time series produces a parameter instability condition of the model. If linear approaches are used, it will lead to spurious inference (Stock and Watson, 1996). The second reason is nonlinearities contribute to the dynamic correlation between energy prices and the overall economy (Filis et al., 2011). The third reason is linear approaches ignore asymmetric adjustment of agricultural futures prices under specific circumstances (Beckmann and Czudaj, 2014). This study emphasizes the cross-correlation functions of standardized squared residuals to test variance dependence between return and volume because it acts as a proxy for information arrival and dissemination in the market (Ross, 1989; Engle et al., 1990).

For CPO traders and producers who are concerned about the market dynamics in the short run, the findings are expected to assist them in assessing the quality of price to allocate CPO inventories optimally for production across the financial crisis. To determine an expected output price, the findings of information spillover from the cross-correlations between price changes and volume and their time span of correlations perspectives can provide the direction of a CPO futures price change. For example, if the finding indicates that trading volume acts as a proxy variable for the rate of daily information for CPO prices, they can use information of price based on trading volume in a way to deleverage their explore risk in making decisions at a better market timing.

This chapter is organized as follows: This section is followed by a literature review. The subsequent section explains about data and methodology. Then, it is followed by empirical results and findings. The last section concludes the discussion of the study.

3.2 Literature Review

The old Wall Street adage asserts "it takes volume to move prices". Therefore, trading volume is believed to be positively associated with return. This market folklore is demonstrated by several researchers. For instance, Ying (1966) uses chi-square analysis of variance and cross-spectral to test the relationship between volume and changes in price in the New York Stock Exchange (NYSE) during 1957-1962. His finding indicates that positive correlation between both series. Clark (1973) conducts a similar study on the cotton market during 1945-1958 and finds that a positive correlation between absolute return and trading volume. This finding is in line with the studies by Tauchen and Pitts (1983) for the T-bill futures contracts during 1976-1979. Furthermore, the past findings on the price- volume relation are categorized into the following four main hypotheses.

3.2.1 Volatility-volume hypotheses

Trading volume is composed of two components: the number of trades and the size of trades. With both components, transactions can be generally based on either liquidity-driven trading or information-driven trading. As a result, trading volume can be either positively or negatively correlated with price changes, leading to the asymmetric relationship between volatility and volume.

From studies by Wang (1994), Xu and Wu (1999), Chan and Fong (2000), and Llorente et al. (2002), informed traders in the competitive markets are likely to trade large amounts of volume in one transaction. This large size of trades subsequently stimulates price changes to be positively correlated with trading volume. Wang (1994) proposes the Liquidity-Driven Trade hypothesis to explain the positive relationship between volume and absolute changes in prices for both informational and non-informational motives with his heterogeneous investor model.[2] According to his hypothesis, informed investors tend to trade at high absolute changes in price and dividends in a subsequent period because of better information about individual publicly traded stocks.

[2] Informed investors use non-informational trading as noise trading (also known as liquidity trading) when their private investment opportunity changes. The consequence of the including this variable into welfare analysis leads to problematic in his analysis (Wang, 1994: p. 131).

This hypothesis is further supported by Llorente et al. (2002). Among selected individual stocks on the NYSE and American Stock Exchange (AMEX), they find that low degree of informational trading will eventually lead to hedging-motivated trades which reverse themselves to generate returns. For stocks with higher information asymmetry, the return will be generated by speculative-motivated trades which tend to continue themselves. Furthermore, Louhichi (2011) finds that the number of trades is a good proxy for market activity and information flow in the Euronext Paris. This suggests that the asymmetric behavior of traders in camouflaging their private information to perform their trading strategic can generate positive relationships between volatility and volume. However, Liu et al. (2015) confirm that a condition in producing such relation in the artificial stock markets is produced by trade size instead of information-driven trade.

On the contrary, Stickel and Verrecchia (1994), Giot et al. (2010), and Louhichi (2011) state that informed traders can camouflage their private information by increasing their number of transactions. This can be done by splitting a large number of trades into several small numbers of trades. This information-driven trade subsequently contributes to the negative correlation of both series. Stickel and Verrecchia (1994) use multivariate and graphical analyses of the NASDAQ stocks during 1982-1990. They find that weak changes in volume on previous day contribute to large price changes for the next day. This evidence of the negative correlation between return and trading volume supports the Information-Driven-Trade hypothesis. Their finding implies that investors should cautious in interpreting large daily stock price changes due to weak volume. In the crude oil futures market, Moosa et al. (2003) find that a strong negative relationship of both series due to an arrival of the bad news has a stronger effect than the good news.

In the United States equity indices, Connolly and Stivers (2003) find that unexpected high turnover in trading volume leads to substantial momentum in consecutive weekly stock returns during 1962-2000. When the latter week has an unexpectedly low turnover, they are substantial reversals on consecutive weekly stock returns. Additionally, in the Warsaw Stock Exchange during 1996-2000, Gebka (2005) finds that the prevalence of uninformed traders leads to a high volume which provides strong price reversals.

3.2.2 Information-based hypotheses

Information transmission is a keyword in examining a market microstructure. Apart from that, the price-volume relation used to differentiate competing theoretical models and hypotheses in explaining behavioral of market participants from the perspective of information spillover. To quantify its existence, several methods such as cross-correlation, autocorrelation, and dynamic causality testing are used. According to Ross (1989), variance is claimed to be a proxy for information arrival in the market based on his no-arbitrage model. Engle et al. (1990) demonstrate that market participants' action in processing the arrival of new information can influence variance, where their action indirectly reveals the existing information flow in the market across time. Andersen (1996) further demonstrates that stochastic process and generalized standard autoregressive conditional heteroscedasticity (ARCH) specification can model information flow which reflects dynamic features in the financial data.

Theoretically, volatility of prices responds to the arrival of new information. If the trading volume links to new information that enters the market, there will be a significant relationship between price changes and trading volume. There are four hypotheses in the prior research to explain on how information is transmitted between price and trading volume, namely a mixture of distribution hypothesis (MDH), sequential information arrival hypothesis (SIAH), noise traders' hypothesis and non-tax-related motives hypothesis.

According to the MDH, information transmission between price changes and trading volume is contemporaneous along the ARCH process. This relationship depends jointly upon a common event or a directing variable as a rate of information flow (Clark, 1973; Epps & Epps, 1976; Cornell, 1981; Tauchen & Pitts, 1983; Harris, 1987). Andersen (1996) further develops the Modified MDH based on five common stocks during 1973-1991.To respond the arrival of new information through such hypothesis, stylized microstructure framework in which informational asymmetries and liquidity are used to derive a contemporaneous relationship between return volatility and trading volume.

In the Polish stock market, Gurgul et al. (2005) find that the MDH is held during 1995-2005 because trading volume has little additional explanatory power for subsequent price changes. In the Korean stock market, Choi et al. (2012) use the exponential-GARCH model and find that the arrival of bad news has a large effect on return volatility. This effect subsequently contributes to a contemporaneous relationship between return and trading volume during 2000-2010. Apart from studying the price-volume relation in stock markets, the focus also shifts in commodity markets. For instance, Biswas and Rajib (2011) find that this contemporaneous correlation between trading volume and absolute return happens in the Indian gold, silver and crude oil futures markets during 2005-2009.

In a subsequent hypothesis, Copeland (1976) and Jennings et al. (1981) propose the SIAH. In contrast, this hypothesis reveals that information transmission between price and trading volume exhibit dynamic effect, indicating that past value of trading volume has ability to predict the future absolute return and /or vice versa (Copeland, 1976; Jennings et al., 1981; Tauchen and Pitts,1983; Garcia et al., 1986). During the 1990s and onwards, the majority of studies are found to turn their focus in examining dynamic causality between price changes and trading volume. For instance, Moosa and Silvapulle (2000) find evidence of past volume causes current price changes in a linear form in the crude oil futures market during 1985-1996. Bhar and Hamori (2005) find causality-in-variance from past return to current trading volume in the crude oil futures market during 1990-2000.

However, several studies find that this causality is turned to be a bi-directional in a non-linear form. For instance, Chen et al. (2008) find that trading imbalance sequentially transmits private information to explain return volatility in the E-mini S&P 500 index futures and Japanese Yen Foreign Exchange futures during 1998-2005. The Chicago Board Options Exchange during 2003-2008, Le and Zurbruegg (2010) find the evidence of SIAH to indicate that an incorporating option implied volatility and trading volume into the exponential-GARCH model provides the better prediction of volatility in the future.

Despite the interesting explanation given by the MDH and SIAH, both hypotheses overlook behavioral of noise trading. In fact, fundamental analysis is rarely carried out by some market participants on their investments, where they make better decisions based on irrelevant information rather than deciding based on the analytical information. This type of trading behavior causes price volatility attributable to noise traders. For instance, Shleifer and Summers (1990) state that noise traders are market participants who demand their securities with certain criteria based on irrelevant information to make profits. In the other words, they do not or rarely carry out fundamental analysis on their investments. Their existence ensures the market to be more liquid because it would affect price change of a security to achieve at the equilibrium level. Furthermore, De Long et al. (1990), Shleifer and Vishney (1997), and Dow and Gorton (2006) argue that there must be a certain limit on arbitrage as there are still a lot of noise traders around. One of the possibilities is informed traders have a limited horizon over where a trader could take place.

In the crude oil futures market during 1990-2000, Bhar and Hamori (2005) find one-way causality from a return to trading volume in the second moment that reveals evidence of mildly supports the noise traders' hypothesis. Their finding suggests that the past trading volume is not a helpful vehicle for speculators to forecast short-term price movement. By using the threshold-GARCH model, Girard and Omran (2009) find that the presence of noise trading increases the explanatory power for the size of volatility shock instead of leverage effect of conditional variance in the Cairo and Alexandria Stock Exchange during 1998-2005.

For the last hypothesis, Lakonishok and Smidt (1986) propose tax and non-tax-related motives based on their study in the NYSE during 1968-1982. They use several numbers of parametric tests, such as one-way and four-way analyses of variance to determine the combined effect of price increases or decreases over previous five, eleven, twenty-three and thirty-five months. Their finding indicates that non-tax incentives trading have a stronger effect than tax incentives on trading volume. This effect directly influences movement in prices. Their finding is further supported by Bremer and Kato (1996) in Tokyo Stock Exchange during 1975-1990 based on residuals to out-of-sample market model regression coefficient procedure.

3.2.3 Dispersion of beliefs / expectation

Shalen (1993) proposes dispersion of beliefs based on his own two-period noisy rational expectations model of the futures market. He states that different types of traders tend to interpret similar information in different ways at the same time. His results indicate that uninformed traders' dispersions of beliefs will increase volatility and create excess volume as compared to informed traders.[3] Subsequently, Harris and Raviv (1993) develop a model of trading based on different opinion among traders in speculative markets, indicating that traders tend to speculate on the market when their current beliefs are more diffuse.

Then, Daigler and Wiley (1999) categorize futures traders into four types: local floor traders, clearing members, executing trades and off-the-floor customers. Their findings support that trader who without precise information on order flow would cause a stronger relationship between volatility and volume. For Treasury bond futures contracts that are traded on the Chicago Board of Trade, Coval and Shumway (2005) find that futures traders' dispersion of beliefs depends on whether they are holding a daily gain or loss in the morning and afternoon.

3.2.4 Asymmetric hypotheses

The existence of heterogeneity of trading behavior leads to market adjusts partially to new information. Consequently, this information arrival leaves investors to expose reaction differently on market shock in a subsequent period, thereby resulting in asymmetric information. This asymmetric information has been a challenge for the efficient market hypothesis as a source of important and enduring insights for many years. Following to Epps (1975), the "heterogeneity of traders" hypothesis is tested by

[3] The excess volatility and excess volume of trade are induced by "noisy" liquidity demand of futures hedges.

distinguishing the price-volume relation under bull and bear markets, respectively. The reason is investors would behave asymmetrically in their trading due to different costs of short-selling activities under upward and downward trends, respectively. This hypothesis is supported by Jennings et al. (1981), where they state that an "optimist" trader used high volumes in the bull trend as signals of higher future stock prices in responding to new information faster than "pessimist" traders.

From this insight, Karpoff (1987) further proposes the short-selling constraint hypothesis to explain the different reactions between traders who have bullish and bearish expectations. Furthermore, Chen (2012) finds that the return and volume exhibit a contemporaneous correlation in bull and bear stock markets for the S&P500 during 1973-2008. In dynamic relation, asymmetric information flow does not exist in both market trends, where the stock return is found to have capable of predicting trading volume. However, Go and Lau (2014) find that traders in the Malaysian futures market who have the bearish expectation are more risk averse and tend to react to new information faster than who have the bullish expectation.

3.3 Data and Preliminary Empirical Results

This study uses daily data of the Malaysian three months for CPO futures prices (P_t) in RM per metric tonne and trading volume $(Volume_t)$ in metric tonne which cover from January 3, 2000 to July 2, 2012. This sample period comprises of 3,059 observations. These data are extracted from the Bursa Malaysia[4] and Thomson DataStream. To reduce variability and achieve stationarity of both series, we transform daily futures prices

[4] http://www.bursamalaysia.com/market/derivatives/market-statistics/historical-data/, retrieved on 30 Oct 2015.

become daily returns (R_t) as changes of futures prices in natural logarithmic form at time t. For trading volumes ($Volume_t$), we use V_t in the same form.

In Table 3.1, augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are implemented using two auxiliary regression models, where the first model with a constant term only (drift) and the other model with a constant term along deterministic trend. Both tests support the rejection of the null hypothesis of a unit root of the series, suggesting that both daily return and trading volume in each period are stationary in level form.

Table 3.1: Result of unit root test

	Pre-crisis		Crisis		Post-crisis	
	R	V	R	V	R	V
Augmented Dickey-Fuller:						
Drift	-41.231*** (0)	-3.513*** (8)	-7.382*** (2)	-2.883* (2)	-25.135*** (1)	-7.39*** (2)
Drift & Trend	-41.236*** (0)	-6.967*** (5)	-7.62*** (2)	-3.412* (2)	-25.141*** (1)	-8.4*** (2)
Phillips-Perron:						
Drift	-41.51***	-17.538***	-12.504**	-8.060***	-41.373***	-15.8***
Drift & Trend	-41.51***	-29.419***	-12.813***	-8.394***	-41.472***	-17.1***

Notes: Pre-crisis period is from January 3, 2000 to December 29, 2006. Crisis period is from July 1, 2008 to December 31, 2008. Post-crisis period is from July 2, 2009 to July 2, 2012. R and V are denoted as the daily futures return and trading volume in natural logarithmic form. ***, ** and * show that null hypothesis of existence of unit root is rejected at the 1%, 5% and 10% levels, respectively. The optimal lag length of ADF test is reported into ().

As observed in Table 3.2, standard deviation of 0.037 for return in crisis is found to be slightly higher than 0.026 and 0.0153 in pre-crisis and post-crisis, respectively. This suggests that return movement in crisis is slightly more volatile than in non-crisis. The volatility of trading volume reduces by half from 0.4082 to 0.816 in pre-crisis and post-crisis periods. Correspondingly, changes in the volume of volatility are expected to change the degree of noisiness in measuring the rate of information flow, so return and trading volume dependence may be affected across the crisis period.

Table 3.2: Descriptive statistics

	Pre-crisis		Crisis		Post-crisis	
	R	V	R	V	R	V
Mean	0.0003	7.6383	-0.0060	8.8676	0.0004	9.2753
SD	0.0153	0.8161	0.0366	0.3223	0.0260	0.4082
Jarque-Bera	917.1081 (0.0000)	59.8996 (0.0000)	0.071 (0.9651)	12.911 (0.0016)	889567.5 (0.0000)	681.021 (0.0000)
Skewness	0.3328	-0.4510	-0.0278	-0.6589	0.6577	-0.9687
Kurtosis	6.5276	2.8321	3.1026	3.8616	172.8502	7.2818
Q (9)	26.660 (0.009)	10992 (0.0000)	26.983 (0.001)	162.15 (0.0000)	92.644 (0.0000)	1432.2 (0.0000)
ARCH (9)	179.7312 (0.0000)	71.6055 (0.0000)	12.4364 (0.1898)	17.1825 (0.0459)	131.5026 (0.0000)	149.443 (0.0000)
Observations	1708	1708	125	125	740	740

Notes: Pre-crisis period is from January 3, 2000 to December 29, 2006. Crisis period is from July 1, 2008 to December 31, 2008. Post-crisis period is from July 2, 2009 to July 2, 2012. R and V are denoted as the daily futures return and trading volume in natural logarithmic form. SD stands for standard deviation. P-values are reported in ( ).

The Ljung-Box (Q(9)) statistic for 9th order autocorrelation is statistically significant for both series, implying that both series are autocorrelated. While ARCH test at 9th order indicates volatility of both series is serially correlated in each sub-period. Therefore, unsurprisingly ARCH is a strong feature of the data set, especially during the pre- and post-crisis periods. To distinguish distribution of the conditional variance of both series in the pre- and post-crisis periods, a normal distribution is used to model conditional variance of return because kurtosis of return is extremely larger than kurtosis of trading volume, while Student-t distribution is used to model conditional variance of trading volume.

3.4 Cross-Correlation Function of Standardized Residuals and Standardized Squared Residuals (CCFs)

As stated by Cheung and Ng (1996), there are three advantages in using the CCFs approach. First, it does not involve simultaneous modeling for both intra- and inter-variables dynamics. Second, it is asymptotically robust to distributional assumptions. Third, it detects significant non-linear causal effects in a large number of series at longer lags (Cheung and Ng, 1996: 36). This approach is further used by Hong (2001), and Go and Lau (2014), where it involves two analyses.

The first analysis is to control for any serial dependence in returns and trading volumes. In this regard, univariate analysis is used to capture the conditional mean and variance of both series across time based on its own lagged terms. The conditional mean of a series is characterized as Autoregressive Moving Average (ARMA) process because it provides a parsimonious representation of autocorrelation in a series. Meanwhile, conditional variance of a series is modeled as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process (Bollerslev, 1986). The number of orders in univariate ARMA-GARCH model is based on correlograms of autocorrelation function (ACF), partial autocorrelation function (PACF) and the minimum Schwarz information criterion (SIC). These univariate models are written as Equations (3.1), (3.2), (3.3) and (3.4).

$$R_t = a_0 + \sum_{i=1}^{P1} a_i R_{t-i} + \sum_{i=1}^{P2} b_i \varepsilon_{R,t-i} + \varepsilon_{R,t}, \quad \varepsilon_{R,t} | \phi_{t-1} \sim N(0, \sigma^2_{R,t}) \tag{3.1}$$

$$\sigma^2_{R,t} = w + \sum_{i=1}^{P3} \alpha_i \varepsilon^2_{R,t-i} + \sum_{i=1}^{P4} \beta_i \sigma^2_{R,t-i} \tag{3.2}$$

$$V_t = a_0 + \sum_{i=1}^{P5} a_i V_{t-i} + \sum_{i=1}^{P6} b_i \varepsilon_{V,t-i} + \varepsilon_{V,t}, \quad \varepsilon_{V,t} | \phi_{t-1} \sim N(0, \sigma^2_{V,t}) \tag{3.3}$$

$$\sigma^2_{V,t} = w + \sum_{i=1}^{P7} \alpha_i \varepsilon^2_{V,t-i} + \sum_{i=1}^{P8} \beta_i \sigma^2_{V,t-i} \tag{3.4}$$

where, R_t is natural logarithm of a daily return at time t, $\sigma^2_{R,t}$ is conditional variance of a daily return at time t, $\varepsilon_{R,t}$ is an unexpected daily return that cannot be predicted based on all information available up to the preceding period, V_t is natural logarithm of a daily trading volume at time t, $\sigma^2_{V,t}$ is conditional variance of a daily trading volume at time t, and $\varepsilon_{V,t}$ is an unexpected daily trading volume that cannot be predicted based on all information available up to the preceding period.

Based on univariate estimated results, standardized residuals of both series are denoted as U_t and W_t, respectively. In squared form, they are denoted as U_t^2 and W_t^2, respectively.

$$U_t = \left(\left(R_t - \mu_{R,t}\right) / \sigma_{R,t}\right) \tag{3.5}$$

$$W_t = \left(\left(V_t - \mu_{V,t}\right) / \sigma_{V,t}\right) \tag{3.6}$$

$$U_t^2 = \left(\left(R_t - \mu_{R,t}\right)^2 / \sigma_{R,t}^2\right) \tag{3.7}$$

$$W_t^2 = \left(\left(V_t - \mu_{V,t}\right)^2 / \sigma_{V,t-i}^2\right) \tag{3.8}$$

The sample cross-correlation between Equations (3.5) and (3.6) at specific lag k is computed using Equation (3.9). While cross-correlation between Equations (3.7) and (3.8) at specific lag k is computed using Equation (3.10).

$$r_{UW}(k) = \frac{C_{UW}(k)}{\sqrt{C_{UU}(0) C_{WW}(0)}} \tag{3.9}$$

$$r_{U^2W^2}(k) = \frac{C_{U^2W^2}(k)}{\sqrt{C_{U^2U^2}(0) C_{W^2W^2}(0)}} \tag{3.10}$$

where, $r_{UW}(k)$ is k -th lag sample cross-correlation between standardized residuals of return and trading volume, $C_{UW}(k)$ is k -th lag sample covariance between standardized residuals of return and trading volume, $C_{UU}(0)$ is sample variance of standardized residuals of return, $C_{WW}(0)$ is sample variance of standardized residuals of trading volume, $r_{U^2W^2}(k)$ is k -th lag sample cross-correlation between standardized squared residuals of return and trading volume, $C_{U^2W^2}(k)$ is k -th lag sample covariance between standardized squared residuals of return and trading volume, $C_{U^2U^2}(0)$ is sample variance of standardized squared residuals of return, and $C_{W^2W^2}(0)$ is sample variances of standardized squared residuals of trading volume.

Both Equations (3.9) and (3.10) are further used in Equations (3.11) and (3.12) to compute test statistics. The rejection of the null hypothesis of no feedback in the mean and variance between the return and trading volume at specific lag k when the absolute value of test statistic is greater than a standard normal critical value (Cheung & Ng, 1996: p. 37).

$$\sqrt{T} r_{UW}(k) \xrightarrow{L} N(0,1) \tag{3.11}$$

$$\sqrt{T} r_{U^2W^2}(k) \xrightarrow{L} N(0,1) \tag{3.12}$$

The second analysis is to capture the interaction between return and trading volume in mean and variance based on univariate analysis. This can be done through the following estimation of augmented equations.

$$R_t = a_0 + \sum_{i=1}^{P1} a_i R_{t-i} + \sum_{i=1}^{P2} b_i \varepsilon_{R,t-i} + \sum_{i=1}^{P3} c_i V_{t-i} + \varepsilon_{R,t},\ \varepsilon_{R,t} \big| \phi_{t-1} \sim N(0, \sigma^2_{R,t}) \tag{3.13}$$

$$\sigma^2_{R,t} = w + \sum_{i=1}^{P4} \alpha_i \varepsilon^2_{R,t-i} + \sum_{i=1}^{P5} \beta_i \sigma^2_{R,t-i} + \sum_{i=1}^{P6} \lambda_i V^2_{t-i} \tag{3.14}$$

$$V_t = a_0 + \sum_{i=1}^{P7} a_i V_{t-i} + \sum_{i=1}^{P8} b_i \varepsilon_{V,t-i} + \sum_{i=1}^{P9} c_i R_{t-i} + \varepsilon_{V,t},\ \varepsilon_{V,t} \big| \phi_{t-1} \sim N(0, \sigma^2_{V,t}) \tag{3.15}$$

$$\sigma^2_{V,t} = w + \sum_{i=1}^{P10} \alpha_i \varepsilon^2_{V,t-i} + \sum_{i=1}^{P11} \beta_i \sigma^2_{V,t-i} + \sum_{i=1}^{P12} \lambda_i R^2_{t-i} \tag{3.16}$$

To reveal the interplay or spillover in mean and variance from trading volume to return using Equations (3.13) and (3.14), lagged trading volume in level and square forms (V_{t-i} and V_{t-i}^2) are included. Significant coefficients of c_i in Equation (3.13) reveal presence of spillover effects in mean from trading volume to return subsequently. Meanwhile, significant coefficients of λ_i in Equation (3.14) reveal the effect of volatility spillover from trading volume to return. Following the same line of analysis to capture spillover effect in mean and variance from return to trading volume, lagged return (R_{t-i}) is included into conditional mean equation (Equation (3.15)) as well as lagged squared return (R_{t-i}^2) is included into conditional variance equation (Equation (3.16)). Significant coefficients of c_i in Equation (3.15) and significant coefficients of λ_i in Equation (3.16) reveal spillover effects in respective mean and variance.

This study focuses on causality-in-variance of both series from the augmented analysis because it provides a better description on dynamic lead-lag of price-volume relation and a proxy of new arrival of information in the market (Ross, 1989). According to Bhar and Hamori (2005), dependence causality-in-variance can capture information arrival between price changes and trading volume.[5]

3.5 Empirical Results from Univariate Analysis

For the crisis, conditional mean of daily return is explained by ARMA(3,3) model. The squared residuals are obtained from conditional mean equation further indicate daily returns do not exhibit ARCH process. This finding is in line with the Jarque-Bera test statistic of 0.071 as shown in Table 3.2, indicating that the return has a normal

[5] Dependence causality-in-variance is also known as interaction in the second moment or volatility spillover.

distribution. For trading volume, ARCH(2) is suggested to be a sufficient model to capture serial correlation of its volatility. Over the period of pre- and post-crisis, ARMA(3,3)-GARCH(1,1) and MA(1)-ARCH(2) for return as well as AR(3)-GARCH(1,1) and AR(1)-GARCH(1,1) for trading volume are relative goodness of fit of models in explaining conditional mean and variance. The estimated results are summarized in Table 3.3.

Table 3.3: Empirical result of univariate models

	Pre-crisis		**Crisis**		**Post-crisis**	
Parameter	R	V	R	V	R	V
Conditional mean equation:						
a_0	5.35×10^{-5} (0.0001)	0.7250*** (0.1055)	-0.0043 (0.0008)	2.4713*** (0.736)	0.0030*** (0.001)	3.3234 *** (0.2864)
a_1	-0.6215*** (0.131)	0.4840*** (0.0239)	-0.0073 (0.3967)	0.0544 (0.0798)	-	0.6422 *** (0.0309)
a_2	0.3475* (0.1975)	0.1781*** (0.0276)	0.3487 (0.5181)	0.4830*** (0.0762)	-	-
a_3	0.8851*** (0.13)	0.2443*** (0.0238)	0.4062 (0.3031)	0.185 *** (0.0489)	-	-
b_1	0.6339 *** (0.1415)	-	0.3922 (0.3668)	-	0.0147 (0.0768)	-
b_2	-0.3232 (0.2128)	-	-0.1813 (0.4654)	-	-	-
b_3	-0.8697*** (0.1403)	-	-0.6633** (0.3163)	-	-	-
Conditional variance equation:						
w	1.05×10^{-6}*** (4.05×10^{-7})	0.0272* (0.0155)	-	0.0317** (0.0104)	0.0004*** (3.44×10^{-5})	0.0254** (0.0099)
α_1	0.0687*** (0.0065)	0.0546*** (0.0208)	-	-0.0339 (0.0524)	0.2481*** (0.0392)	0.1130*** (0.0422)
α_2	-	-	-	0.6142*** (0.2224)	-0.0038** (0.0017)	-
β_1	0.931*** (0.0066)	0.8013*** (0.0958)	-	-	-	0.6153*** (0.1381)
$\alpha+\beta$	0.9997	0.853	-	0.5803	0.2442	0.7283
Log-likelihood	4905.886	-975.7563	241.7350	5.3940	1865.189	-161.0037
ARCH-LM test Statistic	0.0156 [0.9007]	1.2877 [0.2565]	0.0176 [0.8946]	1.1802 [0.5543]	0.3198 [0.8522]	0.5145 [0.4732]
Serial correlation-LM test Statistic	-	-	1.9122 [0.3844]	-	-	-
Q²(20)	13.373 [0.711]	18.985 [0.523]	-	14.067 [0.827]	0.4639 [1.000]	28.186 [0.105]

Notes: These models are estimated based on Equations (3.1), (3.2), (3.3) and (3.4). R and V are denoted as the daily futures return and trading volume in the natural logarithmic form. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors and p-values are reported in ( ) and [ ], respectively.

In Table 3.3, almost all coefficients of α_i (ARCH term, the impact of past volatility shock) and β_i (GARCH term, the impact of past conditional volatility) are statistically significant. Both coefficients are found to have a sum of approximate unity, suggesting that stability of volatility for both series. The Lagrange Multiplier (LM) test, Ljung-Box test on standardized squared residual (Q^2) at lag 20 and ARCH Lagrange Multiplier (LM) test further indicate that these univariate estimation results are free from autocorrelation and heteroskedasticity problems in their standardized residuals. Then, cross-correlations between standardized residuals of return and trading volume as well as between standardized squared residuals of both series are computed up to 20 lags in each sub-period.

As observed in "Level" column of Table 3.4 for pre-crisis, standardized residuals of past trading volume and current return are significantly correlated at the lag 7 days and lag 19 days. This reveals that mean of trading volume in 7 and 19 days ago causes mean of current return. In a crisis, mean of current return and future trading volume is turned to be significantly correlated at the lag 1 day. It is further observed that mean of current return is frequently correlated with mean of future trading volume in post-crisis at lags 2, 3, 7, 9, 12 and 13, respectively. As observed in "Square" column of Table 3.4 for pre-crisis, there are significant cross-correlations between standardized squared residuals of past trading volume and current return with 0.0979 and 0.0599 at lag 1 and lag 18. For post-crisis, standardized squared residuals of current return and future trading volume are correlated significantly with 0.3217, 0.3106, 0.0744 and 0.1112 at lags 3, 9, 12 and 13, respectively. This observation suggests that feedback effect in variance between both series occurs asymmetrically after the exceptionally volatile period.

Table 3.4: Cross-correlation in the levels and squares of standardized residuals resulting from the univariate models reported in Table 3.3

Lag (i)	Pre-crisis				Crisis				Post-crisis			
	Level		Square		Level		Square		Level		Square	
	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)
0	**0.052***		**0.151****		-0.079		-0.182	**-0.182***	-0.068		-0.014	
1	0.0133	0.0090	**0.0979****	-0.0382	0.0022	**-0.2004***	-0.0045	0.0312	-0.0212	-0.0539	-0.0143	0.0015
2	0.0204	0.0402	0.0096	-0.0205	-0.0742	-0.0590	0.1031	0.1338	0.0138	**-0.113****	-0.0184	-0.0012
3	-0.0180	-0.0120	-0.0220	-0.0121	0.0614	-0.0456	-0.0361	-0.0820	-0.0386	**0.1279****	-0.0055	**0.3217****
4	0.0070	-0.0184	-0.0438	**-0.0498***	-0.0429	0.0139	-0.0725	-0.0207	-0.0041	-0.0033	-0.0195	-0.0061
5	-0.0165	0.0045	0.0020	-0.0468	-0.0778	-0.1740	-0.0596	-0.0125	-0.0041	-0.0141	-0.0017	0.0108
6	0.0195	0.0054	-0.0277	0.0029	0.1054	0.0582	0.0691	-0.0130	-0.0499	-0.0097	0.0128	-0.0067
7	**0.0733****	-0.0002	0.0076	-0.0361	0.0593	0.0579	0.0679	0.0398	-0.0756	**0.1065****	-0.0152	0.0991
8	0.0285	-0.0148	-0.0114	-0.0133	-0.1059	-0.0234	0.0015	0.0271	0.0375	0.0155	-0.0116	-0.0167
9	-0.0204	0.0337	-0.0364	-0.0094	-0.1577	-0.0231	-0.0364	-0.0147	0.0341	**0.0780***	-0.0143	**0.3106****
10	-0.0053	0.0390	0.0281	-0.0250	-0.0530	-0.0689	-0.1219	-0.0331	-0.0362	-0.0436	-0.0188	0.0005
11	0.0051	0.0304	-0.0054	-0.0321	-0.1259	-0.1142	0.0072	0.0322	-0.0293	0.0116	-0.0181	0.1087
12	0.0324	0.0000	0.0152	-0.0013	-0.0921	0.1011	0.0012	0.0247	0.0406	**0.0949***	-0.0145	**0.0744***
13	-0.0233	0.0371	0.0173	-0.0103	-0.0798	-0.0270	-0.0993	-0.0064	-0.0014	**-0.105****	-0.0059	**0.1112****
14	-0.0091	-0.0129	0.0211	-0.0222	-0.1139	-0.0633	-0.0009	-0.0507	-0.0397	0.0076	-0.0183	-0.0163
15	0.0132	-0.0072	0.0044	0.0059	0.0201	-0.0309	0.1654	-0.0679	-0.0250	-0.0337	-0.0143	-0.0195
16	0.0384	-0.0286	-0.0231	-0.0147	0.0464	-0.1512	-0.0537	0.0915	-0.0202	0.0420	-0.0031	-0.0186
17	-0.0089	0.0288	0.0032	0.0011	0.0034	-0.1257	0.0366	-0.0396	-0.0005	0.0092	-0.0097	-0.0198
18	0.0185	0.0218	**0.0599***	0.0012	0.0017	0.1270	0.0808	-0.0210	-0.0544	-0.0272	0.0598	-0.0195
19	**-0.0497***	0.0401	0.0426	0.0008	-0.0667	-0.1770	-0.0220	-0.0843	**0.0871***	0.0114	**0.0771***	-0.0169
20	-0.0155	0.0093	0.0132	-0.0361	0.0183	-0.2004	0.0250	0.0312	-0.0525	-0.0050	-0.0093	-0.0153

Notes: R and V are denoted as the daily return and trading volume, respectively. i is the number of days the trading volume lags or leads the return. ** indicates test statistic is more than +2.58 or lesser than -2.58 (statistical significance at the 1% level). * indicates test statistic is more than +1.96 or lesser than -1.96 (statistical significance at the 5% level). "V(-i)→R" represents cross-correlations for lag-effect of past daily trading volume on current daily return, while "R→V(+i)" represents cross-correlations for lead-effect of current daily return on future daily trading volume. The significance of cross-correlations in "Level" column reveals evidence of feedback effect in mean of two series. In the "Square" column, it reveals as evidence of feedback effect in variance.

3.6 Empirical Results from Augmented Analysis

To capture interaction between daily return and trading volume in mean and variance based on significant cross-correlations of both series in Table 3.4, lagged returns and trading volume in level and square forms are incorporated into the respective univariate conditional mean and variance models (Equations (3.1), (3.2), (3.3) and (3.4)). These reconstructive models provide augmented models as Equations (3.13), (3.14), (3.15) and (3.16). The results of these models are summarized in Table 3.5.

Table 3.5: Empirical result of augmented models

	Pre-crisis		Crisis		Post-crisis	
Parameter	R	V	R	V	R	V
Conditional mean equation:						
a_0	-0.0026 (0.0052)	0.728*** (0.1032)	-0.0043 (0.0008)	2.4845*** (0.5275)	-0.0236** (0.0120)	3.415 *** (0.2606)
a_1	-0.2153 (0.3405)	0.4834*** (0.0247)	-0.0073 (0.3967)	0.1307** (0.0546)	-	0.6328*** (0.0282)
a_2	-0.1631 (0.3263)	0.1849*** (0.0273)	0.3487 (0.5181)	0.3233*** (0.0714)	-	-
a_3	-0.1485 (0.2750)	0.2376*** (0.0231)	0.4062 (0.3031)	0.2680*** (0.0555)	-	-
b_1	0.1968 (0.3416)	-	0.3922 (0.3668)	-	-0.0147 (0.0768)	-
b_2	0.1278 (0.3275)	-	-0.1813 (0.4654)	-	-	-
b_3	0.1603 (0.2769)	-	-0.6633** (0.3163)	-	-	-
c_1	0.0003 (0.0006)	1.2827** (0.5221)	-	-1.2585** (0.6350)	0.0027** (0.0013)	- 1.5016*** (0.3455)
c_2	0.0014** (0.0007)	-	-	-	-	0.5806** (0.2709)
c_3	-0.0014** (0.0006)	-	-	-	-	1.3856*** (0.3275)
c_4	-	-	-	-	-	0.7908** (0.3257)
c_5	-	-	-	-	-	2.4476*** (0.3948)

Notes: These models are estimated based on Equations (13), (14), (15) and (16). R and V are denoted as the daily futures return and trading volume in the natural logarithmic form. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors are reported in ( ).

Table 3.5: (Continued)

Parameter	Pre-crisis		Crisis		Post-crisis	
	R	V	R	V	R	V
Conditional variance equation:						
w	1.02×10^{-5}** (4.01×10^{-6})	0.0708** (0.0304)	-	0.0538*** (0.0114)	0.0001 (0.0001)	0.0087 (0.0053)
α_1	0.0765*** (0.0121)	0.0775*** (0.0289)	-	-0.0737*** (0.0167)	0.6443*** (0.0433)	0.0607** (0.0262)
α_2	-	-	-	0.2045** (0.1018)	-0.0042 (0.0208)	-
β_1	0.8781*** (0.0174)	0.5637*** (0.1718)	-	-	-	0.8486*** (0.0745)
λ_1	4.28×10^{6}*** (3.61×10^{-7})	-15.298 * (8.2955)	-	-5.1392*** (1.7038)	6.88×10^{-7} (1.43×10^{-6})	-0.8002*** (0.2037)
λ_2	-4.3×10^{-6}*** (3.60×10^{-7})	-	-	-	-	-
$\alpha+\beta$	0.9547	0.6412	-	0.1308	0.6401	0.9093
Log-likelihood	4922.2	-967.2888	241.735	8.4861	1897.73	-135.3614
ARCH-LM test Statistic	0.241610 [0.6230]	0.1949 [0.6588]	0.0176 [0.8946]	4.3882 [0.1115]	0.2485 [0.8832]	0.0220 [0.8820]
Serial correlation-LM test Statistic	-	-	1.9122 [0.3844]	-	25.284 [0.151]	-
$Q^2(20)$	21.420 [0.208]	17.080 [0.648]	-	14.067 [0.827]	0.7441 [1.000]	11.738 [0.925]

Notes: These models are estimated based on Equations (3.13), (3.14), (3.15) and (3.16). R and V are denoted as the daily futures return and trading volume in the natural logarithmic form. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors and p-values are reported in ( ) and [ ] respectively.

Based on Table 3.5, significant ARCH and GARCH terms in the respective of the conditional variance equation and volatility persistence (sum of ARCH and GARCH terms) in the pre- and post-crisis periods further suggest that shocks on current volatility still remain as important. This serially correlated volatility due to shocks still persists across time after interaction of both series is taken into account. For trading volume, there is a similar finding in the crisis period.

To test the robustness of results from augmented equations, the Ljung-Box Q and ARCH Lagrange Multiplier tests on standardized residuals are not significant at the conventional level. This again suggests that the estimated results adequately describe the first and second moments of both return and volume series.

Table 3.6 reports values of the maximum log-likelihood estimate for univariate and augmented models in each sub-period. The incremental maximum log-likelihood values of all augmented models indicate that included augmented variables in univariate models attribute to high explanatory power in both conditional mean and variance equations of the respective series. This result suggests that misspecification error in univariate models is possible if the interaction of both series is ignored.

Table 3.6: Maximum log-likelihood of univariate and augmented models

	Pre-crisis		**Crisis**		**Post-crisis**	
	Univariate equation	Augmented equation	Univariate equation	Augmented equation	Univariate equation	Augmented equation
R	4905.886	4922.2	241.7350	241.7350	1865.189	1897.730
V	-975.7563	-967.2888	5.3940	8.4861	-161.0037	-135.3614

Notes: Pre-crisis period is from January 3, 2000 to December 29, 2006. Crisis period is from July 1, 2008 to December 31, 2008. Post-crisis period is from July 2, 2009 to July 2, 2012. R and V are denoted as the daily futures return and trading volume in the natural logarithmic form.

3.6.1 Volatility persistence and informational dependence between return and trading volume

Since the interaction of both series is documented in the crisis period and thereafter, volatility persistence of both series in the pre- and post-crisis periods as shown in Table 3.7 attributes to transmission mechanism. In this aspect, it is important to identify how volatility persistence and transmission of shocks between return and trading volume may be related.

Table 3.7: Summary of model specification, augmented variables and volatility persistence

	Model specification		Augmented variables	Volatility persistence		Difference
	Conditional mean	Conditional variance		Univaiate equation	Augmented equation	
Pre-crisis						
R	ARMA (3,3)	GARCH (1,1)	V_t , V_t^2 , V_{t-1}^2	0.9997	0.9547	-0.045
V	AR(3)	GARCH (1,1)	R_t , R_{t-4}^2	0.853	0.6412	-0.2118
Crisis						
R	ARMA (3,3)	-	-	-	-	-
V	AR (3)	ARCH (2)	R_{t-1} , R_t^2	0.5803	0.1308	-0.4495
Post-crisis						
R	MA (1)	ARCH (2)	V_{t-19} , V_{t-19}^2	0.2442	0.6401	0.3959
V	AR (1)	GARCH (1,1)	R_{t-2} , R_{t-3} , R_{t-7} , R_{t-9} , R_{t-12} , R_{t-13}^2	0.7283	0.9093	0.181

Notes: Pre-crisis period is from January 3, 2000 to December 29, 2006. Crisis period is from July 1, 2008 to December 31, 2008. Post-crisis period is from July 2, 2009 to July 2, 2012. R and V are denoted as the daily futures return and trading volume in the natural logarithmic form. Volatility persistence = ARCH term + GARCH term. Difference=Volatility persistence in augmented equation -Volatility persistence in univariate equation.

As shown in Table 3.7, for the pre-crisis, incorporating lag 0 and lag 1 of squared trading volumes into the conditional variance of return equation lead to volatility persistence of return slightly declines from 0.9997 to 0.9547. The incorporating trading volume contributes to a high persistence of 0.9547 for return suggests that shock of trading volume persist for a long time to increase volatility and flow of information to return series. This finding is inconsistent with the finding by Pati and Rajib (2010) in the futures market, where they find that incorporating trading volume into the conditional variance equation for return significantly reduces volatility persistence. Apart from this high persistence, standardized squared residuals of past trading volume and standardized squared residuals of current return are significantly correlated with 0.0938, 0.0891, 0.0484 and 0.0493 at lags 0, 1, 18 and 19, respectively ("Square" column in Table 3.8). These lags correspond to information before days, implying that the information content of trading volume before 1, 18 and 19 days have a significant impact on current return.

However, trading volume has the most pronounced decrease in volatility persistence, where its persistence sharply declines from 0.853 to 0.6412 after incorporating the significant lag 0 of return and lag 4 of squared return (Table 3.7). This indicates that shock of return fully reflects shock of trading volume. Consequently, its low persistence leads to the volatility of return is not correlated with the volatility of trading volume, suggesting that investors would not use return to forecast trading volume ("Square" column in Table 3.8).

For the crisis, none of the series shows any significant cross-correlations of standardized squared residuals ("Square" column in Table 3.8). In post-crisis, adding returns at lags 2, 3, 7, 9 and 12 as well as lag 13 of squared return increase volatility persistence for trading volume from 0.7283 to 0.9093 (Table 3.7). This high volatility persistence consequently provides significant correlations between the volatility of current return and volatility of future trading volume. The significant cross-correlations between both series at lag of 4, 9 and 11 days are recorded as 0.0924, 0.2385 and 0.1884, respectively ("Square" column in Table 3.8). While including the lag 19 days of trading volume in level and square forms increase volatility persistence for return from 0.2442 to 0.6401 (Table 3.7).

Due to its low volatility persistence, the shock of trading volume on return is turned to be transitory, causing volatility of trading volume in 19 days ago and volatility of current return is significantly correlated at 0.0910 ("Square" column in Table 3.8). The increase of persistence engenders the level of informational inefficiency. Apart from this finding, it suggests that increasing volatility persistence in post-crisis reduces the degree of noisiness which relates to the rate of information flow.

In regard to the contemporaneous correlation between the return and volume in pre-crisis, both series are found to have a significant correlation of 0.093 (“Square” column in Table 3.8). This indicates that high return is accompanied by increasing trading volume in the information function of the market. As further observed in column “Square” of Table 3.8, contemporaneous correlations in both crisis and post-crisis are insignificant. For the aspect of dynamic spillover between both series, in pre-crisis, volatility of 19-day-old trading volume is found to Granger-cause volatility of current return. In post-crisis, volatility of 11-day-current return is found to Granger-cause volatility of future trading volume. This volatility spillover occurs with a correlation of 0.1884. In addition, the causality between the volatility of 19-day-old trading volume and volatility of current return is also present with a weak correlation of 0.091.

Such asymmetric behavior in reacting market shocks from the degree of correlation and time span perspectives, supporting the “heterogeneity of traders” hypothesis. The explanation of this finding is most of market participants become risk averse due to their lost confidence in market performance after the crisis, so they will prefer low returns with known risk instead of higher returns with unknown risk. This consequently makes them prefer to use returns in forecasting trading volume with a shorter time span. At the same time, they would mildly use information content of trading volume to forecast returns, providing illiquidity of the market transaction and less informational efficiency.

The significant cross-correlations between the volatility of past trading volume and current return occur with inconsistent time span in the pre- and post-crisis periods. For example, in pre-crisis, these cross-correlations are found to be significant at the lag of 0, 1, 18, and 19 days ("Square" column in Table 3.8). In post-crisis, correlation of both series is only turned to be significant at the lag of 19 days ("Square" column in Table 3.8). For volatility of current return and future trading volume in the same period, they have significant correlations at the lag of 4, 9 and 11 days ("Square" column in Table 3.8).

This unsystematic pattern of time span and different degrees of correlation between the volatility of volume and volatility of return during the period of pre- and post-crisis support the noise traders' hypothesis of price-volume interaction. This suggests that investors tend to hold short or long positions randomly instead of fundamental trading. In this respect, our finding based on CPO futures differs from those in the study by Bhar and Hamori (2005). These authors' finding of causality from a return to volume in the crude oil futures market mildly supports the noise traders' hypothesis because this causality happens with consistent time span at the lag of 3, 9 and 15 days.

Table 3.8: Cross-correlation in the levels and squares of standardized residuals resulting from the augmented models reported in Table 3.5

Lag (i)	Pre-crisis				Crisis				Post-crisis			
	Level		Square		Level		Square		Level		Square	
	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)	V(-i)→R	R→V(+i)
0	-0.0009		**0.0938****		-0.0632		-0.1113		**-0.0809***		-0.0079	
1	0.0154	0.0161	**0.0891****	-0.0348	0.0218	0.0155	-0.061	-0.0800	-0.0237	**-0.104****	-0.0139	0.0078
2	0.0175	0.0286	-0.0165	-0.0335	-0.033	-0.0700	0.0014	0.0660	-0.0089	-0.0130	-0.0187	-0.0001
3	-0.015	-0.0068	-0.0339	-0.0094	0.0031	-0.0216	-0.056	-0.0055	-0.0559	0.0092	-0.0039	0.0063
4	0.0163	-0.0084	-0.0378	-0.0341	-0.005	-0.0646	-0.028	-0.0648	-0.0337	0.0145	-0.0187	**0.0924***
5	-0.014	0.0099	-0.0008	-0.0284	-0.098	**-0.1851***	0.0320	-0.0003	-0.0178	-0.0289	0.0063	0.0402
6	0.0120	-0.0095	-0.0374	0.0043	0.1006	0.0650	-0.03	-0.0478	-0.0663	-0.0119	0.0142	-0.0024
7	0.0190	-0.0035	-0.0128	-0.0268	0.0465	0.0333	0.0371	-0.0493	**-0.074***	0.0095	-0.0122	-0.0045
8	0.0154	-0.0184	-0.0245	-0.0020	-0.092	-0.0115	-0.035	-0.0207	0.0050	0.0487	-0.0112	0.0318
9	-0.008	0.0313	-0.0383	-0.0002	-0.161	-0.0753	-0.037	0.0328	0.0376	-0.0041	-0.0082	**0.2385****
10	-0.011	0.0385	0.0227	-0.0240	-0.083	-0.0475	-0.125	-0.0060	-0.0385	-0.0627	-0.0198	-0.0079
11	-0.003	0.0272	-0.0147	-0.0215	-0.108	-0.0833	-0.077	-0.0096	-0.0271	0.0286	-0.0191	**0.1884****
12	0.0287	-0.0001	0.0227	-0.0080	-0.098	0.1140	0.0172	0.0302	0.0341	-0.0685	-0.0018	0.0074
13	-0.037	0.0349	0.0039	-0.0127	-0.036	-0.0219	-0.081	-0.1056	0.0067	**-0.098****	-0.0138	0.0699
14	-0.010	-0.0136	0.0282	-0.0282	-0.126	0.0181	0.0325	-0.0287	-0.0479	-0.0199	-0.0122	-0.0096
15	0.0088	-0.0147	0.0056	-0.0090	0.0186	-0.0088	0.0892	-0.0571	-0.0284	-0.0296	-0.0119	-0.0170
16	0.0201	-0.0279	-0.0401	-0.0047	0.0517	-0.1194	-0.115	0.0384	-0.0115	0.0246	-0.0023	-0.0129
17	-0.018	0.0307	-0.0087	0.0058	-0.044	-0.0834	0.1488	0.0785	-0.0010	0.0338	-0.0066	0.0002
18	0.0036	0.0239	**0.0484***	-0.0079	0.0581	0.0761	0.0840	-0.0252	-0.0522	-0.0270	0.0722	-0.0218
19	-0.005	0.0383	**0.0493***	-0.0059	-0.083	**-0.1883***	0.0428	-0.0492	0.0354	0.0189	**0.0910***	0.0064
20	-0.018	0.0114	0.0030	-0.0182	0.0204	0.0342	0.0166	-0.0443	-0.0537	0.0027	-0.0055	-0.0099

Notes: R and V are denoted as the daily return and trading volume, respectively. i is the number of days the trading volume lags or leads the return. ** indicates test statistic is more than +2.58 or lesser than -2.58 (statistical significance at the 1% level). * indicates test statistic is more than +1.96 or lesser than -1.96 (statistical significance at the 5% level). "V(-i)→R" represents cross-correlations for lag-effect of past daily trading volume on current daily return, while "R→V(+i)" represents cross-correlations for lead-effect of current daily return on future daily trading volume. The significance of cross-correlations in "Level" column reveals evidence of mean dependence of two series. In the "Square" column, it reveals as evidence of variance dependence.

3.7 Conclusion

Price-volume interaction has been the basic framework in determining demand and supply of a commodity. Unlike the existing literature, such interaction in times of low and high extreme price movements is emphasized in the CPO futures market since the market provides information transmission more effectively than the underlying market. Apart from that, different movement of conditional volatility of futures return during 2000-2012 is separated into the pre-crisis, crisis and post-crisis periods.

There are three findings from the analysis. First, during the pre-crisis period, information transmission between trading volume and return is found to occur contemporaneously. Second, during the crisis period, there is no volatility spillover between both series. Third, in post-crisis period, volatility spillover occurred from the current return to future trading volume, in addition to volatility spillover from past trading volume to current return which is also present.

As for comparisons between the findings in pre-crisis and post-crisis, this study finds evidence in supporting the "heterogeneity of traders" hypothesis from two perspectives. From the perspective of correlation, current return and future trading volume in post-crisis are highly correlated as compared to the correlation between past trading volume and current return to pre-crisis. From the perspective of time span, volatility of trading volume required a longer time span to correlate with the volatility of return in post-crisis as compared to pre-crisis.

Furthermore, the incorporating interaction between the return and volume increases volatility persistence of return in post-crisis. This indicates that the process of incorporating private information into prices reduces the degree of noisiness, indicating that information flow is less efficient. Particularly significant cross-correlations between the volatility of past trading volume and current return occurred with inconsistent time span in the pre- and post-crisis periods, indicating that participants respond randomly to the information content of trading volume in forecasting return. This evidence supports the noise traders' hypothesis.

Overall, an important finding of this study indicates that return predictability based on trading volume is required longer time span after crisis as compared to before the crisis. This behavior of CPO futures contracts across the crisis is different from those reported in the literature for non-agricultural futures. This study hypothesizes that such finding is probably due to a higher risk as perceived by uninformed traders that causes the distortion and imbalance in CPO trading, particularly after the crisis.

To support such finding, this study provides an intuitive explanation. After the deteriorating economic condition, the under confidence among market participants would result them to become more risk averse by preferring low returns with known risk instead of higher returns with unknown risk. This makes them prefer to use return to forecast trading volume with a shorter time span. As a consequence, the illiquidity of transaction in the marketplace would lead to prices may take a longer time to reflect the full set of information from trading volume.

The policy implication is clear. Although trading volume is found to be less efficient in transmitting information to reflect price shocks after the economic downturn, market participants can use such finding that relates to possible shocks to limit uncertainty in their futures trading with a better market timing. Furthermore, by understanding the interaction between both series, producers can make use of interaction between both series to assess the quality of price in allocating CPO inventories optimally for their production based on the direction of change in CPO futures price as an expected output price.

CHAPTER 4: INVESTOR DEMAND, MARKET EFFICIENCY AND SPOT-FUTURES RELATION: FURTHER EVIDENCE FROM CPO

4.1 Introduction

Explaining the relationship between commodity spot and futures prices has been a long-standing agenda in financial economics. Such price relationship either price level in the long run or price changes in the short run is frequently determined by investor demand, in part because not all market participants are involved in producing or consuming a commodity, but also due their expectation to make a profit by holding physical stock of a commodity from a subsequent price rise. For those who have such expectation, they tend to intervene in the futures markets by selling futures contracts with higher prices to those who wish to acquire the stocks or inventories. As a consequence, producers or stock owners are required to pay a high premium in the form of the difference between spot and futures prices at maturity of the contract.

To protect income, producers make decisions by pushing commodity price until the futures price is sufficiently higher than the spot price. To obtain riskless profit, rational arbitrageurs who recognize this inefficient market are encouraged to simultaneously buy a commodity in the spot market and sell futures to cover net carrying costs. Their participation theoretically enhances market liquidity and improves prediction of future spot prices based on futures prices. However, the rise of commodity price that originates from the futures markets is presumed to overshoot spot prices, leading to the occurrence of persistent and significant speculative bubbles. Subsequently, it might cause consumers to suffer from it. Moreover, this price distortion due to the unpredictability of producers' income tends to reduce investment and economic growth (Loayza, et al., 2007). Therefore, this chapter attempts to answer the following research question: **how does the efficiency of CPO futures price changes influence its correlation with CPO spot price changes when both markets stay in strong contango, weak contango and backwardation?** This question has been of utmost importance to participants in the spot and futures markets to offset their positions in strengthening their portfolio investments. This can be done by emphasizing how different market transition contribute to investor demand and cause the commodity price to oscillate beyond its normal range. In this chapter, the presence of structural break of series is taken into account by separating the market conditions into strong contango, weak contango and backwardation.

Tilton et al. (2011) and Östensson (2011) state that the shifting investor demand for or supply of spot of a commodity varies when market transition either from contango to backwardation or vice versa. From this aspect, the efficiency of the futures market is expected to influence the implication of commodity prices in stabilizing investors' returns. As an example, if futures market is efficient, investors can adjust their decisions in executing inter-temporal arbitrage strategies between spot and futures markets by trading liquid and physical stocks of the commodity. For producers, they can relate the efficient futures market to the spot market under different market conditions as a benchmark of their precautionary demand for the commodity.

Numerous studies have looked the aspect of whether investors in the futures markets act as a major force that distorts and drives up the prices up in a variety of situations. For instance, Kocagil (1997) tests the hypothesis of speculation that stabilizes spot prices for the copper, gold, silver and aluminum. From the sample period of 1980-1990, the author's result rejects this stabilization hypothesis for all four markets. Kaufmann and Ullman (2009) consider the roles of hedgers and speculators in the West Texas Intermediate (WTI), Brent-Blend, Maya, Bonny Light and Dubai-Fateh crude oil markets. Their result supports that speculation activities are likely to exacerbate the market fundamentals when high fluctuations in futures prices as opposed to spot prices. Bos and Van der Molen (2012) develop and use their own non-parametric test and empirical model to examine the impact of futures speculation on prices of coffee in the Arabica during 1989-2008. They find that factors such as harvest sizes, inventories, futures market microstructure, and price elasticity of demand enhance the impact of futures speculation on rising coffee price. They also suggest that speculation is one of the contributors of input for the other commodities.

Following the study by Mahalik et al. (2014) in the case of Indian commodity markets during 2005-2008, they find that effect of past innovation in the futures market on spot volatility happens frequently in the agricultural future index, energy future index and aggregate commodity index. In the recent study by Huchet and Fam (2015), they find that the coffee, sugar, corn and wheat returns are systematically modified by speculative transactions in futures markets during 1998-2013. In the same sample period, speculative pressure from futures markets seems to have the weak effect or no effect on rice, cocoa and soybean prices due to their different market features. For examples, the rice return is found to be insufficiently correlated with the size of futures markets and the relative share of long positions taken by speculators among the sum of open positions. Next, cocoa returns are not excessively speculated even through fundamental factors explain a continuous rise in its price. In addition, the soybean returns are found as not sensitive to positions taken by non-hedgers. Consequently, its returns do not depend on speculation, even though its market seems to be highly efficient and liquid.

With market features, studies on the spot-futures relation should be expected to produce mixed findings, depending on different types of commodity. However, in the particular case of soft commodities with one of the most liquid and active futures markets in the world such as the Malaysian crude palm oil (CPO) futures market has been rather little in terms of its influence on the spot market. Moreover, examining the relationship between spot and futures prices without relating to the efficient futures pricing could potentially provide the spurious explanation about the impact of investor demand on commodity prices. Therefore, this study adds to the current literature by focusing on whether efficiency for spot market or futures market or both has indeed increased the correlation between spot and futures prices in the case of Malaysian CPO during the strong contango period instead of weak contango and backwardation periods.

CPO is of interest among market participants due to the growing demand for biofuels and foods in the emerging countries. In this regard, some policies have implications for energy and food consumptions. In Malaysia, the National Biofuel Policy has been implemented since March 21, 2006 to promote the use of biodiesel derived from palm oil as environmental friendly and sustainable energy source in order to reduce dependency on fossil fuels. It also aims to stabilize and boost palm oil prices through export, research and development activities (Gain Report, 2014). In solving the issue of inequality of income distribution and poverty, the National Agro-Food Policy has been implemented since September 28, 2011, ensuring steady and resilient food related industries through the developing agricultural sector. This, in turn, would increase farmers' revenue and directly curb inflation to maintain a sufficient amount of food supplies for consumption in the country (Ministry of Agricultural & Agro-Based Industry Malaysia, 2014).

More specifically for this study, the degree of weak-form efficiency in terms of return and variance for spot and futures markets during the strong contango, weak contango and backwardation periods are measured by using various tests. Then, correlation coefficients between spot and futures price changes are computed for convenience yields of 0 per cent, 1 per cent, 2.5 per cent, 5 per cent and 10 per cent during each sub-period. To that end, the association between the degree of pricing efficiency for spot and futures markets and the degree of correlation coefficients of both markets is emphasized for three sub-periods. Apart from the spot-futures relation in the case of Malaysian CPO, the empirical result which relates to the degree of efficient futures pricing can provide implications for market participants to adjust their response based on the arrival of new information in making decisions under different market transition.

This chapter is organized as follows. Section 4.2 briefly explains the linkages between market transition and investor demand/supply by emphasizing the argument from Tilton et al. (2011) and Östensson (2011). Apart from their argument, spot and futures prices should have closed correlation during strong contango instead of weak contango and backwardation. Section 4.3 explains the market efficiency for the respective commodity spot and futures markets or both. In turn Section 4.4 presents the data and methodology: identifying period of strong contango, weak contango and backwardation based on the cost-of-carry model (Section 4.4.1); various tests of weak-form efficiency for respective spot and futures markets (Section 4.4.2); and, simple correlation coefficient between spot and futures price changes (Section 4.4.3). Subsequently, Section 4.5 presents empirical results and findings for strong contango, weak contango and backwardation in terms of two perspectives: weak-form market efficiency of CPO spot and futures markets (Section 4.5.1); and correlation coefficients between daily CPO spot and futures price changes (Section 4.5.2). Lastly, Section 4.6 concludes the discussion of the study.

4.2 Linkages between Market Transition and Investor Supply/Demand

In considering the market transition from contango to backwardation or vice versa, Keynes (1930) who firstly observes that speculators who are holding long positions in the futures contract will obtain a risk premium during the backwardation period. When they take short positions in order to receive a risk premium, the contango period will be in existence. This demonstrates that the occurrence of backwardation or contango depends on whether speculators are "net long" or "net short". However, Working (1953) opposes this theory because speculators require a risk premium based on their different opinions about future price changes of a commodity, where futures price is regarded as being equal to the expected spot price. The futures price is also interrelated with current spot price based on storage theory, where the futures price should not be greater than the current spot price plus various carry charges such as storage cost and the convenience yield.

The futures market is in strong contango when the futures price exceeds the expected future spot price as well as the discounted futures price also greater than the current spot price. The rising futures price relative to spot price provides a situation for a commodity to be available for sale to prompt market at a discount with the same commodity for delivery at future dates. The weak backwardation occurs when current spot price lesser than futures price and greater than the discounted future spot price, while zero backwardation occurs if the current spot price equals the discounted future spot price. According to Pindyck (2001, p.17), weak backwardation and zero backwardation are said to be in contango, but this study refers both market conditions as weak contango.

When the futures market is in backwardation, both contemporaneous futures and discounted futures prices are lesser than expected future spot price. In the other word, the futures prices of a commodity are either below the spot prices or insufficiently above the spot price to cover storage cost, which allows participants to buy a commodity in the futures market and sell the same commodity in the spot market. In this situation of scarcity, future stocks will be not physically available for sale today because a greater storage and inventories of a commodity are needed to reallocate for the short-run production by reducing production costs. Consequently, demand for storage and convenience yield will be quite high because market participants anticipate that near-term supplies are inadequate. To provide a buffer against high fluctuation in production due to the unpredictable shift in demand-supply during that period, the high short-run production cost is required instead of the long-run production cost.

As mentioned in the Introduction section, without using the available data for copper prices, Tilton et al. (2011) develop curves for producer supply, consumer demand, investor demand and total demand. They illustrate that speculators or investor demand in the futures market can comparably influence spot prices when the market in the contango (exceeds the cost of storage and interest). They conclude that investor demand, which is associated with rising futures prices in excess supply condition for future production will depress spot prices. As a result, investor demand is most likely to be occurred during the strong contango period for copper due to investors' decision in buying stocks drive the commodity price up even their stocks are declining.[6] Overall, their hypothesis of investor demand in the case of copper, stating that futures market dominates a role of investor demand during the strong contango period because future stocks are physically available for sale in the futures market. As a result, spot and futures prices would be closely correlated in the strong contango.

They further provide two possible explanations to argue that investor demand in the copper futures market may also play its role in the backwardation or weak contango. First, investors anticipate that inadequacy of short-term supply of actual physical copper before the maturity date of the futures contracts. Second, investors are willing to pay a premium to hold physical copper. However, investor demand on the futures market is determined by the short-term consideration which contributes to the weak effect of futures prices on spot prices. Furthermore, the higher spot price than the futures price cannot allow investors to buy physical stocks on futures markets and sell them immediately on the spot market. This unfeasible of inter-temporal arbitrage makes the

[6] Refer to Tilton et al. (2011), they address that investor demand likely occurrs during the period of strong contango (p.191, para 7) and it can push up the price of a commodity even when investors' stocks are declining (p.193, para 2).

correlation between spot and futures prices is turned to be weaker during the backwardation period.

They depict an investor demand curve for spot material that is a function of the spot price. In this sense, Östensson (2011) concurs with their basis of conceptual and theoretical arguments on spot and futures prices during the period of strong contango and backwardation by considering investor demand for and supply of spot material should be a function of the difference between futures and spot prices. As shown in Figure 4.1, when this difference is larger than the cost of holding stocks, there is a strong contango and investors demand spot material. When this difference is lower than the cost of holding stocks but larger than zero, the market is in a weak contango and investors supply spot material to the market. Finally, if such difference is less than zero, the market is in backwardation and again, investors supply spot material (Östensson, 2011: p. 373).

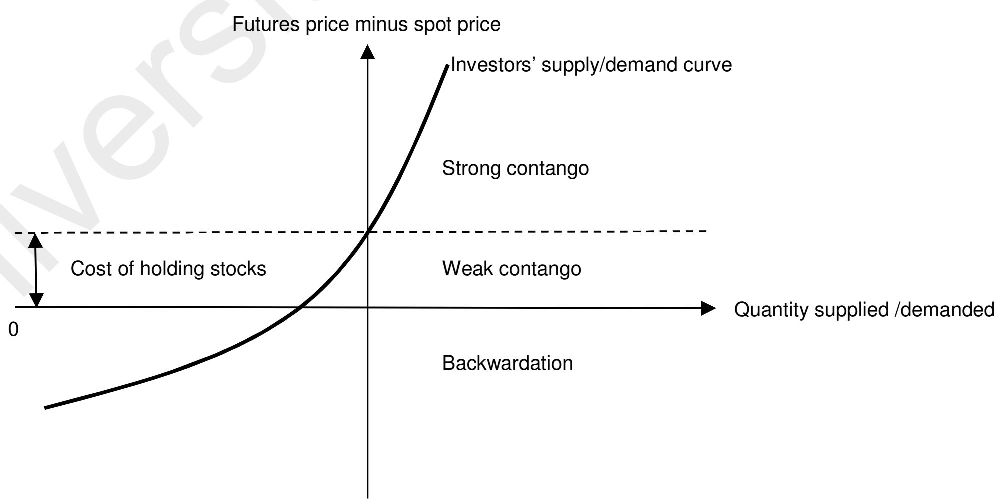

Figure 4.1: Investor demand for and supply of spot material
Source: Adopted from Östensson (2011, p. 373).

With empirical evidence for copper, Gulley and Tilton (2014) further find that the value of correlation coefficient between spot and futures price changes approximate to one during the period of strong contango. Meanwhile, this correlation is found to be considered as high during the period of backwardation and weak contango due to market participants' concern about their near-term shortages. Moreover, Fernandez (2015) extends the scope of examining this hypothesis of investor demand by considering aluminum, copper, lead, nickel, tin, and zinc from the London Metal Exchange during 1992-2014. The author uses various robustness tests by controlling for conditional heteroscedasticity in returns, detecting unconditional mean-return breakpoints, and detecting and removing outlying observations. These tests indicate that a linkage between spot and futures markets for six industrial metals traded is weak during the contango period. For this study, the soft commodity such as CPO is used in examining such relationship during these sub-periods.

4.3 Efficiency of Commodity Spot and Futures Markets

Market efficiency relates to spot-futures relation. Garbade and Silber (1983), Oellermann et al. (1989), and Schroeder and Goodwin (1991) suggest the futures price plays a vital role in price discovery process for the underlying spot market under the hypothesis of market efficiency. The futures market is efficient when futures prices equal expected future spot prices plus or minus a constant, a time-varying risk premium. Furthermore, Silvapulle and Moosa (1999) find that the futures price more efficient than the spot price. The reason is it responds to new information faster than spot prices. As a result, it provides lower transaction costs and flexibility of short-selling activities in the futures market.

In the recent study, Caporale et al. (2014) incorporate an endogenous convenience yield into the cost-of-carry model to obtain the time-varying spot and futures markets' contribution to price discovery in the West Texas Intermediate (WTI) crude oil. They find that the prices of futures contract with shorter maturities dominant a role of price discovery during 1990-2008. Focusing on the effect of futures prices of four contracts maturing in one, two, three, and four months on spot prices for the WTI crude oil through the application of wavelet coherency analysis, Chang and Lee (2015) find that dynamic correlations between both prices in time-frequency domain contribute to more significant dynamic causality between spot price and futures prices of contract with shorter maturity during 1986-2014.This suggests that the short-term futures prices in the oil markets are more efficient in implementing price discovery mechanism than the long-term futures prices.

To test the efficiency of commodity futures markets, some studies indicate that the condition for a futures market to achieve efficiency is futures and spot prices should be cointegrated. For instance, Tomek and Gray (1970), Kofi (1973), Leuthold (1974), and Martin and Garcia (1981) regress spot prices on lagged one of futures price. They conclude that intercept of zero and a unit slope on futures prices in the simple regression model indicates the market is efficient, suggesting that futures prices should be unbiased predictors of future spot prices. Furthermore, McKenzie and Holt (2002) argue that the market may be efficient and unbiased in the long run, but may experience inefficiency and pricing biases in the short run. With the error correction and generalized-quadratic ARCH models, their argument is found to be supported in the live cattle, hogs, and corn futures markets during 1959-2000. This finding is further found as consistent with the finding by Liu (2009) in the Malaysian CPO futures market during 2001-2007. The author's finding based on vector error cointegration model indicates that CPO spot and futures prices have the long-run relationship for all forecasting horizons, but this model rejects the short-run efficiency.

In terms of econometric modeling, Westerlund and Narayan (2013) state that both spot and futures prices are not necessarily cointegrated with a unit slope on futures prices. This contributes to endogeneity problem, causing the conventional ordinary least squares estimator of slope on futures prices and the test statistic would be biased and misleading. To produce consistent estimators, they incorporate conditionally heteroscedasticity into the model based on the weighted least squares method. Then, they use the model to test market efficiency and unbiasedness of gold, silver, platinum and oil futures prices during 2005-2011. Their result reveals that spot and futures prices for gold, silver and platinum have cointegration relationship with a slope of one and otherwise in the oil market.

Some studies show that different prevailing economic and political conditions cause futures price to exhibit time-varying behavior in predicting future spot price in the long run. For instance, Charles and Darné (2009) use new variance ratio tests to explore the relationship between weak-from efficiency and deregulation in the crude oil spot markets for Brent and West Texas Intermediate (WTI) during 1982-2008. Their result indicates that the Brent crude market seems to be more efficient than the WTI market. This attributed to the process of deregulation during 1994-2008, making the WTI crude oil return to become less predictable.

In the subsequent study, Inoue and Hamori (2014) find that spot and futures prices for the Indian commodities are cointegrated during the more recent sample period of 2009-2011.This suggests that increasing trading volume of the futures market since 2009 improves the efficiency of futures price in producing an unbiased predictor of the spot price. To account the possibility of a structural break in testing the efficiency of futures market for crude oil, Stevens and de Lamirande (2014) generalize the basis regression by testing the parameter stability for two sub-periods: 1985-2008 and 2008-2013. With a strong rejection of the null hypothesis of parameter stability, they further test the generalized null hypothesis of efficiency. Then, they find that a structural change in the behavior of the futures market in May 2008 which reveals the evidence of inefficiency.

The market efficiency is also characterized by different commodities. As an example for futures markets, Kristoufek and Vosvrda (2014) propose the Efficiency Index to examine the degree of futures markets for twenty-five types of commodity during 2000-2013. These commodities are categorized into metal, energies, soft commodities, grains and other agricultural commodities. They find that energy commodities are the most efficient, followed by soft commodities, grains, and metals, while the other agricultural commodities, namely gold live cattle and feeder cattle are the least efficient. For spot markets, Charles et al. (2015) evaluate the weak-form market efficiency and degree of return predictability for three precious metals such as gold, silver, and platinum during 1977-2013. With the application of automatic portmanteau and variance ratio tests, they find that the gold and silver markets exhibit a downward trend in return predictability which reveal evidence of improving pricing efficiency from the late 1970s. In both efficient markets, the gold market is found to be the most efficient due to it acts as an attractive investible asset in providing an effective risk management. Meanwhile, such a downward trend of return predictability cannot be found in the platinum market, indicating that the market is inefficient.

4.4 Data and Methodology

Data for the daily CPO spot prices and the daily CPO futures prices of four contracts maturing in three, six, nine, and twelve months are chosen for this study, covering the period from January 3, 2000 to December 31, 2014 for each series. These futures contracts of CPO are officially traded as two sessions from the trading floor of the Bursa Malaysia. The first trading session: Malaysian time from 10:30 a.m. to 12:30 p.m. The second trading session: Malaysian time from 3:00 p.m. to 6:00 p.m. Each futures contract expires on the 15th day of the delivery month. These daily prices are obtained from the Bursa Malaysia and transformed to become daily changes in the logarithmic prices based on Equation (4.1).

$$R_t = \ln(P_t / P_{t-1}) \tag{4.1}$$

where, R_t = the rate of daily return for CPO spot and futures at time t; P_t = the daily CPO spot and futures prices at time t (RM); and $\ln$ = the natural logarithm.

For the same sample period, the daily data of deposit rates which are obtained from the Central Bank of Malaysia will be further used in the analysis. This study involves three-step analysis. The preliminary step is to identify the strong contango, weak contango and backwardation periods based on the cost-of-carry theory by assuming convenience yields are 0 per cent, 1 per cent, 2.5 per cent, 5 per cent and 10 per cent, respectively. Then, it is followed by testing the efficiency of spot and futures markets for each sub-period by assuming no convenience yield. Lastly, correlation coefficients between spot and futures price changes are computed for convenience yields of 0 per cent, 1 per cent, 2.5 per cent, 5 per cent and 10 per cent during each sub-period.

4.4.1 Cost-of-carry model: identifying period of strong contango, weak contango and backwardation

Under the situation of no-arbitrage, the relationship between spot and futures prices of a commodity is explained by the cost-of-carry model (Pindyck, 2001). With the application of the model which is given by Equation (4.2), the expected (future) spot price or futures price is obtained for delivery for T months forward $(F_{t,T})$.

$$F_{t,T} = S_t(1 + r_t + C_t - \psi_t)^{t,T} \tag{4.2}$$

where, S_t = current spot price at time t ; C_T = annualized storage cost in per cent, which includes the costs of handing, spoilage, shrinkage, shipping and others; ψ_t = convenience yield at time t; r_T = the deposit rates at time t; and T = the number of months divided by 12 (3/12, 6/12, 9/12, and 12/12).

The prices of delivery for 3-month, 6-month, 9-month and 12-month forward are obtained by assuming convenience yields of 0 per cent, 1 per cent, 2.5 per cent, 5 per cent and 10 per cent, respectively.[7] These futures prices are discounted and compared to spot prices. $\hat{F}_{t,T}$ from Equation (4.2) is compared with S_t in order to identify the strong contango, weak contango and backwardation periods in the sample. Specifically, the different conditions are shown as follows:

[7] Since spoilage of CPO depends on seasonal production, storage cost of the commodity will vary from time to time. In this regard, this study assumes that the annual cost is 5 per cent.

If $\hat{F}_{t,T} > S_t$ and $\frac{\hat{F}_{t,T}}{(1+r_t+C_t-\psi_t)^{t,T}} > S_t$, the futures market will be in strong contango;

if $\hat{F}_{t,T} > S_t$ and $\frac{\hat{F}_{t,T}}{(1+r_t+C_t-\psi_t)^{t,T}} < S_t$, the futures market will be in weak contango;

and

if $\hat{F}_{t,T} < S_t$ and $\frac{\hat{F}_{t,T}}{(1+r_t+C_t-\psi_t)^{t,T}} < S_t$, the futures market will be in backwardation.

4.4.2 Various tests of weak-form market efficiency

To achieve efficiency for spot and futures markets, price movements in spot and futures should be characterized by a random walk process. Then, linear movement of changes in the basis (difference between futures and spot prices) should be uncorrelated. Furthermore, there is no transaction cost on the basis. To check whether the respective spot and futures price changes on a particular day contain all predictable information about its own past values or the other markets, the efficient market is investigated by testing the random walk hypothesis from three perspectives.

First, the autocorrelation of returns is examined via the Ljung-Box Q test (Ljung and Box, 1978) and runs test (Wald and Wolfowitz, 1940). The null hypothesis of no autocorrelation coefficients for the first lag k is rejected, if the Ljung-Box Q test statistic (Equation (4.3)) is greater than the critical value from the chi-squared distribution with k degree of freedom.

$$Q(k) = T(T+2)\sum_{i=1}^{k} \hat{\rho}_k^2 / (T-k), \text{ where } \hat{\rho}_k^2 = \frac{Cov_{R_t, R_{t-k}}}{\sqrt{Var_{R_t} Var_{R_{t-k}}}} \tag{4.3}$$

For the runs test, there are three types of price changes: positive (m+), negative (m-) and no changes (m0). Random walk process means that change of prices with same sign happens frequently. Based on expected number of runs $(E(R))$ and variance for a number of runs $(Var(R))$, price changes are revealed do not follow random walk process if absolute test statistic (Equation (4.4)) is greater that absolute critical value which asymptotically follows the standard normal distribution.

$$Z(R) = \frac{R \pm 0.5 - E(R)}{\sqrt{Var(R)}} \sim N(0,1) \tag{4.4}$$

where, $E(R) = (T+1) - \left[\sum_{i=1}^{3} m_i^2\right] / T$; $Var(R) = \frac{\sum_{i=1}^{3} m_i^2 \left[\sum_{i=1}^{3} m_i^2 + T(T+1)\right] - 2T\sum_{i=1}^{3} m_i^3 - T^3}{T^2(T-1)}$;

and -0.5 if $R < E(R)$ and +0.5 if $R > E(R)$.

Second, basis (b_t , difference between natural logarithms of spot and futures prices at time t) is a linear combination of spot and futures prices, where its autocorrelations are assessed via the Ljung-Box Q test Autoregressive (AR) model at order one as Equation (4.5) (Brookfield and Garret, 1996).

$$b_t = \alpha b_{t-1} + \varepsilon_t, \tag{4.5}$$

Then, b_{t-1} is subtracted in both sides of Equation (4.5). The expression for changes in the basis as Equation (4.6) is used to obtain the first order of autocorrelation for basis changes.

$$b_t - b_{t-1} = \alpha b_{t-1} + \varepsilon_t - b_{t-1}$$

$$\Delta b_t = (\alpha - 1) b_{t-1} + \varepsilon_t \tag{4.6}$$

Based on Equation (4.6), if $\alpha = 1$, the following Equation (4.7) produces $\rho(1) = 0$ and indicates that the basis is unpredictable. This case suggests that spot and futures markets are inefficient because there is nothing to pull both prices back to an equilibrium level.

$$\rho(1) = \frac{Cov(\Delta b_t, \Delta b_{t-1})}{Var(\Delta b_{t-1})} = \frac{(\alpha - 1)}{2} \tag{4.7}$$

If $\alpha = 0$, the basis has stationary movement with white noise process. Subsequently, it is predictable because $\rho(1) = -0.5$. This predictability of basis ensures that prices of spot and futures markets have cointegration relationship and function as one market. Under this situation, the first order autocorrelation coefficient from Equation (4.7) should be negative $(\alpha < 1, \rho < 0)$ in basis changes (Brookfield & Garret, 1996).

The significance of Ljung-Box statistic on autocorrelation properties of the basis and basis changes, suggesting that both markets are efficient because predictably of basis changes reveals adjustment of any deviation of the basis from zero occurs simultaneously. The autocorrelation coefficient of basis changes relates to the market efficiency with the respect to mean reversion for basis changes. The higher absolute autocorrelation coefficient in basis changes contributes to large mean reversion and hence the market becomes more efficient.

Third, the variance of returns is assessed by the Lagrange multiplier (LM) test for autoregressive conditional heteroscedasticity (ARCH) (Engle, 1982) and variance ratio (Lo & Mackinlay, 1988, 1989; Wright, 2000). ARCH model is written as Equation

(4.8). The test statistic value (Equation (4.9)) greater than critical value from chi-squared distribution indicates that the existence of volatility clustering.

$$\sigma_t^2 = w + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 \tag{4.8}$$

$$\chi^2 = R^2 T \tag{4.9}$$

where, σ_t^2 = variance of error terms; R^2 = R-squared from Equation (4.8); and T = the number of observations.

In testing the increment of variance of random walk by the variance-ratio (VR) methodology, the null hypothesis of homoscedastic increments is set to indicate that the variance of error terms is independently and identically distributed with normal random variables (IID). This distribution follows a martingle difference sequence. Based on the seminal works of Lo and Mackinlay (1988, 1989) and Poterba and Summers (1988), VR at lag q is defined as the ratio between (1/q) th of the q-period return to the variance of the one-period return. Following Wright (2000), the VR is written as Equation (4.10).

$$VR(q) = \frac{\sigma_c^2(q)}{\sigma_a^2(q)} \tag{4.10}$$

where, $\sigma_c^2(q) = (Tq)^{-1} \sum_{t=q}^{T} \left(x_t + ... + x_{t-q+1} - q\hat{\mu} \right)^2$; $\sigma_a^2(q) = T^{-1} \sum_{t=1}^{T} \left(x_t - \hat{\mu} \right)^2$; and

$$\hat{\mu} = T^{-1} \sum_{t=1}^{T} (x_t)$$

Under the assumption of homoscedasticity, the null hypothesis of $VR(q) = 1$ is set. Test statistic which follows the standard normal distribution asymptotically is given as

Equation (4.11). The test statistic value is greater than the critical value from a standard normal distribution reveals rejection on the null hypothesis of homoscedasticity.

$$Z(q) = \frac{VR(q) - 1}{\phi^*(q)^{1/2}} \sim N(0,1) \tag{4.11}$$

where, $\phi^*(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q} \right]^2 \delta(j)$; and $\delta(j) = \frac{\sum_{t=j+1}^{T} \left(x_t - \hat{\mu}\right)^2 \left(x_{t-j} - \hat{\mu}\right)^2}{\left[\sum_{t=1}^{T} \left(x_t - \hat{\mu}\right)^2 \right]^2}$

4.4.3 Simple correlation coefficient between spot and futures price changes

The simple correlation coefficient between the changes in spot and futures prices $\left(r_{R_S,R_F}\right)$ is calculated for each sub-period by using Equation (4.12).

$$r_{R_S,R_F} = \frac{Cov_{R_S,R_F}}{\sqrt{Var_{R_S} Var_{R_F}}} \tag{4.12}$$

where, Cov_{R_S,R_F} = sample covariance between CPO spot and futures returns; Var_{R_S} = sample variance of CPO spot return; and Var_{R_F} = sample variance of CPO futures return.

4.5 Results

4.5.1 Weak-form market efficiency of CPO spot and futures markets: strong contango, weak contango and backwardation

Table 4.1 presents the results of Ljung-Box statistics of order 10 for four series (spot return, futures return, basis and basis change) and runs test statistics for two series (spot and futures returns). Their results of hypothesis testing on weak-form market efficiency are based on independence of changes in price by assuming constant variance and identical distribution of returns perspectives.

By using Equation (4.3), Ljung-Box statistics of order 10 for spot return during the strong contango and weak contango periods are found cannot reject the null hypothesis of independence and identical distributions. This null hypothesis for futures return is only failed to be rejected during the strong contango period. In contrast, by using Equation (4.4), runs test statistics provide rejections of a random walk for both returns in the same periods. This attributed to the number of runs is significantly lower than expected run.

As shown in Table 4.1, significant Ljung-Box statistics of basis and basis change indicate that basis changes do not follow a random walk process. This further suggests that basis changes are predictable and market participants can use the historical pattern of price in forecasting the future movement for both returns. It is further observed that the strong contango period provides the highest first order autocorrelation coefficients for basis change with the value of -0.305. This indicates that basis bounces faster towards its mean. Eventually, both returns move faster back to their average. This subsequently produces predictable of proportional of changes in both returns.

Table 4.1: Results of weak-form efficiency from mean perspective, 2000-2014

Lag	Strong contango				Weak contango				Backwardation			
	Spot return	Futures return	Basis	Basis change	Spot return	Futures return	Basis	Basis change	Spot return	Futures return	Basis	Basis change
1	0.075	0.060	0.851	-0.305	0.008	0.050	0.734	-0.285	-0.018	-0.025	0.921	-0.209
2	-0.068	-0.012	0.792	-0.061	0.016	0.048	0.623	-0.080	0.103	0.087	0.874	-0.045
3	0.024	0.038	0.751	0.016	-0.017	0.018	0.553	0.011	-0.027	-0.025	0.835	-0.008
4	0.082	0.054	0.705	-0.019	0.005	-0.038	0.475	-0.085	0.028	0.049	0.797	-0.043
	-0.017	0.015	0.665	0.039	-0.010	-0.022	0.448	0.041	-0.051	-0.059	0.766	-0.024
6	-0.013	0.065	0.614	-0.037	-0.010	-0.021	0.397	-0.016	0.059	0.082	0.739	0.027
7	0.018	0.012	0.573	-0.077	-0.016	-0.043	0.357	0.003	-0.046	-0.030	0.707	-0.058
8	0.037	0.048	0.555	0.056	-0.006	0.007	0.313	-0.041	0.116	0.132	0.685	0.049
9	0.004	-0.039	0.521	0.038	0.052	0.079	0.289	-0.020	-0.003	-0.006	0.655	-0.019
10	-0.028	0.008	0.476	-0.016	0.012	0.036	0.278	0.037	0.059	0.040	0.628	-0.068
LB (10)	12.204	9.9672	2614.2**	65.893**	4.4787	19.023*	2475.3**	112.66**	67.802**	74.589**	10597**	107.58**
m+	136	144	-	-	282	269	-	-	439	451	-	-
m-	142	148	-	-	279	272	-	-	448	453	-	-
m0	32	13	-	-	37	22	-	-	50	31	-	-
E(R)	525.966	520.688	-	-	978.1466	988.786	-	-	1577.675	1570.081	-	-
Var (R)	59.1014	63.256	-	-	108.612	100.916	-	-	138.3729	141.6249	-	-
Runs test statistic	-28.03**	-27.06**	-	-	-36.4**	-42.34**	-	-	-54.422**	-53.323**	-	-

Notes: Weak contango includes weak backwardation. Backwardation is known as normal backwardation or strong backwardation. LB(10) corresponds to the Ljung-Box test for autocorrelation with 10 lags, where its Q statistics are calculated by using Equation (4.3). m+ denotes as the number of occurrences for positive value. m- denotes as the number of occurrences for negative value. m0 denotes as the number of occurrences for zero value. The runs test statistics are calculated by using Equation (4.4). The autocorrelation coefficients for basis changes at lag 1 are calculated by using Equation (4.7). ** denotes as significant at the 1% level. * denotes as significant at the 5% level.

To explore further market efficiency based on the variance of returns, ARCH-LM and variance-ratio (VR) tests are employed by using Equation (4.9) and Equation (4.11), respectively. Table 4.2 shows that order 10 of ARCH-LM test statistics are significant at the 1 per cent level. These statistics provide evidence of existing ARCH effect in both markets for all three sub-periods. This study further examines mean reversion using VR tests which are associated with intervals q = 2, 4, 8 and 16. Under the maintained hypothesis of homoscedasticity, the VR test provides weak rejection of the null hypothesis of a random walk process for the CPO spot market during the backwardation period at the 10 per cent level (one rejection out of the four cases examined).

For the CPO futures market, a similar test only provides weak rejection of the null hypothesis of a random walk process at the 5 per cent level during the backwardation period (one rejection out of the four cases examined). Meanwhile, during the strong contango period, strong rejections on the null hypothesis for the CPO futures market at the 5 and 10 per cent levels (two out of the four cases), indicating that the futures market during that period is the least efficient. While during the weak contango period, this market is found to be the most efficient.

Based on mean perspective, high mean reversion during the strong contango period consequently leads to the occurrence of a random walk process in the futures market. However, from variance perspective, the futures return does not follow random walk process when there is a sufficient futures price above spot price. This finding can be explained by the fact of strong contango period still provides a role of futures return in speculating CPO prices. In this regard, our results indicate that a non-random walk process cannot be a complete description of market price behavior because it ignores existing infrequent trading or time-varying volatilities in both markets. The rejection of a random walk hypothesis does not necessarily imply the inefficiency of market price formation (LeRoy, 1973; Lucas, 1978).

Under the assumption of risk neutrality, the weak form of the efficient market hypothesis reduces to the random walk hypothesis, the statement that returns are entirely unpredictable based on its own past movement. Although there is a lack of evidence of daily CPO futures price changes follow a non-random walk process during weak contango period, this study concludes that the futures market in weak contango period is the most efficient. Then, it is followed by backwardation. The futures market in strong contango period is the least efficient.

Table 4.2: Results of weak-form efficiency from variance perspective, 2000-2014

Sub-period	Observation	ARCH (10) test statistic	Number q of base observations forming variance ratio			
			2	4	8	16
Strong contango						
Spot return	592	27.6818***	1.0776 (1.3941)	1.0609 (0.6197)	1.1454 (0.9851)	1.2662 (1.2519)
Futures return		31.5803***	1.0633 (1.2139)	1.1038 (1.0929)	1.2605 (1.8113)*	1.4927 (2.3637)**
Weak contango						
Spot return	1,119	108.8983***	1.0097 (0.1953)	1.0220 (0.2318)	1.0082 (0.0554)	1.0907 (0.4245)
Futures return		177.4201***	1.051 (1.0566)	1.1372 (1.5211)	1.1175 (0.8379)	1.2064 (1.0256)
Backwardation						
Spot return	1,798	214.0717***	0.9830 (-0.4609)	1.0655 (0.9294)	1.1038 (0.9367)	1.2743 (1.7292)*
Futures return		306.2612***	0.9755 (-0.6704)	1.0401 (0.5732)	1.1009 (0.9129)	1.3027 (2.0061)**

Notes: ARCH (10) stands the Lagrange multiplier test for conditional heteroscedasticity with 10 lags. The significance of ARCH (10) test statistics indicate that the null hypothesis of homoscedasticity in variance of a series is rejected. Variance ratios VR (q) are calculated by using Equation (4.10). Variance-ratio test statistics Z (q) are calculated by using Equation (4.11) and reported in the parentheses. The significance of test statistics indicates that the null hypothesis of VR (q) equals one is rejected. *** denotes as significant at the 1% level. ** denotes as significant at the 5% level. * denotes as significant at the 10% level.

4.5.2 Correlation coefficients between daily CPO spot and futures price changes: strong contango, weak contango and backwardation

Tilton et al. (2011) contend that spot and futures markets in the strong contango provide investor demand to drive up the futures price which is sufficient to cover the cost of storage. This situation leads to spot and futures prices are closely correlated.

As shown in Table 4.3, by assuming convenience yield is 0 per cent, correlation coefficients between changes in CPO spot and futures prices for a 3-month, 6-month and 9-month during the strong contango period are the lowest. When the convenience yield is increased from 1 per cent to 10 per cent, these correlations are found to rise. This result suggests that market participants keep the CPO as inventories for the future production are sensitive to the rising convenience yield.

Meanwhile, these correlations are found to be high during the period of weak contango and backwardation. This finding prevails over four futures prices and convenience yields from 1 per cent to 10 per cent. However, the futures market never in weak contango over the period at convenience yield of 10 per cent, providing that no correlation between spot and the 3-month, 6-month, 9-month and 12-month futures prices. In addition, these correlations during the weak contango period are rising given convenience yields from 1 per cent to 2.5 per cent. This explains that market participants who are concerned on the convenience yield tend to keep the CPO as inventories for future production. Furthermore, these correlations are found to remain as same during the backwardation period when convenience yield is increased from 1 per cent to 5 per cent, suggesting that the greater short-run production is needed rather than keeping the commodity as storage and inventories. Such behavior is due to their higher expectation on the short-run production.

Table 4.3: Correlation coefficients between daily changes in CPO spot and futures prices, 2000-2014

0 per cent convenience yield	3-month	6-month	9-month	12-month	Average
Strong contango	0.8032	0.7746	0.789	0.8807	0.8119
Weak contango	0.9215	0.8966	0.9737	0.8241	**0.9040**
Backwardation	0.8849	0.8614	0.8789	0.9151	0.8851
1 per cent convenience yield	3-month	6-month	9-month	12-month	Average
Strong contango	0.8090	0.7887	0.7843	0.8011	0.7958
Weak contango	0.9261	0.8946	0.974	0.8665	**0.9153**
Backwardation	0.8849	0.8614	0.8789	0.8894	0.8787
2.5 per cent convenience yield	3-month	6-month	9-month	12-month	Average
Strong contango	0.8238	0.7837	0.7896	0.7613	0.7896
Weak contango	0.9275	0.9074	0.9751	0.8896	**0.9249**
Backwardation	0.8849	0.8614	0.8789	0.8894	0.8787
5 per cent convenience yield	3-month	6-month	9-month	12-month	Average
Strong contango	0.8475	0.8155	0.8838	0.8026	0.8374
Weak contango	0.9335	0.9182	0.9345	0.8872	**0.9184**
Backwardation	0.8849	0.8614	0.8789	0.8894	0.8787
10 per cent convenience yield	3-month	6-month	9-month	12-month	Average
Strong contango	0.8781	0.8567	0.9065	0.8247	0.8665
Weak contango	N/A	N/A	N/A	N/A	N/A
Backwardation	0.8801	0.8453	0.87	0.9	0.8739

Notes: CPO denotes as crude palm oil. Correlation coefficients between daily CPO spot and futures price changes are calculated by using Equation (4.12).Convenience yields during the period of strong contango are assumed to be 0%, 1%, 2.5%, 5% and 10%, respectively.

However, both price changes in strong contango period are found to be not closely correlated and are less than their correlation in weak contango and backwardation periods. Such finding differs from Tilton et al. (2011) who contend that spot and futures prices in the strong contango are closely correlated in the case of copper due to the investor demand who drives up the futures price to sufficiently cover the cost of storage. In the case of CPO in strong contango period, our finding validates that the availability of the physical fruit in the future period is not always guaranteed due to seasonality and spoilage. This supports that a cause of spoilage in the physical fruit makes futures traders encounter difficulty in selling CPO.

4.6 Conclusion

Distinct from the theoretical exposition by Tilton et al. (2011) that investor demand exists when spot and futures prices for the commodity are closely correlated during the strong contango period due to an inter-temporal arbitrage, this study extends their paper in two aspects. First, this study takes into account market efficiency of the futures market as it is related to the spot-futures relation. If the futures market is more efficient, its price changes tend to be highly correlated with the changes in the spot price. Second, this study follows the analysis by Gulley and Tilton (2014) who compare the degree of correlation during strong contango, weak contango and backwardation periods in copper futures.

From the survey of the literature, there is a lack of literature that links market efficiency to spot-futures relation in the soft commodity markets. Hence, this study attempts to examine investor demand in the case of Malaysian CPO futures based on the above authors' theoretical exposition in the context of weak-form market efficiency for CPO spot and futures markets. Following their line of research by incorporating various tests in measuring the degree of weak-form efficiency for spot and futures markets, the degree of market efficiency is further incorporated to ascertain whether it can be related to the degree of spot-futures correlations.

Our results show that investor demand on CPO differs from the findings of Tilton et al. (2011) and Gulley and Tilton (2014) in terms of two aspects: First, spot and futures prices are closely correlated during weak contango period. Second, investor demand on the futures market is highly correlated with spot and futures prices during the weak contango period, but lesser during backwardation, and the least correlated during strong contango. Third, it is found that the efficiency of the futures market is related to the degree of correlation between spot and futures price changes. Higher degrees of efficiency are linked to the high correlation between spot and futures market and vice versa.

As a commodity, CPO is susceptible to seasonality due to natural growing cycle. During weak contango, market participants anticipate insufficient supply of CPO inventories for the short-term production and are willing to pay a premium in the form of convenience yield to hold the inventories in hand in order to meet the production. The efficient of futures market allows investors to take a long position in holding physical CPO. Hence, the futures market is found to be more efficient as variance ratio is the lowest. In addition, there is a greater role of investor demand in influencing the changes in CPO prices. This provides the explanation for a strong correlation between spot and futures returns.

In contrast, during strong contango, market participants adjust their decisions by buying CPO in the spot market and selling it in the futures market. However, due to seasonality, spoilage, and availability of the physical fruit of CPO in the future period is not always guaranteed. Consequently, price changes in the CPO futures market are less correlated with price changes in the spot market. There is a lesser role of investor demand in influencing the changes in CPO prices. The empirical results show that market efficiency is the lowest as variance ratio is the highest. Lastly, during backwardation, the degree of market efficiency and degree of correlation between price changes in spot and futures markets is in between the above two market conditions.

CHAPTER 5: CAUSALITY-IN-MEAN AND CAUSALITY-IN-VARIANCE BETWEEN CPO SPOT AND FUTURES MARKETS

5.1 Introduction

The dynamic relationship between spot and futures prices for commodities is characterized by a transition between contango and backwardation. This market transition directly affects investors' expectation towards the trend of future spot price. In this respect, investors can use the futures price as an efficient price discovery to determine the reference price of an asset under consideration at a given time and marketplace (Newberry, 1992). Producers can use information about this dynamic relationship to make supply decisions on the commodity futures contract prices (Neibergs & Thalheimer, 1997). Physical traders might use the same information to price their commodities (Kolodziej & Kaufmann, 2013). In addition, hedgers require information on volatility spillover between spot and futures markets to make an adjustment in their hedging strategies during the financial crises (Go & Lau, 2015).

Since the spot-futures relation stimulates decision marking in trading, production and hedging, so this relationship attracts the attention of many observers. With the exception of few studies, most studies use empirical approaches and provide direction for information transmission between spot and futures markets. However, the results on such relationship are mixed. For example, Kaufmann and Ullman (2009) and Bos and Van der Molen (2012) report that causality flows from futures prices to spot prices. Lee and Zeng (2011) and Alzahrani et al. (2014) find that spot prices Granger cause futures prices. Maslyuk and Smyth (2009) and Liu et al. (2011) further find that causality between spot and futures prices happens in both directions. This ambiguity is due to lack of study to distinguish between backwardation and contango in commodity markets. By detecting the market transition from backwardation to contango or vice versa, information which is tied to current economic conditions can be obtained to serve as an indication of future price movement.

The academic research on spot-futures relation in the case of crude palm oil (CPO) is relatively scarce, even though CPO is of interest among market participants as a source of energy of biofuel and edible oil. In particular, if such of relationship exists, **how does CPO spot changes cause CPO futures price changes in both mean and variance or vice versa during weak contango, strong contango and backwardation periods?** For this respect, the non-linear approach is required to establish a "period by period" prediction of spot prices conditional on the prediction of futures prices, and vice versa. The reason is ignoring the non-linearity problem of commodity prices may produce spurious regression. For this purpose, the non-uniform weighting cross-correlation developed by Hong (2001) is employed in this study to test causality-in-mean and causality-in-variance through cross-correlation functions of standardized residuals and squared standardized residuals (CCFs). The advantage of this approach includes its considerable flexibility in forming one-dimensional models for return with the lack of normality of a series.

Based on the traditional of linear Granger-causality test developed by Granger (1969, 1980), the Granger causality of a series with respect to past information of other series is found as too general to be operational as both series are assumed to have time-invariant conditional variance. However, with time-varying conditional variances of both series, the general Granger causality test would produce spurious results. According to Hong (2001: 187), no causation is found in mean and variance does not necessarily imply that no general causality, while the general causality would be in the existence if causation is found in mean or variance or both. The testing for causality-in-mean should be delivered immediately and filtered out in order to ensure that this causality has no impact on the causality-in-variance (Hong, 2001: 194-198). As stated by Hong (2001: 187), detection of causality-in-variance under the possibility of the existing general causality without causality-in-mean in finance and macroeconomics is particularly important. The reason is testing for the causality-in-variance aims to reveal information flow or volatility spillovers across different assets or markets as Ross (1989) points out. For this study, the causality-in-variance is used to examine the conditional volatility dependence between CPO spot and futures markets.

Based on the data extracted from the Bursa Malaysia, market conditions for CPO such as strong contango, weak contango and backwardation are identified using the cost-of-carry model. Table 5.1 identifies several events which are related to policy implementation, weather climate and financial crisis that occur during strong contango, weak contango and backwardation periods, respectively.

In fact, CPO price is subject to external influences such as economic growth and weather. The CPO price was quite unsettled during July 2008 due to it has a strong correlation with oil price. Although a further increase in CPO price was recorded at the end of 2010, lower CPO production with an increase in export demand led to the reduction of palm oil stocks. These economic or environmental factors subsequently contribute to the deviation from spot-futures relation and violate the spot-futures parity.

This deviation from spot-futures relation can be adjusted in achieving the market equilibrium through riskless arbitrage (Kolb, 2000). For example, if the futures price is found to be higher than the cost-of-carry price, traders will implement “cash-and-carry” arbitrage strategy by buying the underlying commodity and selling the futures contracts. On the other hand, if the futures price is lower than the cost-of-carry price, traders will make use a reverse “cash-and-carry” arbitrage opportunity to buy the futures contract and sell the underlying commodity. For this case, the short-selling activity and lending the underlying asset without cost are not possible when market participants could obtain a benefit or convenience yield from holding a commodity on hand.

Table 5.1: Episodes for the Malaysian CPO market

Strong contango:	
December 31, 2009	Total CPO futures contract traded has increased from 3,003,549 contracts to 4,008,882 contracts steadily with the rising of demand from both China and India.
December 2012	An imposition of a 300% tax on palm oil, popularly dubbed as the “Nutella Tax” was gunned down.
Weak contango:	
December 3, 2007 – January 31, 2008	Zero export of Malaysian biodiesel.
July 1, 2008 – September 30, 2008	Oil returns were strongly correlated with daily returns for most commodities traded in futures markets due to the financial crisis.
November 11, 2008 – December 18, 2008	Palm oil export was dropped from RM13, 504 million to RM9, 271 million due to heavy rainfall and lower fresh fruit bunches.
December 2014	Palm oil prices fell by 6% due to high stocks and expectation on low demand for biodiesel.
Backwardation:	
October 3, 2008 – October 31, 2008	Oil returns were strongly correlated with daily returns for most commodities traded in futures markets due to the financial crisis.
June 2009 – May 2010	Palm yields have been reduced during the El-Nino event.
January 2010 - December 2010	Palm oil stocks were reduced from 2,239,257 tonnes to 1,615,618 tonnes by 27.85%. This decline was mainly due to lower CPO production by 3.3% coupled with an increase in the export demand by 4.9%.
October 2010 - December 2010	The CPO futures was raised by 38% due to the declining CPO production from 17,564,937 tonnes to16, 993,717 tonnes.
July 2010 – April 2011	Palm yields have been increased during the La-Nina event.
January 2011 - December 2011	The government of Australia claimed that palm oil produced unhealthy food related-products.

Table 5.1: (Continued)

Backwardation:	
March 2011 - December 2011	CPO yields rose significantly.
October 2011	The government of Indonesia has reduced export taxes for respective refined, bleached and deodorized (RBD) palm oil and RBD palm stearin from 11% and 7.5% to 5%. For RBD palm olein, an export tax was reduced from 12.5% to 7%.
April 2011 - June 2011	The sharp improvement in CPO demand coincided with a larger soyoil premium over CPO.
January 2012	The Environmental Protection Agency in the United States rejected palm-oil based biodiesel for Renewable Fuels Program because it failed to meet a requirement in reducing emissions relative to conventional gasoline by 20%.

Sources: United Nations Development Program (2009), Central Bank of Malaysia (2009), Malaysian Palm Oil Board (2010), Standard Charted Research (2011), International Monetary Fund (2015), and World Bank (2015).

The result of this study has implications for market practitioners. For example, producers or stock owners can avoid paying a high premium in the form of difference between spot and futures prices at maturity of contract. By knowing the effect of market transition on future price movement, they can make appropriate timely decisions in protecting their ordinary monetary incomes from price oscillation by holding long or short positions in the futures market. On the other hand, investors in the CPO futures market can infer what effects of contango and backwardation may have on their risk exposures in the particular period. By doing so, they can adjust appropriately their short-selling activities towards the market transition.

This chapter is organized as follows. This section is followed by a literature review. The subsequent section explains about data and methodology, followed by findings and empirical results. The last section concludes the discussion and suggests the implication.

5.2 Literature Review

Earlier studies on interactions between spot and futures commodity prices, Keynes (1930) is found to firstly develop the theory of the forward market to seek explanation on market condition for producers' perspective. According to him, commodity market in backwardation is known as a "normal backwardation" for producers because they are more prone to hedge their price risk by selling the long-term futures as compared to consumers. His theory is further related to risk bearers, explaining that such market situation can provide speculators to realize a profit for who have the bearish expectation on a risk premium by holding a long position in the futures market. In this regard, under this market condition, it should satisfy that "forward price must fall short of the expected price by the amount of the marginal risk premium". However, his theory fails to answer two questions. First, why spot and futures prices seem to exhibit time-varying relationship? Second, why this relationship disappears at the certain point of time?

Kaldor (1939) further finds that this traditional theory does not mention the existence of a prefect or semi-perfect market and low carrying cost for the effect of speculation on a general level of economic activities. In this regard, the author introduces the term of the "marginal convenience yield" into the theory of the forward market by deducting a yield from the marginal carrying cost. To explain the non-arbitrage theory, he generalizes cost-of-carry model in providing that the futures price should equal the interest cost, current spot price plus net marginal carrying cost for the underlying good from now until the delivery and marginal risk premium.

By using the cost-of-carry model in explaining "inverse carrying charges" (futures price below spot prices), Working (1949) points out that the net marginal carrying cost in calculating forward price ignores two things. First, who decides to store the commodities would not hedge the risk. Second, a gross monetary return per unit marginal outlay received by firms is not exactly equal to the marginal outlay. To express the net marginal cost of storage in the condition of "inverse carrying charges" in the futures market, Brennan (1958) incorporates the marginal risk-aversion factor into consideration because he finds that total risk aversion has an increasing function of stocks.

Furthermore, Brenner and Kroner (1995) note that the cost-of-carry model can explain the difference between futures price and subsequent cash price. With such a case, they argue that this model does not allow for the prediction on the subsequent cash prices due to ignoring the efficient market hypothesis (EMH) based on Fama (1970). As a contrast, Heaney (2002) finds that the cost-of-carry model elements such as inventory level change and change in futures price have a significant short-run effect on cash price change in the case of London Metal Exchange lead contract during 1964-1995. In addition, Alizadeh and Nomikos (2004) incorporate the transportation cost to express crude oil futures prices in the tanker freight markets during 1993-2001. However, they find that difference between physical and futures crude oil prices does not reflect the transportation cost, suggesting that arbitrage opportunities still exists due to regional supply and demand imbalances between oil derivatives and tanker freight markets.

Based on the EMH, the asset pricing theory is developed to establish the relationship between a futures price and expected future spot price conditional on a set of information. According to this theory, the futures price should be an unbiased estimate of the future spot price. In this same field of investigation, studies such as Garbade and Silber (1983), Oellermann et al. (1989), and Schroeder and Goodwin (1991) empirically support that a futures price dominates a role of price discovery under the EMH. However, for the usual rationalization of spot-futures relation in commodity markets, many empirical studies find that this is not the case. It may provide futures prices either lead or lag spot prices due to both prices reflect the same aggregate value of underlying asset under the short-run market inefficiency.

Table 2 presents and summarizes the past studies on the direction of a lead-lag relationship between spot and futures prices in commodity markets. This direction is categorized into three ways as the futures price leads to the spot price, the spot price leads to the futures price and bi-directional causal effect happens between both prices. Early empirical studies focus whether the futures price is a determinant of the spot price. Some studies find that futures price leads to spot price changes. For instance, Garbade and Silber (1983), Oellermann et al. (1989), and Schroeder and Goodwin (1991) suggest the futures price plays a vital role in price discovery process for the underlying spot market under the theory of market efficient. Newberry (1992) further states that futures price which acts as an efficient price discovery can determine the reference price of an asset under consideration at a given time and marketplace. According to Silvapulle and Moosa (1999), futures prices respond to new information faster than spot prices. Such of effect implies that less restrictive regulation or lower transaction cost, flexibility of short-selling activities and greater liquidity in the futures markets as compared to the spot market.

The price-discovery function has been detected in a number of commodity markets. For instance, Wu and McCallum (2005) report that futures-based forecast models have a lower mean squared prediction error than a random walk model of spot prices. This suggests that the futures-based forecast models such as Hotelling's futures and futures-spot spread models produce unbiased predictors of the spot price of oil during 1987-2005. Similarly, as compared to the random walk model, Coppola (2008) finds that improvement of forecast accuracy for the futures-based forecast models only can be achieved at the 1-month horizon, but not at longer horizons. This empirical finding is observed to explain why a lead-lag relationship from futures to the underlying spot market.

To explain the hypothesis of futures prices lead spot prices theoretically and empirically, Kaufmann and Ullman (2009) consider roles of hedgers and speculators in the West Texas Intermediate (WTI), Brent-Blend, Maya, Bonny Light and Dubai-Fateh crude oil markets. Their result supports that speculation activities likely occur to exacerbate the market fundamentals when high fluctuations in futures prices as opposed to spot prices. As illustrated by Bos and Van der Molen (2012) in the Arabica coffee market during 1989-2008 with their own non-parametric test and empirical model, they find that factors such as harvest sizes, inventories, futures market microstructure and price elasticity of demand could enhance the impact of futures speculation on rising prices of coffee. They also suggest that speculation is one of the contributors of input for the other commodities.

Without using the available data for metal prices, Tilton et al. (2011) develop curves of producer supply, consumer demand, investor demand and total demand. They illustrate that speculators or investor demand in the futures market could comparably influence spot prices when the market is in strong contango (exceeds cost of storage and interest). They conclude that investor demand which is associated with rising metal futures prices in excess supply condition for future production would depress spot prices. The spot-futures relation is also likely to be governed by fundamentals. They further provide two possible explanations to argue that investor demand may also play a role when the metal futures market stays in backwardation (weak contango). First, investors anticipate that inadequacy of short-term supply for actual physical metal before the maturity date of the futures contracts. Second, investors are willing to pay a premium to hold physical metal. However, investor demand on futures market which is determined by the short-term consideration contributes to the weak effect of futures prices on spot prices. As a result, a correlation between spot and futures prices should be weak during backwardation period.

In this sense, Östensson (2011) concurs with their basis of conceptual and theoretical arguments on spot and futures prices during the strong contango and backwardation. To support this theoretical empirically, Gulley and Tilton (2014) find that strong correlation coefficients between changes in the copper spot and futures prices during 1994-2011 when the market is in strong contango instead of backwardation (weak contango). Following the study by Mahalik et al. (2014), they obtain similar finding in the Indian commodity markets during 2005-2008 using vector error correction and bivariate exponential GARCH models. Their finding indicates that effect of past innovation in the futures market on spot volatility happens frequently in the agricultural future index, energy future index and aggregate commodity index.

Although futures prices respond to information faster than spot prices, but there is empirical evidence to reveal that spot prices have a similar impact on futures prices. For instance, under the hypothesis of no arbitrage rule in the WTI crude oil market during 1986-2009, Lee and Zeng (2011) use the quantile cointegrating regression and find that non-linear behavior of both oil prices leads to spot prices to have a causal effect on prices for a longer length of futures contracts. However, it cannot reflect all available information for the shorter length of a futures contract. Moreover, finding of Alzahrani et al. (2014) supports the hypothesis of spot prices lead futures prices during the period of high price fluctuation in the light sweet oil market as compared to those of the pre-crisis period. They suggest that speculators who are active in the futures market for oil during the time of financial crisis cannot dominate a role of price discovery.

Some studies validate that spot-futures relation has bi-directional causality as spot and futures markets can provide information each other. For instance, Silvapulle and Moosa (1999) demonstrate the existence of non-linear behavior in the movement of spot and futures prices for the WTI crude oil during 1985-1996 due to transaction cost and market microstructure. This non-linear behavior contributes to heterogeneous among participants in responding the arrival of new information. With the heterogeneous of participants' behavior, they will make decisions which are relevant to their spot or futures positions, leading to bi-directional effect exists in between spot and futures prices for oil.

To account for such non-linearity, Bekiros and Diks (2008) move away from linear tests and use non-linear tests such as non-parametric test of Diks and Panchenko (2006), vector error correction model (VECM), filtered model residuals and GARCH-BEKK model by considering an assumption of asymmetric GARCH effect. They confirm that a strong of bi-directional causality shifts the pattern of leads and lags during two sub-periods of reduction in the spare capacity in the WTI crude oil market (1991-1999 and 1999-2007) for the organization of the petroleum exporting countries. However, this causality is turned to be unidirectional in the non-linear movement under some restricted conditions.

Another feature associated with bi-directional causality is an adjustment toward the long-run equilibrium between spot and futures prices. Although the cointegration between the oil spot and futures prices is proven, Maslyuk and Smyth (2009) state that this relationship is driven by the same fundamentals such as interest rate and macroeconomic indicators. Apart from that these fundamentals, spot and futures prices should be expected to have a bi-directional adjustment toward the long-run equilibrium.

However, in the WTI market during 2004-2009, Liu et al. (2011) use bivariate threshold error correction GJR-GARCH model and point up that positive and negative bases provide asymmetric adjustment in the long-run relationship of both oil prices. With the bi-directional causal effect, spot prices are reverted in the long-term equilibrium with stronger adjustment to a positive basis than a negative basis, while the futures prices act as price adjustment on a positive basis but not on a negative basis.

Since both spot and futures prices are expected to have the long-run relationship, their direction of causality can be determined using dynamic analysis. During 1986-2011 in the same market, Wang and Wu (2013) expect that presence of heterogeneous behavior among participants due to vary trading horizons. In this regard, they revisit this cointegration with different maturities. They find that this behavior contributes to asymmetric adjustment of both prices in the long run and short run toward equilibrium level. For example, a non-linear threshold vector error correction model indicates that spot and futures prices adjust each other in the long run to eliminate disequilibrium level, whereas futures price could adjust spot price in the short run to achieve the long-run equilibrium.

Together with the WTI market, Kolodziej and Kaufmann (2013) argue that this cointegration would not exist if trader positions and oil inventories are ignored. With the long-run relationship between oil inventories and trader positions, they find that different expiration dates between the near-month and far-month futures contracts could provide a bi-directional causality of both oil prices. For example, participants use oil prices for near-month futures contracts to implement price discovery process to trade in the spot market, while this process that based on the spot market could be used to trade the far-month futures contracts.

In the same crude oil market, Chen et al. (2014) find that the long-run relationship between spot and futures prices stays during the period of backwardation. To test the causality between spot and futures prices using a non-linear parametric test, they incorporate the break point that occurs in July 2004 for the sample period of 1986-2012. In forecasting oil futures volatility, they conclude that considering the structural break for the long-run relationship of both prices could be better than those without the structural break. Their result indicates that incorporating break point sways relationship between spot and futures prices. For example, the futures price is found to lead the spot price before the break point. After the break point, this causality is found as not in the existence.

By using a recursive bivariate vector autoregressive model, Nicolau and Palomba (2015) found that the bi-directional causality and interaction between the spot price and futures price with different maturity in the WTI crude oil market vary over the period of 1997-2014. For example, weakly exogeneity of one-month futures price is rejected before the end of September 2008 and accepted after this date. During 2009-2012, a strong exogeneity of one-month futures prices is not rejected. However, in the same period, weakly exogeneity of spot price allows four-month futures price to Granger cause spot price. This dynamic causality disappears when this exogeneity of the spot is turned to be strong and cointegration relationship still exists. With the regard to result for the natural gas market, a strong exogeneity exists in spot and futures prices and consequently contributes to Granger non-causality of both prices. This dynamic relationship does not depend on contract maturity. In the gold market, causality between spot and futures prices happens in both directions.

Theoretically, most of the previous studies support that the futures price acts as price discovery tool to predict future spot price. The reason is the futures markets have less restrictive regulation, lower transaction cost, flexibility of short-selling activities and greater liquidity as compared to the spot markets. This consequently leads to futures prices respond to new information faster than spot prices. However, recent empirical evidence also suggests that this relationship is not clear, where futures price does not completely play this role due to different market conditions, types of commodity, locations and sample period of the study surveyed. For that reason, this study adopts the non-linear approach of Hong (2001) in order to examine further on how the market transition between backwardation and contango influence the causal relationship between spot and futures prices in the Malaysian CPO market.

Table 5.2: Past studies examining the relationship between spot and futures prices for commodities

Author(s)	Journal	Country	Commodity	Period	Methodology	Results
Garbade and Silber (1983)	Journal of Business	United States	Wheat, corn, oats, soybeans, frozen pork bellies, coffee, live hogs, soybean meal, soybean oil, live slaughter cattle, sugar, cocoa and gold	1978-1980	Garbade and Silber approach	$F \rightarrow S$
Oellermann et al. (1989)	Journal of Futures Markets	United States	Live cattle and feeder cattle	1979-1986	Garbade and Silber approach	$F \rightarrow S$
Schroeder and Goodwin (1991)	Journal of Futures Markets	United States	Live hog	1975 -1989	Cointegrating test based on Garbade and Silber approach	$F \rightarrow S$
Silvapulle and Moosa (1999)	Journal of Futures Markets	United States	West Texas Intermediate crude oil	Jan 2, 1985-Jul 11, 1996	Hsio's (1981) linear causality test based on bivariate vector autoregressive model and Baek-Brock's (1992) non-linear causality test based on non-parametric approach	$F \rightarrow S$
Wu and McCallum (2005)	FRBSF Economic Letter	United States	Light and sweet crude oils	1987-2005	Random walk model, Hotelling's model, futures model, and futures-spot spread model	$F \rightarrow S$
Coppola (2008)	Journal of Futures Markets	United States	West Texas Intermediate crude oil	Jan 1986-Sep 2006	Random walk model and vector error correction model	$F \rightarrow S$
Maslyuk and Smyth (2009)	Energy Policy	United States	West Texas Intermediate and Brent crude oils	Jan 1991-Nov 2008	Residual-based cointegration test based on one structural break in the cointegrating vector	$F \leftrightarrow S$
Kaufmann and Ullman (2009)	Energy Economics	United States, United Kingdom, Mexico, Nigeria and Arab Saudi	West Texas Intermediate, Brent-Blend, Maya, Bonny Light and Dubai-Fateh crude oils	1986- 2008	Two step DOLS error correction model and full information maximum likelihood estimate for a vector error correction model	$F \rightarrow S$
Liu et al. (2011)	Energy Procedia	United States	West Texas Intermediate crude oil	Jan 1, 2004-Sept 30, 2009	Bivariate threshold error correction GJR-GARCH model	$F \leftrightarrow S$

Note: "$F \rightarrow S$" stands for futures lead spot, "$S \rightarrow F$" stands for spot leads futures, "$F \leftrightarrow S$" stands for bi-directional causality and "$F - S$" stands for spot and futures are independent.

Table 5.2: (Continued)

Author(s)	Journal	Country	Commodity	Period	Methodology	Results
Lee and Zeng (2011)	Energy Economics	United States	West Texas Intermediate crude oil	Jan 2, 1986- Jul 6, 2009	Quantile cointegrating regression	$S \rightarrow F$
Tilton et al. (2011)	Resources Policy	United Kingdom	Copper	-	Theoretical and conceptual framework	$F \rightarrow S$
Östensson (2011)	Resources Policy	United Kingdom	Copper	-	Theoretical and conceptual framework	$F \rightarrow S$
Bos and Van der Molen (2012)	Research Memorandum	United States	Arabica Coffee	1989-2008	Non-parametric and empirical model	$F \rightarrow S$
Wang and Wu (2013)	Economic Modelling	United States	West Texas Intermediate crude oil	Jan 3, 1986 - Feb 18, 2011	Non-linear threshold vector error correction model	$F \leftrightarrow S$
Kolodziej and Kaufmann (2013)	Energy Economics	United States	West Texas Intermediate crude oil	Jan 6, 1997- Dec 21, 2010	Cointegrating vector autoregression model	$F \leftrightarrow S$
Alzahrani et al. (2014)	Journal of International Money and Finance	United States	Light sweet and West Texas Intermediate crude oils	Feb 20, 2003- Apr 19, 2011	Linear and non-linear Granger causality tests based on wavelet method	$S \rightarrow F$
Gulley and Tilton (2014)	Resources Policy	United Kingdom	Copper	Apr 1994- Apr 2011	Correlation coefficients between changes in spot and futures prices	$F \rightarrow S$
Mahalik et al. (2014)	Journal of Advances in Management Research	India	Metal, bullion, fiber, energy, spices, plantations, pulses and petrochemicals	2005-2008	Vector error correction model, bivariate exponential GARCH model	$F \rightarrow S$
Chen, Lee and Zeng (2014)	Energy Economics	United States	West Texas Intermediate crude oil	Jan 1986-Dec 2012	Non-linear non-parametric method of Diks-Panchenko	$F \rightarrow S$ (before structural break) $F - S$ (after structural break)
Nicolau and Palomba (2015)	Resources Policy	United States	Gold, West Texas Intermediate crude oil and Henry Hub natural gas	Jan 7,1997- May 30,2014	Recursive bivariate vector autoregressive model	$F \leftrightarrow S$ (gold) $F \leftrightarrow S$ (crude oil) $F - S$ (natural gas)

Note: "$F \rightarrow S$" stands for futures lead spot, "$S \rightarrow F$" stands for spot leads futures, "$F \leftrightarrow S$" stands for bi-directional causality and "$F - S$" stands for spot and futures are independent.

5.3 Data and Methodology

Data for daily spot and futures prices with 3-month maturity of CPO from January 3, 2000 to December 31, 2014 are used in this study. This study uses the price of 3-month futures contract because it is the most active futures contract traded on the platform of Bursa Malaysia. The futures prices of CPO are officially closing price at 6 p.m. from the trading floor of the Bursa Malaysia. Each futures contract expires on the 15th day of the delivery month. These daily prices are obtained from Bursa Malaysia with totally 4,834 observations. To reduce variation and achieve stationary movement, these daily prices are transformed to become daily change in the logarithmic prices (daily return) using Equation (5.1).

$$R_t = \ln\left(P_t / P_{t-1}\right) \tag{5.1}$$

where R_t is the daily spot and futures returns of CPO at time t, P_t is the daily spot and futures prices of CPO at time t (RM), and $\ln$ is the natural logarithm.

Furthermore, the following data used in the analysis are daily deposit rates from the same sample period. They are obtained from the Central Bank of Malaysia. The analysis in testing lead-lag relationship is employed with the following two steps. First, the cost-of-carry model is used to determine the period of strong contango, weak contango and backwardation. Second, the procedure developed by Cheung and Ng (1996) and further standardized by Hong (2001) is used to examine the causality-in-mean and causality-in-variance between spot and futures returns of CPO during the period of strong contango, weak contango and backwardation, respectively.

5.3.1 The cost-of-carry model

The efficient of futures market can be achieved when price change on a particular day at current contains all part and predictable information about its own past price changes and price changes from the other markets. In this regard, the movement of spot and futures prices does not exhibit predictable price patterns, where both prices cannot be predicted each other. Under this market situation, there is a no-arbitrage relationship between spot and futures prices in commodity markets (Pindyck, 2001). To explain this situation, the cost-of-carry model which is given by Equation (5.2) is used to compute the expected (future) spot price of delivery for T months forward $(F_{t,T})$.

$$F_{t,T} = S_t(1 + r_t + C_t)^{t,T} \tag{5.2}$$

where S_t is current spot price at time t, C_T is annualized storage cost in per cent which includes the costs of handing, spoilage, shrinkage, shipping and others, r_T is the deposit rates at time t, and T is the number of months divided by 12 (3/12).

Based on Equation (5.2), discounted futures price and spot price as well as between futures price and spot price are compared.[8] Strong contango period occur when the futures price exceeded the expected future spot price as well as discounted futures price also greater than the spot price. Weak backwardation occurs when spot price lesser than futures price and greater than the discounted future spot price, while zero backwardation occurs if spot price equals the discounted future spot price. Both of weak backwardation and zero backwardation are said to be in contango. This study refers this situation as weak contango period. Backwardation period occurs when both contemporaneous futures and discounted futures prices are lesser than expected future spot price. In the

[8] The spoilage of CPO depends on seasonal production, storage cost of the commodity will vary from time to time. As referred to Topic 2 entitled "Commodity Futures-Crude Palm Oil Futures" from Malaysian Futures and Options: Examination Study Guide, Module 2: Futures issued by the Security Commission, Malaysia and Securities Institute Education, Australia (2005), this study assumes that annual cost is 5 per cent.

other word, the futures prices of a commodity are either below the spot prices or insufficiently above the spot price to cover storage cost.

5.3.2 Basic concept of causality-in-mean and causality-in-variance

Suppose that there are two returns at time t, spot return (SR_t) and futures return (FR_t). The following three sets for information are defined as Equations (5.3), (5.4) and (5.5).

$$I_{S,t} = \left(SR_{t-j}; j \geq 0\right) \tag{5.3}$$

$$I_{F,t} = \left(FR_{t-j}; j \geq 0\right) \tag{5.4}$$

$$I_{SF,t} = \left(SR_{t-j}, FR_{t-j}; j \geq 0\right) \tag{5.5}$$

Equation (5.6) indicates that futures return causes spot return in mean with respect to $I_{SF,t-1}$. Similarly, Equation (5.7) indicates that spot return causes futures return in mean with respect to $I_{SF,t-1}$.

$$E\left[SR_t \middle| I_{S,t-1}\right] \neq E\left[SR_t \middle| I_{SF,t-1}\right] \tag{5.6}$$

$$E\left[FR_t \middle| I_{F,t-1}\right] \neq E\left[FR_t \middle| I_{SF,t-1}\right] \tag{5.7}$$

A similar definition is applied for causality-in-variance. Equation (5.8) indicates that futures return causes spot return in variance with respect to $I_{SF,t-1}$, while Equation (5.9) indicates that spot return causes futures return in variance with respect to $I_{SF,t-1}$.

$$E\left[\left(SR_t - \mu_{SR,t}\right)^2 \middle| I_{S,t-1}\right] \neq E\left[\left(SR_t - \mu_{SR,t}\right)^2 \middle| I_{SF,t-1}\right] \tag{5.8}$$

$$E\left[\left(FR_t - \mu_{FR,t}\right)^2 \middle| I_{F,t-1}\right] \neq E\left[\left(FR_t - \mu_{FR,t}\right)^2 \middle| I_{SF,t-1}\right] \tag{5.9}$$

where μ_{SRt} is the mean of spot return conditioned on $I_{S,t-1}$, and $\mu_{FR,t}$ is the mean of futures return conditioned on $I_{F,t-1}$.

5.3.3 Cross-correlation function of standardized residuals and squared standardized residuals (CCFs)

The CCFs approach is firstly developed by Cheung and Ng (1996) in examining the causality between two stationary series. Based on cross-correlation of standardized residuals and their squares, this approach can detect non-linear causal relationship in mean (first moment) and variance (second moment) of both series (Henry, Olekalns & Lakshman, 2007: p.123). Furthermore, this approach has the ability to specify correctly the first moment dynamic (mean) and second moment dynamic (variance), detect significant causality of both series for a large number of observations at longer lags and reveal useful information on the causality pattern (Cheung & Ng, 1996: p. 36).

When cross-correlations decay as the lag order increases, the test based on Cheung and Ng (1996) allocates equal weighting to each lag can be subject to severe size distortions in the presence of causality-in-mean. Furthermore, the pattern of non-linear causality-in-variance is also failed to be detected with zero cross-correlation between innovations. To overcome this limitation, Hong (2001) develops the non-uniform weighting cross-correlations in a simulation study by providing flexible weighting scheme for cross-correlation at each lag. For example, larger weights are permitted for cross-correlations at lower order lags and otherwise. This non-uniform weighting is expected to give better power against the alternative whose cross-correlations decay to zero as the lag order increases (Hong, 2001: p. 185). Overall, the greatest advantage of this approach is the possibility to flexibly specify the innovation process and robustness to asymmetric and leptokurtosis errors.

This approach involves the two-step procedure. In the first step, the appropriate order for autoregressive (AR) that maximizes the log likelihood function is determined using correlograms of the partial autocorrelation function (PACF). Meanwhile, the orders for moving average (MA) are determined based on correlograms of the autocorrelation function (ACF). These univariate equations such as AR, MA and ARMA are used to explain the conditional mean of a series.

The further examination of ACF and PACF correlograms on squared residuals based on the conditional mean equation is to check the existence of generalized autoregressive conditional heteroskedasticity (GARCH) effect. The conditional mean equation (ARMA) and conditional variance equation (GARCH) with a generalized error distribution (GED) for both returns are written as Equations (5.10), (5.11), (5.12) and (5.13).

$$SR_t = a_0 + \sum_{i=1}^{P1} a_i SR_{t-i} + \sum_{i=1}^{P2} b_i \varepsilon_{SR,t-i} + \varepsilon_{SR,t}, \varepsilon_{SR,t} = \sigma_{SR,t} z_{SR,t}, z_{SR,t} \sim GED \ (\kappa) \tag{5.10}$$

$$\sigma^2_{SR,t} = w + \sum_{i=1}^{P3} \alpha_i \varepsilon^2_{SR,t-i} + \sum_{i=1}^{P4} \beta_i \sigma^2_{SR,t-i} \tag{5.11}$$

$$FR_t = a_0 + \sum_{i=1}^{P1} a_i FR_{t-i} + \sum_{i=1}^{P2} b_i \varepsilon_{FR,t-i} + \varepsilon_{FR,t}, \varepsilon_{FR,t} = \sigma_{FR,t} z_{FR,t}, z_{FR,t} \sim GED \ (\kappa) \tag{5.12}$$

$$\sigma^2_{FR,t} = w + \sum_{i=1}^{P3} \alpha_i \varepsilon^2_{FR,t-i} + \sum_{i=1}^{P4} \beta_i \sigma^2_{FR,t-i} \tag{5.13}$$

where SR_t is the daily spot return of CPO at time t; $\varepsilon_{SR,t}$ is the error term for spot return of CPO with heteroscedasticity at time t; $\sigma^2_{SR,t}$ is the conditional variance of $\varepsilon_{SR,t}$ at time

t; FR_t is the daily futures return of CPO at time t; ε_{FRt} is the error term for futures return of CPO with heteroscedasticity at time t; σ^2_{FRt} is the conditional variance of ε_{FRt} at time t; κ is a positive parameter measuring the skewness of the distribution; and $z_{SR,t}$ and z_{FRt} are two independent white noise process with zero mean and unit variance.

Based on Equations (5.10) - (5.13), the number of lags for dependent variable, forecasted error, squared error and conditional variance is based on the minimum Schwarz information criterion. These univariate equations should adequately account and explain the serial correlation of the data in the first and second moments in order to produce stationarity of standardized residuals in level and square forms.

In the second step, the standardized residuals by the conditional mean are used for the causality-in-mean test. While the standardized squared residuals by the conditional variance are used for the causality-in-variance test.

5.3.3.1 Causality-in-mean test

Equations (5.14) and (5.15) are used to construct standardized innovations for respective spot and futures returns of CPO (u_t, w_t).

$$u_t = \frac{SR_t - \mu_{SR,t}}{\sqrt{\sigma^2_{SR,t}}} \tag{5.14}$$

$$w_t = \frac{FR_t - \mu_{FR,t}}{\sqrt{\sigma^2_{FR,t}}} \tag{5.15}$$

Since both u_t and v_t are unobservable, their values are estimated consistently using standardized residuals by their conditional variance estimators, where their conditional variance estimators are denoted as $\hat{u}_t$ and $\hat{w}_t$. Based on their values, the sample cross-correlation coefficient at the lag k, $\hat{r}_{uw}(k)$ is calculated using Equation (5.16).

$$\hat{r}_{uw}(k) = \frac{C_{uw}(k)}{\sqrt{C_{uu}(0)C_{ww}(0)}} \tag{5.16}$$

where, $C_{uw}(k)$ is the k-th lag sample cross-covariance given by

$$C_{uw}(k) = \begin{cases} T^{-1}\displaystyle\sum_{t=k+1}^{T} \hat{u}_t\,\hat{v}_{t-k}, k \geq 0 \\ T^{-1}\displaystyle\sum_{t=-k+1}^{T} \hat{u}_{t+k}\,\hat{v}_t, k < 0 \end{cases} \tag{5.17}$$

$C_{uu}(0)$ is the sample variance of standardized residuals for spot return of CPO, and $C_{ww}(0)$ is the sample variance of standardized residuals for futures return of CPO.

Under the regularity condition, the following condition as stated in Equation (5.18) holds.

$$S_1 = T\left[\sum_{i=1}^{k}\left(\hat{r}_{uw}(k)\right)^2\right] \xrightarrow{L} \chi^2(k) \tag{5.18}$$

The value if this test statistic (from Equation (5.18)) is compared with the chi-square distribution (χ^2) in testing the null hypothesis of no causality-in-mean from lag 1 to lag k. This null hypothesis is rejected if the test statistic value larger than the critical value of the chi-square distribution. When the degree of freedom of k is large, this test statistic is transformed into a standard normal distribution by subtracting the mean, k and dividing by standard deviation, $(2k)^{1/2}$ (Hong, 2001:192). As a consequence, the standardized version of S_1 is written as Equation (5.19).

$$M_1 = \frac{S_1 - k}{\sqrt{2k}} \xrightarrow{L} N(0,1) \tag{5.19}$$

Then the upper-tailed critical values from a standard normal distribution are used because the test statistic based on Equation (5.19) is the one-sided test. The rejection of the null hypothesis of no causality-in-mean can be achieved when the test statistic is greater than the critical value of a standard normal distribution.

5.3.3.2 Causality-in-variance test

From the aspect of CCFs approach, causality-in-variance does not depend upon the causality-in-mean. On the other words, the lack of both causalities in mean or variance does not necessarily imply the lack of general causality, so causality-in-variance can occur with or without the presence of causality-in-mean.

Equations (5.20) and (5.21) are used to construct squares of the standardized innovations. Let ψ_t and ξ_t be squares of the standardized innovations for respective spot and futures returns of CPO.

$$\psi_t = \frac{(SR_t - \mu_{SR,t})^2}{\sigma^2_{SR,t}} \tag{5.20}$$

$$\xi_t = \frac{(FR_t - \mu_{FR,t})^2}{\sigma^2_{FR,t}} \tag{5.21}$$

Since both ψ_t and ξ_t are unobservable, squared standardized residuals by their conditional variance estimators are used to estimate consistently their values and obtain $\hat{\psi}_t$ and $\hat{\xi}_t$. Then, both of their estimated values are used to calculate the sample cross-correlation coefficient at lag k, $\hat{r}_{\psi\xi}(k)$ using Equation (5.22).

$$\hat{r}_{\psi\xi}(k) = \frac{C_{\psi\xi}(k)}{\sqrt{C_{\psi\xi}(0)C_{\psi\xi}(0)}} \tag{5.22}$$

where, $C_{\psi\xi}(k)$ is the k-th lag sample cross-covariance given by

$$C_{\psi\xi}(k) = \begin{cases} T^{-1}\sum_{t=k+1}^{T} \hat{\psi}_t \hat{\xi}_{t-k}, k \geq 0 \\ T^{-1}\sum_{t=-k+1}^{T} \hat{\psi}_{t+k} \hat{\xi}_t, k < 0 \end{cases} \tag{5.23}$$

$C_{\psi\psi}(0)$ is the sample variance of squared standardized residuals for spot return of CPO, and $C_{\xi\xi}(0)$ is the sample variance of squared standardized residuals for futures return of CPO.

Under the regularity condition, the following condition as stated in Equation (5.24) holds.

$$S_2 = T\left[\sum_{i=1}^{k}\left(\hat{r}_{\psi\xi}(k)\right)^2\right] \xrightarrow{L} \chi^2(k) \tag{5.24}$$

To test the null hypothesis of no causality-in-variance from lag 1 to lag k, the test statistic (Equation (5.24)) is compared with the chi-square distribution (χ^2). The null hypothesis is rejected if the test statistic value larger than the critical value of the chi-square distribution.

As stated above, when the degree of freedom of k is large, Equation (5.24) is transformed into a standard normal distribution by subtracting the mean of k and dividing by standard deviation of $(2k)^{1/2}$ (Hong, 2001:192). The standardized version of

S_2 is written as Equation (5.25).

$$M_2 = \frac{S_2 - k}{\sqrt{2k}} \xrightarrow{L} N(0,1) \tag{5.25}$$

Then the upper-tailed critical values from a standard normal distribution are used to compare to the one-sided test statistic as Equation (5.25). If the test statistic is greater than the critical value of the standard normal distribution, the rejection of the null hypothesis of no causality-in-variance reveals the existence of information on lead-lag pattern of interaction between spot and futures returns of CPO. This provides evidence of market participants to evaluate, assimilate and reflect the arrival of new information in affecting market volatility.

5.4 Empirical Results

5.4.1 Preliminary analysis

Table 5.3 presents the result of augmented Dickey-Fuller (ADF) unit root test for spot and futures returns of CPO during strong contango, weak contango and backwardation periods, respectively. The result shows that the null hypotheses of a unit root for both CPO spot and futures returns during three sub-periods are rejected at the 1 per cent level. This indicates that both returns are stationary for all sub-periods.

Table 5.3: Result of ADF unit root test for spot and futures returns of CPO

	Strong contango		Weak contango		Backwardation	
	Spot	Futures	Spot	Futures	Spot	Futures
Constant	-22.53*** (0)	-22.859*** (0)	-33.135*** (0)	-31.8*** (0)	-27.251*** (1)	-27.789*** (1)
Constant & Trend	-22.52*** (0)	-22.911*** (0)	-33.129*** (0)	-31.788*** (0)	-27.244*** (1)	-27.784*** (1)

Notes: *** shows that the null hypothesis of existence of a unit root is rejected at the 1% level. The optimal lag length of ADF test is reported into ().

Then, Table 5.4 presents descriptive statistics of the spot and futures returns for CPO during strong contango, weak contango and backwardation periods, respectively. CPO spot return during strong contango and weak contango periods has means of 0.0000143 and 0.0007, respectively. While mean for CPO spot return during backwardation period is turned to be -0.0002. This situation also happens for CPO futures return, where it has mean values of 0.0013, 0.0012 and -0.0009 during strong contango, weak contango and backwardation periods, respectively.

During strong contango period, CPO spot and futures returns have their respective standard deviations of 0.0186 and 0.0175 which are higher than their standard deviation during weak contango and backwardation periods. In this sense, both returns are more volatile during strong contango period. Jarque-Bera test statistic and its p-value show that CPO spot and futures returns have non-normal distribution at the 1 per cent level. This finding is further shown by kurtosis with the value greater than 3, indicating that kurtosis exhibits a leptokurtic distribution. This non-normal distribution is attributed by spot and futures returns of CPO exhibit serial correlation. In addition, both returns account volatility clustering. To account for any possible serial correlation and volatility clustering in the conditional variance of series, the conditional mean equation which is specified as an AR, MA or ARMA model with non-zero mean and GARCH error term is used.

Table 5.4: Descriptive statistics for daily spot and futures returns of CPO

	Strong contango		**Weak contango**		**Backwardation**	
	Spot	Futures	Spot	Futures	Spot	Futures
Mean	1.43×10^{-5}	0.0013	0.0007	0.0012	-0.0002	-0.0009
Standard deviation	0.0186	0.0175	0.0175	0.017	0.0163	0.0173
Maximum	0.0932	0.0703	0.0992	0.0975	0.0976	0.0950
Minimum	-0.0991	-0.0886	-0.1104	-0.0848	-0.1075	-0.109
Skewness	0.226	0.1017	-0.2858	-0.0466	-0.0919	-0.2367
Kurtosis	5.8989	5.0644	9.1480	7.5082	8.1246	6.7935
Jarque-Bera	212.331	106.1459	1777.59	948.019	968.87	094.286
p-value**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: ** p-value is the probability value of the Jarque-Bera test statistic.

5.4.2 Estimation of univariate time-series models

Table 5.5 reports the estimation results of the conditional mean and variance equations for CPO spot and futures returns during strong contango, weak contango and backwardation periods, respectively. The selected univariate models are based on the basis of the Schwarz's information criterion. During the period of strong contango, the best model for variable filtered return for CPO spot is ARMA (1,1)-Threshold (1) GARCH(1,1) and CPO futures is ARMA(1,1)-GARCH(1,1). During the period of weak contango, the best model for variable filtered return for CPO spot is AR(2)-GARCH(1,1) and CPO futures is AR(3)-GARCH(1,1). During the period of backwardation, the best model for variable filtered return for CPO spot is AR(4)-GARCH(1,1) and CPO futures is AR(3)-GARCH(1,1).

For conditional variance equation in all sub-periods, significant coefficient of α_1 (ARCH term) and coefficient of β_1 (GARCH term) suggest that existing volatility clustering. For strong contango period, one only coefficient of θ_1 (threshold term) as an indicator of the effect of threshold measure for CPO spot return is statistically significant at the 10 per cent level. This coefficient of 0.0835 indicates that the future conditional variance of CPO spot return increases more in response to negative shocks than in response to positive shocks of the same magnitude. This suggests that negative spot returns generate more volatility than positive spot returns. Furthermore, volatility persistence of both CPO returns is found to be strong and stable. For all sub-periods, CPO futures return is found to be nearly integrated with GARCH process as compared to CPO spot return.

In addition, Ljung-Box test statistics for autocorrelation in standardized residual and squared standardized residual at the first 20 lags provide the p-values above the 10 per cent level. The ARCH-LM test statistics produce p-value more than the 10 per cent level. Both tests indicate that these models for CPO spot and futures returns are free from autocorrelation and heteroscedasticity problems. This suggests that all estimated models are adequately fitted to data during all sub-periods.

Table 5.5: Estimation results

	Strong contango		Weak contango		Backwardation	
	Spot	Futures	Spot	Futures	Spot	Futures
	ARMA(1,1)-TGARCH(1,1)	ARMA(1,1)-GARCH(1,1)	AR(2)-GARCH(1,1)	AR(3)-GARCH(1,1)	AR(4)-GARCH(1,1)	AR(3)-GARCH(1,1)
Conditional mean equation:						
Constant (a_0)	-0.0006	0.0004	0.0005	0.0008**	-6.55×10^{-5}	-0.0009***
AR(1) (a_1)	-0.37	0.4762	0.0148	0.0347	-0.0085	-0.0026
AR(2) (a_2)	-	-	0.0196	0.0195	0.0456**	0.0253
AR(3) (a_3)	-	-	-	-0.0074	0.0286	0.0171
AR(4) (a_4)	-	-	-	-	-0.0017	-
MA(1) (b_1)	0.4462	-0.4311	-	-	-	-
Conditional variance equation:						
Constant (w)	4.13×10^{-6}*	4.95×10^{-6}	4.86×10^{-6}***	3.19×10^{-6}**	5.44×10^{-6}***	4.05×10^{-6}***
ARCH (α_1)	0.0822**	0.1136***	0.1404***	0.1319***	0.0741***	0.0682***
GARCH (β_1)	0.879***	0.8787***	0.8485***	0.8632***	0.9032***	0.9170***
TGARCH (θ_1)	0.0835*	-	-	-	-	-
Volatility persistence	0.9612	0.9923	0.9889	0.9951	0.9773	0.9852
Log-likelihood value	1589.627	1602.446	3206.897	3200.8	5099.538	4960.911
Schwarz information criterion	-5.2931	-5.3472	-5.698	-5.6859	-5.6507	-5.4971
Q (20)	17.705	14.270	9.6728	12.277	33.994	35.017
	[0.542]	[0.768]	[0.974]	[0.906]	[0.026]	[0.020]
Q^2 (20)	10.788	14.008	14.951	11.610	21.677	25.263
	[0.931]	[0.783]	[0.779]	[0.929]	[0.358]	[0.192]
ARCH-LM	8.38×10^{5}	0.3885	8.38×10^{6}	1.8191	2.1276	1.35×10^{7}
	[0.9927]	[0.5331]	[0.9927]	[0.1774]	[0.1447]	[0.9997]

Notes: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Q (20) and Q^2 (20) denote as the Ljung-Box test statistic for autocorrelation of standardized residuals and squared standardized residuals up to 20 lags, respectively. ARCH-LM stands for the Lagrange multiplier test for autoregressive conditional heteroscedasticity. All p-values are reported in [ ].

5.4.3 Tests for causality-in-mean and causality-in-variance

Based on standardized residuals obtained from the estimated models in Table 5.5, Table 5.6 reports correlation coefficients between standardized residuals of CPO spot and futures returns using Equation (5.16), where these correlations are interpreted as a contemporaneous causality between CPO spot and futures returns. The standardized residuals of CPO spot and futures returns are highly correlated at 0.9158 during the weak contango period. However, this finding is contradicted with the early finding by Gulley and Tilton (2014), where they find a high correlation strong contango in the case of copper. The contradiction of finding is probably to the inelastic production of CPO which in return causes the spot price to be higher than futures in weak contango due to short supply of the commodity. This is attributed by a strong correlation between crude oil returns and returns for most commodities traded in futures markets especially for types of vegetable oil during the episode of July 2008 in weak contango period.[9]

Table 5.6: Correlation coefficients between standardized residuals

	Strong contango		**Weak contango**		**Backwardation**	
	Spot	Futures	Spot	Futures	Spot	Futures
Spot	1.0000	0.7955	1.0000	0.9158	1.0000	0.8601
Futures	0.7955	1.000	0.9158	1.0000	0.8601	1.0000

Notes: This table shows correlation coefficients are calculated by using Equation (5.16). All correlation coefficients are statistically significant at the 1% level.

To test whether mean of CPO spot return Granger-causes mean of CPO futures return with respect to $I_{SF,t-1}$ and vice versa, cross-correlation functions between both standardized residuals for CPO spot and futures returns are used to estimate test statistics of M_1 for lags of 5, 10, 15, 20, 25, 30, 35 and 40 days as indicated in Equation (5.19). Table 5.7 reports the results of causality-in-mean with M_1. If test statistics are higher than the upper-tailed of critical values from a standard normal distribution,

[9] As shown in Table 5.1, during weak contango period, oil returns were strongly correlated with daily future returns from July 1, 2008 to September 30, 2008. It is further indicated by the World Bank Quarterly Report on January 2015 entitles "Commodity Markets Outlook" on p. 8 and p. 9.

causality-in-mean of both CPO returns exists.

As observed in Table 5.7, causality-in-mean from spot return to futures return occurs when lag equals to 20, 25, 30, 35 and 40 days during the period of backwardation. This indicates that mean-causality for the CPO spot market is a long-lived phenomenon due to the occurrence of seasonal environmental factors. For example, El-Nino (June 2009 - May 2010) and La-Nina (July 2010 - April 2011) events during the period which contributed to an inadequacy of short-term supply. Due to both events, palm oil stocks and CPO productions are expected to be declined. This decline would increase CPO futures price. [10]

The significant direction of causality from CPO futures return to CPO spot return in mean is found further to be occurred in lower-order lags of 10 and 15 days as well as in higher-order lags of 20, 25 and 40 days. This indicates that mean-causality for CPO futures market is a short-lived phenomenon because a transfer of futures price changes occurs not only in higher-order lags but also in lower-order lags. This causality is associated with the rejection of Environmental Protection Agency in the United States on palm-oil based biodiesel for Renewable Fuels Program.[11]

[10] As shown in Table 5.1, El-Nino and La-Nina events have occurred during backwardation period.
[11] As shown in Table 5.1, this event occurred on January 2012 during backwardation period.

Table 5.7: Causality-in-mean test results (Hong, 2001)

	k	5	10	15	20	25	30	35	40
Strong contango:									
$S \rightarrow F$	M_1	-0.121	-0.268	-0.167	-0.098	0.275	-0.241	-0.472	0.043
$F \rightarrow S$	M_1	0.107	0.187	-0.087	-0.538	-0.54	-1.063	-0.984	-0.587
Weak contango:									
$S \rightarrow F$	M_1	-0.965	-0.551	-1.101	-1.566	-1.7	-1.995	-2.278	-2.097
$F \rightarrow S$	M_1	-0.217	-0.15	-0.707	-1.004	-1.5	-1.937	-2.174	-2.098
Backwardation:									
$S \rightarrow F$	M_1	-0.285	1.251	0.656	2.313**	2.36**	1.883*	2.91***	2.72***
$F \rightarrow S$	M_1	0.137	1.934**	1.35*	2.039**	1.78**	1.248	1.263	1.688**

Notes: This table shows the causality test statistic calculated from Equation (5.19). "$S \rightarrow F$" stands for spot return Granger-causes futures return in mean respect to $I_{SF,\,t-1}$. "$F \rightarrow S$" stands for futures return Granger-causes spot return in mean respect to $I_{SF,\,t-1}$. k indicates a truncated lag number. M_1 denotes as the test statistic for causality-in-mean. The null hypothesis of no causality-in-mean is rejected If the test statistic greater than the upper-tailed critical value of the standard normal distribution. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5.8 reports correlation coefficients between squared standardized residuals of CPO spot and CPO futures returns using Equation (5.22). These correlations of residual variance are interpreted as instantaneous causality between the volatility of CPO spot and futures returns. It is noted that during the weak contango period, both returns are correlated at 0.8113, the strongest positive correlation between the squared standardized residuals of CPO spot and its futures returns. Higher correlation during weak contango period signifies heighten risk averse among market participants as there exists the possibility of an inadequacy of short-term supply for actual physical palm oil before the maturity date of future contracts.

Table 5.8: Correlation coefficients between squared standardized residuals

	Strong contango		Weak contango		Backwardation	
	Spot	Futures	Spot	Futures	Spot	Futures
Spot	1.0000	0.4769	1.0000	0.8113	1.0000	0.7321
Futures	0.4769	1.0000	0.8113	1.0000	0.7321	1.0000

Notes: This table shows the correlation coefficient calculated from Equation (5.22). All correlation coefficients are statistically significant at the 1% level.

To test whether volatility of CPO spot return Granger-causes volatility of CPO futures return with respect to information between spot and futures ($I_{SF,\,t-1}$) and vice versa, cross-correlation functions between both squared standardized residuals for CPO spot return and CPO futures return are used to obtain test statistics of M_2 for all lags of

5, 10, 15, 20, 25, 30, 35 and 40 days as indicated in Equation (5.25). Table 5.9 reports the result of causality-in-variance with M_2. Volatility spillover of both CPO returns exists if test statistics are greater that the upper-tailed of critical values from a standard normal distribution.

As shown in Table 5.9, there is significant volatility spillover from CPO futures price changes to CPO spot price changes during weak contango period at the lower lag period of 5, 10 and 15 days. This finding reveals that producers are more concerned with the short-run production. Such finding can be linked to the finding in Chapter Four on the degree of weak-form informational efficiency in the CPO futures market. Based on Chapter Four, the results of random walk hypothesis indicate that the CPO futures market in weak contango period is the most efficient. Efficient market enables market participants to respond faster to new information in the CPO futures market as they anticipate inadequacy of short-term supply for actual physical palm oil before the maturity date of the futures contracts. Such anticipation subsequently leads to the occurrence of volatility spillover from futures price changes to spot price changes.

The finding further shows that there is no causality-in-variance during strong contango period. The explanation of such finding is as follows: CPO is susceptible to seasonal fluctuation in price and spoilage. Due to its natural growing cycle, the market participant will have less intention to pay a premium in having the commodity in the future instead of paying the storage and carry costs of buying such commodity today, making them encounter difficulty in selling physical inventories in the future. As a consequence, the role of speculation in CPO price movement does not dominate during the strong contango period.

Table 5.9: Causality-in-variance test results (Hong, 2001)

	k	5	10	15	20	25	30	35	40
Strong contango:									
$S \rightarrow F$	M_2	-1.581	-2.236	-2.789	-3.16	-3.536	-3.873	-4.183	-4.472
$F \rightarrow S$	M_2	-1.581	-2.236	-2.739	-3.162	-3.536	-3.873	-4.183	-4.472
Weak contango:									
$S \rightarrow F$	M_2	-1.224	-1.251	-1.269	-0.841	-1.085	-1.045	-0.352	-0.302
$F \rightarrow S$	M_2	4.64***	3.026***	1.869**	1.275	0.76	0.554	-1.373	1.368*
Backwardation:									
$S \rightarrow F$	M_2	0.731	0.928	0.999	0.393	0.466	0.067	0.569	0.522
$F \rightarrow S$	M_2	0.039	0.784	0.752	0.437	0.421	0.772	0.167	0.195

Notes: This table shows the causality test statistic calculated from Equation (5.25). "$S \rightarrow F$" stands for spot return Granger-causes futures return in variance respect to $I_{SF,t-1}$. "$F \rightarrow S$" stands for futures return Granger-causes spot return in variance respect to $I_{SF,t-1}$. k indicates a truncated lag number. M_2 denotes as the test statistic for causality-in-variance. The null hypothesis of no causality-in-variance is rejected If the test statistic greater than the upper-tailed critical value of the standard normal distribution. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

5.5 Conclusion

The relationship between commodity spot and futures prices is vital for market participants to set their trading strategies appropriately. This study is different from a number of previous studies in two aspects. One is that taking market transition either from backwardation to contango or vice versa into account to examine such relationship in CPO markets. Following to the studies by Tilton et al. (2011), Östensson (2011), and Gulley and Tilton (2014), their examination on the correlation coefficient between spot and futures price changes is extended to capture dynamic causal relation. By using daily data of 2000-2014, the result of non-uniform weighting cross-correlation for standardized residuals and squared standardized residuals from ARMA-GARCH models provides three findings. First, during backwardation, CPO spot and futures returns are bi-directionally linked and reasonably well integrated in terms of mean causality. Second, during the period of weak contango, volatility of CPO futures return is found to Granger cause volatility of CPO spot return. Third, there is no causality-in-mean and variance during the strong contango period.

There are some intuitive explanations for these findings. In particular, market participants expect environmental factors such as El-Nino and La-Nina events during the backwardation period. Apart from this, the occurrence of a long-lived phenomenon is observed in the CPO spot market. This consequently leads them to use spot price to predict futures price with the longer time span. Furthermore, the rejection of Environmental Protection Agency in the United States on palm-oil based biodiesel for Renewable Fuels Program is observed as the short-lived phenomenon which probably produces mean causality in the CPO futures market. This suggests that market participants who are sensitive towards the policy announcements tend to predict spot price based on futures price within the shorter time span.

In fact, due to its natural growing cycle, CPO is susceptible to seasonal fluctuation in price and spoilage. Hence, the anticipation among market participants on the inadequacy of short-term supply for actual physical palm oil before the maturity date of the futures contracts is presumably high. Since producers are heavily involved in CPO markets, this study concludes that presence of weak contango which causes inventory shortage, this suggests that market participants anticipate inadequacy in the supply of actual physical palm oil before the maturity date of futures contracts. They are often keen to lock in the CPO price for their production in mitigating the risk of future price movement.

CHAPTER 6: EVALUATING THE HEDGING EFFECTIVENESS IN CPO FUTURES MARKET DURING FINANCIAL CRISES

6.1 Introduction

Being one of the world leading producers and exporters of palm oil, Malaysia alone accounted for 39 per cent of world production and 45 per cent of world exports in 2011 based on the data released by the Malaysian Palm Oil Board (MPOB). Given the prominence of this commodity to the economy, Malaysian crude palm oil (CPO) futures market has been in existence in the Kuala Lumpur Commodity Exchange (KLCE) since October 1980, and continued to be one of the active futures market for CPO related derivative product in the world under the platform of Bursa Malaysia Derivative (BMD) Berhad in 2003.

Like other market commodities, the price movement of CPO is subjected to fluctuation throughout various economic climates. As observed in Figure 6.1, it shows that CPO spot and futures returns have high volatility in three distinct periods which correspond to the world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/09. Besides the global economic recession, which happened during 1985-1987, Malaysian palm oil was subject to a series of adverse publicity launched by the American Soybean Association. As a consequence, Malaysian growth was halted abruptly as palm oil price had been halved.

In the aftermath of Asian financial crisis, the depreciation of Ringgit caused the restructuring of the Malaysian derivative market to undergo a series of regulatory reform. In response to this crisis, BMD's CPO futures contracts were traded RM2,700 per tonne at the Commodity and Monetary Exchange (COMMEX) in November 1998 (MPOB, 2011). Subsequently, palm oil has become the top foreign exchange earner, exceeding the revenue derived from crude petroleum, petroleum products by a wide margin.

However, due to the La Nina effect in 2008, Malaysian palm oil export dropped from RM13,504 million in the third quarter to RM9,271 million in the fourth quarter of 2008 due to heavy rainfall and lower fresh fruit bunches (Central Bank of Malaysia, 2009). It was observed that CPO futures price also decreased from an average of RM3506.12 in the first quarter of 2008 to RM1898.93 in the first quarter of 2009. [12]

Since the revival of China and India's gross domestic production growth in 2009, the total CPO futures contract traded has subsequently increased from 3,003,549 contracts in 2008 to 4,008,882 contracts in 2009 steadily with the rising of demand from both countries.[13] After recovery in the global economy in 2010, the rising of petroleum crude oil has continually led to the increase of CPO price and directly reduced pricing volatility after 2011.

The above account testifies that the price movement of CPO is uncertain and often influenced by economic or environmental factors. Hence, to implement better hedging strategies during the economic downturn, there is a need among market participants to focus on futures market as a means to minimize the risk of price fluctuation. However, there is no conclusive evidence to state which model provides the best hedging

[12] It is based on data extracted from Thomson DataStream on 12 January 2013.
[13] See the report of the United Nations Development Program (2009) on p. 68.

performance during extremely volatile economic periods. This study intends to revisit this issue and extends earlier studies by using basis term in modeling the joint dynamics of spot and futures returns. Therefore, this chapter attempts to answer the following research question: **how does the basis term sustain its superiority during highly volatile periods in generating the best hedge ratios and performance in the case of the Malaysian CPO futures market?**

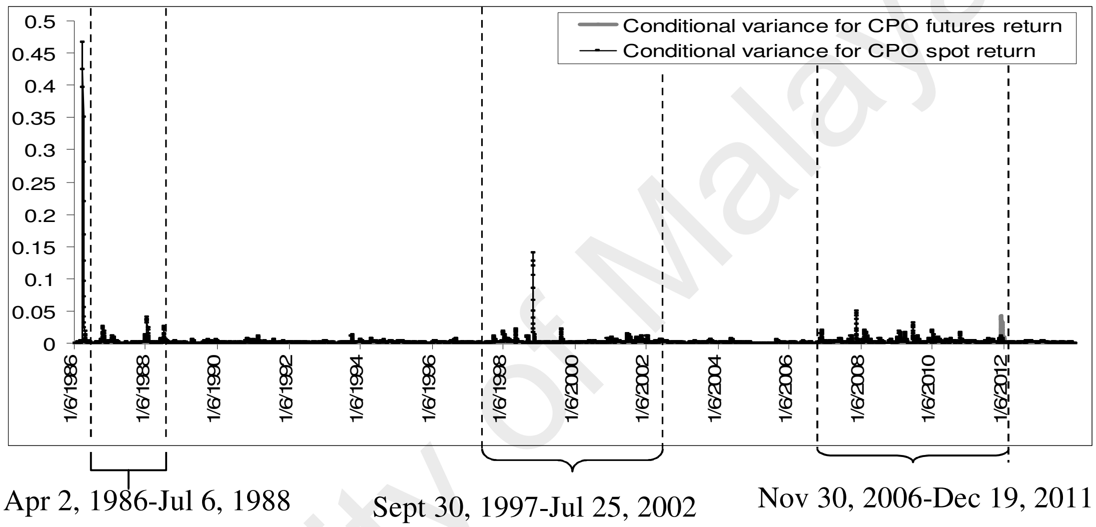

Figure 6.1: Univariate conditional variance of CPO spot and futures returns, 1986-2013

Source: Author's estimation based on Exponential-GARCH model of Malaysian CPO spot and futures returns.

Working (1953) defines hedging as "the purchase or sale of futures in conjunction with another commitment, usually in expectation of a favorable change in the relation between spot and futures prices". On the other hand, Ederington (1979) defines that hedging effectiveness is a variance reduction in the spot return portfolio. In another study, Howard and D'Antonio (1984) define that the hedging effectiveness is the ratio between excess return per unit of risk in the portfolio of the spot and futures positions to excess return per unit of risk in the portfolio of the spot position.

There are two contributions of this study. Firstly, this study investigates whether the superior hedging model can produce asymmetric performance in reducing the variance of portfolio across three sub-periods, namely the world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/09 respectively. This assessment is important for the CPO market participants to know whether they need to adjust or switch their hedging models in mitigating price risk across different market conditions.

Secondly, this study extends the studies of Zainudin and Shaharudin (2011) and Ong, Tan and Teh (2012) on hedging effectiveness in the Malaysian CPO futures market by incorporating basis term (the short-run deviation between CPO spot and futures prices) into conditional variance-covariance structures of Baba-Engle-Kraft-Kroner (BEKK) and Constant Conditional Correlation (CCC) representations. Although the basis term has been confirmed to be a factor influencing the level of spot and futures price movements in the model, this study attempts to verify whether the basis term can sustain its superiority during highly volatile periods in generating the best hedge ratios and performance for the case of the Malaysian CPO futures market.

This chapter 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.

6.2 Literature Review

6.2.1 Hedging model specifications

The debate on econometric models for estimating the minimum-variance futures hedge ratio has been discussed for many years. In early studies, Johnson (1960) was the first to introduce optimal hedge ratio (OHR) in minimizing portfolio variance in hedging strategies. He defined that OHR was the ratio between covariance between spot and futures returns to the variance of futures return. Stein (1961) was the first to use an ordinary least squares (OLS) method to regress the spot returns against futures returns by assuming covariance exhibited time-invariant characteristics. The estimated slope of a model could be interpreted as OHR. The high R-squared from the estimated linear regression model indicated that the OLS hedging strategy was effective. This assumption was further used by Ederington (1979), Anderson and Danthine (1981) and Hill and Schneeweis (1981).

Nevertheless, Ederington (1979) found that the hedging effectiveness based on the R-squared from a simple regression was inappropriate to estimate OHR because the movement of the OHR exhibited time-variant characteristics and correlation between two rates of return also varying across time. This effect leads to risk-minimizing hedge ratios to be time-varying as well. To account for this effect, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework is constructed to display time-varying volatility of both returns. As a result, there have been a number of proponents for the GARCH framework with each of them demonstrated the effectiveness of dynamic hedge ratios with respect to the highest variance reduction (Baillie & Myers, 1991; Park & Switzer, 1995; Tong, 1996; Moschini & Myers, 2002;

Lien, Tse & Tsui, 2002; Floros & Vougas, 2004; Ahmed, 2007; and Zainudin & Shaharudin, 2011).

To explain the conditional covariance between the spot and futures returns and estimate OHR under the time-varying framework, Bollerslev et al. (1988) have extended GARCH model to become a Bivariate GARCH (BGARCH) model. With the respect to this model, Baillie and Myers (1991) found that OHR exhibited non-stationary movement across time in the United States six commodities. This non-stationary movement implied that the assumption of a time-invariant OHR was not longer inappropriate to be used. This demonstrated that the BGARCH model appeared to fit the data well because the considerable time variation in the conditional covariance matrix.

Park and Switzer (1995) further demonstrated its superiority in the corn and soybean markets. In contrast to the evidence as demonstrated above, they found this model could not guarantee to provide the superior hedging strategy to OLS hedging strategy when volatility movement was not stable and high as well as the consideration of transaction cost. As a result, this model contained too many parameters and did not restrict conditional variance-covariance matrix to be a positive semidefinite.

To ensure the positive semidefinite in the variance-covariance matrix, Engle and Kroner (1995) have developed the variance-covariance with BEKK (name after Baba, Engle, Kraft and Kroner) specification. Subsequently, the GARCH model with this specification was turned to be more flexible for the researchers to study hedging performance in variety commodity markets. For instance, Moschini and Myers (2002) used BEKK-GARCH model for hedging of weekly corn prices in Midwest during 1976-1997. They found that this model was the best, but it could not be used to explain deterministic seasonality and time-to-maturity effects. Floros and Vougas (2004) found the superiority of this model in capturing new information arrival in the Greek market for the period 1999-2001. Alizadeh et al. (2004) compared hedging effectiveness across Rotterdam, Singapore and Houston during 1988-2000 using the BEKK-GARCH model. They pointed out that low hedging performance was due to different regional supply and demand of crude oil and petroleum.

As discussed by Brooks et al. (2002), asymmetric effects of positive and negative returns cannot be neglected from BEKK parameterization in estimating hedge ratios. This could be demonstrated through the GARCH model with the asymmetric effects provided the superior hedging performance for in-sample, but its effectiveness was low for the out-of-sample. By using Fama's regression approach (1984) and simple random walk model, Switzer and El-Khoury (2007) have presented the evidence of the asymmetric effect of bad and good news in improving hedging performance in the New York Mercantile Exchange Division light sweet crude oil futures market from 1986 to 2005. During the period 1992-2009, Wu et al. (2011) used the asymmetric version of the BEKK model to account for a possibly asymmetric effect of volatility. They found evidence of hedging strategy across corn and crude oil markets to be slightly efficient than traditional hedging strategy in the corn futures market alone.

As suggested by the efficient markets hypothesis, the cointegration relationship between spot and futures prices should be examined because both prices contain a stochastic trend. Kroner and Sultan (1993) were the first to adopt the GARCH framework with an error correction term in estimating dynamic hedge ratios. They found that this framework provided the superior hedging performance over more conventional hedging measures.

Subsequently, a number of researchers have adopted the GARCH with the error correction term in their studies. For instance, Tong (1996) supported the incorporating the error correction term into mean equation of BEKK-GARCH model could improve hedging performance in the Tokyo stock index during 1980-1987. Choudhry (2002, 2004) found similar results with Tong (1996), where GARCH hedging strategy with the error correction term was outperformed in the Australia, Germany, Hong Kong, Japan, South African and United Kingdom futures markets during 1990-1999. He further made an investigation in the Australia, Hong Kong and Japan stock market during 1990-2000 and confirmed that this error term is crucial in the most of the cases.

The GARCH model has 11 parameters in the conditional variance-covariance structure with BEKK formulation. To obtain a parsimonious model, Bollerslev (1990) has developed the Constant Conditional Correlation (CCC)-GARCH model that consists of 7 parameters in order to provide simple computation and ensure the positive semi-definite in the conditional variance-covariance matrix (Kroner & Sultan, 1993; Ng & Pirrong, 1994; and Lien et al., 2002). Alternative estimation of OHR supported that constant correlation between standardized residuals of spot and futures returns (residuals divided by the GARCH conditional standard deviation) provided high explanatory power to the conditional variance-covariance of both series, and hence CCC-GARCH model was preferred in view of this. Empirical research that used this model includes Lien et al. (2002) and Ahmed (2007).

On the contrary, Lien et al. (2002) found that OLS estimation model was better than a CCC vector GARCH model in the currency futures, commodity futures and stock index futures during 1988-1998. Their results indicated that the underperformance of CCC-GARCH model often generated too variable forecasted variance. According to the authors, a time-varying regime-switching model has appeared to be a better model to improve the accuracy of the model in variance forecasting. Ahmed (2007) compared the effectiveness of time-varying and traditional duration-based constant hedge ratios in the United States Treasury market. His finding indicated that the estimated time-varying hedge ratio from the CCC-GARCH able to capture the conditional heteroskedasticity in the spot market. As a result, this model has provided an advantage in minimizing the variance for bond investors to change their positions in futures market based on the changes in actual yields of spot market during ten years of trading.

6.2.2 Hedging effectiveness in Malaysian CPO futures market

There are empirical works related to hedge ratio analysis for the case of Malaysian palm oil. For instance, Zainudin and Shaharudin (2011) claimed that the different restriction imposed in the conditional mean equation could affect the hedging effectiveness in the Malaysian CPO futures market. They used the BEKK-GARCH model with three different mean specifications comprising the intercept, Vector Autoregressive (VAR) and Vector Error Correction Model (VECM) to examine hedging effectiveness based on risk minimization and utility maximization. Based on risk minimization within the in- and out-of-sample, they found that a parsimonious model such as the BEKK-GARCH models with mean intercept and VAR provided better hedging performance as compared to complicated model such as the BEKK-VECM model. The difference between tested models was small in terms of utility maximization.

In another study by Ong et al. (2012), with an OLS method in estimating the hedge ratio for each month during 2009-2011, they reported that the increasing hedge ratio during January, 2009-June, 2011 has contributed to 19-53 per cent of the hedging effectiveness. They claimed that this low level of hedging performance was due to four events, (1) the rising of petroleum crude oil, (2) recovery of world economy in 2010, (3) weak impact of the tsunami and earthquake in Japan, and (4) debt crisis in Europe has caused stable and consistent movement of volatility in the CPO spot market.

6.3 Data and Methodology

This study uses daily closing CPO spot and futures prices from January 6, 1986 to December 31, 2013 which consist of 6,782 observations. The data are collected from Thomson Reuters DataStream. In order to reduce the variability of both series and achieve stationarity, both prices are transformed to returns in the natural logarithmic form. Subsequently, the whole sample period is divided into three sub-periods: the first sub - period from April 2, 1986 to July 6, 1988, the second sub-period from Sept 30, 1997 to July 25, 2002 and lastly the third sub-period from November 30, 2006-December 19, 2011.

As observed in Table 6.1, the lowest means of both daily returns with negative values are recorded during the Asian financial crisis. In the same period, the lowest standard deviation of 0.0190 indicates that spot market has less volatility. Across the three periods, it is observed that the standard deviation of spot and future returns slightly increased to 0.027 and 0.0267 during the global financial crisis.

Table 6.1: Descriptive statistic of CPO returns

	Panel A: Apr 2, 1986 – Jul 6, 1988		Panel B: Sept 30, 1997 – Jul 25, 2002		Panel C: Nov 30, 2006 – Dec 19, 2011	
	Spot	**Futures**	**Spot**	**Futures**	**Spot**	**Futures**
Observations	549	549	1180	1180	1241	1241
Mean	0.0004	0.0011	-4.88×10^{-5}	-6.56×10^{-5}	0.0004	0.00037
Std deviation	0.0279	0.0211	0.0190	0.0252	0.027	0.0267
Maximum	0.1915	0.0729	0.0975	0.3569	0.211	0.4217
Minimum	-0.3867	-0.0798	-0.0778	-0.1511	-0.3020	-0.4038
Skewness	-4.3620	0.0778	0.3294	2.0373	-2.4272	0.2242
Kurtosis	79.7350	4.268	4.974	43.1774	42.6643	94.2995
Jarque-Bera	136435.3*	37.33*	212.91*	80182.10*	82569.07*	431029.9*

Note: * indicates null hypothesis is rejected at the 1% level.

Based on Table 6.2, augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test statistics support the rejection of null hypotheses of a unit root, implying the unit root is absence for daily CPO spot and futures returns series. Therefore, both returns are stationary in level form. Furthermore, various models with different mean and variance specifications are estimated in each sub-period. Subsequently, the in- and out-of-sample performance for each model is compared to examine the asymmetric performance of hedging across the three events.

Table 6.2: Unit root test results

		CPO Spot	**CPO Futures**
Augmented Dickey-Fuller (ADF)	Drift	-85.5402*	-87.8223*
	Drift and Trend	-85.5339*	-87.8165*
Phillips-Perron (PP)	Drift	-85.5057*	-87.9983*
	Drift and Trend	-85.4994*	-87.9928*

Notes: Null hypothesis states that the existences of unit root in returns. * indicates null hypothesis is rejected at the 1% level.

6.3.1 Model specifications

This study involves three-step approach. The first step is to estimate Minimum-Variance Optimal Hedge Ratio (MVOHR) by using time-varying and time-invariant hedging models. The second step is to compute variance of the portfolio, and finally, we proceed to evaluate the hedging effectiveness using the minimum variance framework in each sub-period.

Two types of time-invariant hedging models are used in this study, namely naïve and Ordinary Least Squares (OLS). However, if conditional variance-covariance matrix is time-variant, GARCH model will be used to estimate OHR. Two versions of GARCH models (BEKK and CCC) representation are used in this study.

6.3.1.1 Mean specifications

In the time-varying framework, we estimate three types of conditional mean specifications. First, this study considers a simple mean model as follows:

$$r_{S,t} = c_S + \varepsilon_{S,t} \; ; \; \varepsilon_{S,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{6.1}$$

$$r_{F,t} = c_F + \varepsilon_{F,t} \; ; \; \varepsilon_{F,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{6.2}$$

where, $r_{S,t}$ is daily CPO spot return at time t; $r_{F,t}$ is daily CPO futures return at time t; $\varepsilon_{S,t}$ is unexpected daily CPO spot return that cannot be predicted based on all information about daily CPO spot return available up to the preceding period; $\varepsilon_{F,t}$ is unexpected daily CPO futures return that cannot be predicted based on all information about daily CPO future return available up to the preceding period; Ω_{t-1} is information set available to time $t-1$; and H_t is conditional variance of daily CPO spot and futures returns at time t respectively.

Second, we model the conditional mean equation by considering both CPO returns lagged term $\left(r_{S,t-i}, r_{F,t-i}\right)$ to capture the short-run association between CPO spot and futures returns. Hence, vector autoregressive (VAR) mean modeling is specified as follows:

$$r_{S,t} = c_S + \sum_{i-1}^{k} a_{S,i} r_{S,t-i} + \sum_{i=1}^{k} b_{S,i} r_{F,t-i} + \varepsilon_{S,t} \;\; ; \; \varepsilon_{S,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{6.3}$$

$$r_{F,t} = c_F + \sum_{i-1}^{k} a_{F,i} r_{S,t-i} + \sum_{i=1}^{k} b_{F,i} r_{F,t-i} + \varepsilon_{F,t} \;\; ; \; \varepsilon_{F,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{6.4}$$

Third, we include a lagged one of basis (Z_{t-1}) to measure the long-run relationship between the CPO spot and futures prices. For the conditional mean equation, this study follows model specification by Lien and Yang (2008).[14] Both conditional means of CPO spot and futures returns are written as Equations (6.5) and (6.6).

$$r_{S,t} = c_S + \sum_{i=1}^{k} a_{S,i} r_{S,t-i} + \sum_{i=1}^{k} b_{S,i} r_{F,t-i} + \eta_S Z_{t-1} + \varepsilon_{S,t} \quad ; \; \varepsilon_{S,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{6.5}$$

$$r_{F,t} = c_F + \sum_{i=1}^{k} a_{F,i} r_{S,t-i} + \sum_{i=1}^{k} b_{F,i} r_{F,t-i} + \eta_F Z_{t-1} + \varepsilon_{F,t} \quad ; \; \varepsilon_{F,t} \big| \Omega_{t-1} \sim N(0, H_t) \tag{6.6}$$

In Equations (6.5) and (6.6), Z_{t-1} is measured by $(\ln P_{S,t-1} - \ln P_{F,t-1})$, where $\ln P_{S,t-1}$ and $\ln P_{F,t-1}$ are denoted as daily CPO spot and futures prices in natural logarithmic form at time $t-1$ respectively. A negative basis indicates that futures price exceeds spot price at time $t-1$. In order to eliminate a deviation from the long-run relationship between both prices, the futures price tends to decease whereas the spot price tends to increase at time t. This leads to $\eta_S \geq 0$ and $\eta_F \leq 0$, as well as at least one of parameter is nonzero. Otherwise, it is for a positive basis.

[14] Refer to Lien and Yang (2008) on p.126.

6.3.1.2 Variance-covariance specifications

If conditional variance-covariance has a time-varying structure, GARCH (1,1) model is used. To maintain positive semidefinite of the estimated parameters in the variance-covariance structure, we adopt the two different specifications of conditional variance-covariance.

The first specification of time-variant model is a general BEKK-GARH (1,1) model (Engle & Kroner, 1995), where H_t is defined as follows:

$$H_t = CC^{'} + A\varepsilon_{t-1}\varepsilon_{t-1}^{'}A^{'} + GH_{t-1}G^{'}$$

$$H_t = \begin{bmatrix} H_{SS} & H_{SF} \\ H_{FS} & H_{FF} \end{bmatrix} ; \; C = \begin{bmatrix} C_{SS} & C_{SF} \\ 0 & C_{FF} \end{bmatrix} ; \; A = \begin{bmatrix} A_{SS} & A_{SF} \\ A_{FS} & A_{FF} \end{bmatrix} ; \; G = \begin{bmatrix} G_{SS} & G_{SF} \\ G_{FS} & G_{FF} \end{bmatrix} ; \text{ and}$$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix} .$$

$$h_{SS,t} = C_{SS} + A_{SS}\varepsilon_{S,t-1}^2 + G_{SS}h_{SS,t-1}$$

$$h_{FF,t} = C_{FF} + A_{FF}\varepsilon_{F,t-1}^2 + G_{FF}h_{FF,t-1}$$

$$h_{SF,t} = C_{SF} + A_{SF}\varepsilon_{S,t-1}\varepsilon_{F,t-1} + G_{SF}h_{SS,t-1}h_{FF,t-1} \tag{6.7}$$

where, H_t is conditional covariance matrix at time t; C is constant coefficient parameters for daily CPO spot and futures returns respectively; A is squared error lagged coefficient parameters for daily CPO spot and futures returns respectively; G is volatility lagged coefficient parameters for daily CPO spot and futures returns respectively; ε_t is error terms for daily CPO spot and futures returns respectively; $h_{SS,t}$ is conditional variance of daily CPO spot return at time t; $h_{FF,t}$ is conditional variance of daily CPO futures return at time t; and $h_{SF,t}$ is conditional covariance at time t.

Based on Equation (6.7), the BEKK parameterization requires estimation of 11 parameters in the conditional variance-covariance structure. This specification assumes that spillover parameters are constant $(A_{SF} = A_{FS}, G_{SF} = G_{FS})$ throughout the entire sample periods without taking correlation into account. [15] With less number of parameters, this model maintains the positive semidefinite of estimated parameters for conditional variance and covariance. This condition can be satisfied by imposing parameter constraints of "$0 < (A+G) \leq 1$".

The second specification of the time-variant model is a CCC-GARCH (1,1) of which is estimated by taking standardized residuals of spot and futures returns (residuals divided by the GARCH conditional standard deviation) into conditional correlation matrix (ρ) (Bollerslev,1990). Based on this model, the conditional correlation is assumed to be time-invariant. Subsequently, H_t is defined as follows:

$H_t = D_t R D_t$, where $D_t = diag\{\sqrt{h_{i,t}}\}$

$$= Var(\varepsilon_{S,t}, \varepsilon_{F,t} | \phi_{t-1}) \equiv \begin{bmatrix} h_{SS,t} & h_{SF,t} \\ h_{FS,t} & h_{FF,t} \end{bmatrix} = \begin{bmatrix} \sqrt{h_{SS,t}} & 0 \\ 0 & \sqrt{h_{FF,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{SS,t}} & 0 \\ 0 & \sqrt{h_{FF,t}} \end{bmatrix}$$

$$h_{SS,t} = \omega_{SS} + \alpha_{SS}\varepsilon^2_{S,t-1} + \beta_{SS} h_{SS,t-1}$$

$$h_{FF,t} = \omega_{FF} + \alpha_{FF}\varepsilon^2_{F,t-1} + \beta_{FF} h_{FF,t-1}$$

$$h_{SF,t} = \rho\sqrt{h_{SS,t} h_{FF,t}}$$

$$\rho = E_{t-1}(\eta_t \eta'_t) = D_t^{-1} H_t D_t^{-1}, \eta_t = \frac{\varepsilon_t}{\sqrt{h_t}} \tag{6.8}$$

[15] Refer to the article of Wu et al. (2011) from p.1056 to 1063.

where, H_t is conditional covariance matrix at time t; R is correlation matrix of standardized residuals for daily CPO spot and futures returns; $h_{SS,t}$ is conditional variance of daily CPO spot return at time t; $h_{FF,t}$ is conditional variance of daily CPO futures return at time t; $h_{SF,t}$ is conditional covariance at time t; and ρ is correlation coefficient between standardized residuals of daily CPO spot and futures returns.

Past studies have used the CCC-GARCH model because it is a parsimonious model with 7 parameters that provides simple computation (see Kroner & Sultan, 1993; Ng & Pirrong, 1994; and Lien et al. 2002). Based on Equation (6.8), a positive semidefinite of the conditional variance-covariance matrix is guaranteed by assuring $h_{SS,t} > 0$ and $h_{FF,t} > 0$, where $\omega > 0, \alpha > 0, \beta > 0$, and $0 < \alpha + \beta \leq 1$ for individual GARCH (1,1) process.

According to Ng and Pirrong (1994), a size of basis affects price volatility in the energy futures market. This implies that spot and futures markets are more volatile when the size of basis is large, suggesting arbitrage activities are ineffective. Kogan et al. (2005) predict that the volatility of spot or futures returns and the basis have a V-shape effect. To capture the effect of the short-run deviation between both prices on the conditional variance-covariance (H_t), the lagged one of basis squared is included into H_t equation that follows BEKK and CCC settings to become Equation (6.9) as follows:

$$h_{k,t} = \omega_k + \alpha_k \varepsilon_{k,t-1}^2 + \beta_k h_{k,t-1} + \theta_k (Z_{t-1})^2 \text{ for } k = SS, FF, SF \tag{6.9}$$

The estimation of all GARCH models above is carried out by maximizing value of log-likelihood using Equation (6.10) as follows:

$$L(\theta) = -T\ln(2\pi) - (1/2)\sum_{t=1}^{T}\left(\ln\left|H_t(\theta)\right| + \varepsilon_t(\theta)H_t^{-1}(\theta)\varepsilon_t^{'}(\theta)\right) \tag{6.10}$$

6.3.2 Minimum-variance hedge ratio (MVHR) estimation

The MVHR at a point in time $\left(h_t|\Omega_{t-1}\right)$ is then calculated using Equation (6.11) as a ratio of the conditional covariance between spot and futures $\left(h_{SF,t}\right)$ to the conditional variance of futures $\left(h_{FF,t}\right)$. The obtained MVHRs from the BEKK-GARCH and CCC-GARCH (1,1) models are used to calculate variance of portfolio and hedging effectiveness.

$$h_t|\Omega_{t-1} = \left(\frac{h_{SF,t}}{h_{FF,t}}\right)|\Omega_{t-1} \tag{6.11}$$

6.3.3 Variance of portfolio

In the time-varying analysis, variance of portfolio $\left(H_{p,t}\right)$ is calculated by substituting dynamic MVHR (from Equation (6.11)), conditional variance in the CPO spot market, conditional variance in the CPO futures market and conditional covariance of both CPO returns into Equation (6.12).

$$H_{p,t} = h_{SS,t} + \left(h_t|\Omega_{t-1}\right)^2 h_{FF,t} - 2\left(h_t|\Omega_{t-1}\right)h_{SF,t} \tag{6.12}$$

6.3.4 Hedging performance measurement

The last step is to evaluate the hedging effectiveness for time-invariant and time-variant models based on risk minimization context, where it is the most frequently used as the hedging performance measure. According to Ederington (1979), the risk minimization is measured using Equation (6.13) to compute the percentage of variance reduction in adjusting hedging strategy. The hedging strategy is effective if the variance of return on a hedged portfolio (refer to Equation (6.12)) approximately equal to zero as compared to the unhedged portfolio.

$$\text{Percentage of variance reduction} = \frac{H_{p,t}(Unhedged) - H_{p,t}(Hedged)}{H_{p,t}(Unhedged)} \times 100 \qquad (6.13)$$

where, $H_{p,t}(Unhedged)$ is variance of portfolio from an unhedged strategy or unconditional variance of daily CPO spot return; and $H_{p,t}(Hedged)$ is variance of portfolio from a hedging strategy (refer to Equation (6.12)).

6.4 Results

6.4.1 BEKK and CCC estimations with different mean and variance-covariance specifications

First of all, the BEKK-GARCH and CCC-GARCH models with different mean and variance specifications are estimated in each sub-period. The estimated results for these models are summarized in Table 6.3 and Table 6.4 respectively.

From Table 6.3, it is observed that the variances of CPO spot and futures returns with BEKK framework are highly influenced by their own past squared residuals (A_{SS} and A_{FF}) and own past variances (G_{SS} and G_{FF}) in the most of cases. Most of the coefficients of A_{SF} and G_{SF} in covariance equations are found as significant, indicating the volatility in both markets exhibit the interactive effect. The coefficients of η_S and

η_F in the conditional mean equation are significant in the most of sub-periods, whereas the coefficients of θ_{SS} , θ_{FF} and θ_{SF} are majority insignificant in the variance-covariance equations, especially during the Asian financial crisis (Panel B). This implies that incorporating lagged one of basis is crucial in modelling the conditional mean instead of the variance-covariance.

As observed in Table 6.4, the constant conditional correlation assumption provides the significant coefficients of α_{SS} and α_{FF} in the most of sub-period. This reveals the past squared residuals have an effect on the conditional variance of spot and futures. A similar finding has been found for the coefficient of β_{SS} . For the coefficient of β_{FF} , it indicates that the past variance of futures market insignificantly affects its own current variance in the most of cases during the Asian financial crisis (Panel B). The coefficient of η_S is found to be highly significant as compared to η_F, indicating the lagged one of basis has an explanatory power in describing the conditional mean of spot market instead of futures market. Both coefficients of θ_{FF} and θ_{SF} indicate that the basis term contributes significant effect on either the conditional variance of spot or futures markets in Panel A and Panel B, but this term is found to have a significant effect on both markets in Panel C. Furthermore, the constant conditional correlations between standardized residual of spot and futures returns are found to be the strongest during the Asian financial crisis (Panel B). These correlations are found to be weak in the subsequent crisis (Panel C).

For diagnostic testing, Ljung–Box statistics of the 15th order are presented in Table 6.3 and Table 6.4. These statistics are based on standardized residuals and their squares, implying there is no need to encompass a higher order ARCH process (Giannopoulos, 1995). In Panel A, it indicates that VAR-BEKK-GARCH model free from serial correlation and ARCH problems in both residual series. Subsequently, in Panel B and Panel C, the GARCH models with the short run and long run relationships of both series have no serial correlation in the standardized residuals and the standardized squared residuals as compared to the intercept-GARCH model. Based on these estimated models, the minimum-variance hedge ratios are constructed and its descriptive statistics for the in- and out-of- sample analysis are reported in Table 6.5.

Table 6.3: The estimation results of BEKK-GARCH (1,1) model by using maximum likelihood during the whole period

	Panel A: Apr 2, 1986 - Jul 6, 1988			Panel B: Sept 30, 1997- Jul 25, 2002			Panel C: Nov 30, 2006 - Dec 19, 2011		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional mean equation:									
c_S	0.0011 (0.001)	0.0002 (0.0011)	0.0163*** (0.0011)	-0.0004 (0.0005)	-0.0004 (0.0005)	0.0005 (0.0006)	0.0006 (0.0008)	0.0007 (0.0008)	0.0056*** (0.001)
$a_{S,1}$	-	-0.1128 (0.0925)	-0.1483 (0.0971)	-	0.0228 (0.0311)	0.0130 (0.0313)	-	-0.102*** (0.0335)	-0.0690** (0.0309)
$a_{S,2}$	-	-0.0198 (0.04)	-0.0362 (0.0505)	-	-	-	-	-	-
$a_{S,3}$	-	-0.0193 (0.0481)	-0.02 (0.0517)	-	-	-	-	-	-
$a_{S,4}$	-	-0.0112 (0.0494)	0.0748*** (0.0233)	-	-	-	-	-	-
$b_{S,1}$	-	0.1107** (0.0549)	0.0061 (0.0329)	-	0.0216 (0.0162)	0.026 (0.0168)	-	0.0838*** (0.0160)	0.0238 (0.0248)
$b_{S,2}$	-	0.0668* (0.0393)	0.1361*** (0.0316)	-	-	-	-	-	-
$b_{S,3}$	-	0.2113*** (0.0443)	0.1084*** (0.0371)	-	-	-	-	-	-
$b_{S,4}$	-	0.2654*** (0.0474)	0.1315*** (0.0326)	-	-	-	-	-	-
η_S	-	-	-0.1595*** (0.0129)	-	-	-0.0073** (0.0038)	-	-	-0.0703** (0.0124)
c_F	0.0007 (0.0008)	0.0007 (0.0007)	0.0039** (0.0016)	-0.0003 (0.0008)	-0.0002 (0.0007)	0.0025** (0.0011)	0.0022*** (0.0005)	0.0023*** (0.0004)	0.003*** (0.0007)
$a_{F,1}$	-	0.1434*** (0.0318)	0.1276*** (0.0263)	-	0.358*** (0.0361)	0.3534*** (0.0391)	-	-0.0246 (0.0166)	-0.018 (0.0167)
$a_{F,2}$	-	0.0250 (0.031)	0.0277 (0.0270)	-	-	-	-	-	-
$a_{F,3}$	-	0.0982*** (0.0345)	0.1018*** (0.0337)	-	-	-	-	-	-
$a_{F,4}$	-	0.0185 (0.0391)	0.0755** (0.0344)	-	-	-	-	-	-
$b_{F,1}$	-	0.1194** (0.0482)	0.1085** (0.0487)	-	-0.1431*** (0.04)	-0.1473*** (0.0407)	-	-0.0614 (0.0429)	0.0777* (0.0449)
$b_{F,2}$	-	-0.0703 (0.0447)	-0.0498 (0.0443)	-	-	-	-	-	-
$b_{F,3}$	-	0.0278 (0.0476)	0.0188 (0.0473)	-	-	-	-	-	-
$b_{F,4}$	-	0.0757* (0.0441)	0.0625 (0.0456)	-	-	-	-	-	-
η_F	-	-	-0.0297* (0.0156)	-	-	-0.0259** (0.011)	-	-	-0.0113 (0.0078)

Table 6.3: (Continued)

	Panel A: Apr 2, 1986 - Jul 6, 1988			Panel B: Sept 30, 1997- Jul 25, 2002			Panel C: Nov 30, 2006 - Dec 19, 2011		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional variance-covariance equation:									
C_{SS}	0.0001***	1.28×10^{-5} **	2.53×10^{-5} *	7.50×10^{-6} ***	1.2×10^{-5} ***	1.3×10^{-5} ***	0.0002***	0.0002***	0.0004***
	(1.14×10^{-5})	(5.03×10^{-6})	(1.38×10^{-5})	(1.77×10^{-6})	(2.7×10^{-6})	(2.87×10^{-6})	(2.5×10^{-5})	(2.94×10^{-5})	(1.6×10^{-5})
C_{FF}	1.57×10^{-5} ***	1.72×10^{-5} **	1.50×10^{-5} *	7.2×10^{-6} **	0.0001***	0.0001**	8.8×10^{-5} ***	8.6×10^{-5} ***	5.05×10^{-5} ***
	(5.64×10^{-6})	(8×10^{-6})	(7.87×10^{-6})	(2.94×10^{-6})	(5.03×10^{-5})	(4.29×10^{-5})	(1.22×10^{-5})	(1.21×10^{-5})	(1.21×10^{-5})
C_{SF}	1.80×10^{-5} **	6.84×10^{-6} **	9.97×10^{-6}	6.16×10^{-6} ***	1.93×10^{-5} ***	1.8×10^{-5} ***	2.9×10^{-5} ***	2.92×10^{-5} ***	0.0001***
	(7.44×10^{-6})	(2.80×10^{-6})	(8.02×10^{-6})	(1.11×10^{-6})	(5.89×10^{-6})	(5.54×10^{-6})	(7.67×10^{-6})	(7.71×10^{-6})	(1.59×10^{-5})
A_{SS}	-0.0023	-0.0842***	0.7636***	0.2806***	0.3321***	0.3327***	0.2271***	0.217***	0.2754***
	(0.0723)	(0.016)	(0.0665)	(0.0175)	(0.023)	(0.0231)	(0.0206)	(0.0231)	(0.0287)
A_{FF}	0.3891***	0.3857***	0.3379***	0.0489***	0.1370***	0.1492***	0.8108***	0.818***	0.8353***
	(0.0472)	(0.0497)	(0.0412)	(0.0116)	(0.0227)	(0.0262)	(0.0179)	(0.02)	(0.0213)
A_{SF}	-0.0009	-0.0325***	0.2581***	0.0137***	0.0455***	0.0496***	0.1842***	0.1775***	0.23***
	(0.0034)	(0.0008)	(0.0027)	(0.0002)	(0.0005)	(0.0006)	(0.0004)	(0.0005)	(0.0006)
G_{SS}	0.8455***	0.9827***	0.6443***	0.9477***	0.9244***	0.9223***	0.7996***	0.8123***	0.1079
	(0.0159)	(0.00672)	(0.0318)	(0.0065)	(0.01)	(0.0103)	(0.0252)	(0.0291)	(0.147)
G_{FF}	0.9002***	0.9010***	0.9258***	0.9933***	0.8806***	0.883***	0.642***	0.6421***	0.5078***
	(0.0231)	(0.0265)	(0.0189)	(0.0026)	(0.0506)	(0.0467)	(0.0224)	(0.0223)	(0.039)
G_{SF}	0.7611***	0.8854***	0.5965***	0.9414***	0.8141***	0.8144***	0.5133***	0.5215***	0.0578***
	(0.0004)	(0.0002)	(0.0006)	(1.73×10^{-5})	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0057)
θ_{SS}	-	-	0.0052***	-	-	1.3×10^{-6}	-	-	0.0149***
			(0.0009)			(2.8×10^{-5})			(0.0011)
θ_{FF}	-	-	1.46×10^{-5}	-	-	0.0003	-	-	0.0031***
			(0.0002)			(0.004)			(0.001)
θ_{SF}	-	-	0.0003	-	-	-1.85×10^{-5}	-	-	-0.0006
			(0.0006)			(4.38×10^{-5})			(0.001)
L	2689.764	2743.990	2791.973	5856.259	5889.206	5908.266	5773.347	5778.103	5943.883
Test for higher order ARCH effect									
Spot equations:									
$Q(15)$	22.983*	21.807	58.080***	28.979**	21.041	15.749	22.164*	15.906	15.221
$Q^2(15)$	27.300**	13.555	48.585***	28.875**	20.214	20.793	19.411	18.241	6.2956
Futures equations:									
$Q(15)$	43.711***	10.570	41.047***	12.185	10.904	12.173	19.614	23.485*	20.023
$Q^2(15)$	12.843	19.730	15.437	1.0329	0.9280	0.6505	0.8195	0.8976	0.9668

Notes: 1. (a) Intercept-BEKK-GARCH models are estimated by Equations (6.1), (6.2) and (6.7). (b) Vector autoregressive (VAR)-BEKK-GARCH models are estimated by Equations (6.3), (6.4) and (6.7). (c) Basis-BEKK-GARCH models are estimated by Equations (6.5), (6.6) and (6.9). 2. *, ** and *** indicate the statistical significance at the 10%, 5% and 1% levels respectively. 3. Numbers in parentheses are the standard errors. 4. L is the value of the log-likelihood function calculated by Equation (6.10). 5. Q and Q^2 are the Ljung–Box statistics of standardized residuals and standardized squared residuals.

Table 6.4: The estimation results of CCC-GARCH (1,1) model by using maximum likelihood during whole period

	Panel A: Apr 2, 1986 - Jul 6, 1988			Panel B: Sept 30, 1997- Jul 25, 2002			Panel C: Nov 30, 2006 - Dec 19, 2011		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional mean equation:									
c_S	0.0010 (0.0013)	0.0006 (0.0011)	0.0133*** (0.0008)	-0.0003 (0.0004)	-0.0003 (0.0005)	0.0006 (0.0006)	0.0009 (0.0008)	0.0009 (0.0008)	0.0063*** (0.0009)
$a_{S,1}$	-	-0.0547 (0.0348)	-0.0604*** (0.0036)	-	0.0261 (0.0314)	0.0151 (0.0322)	-	-0.140*** (0.0426)	-0.0851** (0.0396)
$a_{S,2}$	-	-0.0464 (0.0441)	-0.053*** (0.0207)	-	-	-	-	-	-
$a_{S,3}$	-	-0.0271 (0.0570)	-0.0065 (0.0242)	-	-	-	-	-	-
$a_{S,4}$	-	-0.0318 (0.0529)	0.0973*** (0.0101)	-	-	-	-	-	-
$b_{S,1}$	-	0.0982* (0.0529)	-0.0224 (0.0200)	-	0.0177 (0.0168)	0.0279 (0.0219)	-	0.1268*** (0.0187)	0.0345 (0.0278)
$b_{S,2}$	-	0.0846** (0.0360)	0.1005*** (0.0184)	-	-	-	-	-	-
$b_{S,3}$	-	0.2187*** (0.0408)	0.1149*** (0.0211)	-	-	-	-	-	-
$b_{S,4}$	-	0.245*** (0.0455)	0.1307*** (0.0209)	-	-	-	-	-	-
η_S	-	-	-0.131*** (0.0077)	-	-	-0.0071** (0.0035)	-	-	-0.0741*** (0.0112)
c_F	0.0007 (0.0008)	0.0007 (0.0007)	0.0022 (0.0018)	5.16×10^{-5} (0.001)	-0.0001 (0.0008)	0.002* (0.0011)	0.0024*** (0.0005)	0.0025 (0.0005)	0.0033*** (0.0007)
$a_{F,1}$	-	0.16092*** (0.0407)	0.1437*** (0.0296)	-	0.3582*** (0.0355)	0.3131*** (0.0365)	-	-0.0223 (0.0183)	-0.0116 (0.0175)
$a_{F,2}$	-	0.0289 (0.0309)	0.0341 (0.0358)	-	-	-	-	-	-
$a_{F,3}$	-	0.0949** (0.0371)	0.1046*** (0.0324)	-	-	-	-	-	-
$a_{F,4}$	-	0.0354 (0.0399)	0.0535 (0.0403)	-	-	-	-	-	-
$b_{F,1}$	-	0.1126 ** (0.0487)	0.1008* (0.0542)	-	-0.129*** (0.0421)	-0.0493** (0.0218)	-	-0.0422 (0.0431)	-0.0665 (0.0453)
$b_{F,2}$	-	-0.0678 (0.0456)	-0.0602 (0.0472)	-	-	-	-	-	-
$b_{F,3}$	-	0.0191 (0.0472)	0.0105 (0.0504)	-	-	-	-	-	-
$b_{F,4}$	-	0.0656 (0.0439)	0.0567 (0.0453)	-	-	-	-	-	-
η_F	-	-	-0.015 (0.017)	-	-	-0.0162* (0.0092)	-	-	-0.0146* (0.0077)

Table 6.4: (Continued)

	Panel A: Apr 2, 1986 - Jul 6, 1988			Panel B: Sept 30, 1997- Jul 25, 2002			Panel C: Nov 30, 2006 - Dec 19, 2011		
	Intercept	VAR	Basis	Intercept	VAR	Basis	Intercept	VAR	Basis
Conditional variance-covariance equation:									
ω_{SS}	0.0003 *** (1.10×10^{-5})	0.0002 * (0.0001)	7.47×10^{-5}*** (1.14×10^{-5})	9.2×10^{-6}*** (2.36×10^{-6})	9.11×10^{-10}*** (2.33×10^{-6})	9.91×10^{-6}*** (2.53×10^{-6})	0.0002*** (2.46×10^{-5})	0.0002*** (2.8×10^{-5})	0.0004*** (1.82×10^{-5})
ω_{FF}	1.65×10^{-5}** (2.3289)	1.72×10^{-5}** (8.23×10^{-6})	1.89×10^{-5}** (9.63×10^{-6})	0.0004 (0.0003)	0.0003* (0.0002)	1.25×10^{-5} (3.58×10^{-6})	8.2×10^{-5}*** (1.21×10^{-5})	8.2×10^{-5}*** (1.19×10^{-5})	0.0001*** (1.63×10^{-5})
α_{SS}	-0.02*** (0.0005)	-0.0137 (0.0157)	1.4911*** (0.0304)	0.1198*** (0.0163)	0.1135*** (0.0154)	0.1159*** (0.0158)	0.0573*** (0.0104)	0.0613*** (0.0136)	0.101*** (0.0216)
α_{FF}	0.15*** (0.0369)	0.161*** (0.041)	0.1698*** (0.0437)	-0.007*** (0.0001)	0.0169 (0.0116)	-0.0038*** (0.0003)	0.6499*** (0.0332)	0.6327*** (0.0466)	0.6908*** (0.0395)
β_{SS}	0.58*** (0.0131)	0.4984* (0.2767)	-0.004*** (0.0012)	0.8584*** (0.0178)	0.8642*** (0.0170)	0.8607*** (0.0176)	0.6322*** (0.04)	0.6501*** (0.0366)	-0.0132 (0.0373)
β_{FF}	0.81*** (0.0411)	0.801*** (0.0505)	0.7887*** (0.0524)	0.5204 (0.4224)	0.3978 (0.3306)	0.9811*** (0.0063)	0.4208*** (0.0294)	0.4213*** (0.0296)	0.2617*** (0.0403)
θ_{SS}	-	-	0.0062*** (0.0008)	-	-	-1.34×10^{-5} (1.97×10^{-5})	-	-	0.0147*** (0.0011)
θ_{FF}	-	-	-2.4×10^{-5} (0.0004)	-	-	2.51×10^{-5}*** (6.49×10^{-6})	-	-	0.0029*** (0.001)
Conditional correlation equation:									
ρ	0.103** (0.0439)	0.118 *** (0.0441)	0.1260** (0.0492)	0.2982*** (0.0299)	0.3480*** (0.026)	0.3444*** (0.0267)	0.0554* (0.0301)	0.0621** (0.0316)	0.0696** (0.0315)
L	2687.813	2741.790	2837.206	5827.343	5880.906	5900.151	5767.511	5776.375	5941.987
Test for higher order ARCH effect									
Spot equations									
$Q(15)$	24.064*	18.205	60.143***	27.295**	21.650	15.922	22.116	15.744	15.473
$Q^2(15)$	26.183***	22.914*	40.009***	20.195	20.754	21.448	17.750	14.262	5.9678
Futures equations									
$Q(15)$	43.758***	11.073	11.982	13.2	11.458	15.837	18.966	21.788	18.462
$Q^2(15)$	12.848	18.961	19.560	1.2405	0.9177	2.2377	0.8527	0.9040	0.9922

Notes: 1. (a) Intercept-CCC-GARCH models are estimated by Equations (6.1), (6.2) and (6.8). (b) Vector autoregressive (VAR)-CCC-GARCH models are estimated by Equations (6.3), (6.4) and (6.8). (c) Basis-CCC-GARCH models are estimated by Equations (6.5), (6.6) and (6.9). 2. *, ** and *** indicate the statistical significance at the 10%, 5% and 1% levels respectively. 3. Numbers in parentheses are the standard errors. 4. L is the value of the log-likelihood function calculated by Equation (6.10). 5. Q and Q^2 are the Ljung–Box statistics of standardized residuals and standardized squared residuals.

6.4.2 Impact of structural change on estimated minimum-variance hedge ratio (MVHR)

The summary of results in Table 6.5 indicates that means of hedge ratios changed significantly over the three sub-periods. On average, the high optimal hedge ratios are found during the Asian financial crisis (Panel B) for about 0.5 (in-sample) and 0.3 (out-of-sample). Furthermore, the OLS hedge ratio is found to be similar to GARCH hedge ratios implying hedging effectiveness of CPO futures contract based on OLS and GARCH strategies could be very comparable during the Asian financial crisis.

As observed, hedge ratios estimated by GARCH models for the out-of-sample period in Panel B show higher standard deviations as compared to other sub-periods. This implies that hedgers need to make a higher adjustment in the hedge ratio during the Asian financial crisis as compared to the global financial crisis. The reason to explain this finding is the local palm oil industry helps Malaysia to ride out the global economic downturn during the period of 1997-1998. Subsequently, it allows hedgers to have a competitive advantage during the AFC to implement their risk management strategy in the domestic market. In summary, the impact of the Asian financial crisis on hedge ratios is the largest among the three crises.

Table 6.5: Summary statistic of hedge ratios

Hedge strategy	In-sample		Out-of-sample	
	Mean	SD	Mean	SD
Panel A: Apr 2, 1986 - Jul 6, 1988				
Naïve hedge	1	NA	1	NA
OLS hedge	0.1316	0.0709	0.1137	0.0874
Intercept-BEKK-GARCH hedge	0.2248	0.1037	0.0628	0.1146
VAR- BEKK-GARCH hedge	0.1968	0.0946	0.0431	0.0677
Basis-BEKK-GARCH hedge	0.1718	0.4466	-0.0255	0.0251
Intercept-CCC-GARCH hedge	0.1474	0.0424	0.0836	0.0265
VAR-CCC-GARCH hedge	0.1612	0.0408	0.0777	0.0274
Basis-CCC-GARCH hedge	0.1677	0.1308	0.0321	0.038

Notes: Ordinary least squares (OLS) hedge ratio is a slope of regression by regressing spot return against futures return. The BEKK- and CCC-GARCH hedge ratios are calculated by Equation (6.11). SD is denoted as standard deviation. The SD of the naïve hedge is not available as the ratio remains constant over time. The SD of OLS hedge ratio is a standard error of a slope for futures return.

Table 6.5: (Continued)

Hedge strategy	In-sample		Out-of-sample	
	Mean	SD	Mean	SD
Panel B: Sept 30, 1997 - Jul 25, 2002				
Naïve hedge	1	NA	1	NA
OLS hedge	0.4859	0.0417	0.3332	0.0730
Intercept-BEKK-GARCH hedge	0.5333	0.2601	0.3680	0.1639
VAR- BEKK-GARCH hedge	0.5221	0.2156	0.3929	0.1805
Basis -BEKK-GARCH hedge	0.5216	0.2098	0.3776	0.1633
Intercept-CCC-GARCH hedge	0.5462	0.1595	0.3637	0.0681
VAR-CCC-GARCH hedge	0.5546	0.1591	0.3969	0.1187
Basis -CCC-GARCH hedge	0.537	0.1478	0.3831	0.1072
Panel C: Nov 30, 2006 - Dec 19, 2011				
Naïve hedge	1	NA	1	NA
OLS hedge	0.0385	0.0396	-0.0785	0.0360
Intercept-BEKK-GARCH hedge	0.223	0.2046	0.1771	0.1664
VAR- BEKK-GARCH hedge	0.2421	0.1951	0.1592	0.0958
Basis-BEKK-GARCH hedge	0.1619	0.1352	-0.1538	0.1102
Intercept-CCC-GARCH hedge	0.1335	0.0453	0.0656	0.0310
VAR-CCC-GARCH hedge	0.1472	0.0499	0.1156	0.0683
Basis -CCC-GARCH hedge	0.1446	0.0413	-0.2099	0.167

Notes: Ordinary least squares (OLS) hedge ratio is a slope of regression by regressing spot return against futures return. The BEKK- and CCC-GARCH hedge ratios are calculated by Equation (6.11). SD is denoted as standard deviation. The SD of the naïve hedge is not available as the ratio remains constant over time. The SD of OLS hedge ratio is a standard error of a slope for futures return.

6.4.3 Impact of structural change on hedging effectiveness

Table 6.6 reports the variance of portfolio and variance reduction for unhedged and hedged returns produced by naïve, minimum variance-OLS and various GARCH hedging models.

Table 6.6: Hedging effectiveness of Malaysian CPO futures

Hedge strategy	In-sample		Out-of-sample	
	Variance of portfolio	Variance reduction (%)	Variance of portfolio	Variance reduction (%)
Panel A: Apr 2, 1986 - Jul 6, 1988				
Unhedged CPO portfolio	0.000819	-	0.000627	-
Hedged CPO portfolio:				
Naïve hedge	0.0010908	-33.19068	0.001211	-93.1138
OLS hedge	0.0008126	0.78056	0.000617	1.558
Intercept-BEKK-GARCH hedge	0.0005952	27.3264	0.000618	1.53
VAR-BEKK-GARCH hedge	0.0004022	50.8849	0.000545	13.044
Basis -BEKK-GARCH hedge	0.000621	24.132	0.001863	-197.079
Intercept-CCC-GARCH hedge	0.0007065	13.7282	0.00063	-0.4026
VAR-CCC-GARCH hedge	0.000409	50.114	0.000554	11.624
Basis-CCC-GARCH hedge	0.0007	14.513	0.001806	-187.9868

Notes: 1. The variance of unhedged CPO portfolio is generated from the variance of CPO spot return. 2. The variance of hedged CPO portfolio is computed by Equation (6.12). 3. The risk reduction is calculated by Equation (6.13).

Table 6.6: (Continued)

Hedge strategy	In-sample		Out-of-sample	
	Variance of portfolio	Variance reduction (%)	Variance of portfolio	Variance reduction (%)
Panel B: Sept 30, 1997 - Jul 25, 2002				
Unhedged CPO portfolio	0.000653	-	0.00056	-
Hedged CPO portfolio:				
Naïve hedge	0.000663	-1.0504	0.000698	-24.553
OLS hedge	0.000571	12.612	0.000514	8.176
Intercept-BEKK-GARCH hedge	0.000545	16.504	0.000495	11.622
VAR-BEKK-GARCH hedge	0.000554	15.216	0.000339	39.506
Basis -BEKK-GARCH hedge	0.000564	13.574	0.000316	43.655
Intercept-CCC-GARCH hedge	0.000764	17.0479	0.000512	8.554
VAR-CCC-GARCH hedge	0.00055	15.798	0.000384	31.38
Basis-CCC-GARCH hedge	0.000539	17.476	0.000307	45.146
Panel C: Nov 30, 2006 - Dec 19, 2011				
Unhedged CPO portfolio	0.000781	-	0.000509	-
Hedged CPO portfolio:				
Naïve hedge	0.001245	-59.3563	0.002317	-355.1356
OLS hedge	0.000781	0.095	0.000499	1.892
Intercept-BEKK-GARCH hedge	0.000737	5.682	0.0005	1.837
VAR-BEKK-GARCH hedge	0.000719	7.962	0.000489	3.882
Basis-BEKK-GARCH hedge	0.000681	12.789	0.000421	17.275
Intercept-CCC-GARCH hedge	0.000769	1.531	0.000543	-6.6563
VAR-CCC-GARCH hedge	0.000745	4.617	0.000458	10.075
Basis-CCC-GARCH hedge	0.000719	7.959	0.000539	-5.8768

Notes: 1. The variance of unhedged CPO portfolio is generated from the variance of CPO spot return. 2. The variance of hedged CPO portfolio is computed by Equation (6.12). 3. The risk reduction is calculated by Equation (6.13).

As observed in Table 6.6, it shows that naïve strategy is the worst strategy as it increases the risk of hedged portfolio. The VAR-BEKK-GARCH model is found as the superior model in Panel A as it reduces 50.88 per cent of the risk (in-sample) and 13.04 per cent of the risk (out-of-sample). In Panel B, besides having relatively high dynamic hedge ratios within the range of 0.48-0.56 (in-sample) and 0.33-0.40 (out-of-sample) as shown in Table 6.5, an assumption of CCC-GARCH model with the basis term offers the most effective risk reduction of 17.48 per cent and 45.15 per cent for the in- and out-of-sample respectively. In Panel C, a basis-BEKK-GARCH model achieves the highest risk reduction of over 12-17 per cent for both in- and out-of-sample. Overall, it is clear that the hedging strategies with the basis term generally outperform in reducing the risk of CPO portfolio in Panel B and Panel C.

As compared between Panel B and Panel C, the marginal differences among models suggest that the CPO futures hedging strategies underperform across the Asian and global financial crises for both in- and out-of-sample respectively. As investors more concern about future performance, the out-of-sample shows risk reduction of the superior model declines sharply from 45.15 to 12.28 per cent. The low level of hedging effectiveness is observed when futures return exhibits high volatility and fat-tailed distribution over the period of 2006-2011. This suggests that sharp decline in palm oil prices from July 2008 to January 2009 has resulted in the issue of sustainability of palm oil industry in its production and also export at a larger scale. This in turn reduces the effectiveness of hedging strategy for CPO futures.

Overall, the result indicates that the linkage between spot and futures prices in the long run (basis) is important to fit the extreme volatility during the global financial crisis. In contrast, including a basis effect into the GARCH model cannot sustain its high performance in reducing the risk during the global financial crisis as compared to previous crisis.

6.5 Conclusion

This study extends Zainudin and Shaharudin (2011) on Malaysian crude palm oil (CPO) futures market by examining the hedging effectiveness based on the minimum-variance hedge ratios from eight model specifications. These models were evaluated during the three financial crises namely, the world economic recession in 1986, Asian financial crisis in 1997/98 and global financial crisis in 2008/09 respectively. Subsequently, in-and out of sample of the minimum variance of hedge ratio are compared during each sub-period. As the in- and out-of-sample analysis provides same finding, this study focuses on the out-of-sample forecasting evaluation results.

Notable findings are: First, it is evidently clear that GARCH models with basis term outperform others during the Asian financial crisis (AFC) and global financial crisis (GFC) respectively. Second, during the Asian financial crisis, the high dynamic hedge ratios contribute to the superiority of CCC-GARCH model with risk reduction of 45.15 per cent. The declining hedge ratio in GFC leads to the emergence of BEKK-GARCH model which provides the most risk reduction of 17.26 per cent. Third, from AFC to GFC, the risk reduction of hedging strategy declines sharply from 45.15 to 17.28 per cent. Two possible reasons are; Firstly, unlike AFC, the epicenter of GFC was in the United States and subsequently extended to Europe. Secondly, the episode of bad news was released to the market one after another in a prolonged period, which caused ineffectiveness of hedging strategy as shocks were largely unanticipated.

Overall, this study concludes: First, the high dynamic hedge ratio during the Asian financial crisis implies that CPO market participants are sensitive to CPO spot and futures movement. Second, the superior GARCH model with the basis term cannot sustain its performance in terms of risk reduction during the crisis period. This shows that the Malaysian CPO futures market provides a low level of hedging effectiveness during the global financial crisis, which is mainly caused by excess kurtosis in the markets. This finding is inconsistent with Ong et al. (2012) who find that stable movement of CPO spot price in 2009-2010 contributes to the low level of hedging effectiveness.

The policy implication is clear. Although the effectiveness of Malaysian CPO futures is low during the recent crisis, the minimum-variance hedge ratio analysis has managed to compare the performance of various hedging models. By understanding the effectiveness of various hedging models, the CPO market participants can switch between the models in different volatility periods to cover their risk exposure in the spot market.

CHAPTER 7: CONCLUSION

This chapter summarizes major findings from previous chapters and categorizes them into three aspects. Then, it is followed by suggested implications according to each finding. Lastly, the limitations and future directions for research are suggested.

7.1 Major Findings

There are four findings from this study. **As addressed in Chapter Three, the first finding is that the volatility persistence in the CPO futures prices has increased after the 2008/09 global financial crisis, leading to trading volume turns to be less efficient in transmitting the information.** Apart from that, there is a significant change in cross-correlation between the volatility of futures return and volatility of trading volume after the crisis. For example, the past volume Granger causes the current return in the pre-crisis period, but this causality occurs from the current return to the future trading volume in the post-crisis period. This dramatically changes the direction of information flow between both series which in turn supports the "heterogeneity of traders" hypothesis. Overall, this study suggests that the structural change of volatility causes the information content of return from trading volume to decrease after the crisis.

Furthermore, a change of past volume in the pre-crisis requires maximum 19 days to reflect the changes in volatility of current return, while a change of current return requires 4, 9 and 11 days to reflect the changes in volatility of future volume. However, this time span is inconsistent, indicating that CPO futures investors react randomly toward the arrival of new information. Contrary to the noise traders' hypothesis found in the study by Bhar and Hamori (2005) in the crude oil futures, both authors find that causality from return to volume happens with consistent time span at the lag of 3, 9 and 15 days, where their result mildly supports the noise traders' hypothesis.

Unlike with those reported in the literature for non-agricultural futures, this study suggests that the transaction of an actual physical palm oil through futures market is subject to a trade-off of shortages and loss of sales, particularly when there is a lack of trading activities during crisis. Therefore, this study hypothesizes that the existence of volatility spillover from CPO futures return to trading volume after the crisis is probably due to traders have perceived higher risk on CPO trading volume that closely links to the liquidity.

As addressed in Chapter Four, the second finding is that higher degree of efficiency of CPO futures price changes leads to a higher degree of its correlation with spot price changes. For example, the null hypothesis of variance ratio of one (homoscedasticity) during the weak contango period indicates that the CPO futures market is the most efficient. Consequently, futures price changes are strongly correlated with spot price changes. However, this finding is inconsistent with the finding from Gulley and Tilton (2014) who find that spot and futures price changes are closely correlated during the strong contango period in the case of copper.

During the weak contango period, strong correlation coefficients between both CPO price changes are further found to rise given increasing convenience yield from 1 per cent to 2.5 per cent. This suggests that producers are willing to pay a high premium and hold the inventories on hand in obtaining convenience yield. They have high anticipation on insufficiency of CPO inventories for the short-term production as CPO is susceptible to seasonal fluctuation in price and spoilage. Subsequently, their decision in buying CPO in the spot market directly influences the prices of CPO.

The dynamic causality between both CPO spot and futures price changes in mean and variance are further taken into consideration. **As addressed in Chapter Five, the third finding is during the weak contango period, spillover of information takes place from futures market to spot market**. On the other words, increases the flow of information in the futures market tends to rise volatility in the underlying spot market. This further supports that they are more sensitive towards changes in the futures market instead of the spot market because the difficulty of integrating and handing the commodity in the long-term production process.

During the backwardation period, a change in the mean of spot return is found to require longer time span to Granger cause mean of futures return. Meanwhile, this causality-in-mean from futures return to spot return is found to occur with a shorter time span. This indicates that a change in the spot return is a long-lived phenomenon, while a change in the futures market is a short-lived phenomenon. However, there is no causality-in-mean and causality-in-variance during the strong contango period. In terms of processing and reflecting new information, the result suggests that the CPO futures market plays a dominant role and serves as an effective price discovery function, especially during the weak contango period.

In terms of speculative pressure from the finding of spot-futures relations, the extension for such finding in the case of CPO. Since CPO is susceptible to spoilage under handling and shipping conditions, market participants in contango may have to change the level of inventory from insuring against risk, leading to such relationship does not exist in strong contango period. Furthermore, they tend to have high perceived risk especially during weak contango period towards the hedging demand and trading decision in CPO futures contracts, causing volatility to spill over from CPO futures market to CPO spot market. This finding is considered to be peculiar for palm oil as compared to other types of non-perishable commodity because most of past studies demonstrate that strong contango in a normal period asserts excessive price volatility of non-perishable commodities through the futures market.

As addressed in Chapter Six, the fourth finding is that the hedging models with a basis term stand out among the rest in reducing risk during the Asian financial crisis in 1997/98 (AFC) and global financial crisis in 2008/09 (GFC). For example, the high dynamic hedge ratios during the AFC contribute to the superiority of CCC-GARCH model with the risk reduction of 45.15 per cent, while these hedge ratios during the GFC contribute to the superiority of BEKK-GARCH model with the risk reduction of 17.28 per cent.

As compared to the risk reductions for the superiority of hedging models during ACF and GFC, it is found that the risk reduction of hedging strategy sharp declines from 45.15 per cent during the AFC to 17.28 per cent during the GFC. This indicates that the superior GARCH model with the basis term cannot sustain its risk reduction during the GFC. This suggests that the effectiveness of hedging based on CPO futures contracts is low during the GFC due to an episode of bad news was released to the market one after another in a prolonged period during the epicenter of crisis, which caused ineffectiveness of hedging strategy as shocks were largely unanticipated. However, this finding contradicts with the finding from Ong et al. (2012) who find that stable movement of CPO spot price during the period of 2009-2010 which contributes to the low level of hedging effectiveness.

Overall, there is clear evidence to support a preference for the basis term to estimate minimum-variance hedge ratios in the case of CPO markets. The hedging model with a basis term presented in this study can be adapted to CPO market. A further interesting finding indicates that different conditional variance estimations from various volatility models with a basis term produce inconsistent hedge performance from the period of AFC to GFC. Such performance is due to the superior hedging model for AFC more likely to be a perfect hedge with 1:1 ratio, while the superior hedging model for GFC less likely to be a perfect hedge.

The reason for such finding on hedging effectiveness during the AFC is the local palm oil industry helps Malaysia to ride out the global economic downturn during the period of 1997-1998. This allows hedgers to have a competitive advantage during the AFC to implement their risk management strategy in the domestic market. However, the sharp decline in palm oil prices from July 2008 to January 2009 causes the palm oil industry not being able to sustain its production and export at a larger scale, in turns, reduces the effectiveness of hedging under CPO futures.

7.2 Implications

Based on four findings as discussed above, **the first finding demonstrates that a role of trading volume in transmitting information for hedging strategies and risk management after the crisis becomes less efficient.** As a consequence, a change of futures return further provides faster speed to induce a larger change in diffusive volatility of trading volume, and that a positive dependence exists between two series. Since the CPO futures market becomes less predictable after the crisis, market participants need to assess the liquidity of CPO in terms of how much volume is sufficient for trading such commodity.

To form an expectation on output price, producers can use changes of CPO futures price to assess the quality of price. Before the crisis, trading volume still acts as a tool in identifying bullish and bearish signs in the CPO futures market. This suggests that they can depend on trading volume to determine the direction of a CPO futures price change. After the crisis, the CPO futures trading volume does not matter. In this regard, they are suggested to rely on the return to predict trading volume in deciding the optimal allocation for CPO inventories for the production at the better market timing.

The second and third findings of spot-futures relation show that there is existing investor demand during the weak contango period. Based on such finding, traders still can improve their competitiveness through the futures market, where the market still has the capability to expose the new information through a mechanism of price discovery during the weak contango period. However, during the strong contango period, this study validates that both spot and futures markets of CPO as intricate in incorporating information into prices. The reason is that such perishable commodity with the cost of carry makes market participants encounter difficulty in selling physical inventories in the future. Consequently, the role of speculation in CPO price movement does not dominate during the strong contango period.

The fourth finding shows that Malaysian CPO futures contract during the GFC provides a low effectiveness of hedging as compared to the AFC. Based on the minimum-variance hedge ratio analysis, such finding is obtained by comparing the performance of various hedging models during different high volatile sub-periods. This comparison provides the information to market participants about which hedging model with various mean and variance-covariance specifications should be applied to the issue of effectiveness of Malaysian CPO futures during the financial crises.

There is no improvement in hedging during the GFC as compared with the AFC. As a result, the implication from GARCH model for hedging cannot guarantee a profitable trading strategy across the financial crises. Therefore, this study suggests that market participants do not rely on the model specification with a basis term for hedging purposes though they may remain useful for data description.

Market participants need to have access information that relates to production, stock and price in order to provide them with sustainable performance through hedging. In this regard, they are suggested to manage their risk exposure in the spot market by switching between the models in an effective way across different volatility periods.

7.3 Limitations

This study has a few limitations. In the context of volatility spillover between CPO futures price changes and trading volume in **Chapter Three**, this study only focuses on the 2008/09 global financial crisis. Since 1980, the Malaysian CPO futures market has experienced multiple structural changes in price movement. However, disregarding this aspect may influence inference making about the hypothesis of price-volume relation.

In the context of relationship between spot and futures markets in **Chapters Four and Five**, this study ignores the important external factor in behind the time variation and interaction between CPO spot and futures prices. For example, a change export tax of palm oil in Indonesia and Malaysia may influence volatility transmission between CPO spot and futures markets in Malaysia which is of particular interest among market practitioners. However, a linkage between the export tax on CPO and lead-lag CPO spot-futures relation is yet to be studied.

In the context of hedging effectiveness in **Chapter Six**, this study only focuses on a constant conditional correlation between spot and futures prices. In actual fact, the dynamic correlation between both spot and futures prices may appear because of the existence of transaction costs, seasonal patterns of consumption and different inventory levels leads to the dynamic correlation between energy prices and the overall economy (Filis, Degiannakis & Floros, 2011). Furthermore, this chapter is found to ignore an asymmetric effect of basis term in modeling the GARCH model. For instance, Lien and Yang (2008, a) find that positive basis has the greater impact than negative basis. Then, they demonstrate that the hedging model with this asymmetric effect in basis term can provide a greater risk reduction than the conventional models.

7.4 Future Recommendations

In the light of the findings, this study suggests the several ways for future research in the contexts of Chapters Three, Four, Five and Six. In the context of price-volume relation in **Chapter Three**, the future researchers are suggested to concentrate in examining volatility spillover between price changes and trading volume in the futures market by dealing different structural changes as the Malaysian CPO futures market has experienced multiple structural breaks since 1980. Furthermore, the extension of GARCH model can be applied to include the asymmetric non-linear relationship between trading volume and price changes.

For the context of spot-futures relation in **Chapters Four and Five**, the future researchers are suggested to extend study on this relation by analyzing the impact of Malaysian and Indonesian export taxes for CPO on returns and volatility spillover between Malaysian CPO spot and futures. This extension can investigate the changes in the CPO export tax caused by the economic fundamentals of a country. The reason is, it may have effects on the information content of CPO futures market in terms of price discovery. In designing appropriate investment and production decisions, and the knowledge on whether imposition of the Indonesian export tax on palm oil benefits to participants in the Malaysian CPO markets. Furthermore, it can add to the existing literature because there is no study about the impact of Indonesian CPO export tax on volatility transmission of the CPO markets for its main rival, Malaysia.

Lastly, for the context of hedging effectiveness in **Chapter Six**, the future researchers are suggested to emphasize the Dynamic Conditional Correlation (DCC) (Engle, 2002; Tse & Tsui, 2002) in the variance-covariance specification. The reason is such of a model specification can produce a better estimation of variance-covariance matrix by taking time-varying conditional correlation into account. Employing the GARCH model with the DCC specification to analyze commodity return behavior is much more suitable and realistic. In addition, the basis term is suggested to be decomposed into positive and negative terms and used as two different explanatory variables in modeling time-varying variances and correlation of spot and futures returns.

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