THE OPTIMAL HEDGE RATIO AND HEDGING EFFECTIVENESS OF MALAYSIA CRUDE PALM OIL FUTURES. A COMPARATIVE ANALYSIS OF STATIC AND DYNAMIC MODELS

BY

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DECLARATION

We hereby declare that:

(1) This undergraduate FYP is the end result of our own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

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DEDICATION

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TABLE OF CONTENTS

Copyright Page ii

Declaration iii

Acknowledgement iv

Dedication v

Table of Contents vi-viii

List of Tables ix

List of Figures x

List of Abbreviations xi-xii

List of Appendices xiii

Preface xiv

Abstract xv

CHAPTER 1 INTRODUCTION 1

1.0 Overview 1

1.1 Research Background 1

1.1.1 Background of Malaysia Palm Oil Sector 1-4

1.1.2 Background of Malaysia Crude Palm Oil Futures 4-5

1.1.3 Background of Spot-Futures Relationship 5-8

1.2 Problem Statement 8-13

1.3 Research Objective 13

1.4 Research Questions 13

1.5 Significance of Study 14

1.5.1 Academia 14-15

1.5.2 Hedger 15

CHAPTER 2 LITERATURE REVIEW 16

2.0 Overview 16

2.1 Underlying Theory of Spot-Futures Pricing Mechanism 16

2.1.1 Theory of Storage and Cost-carry Model 17

2.1.2 Efficient Market Hypothesis 18

2.1.3 Law of One Price 18-19

2.2 Empirical Review 19

2.2.1 Hedging Theory Development 19-20

2.2.2 Development of Hedging Model 20-25

2.2.3 Hedging Effectiveness of Malaysia Derivatives 25-27

2.2.4 The Basis Effect on Hedging Effectiveness 27-28

CHAPTER 3 METHODOLOGY 29

3.0 Overview 29

3.1 Data Description 29-31

3.2 Data Summary 32-36

3.3 Methodology 37

3.3.1 Hedging Strategies 37

3.3.1.1 Specification of the Conditional Means 38

3.3.1.2 Specification of the Conditional Variance-covariance 38-39

3.3.2 Model Specification 39

3.3.2.1 Static Models 39-40

3.3.2.2 Dynamic Models 41-54

3.3.3 Procedure of Estimating the Hedging Effectiveness 55

3.3.3.1 Optimal Hedge Ratio 55

3.3.3.2 The Unhedged and Hedged of Portfolio Variance 55-56

3.3.3.3 Hedging Effectiveness 56

3.3.3.4 Log-likelihood 56

CHAPTER 4 RESULTS 57

4.0 Overview 57

4.1 Result of Diag-BEKK, CCC and DCC GARCH 57-64

4.2 Descriptive Statistic of Optimal Hedge Ratio 65

4.2.1 Maturity Effect 65

4.2.2 In-sample Analysis 66

4.2.3 Out-of-sample Analysis 66-69

4.3 Result of Hedging Effectiveness 70

4.3.1 Comparison between Static and Dynamic Models 70

4.3.2 Comparison between Different of Time to Maturity of FCPO 70

4.3.3 In-sample Analysis 71

4.3.4 Out-of-sample Analysis 72-76

CHAPTER 5 CONCLUSION 77

5.1 Major Finding 77-78

5.2 Implication 79-80

5.3 Limitation 80

5.4 Recommendation 80-81

References 82-88

Appendices 89-91

LIST OF TABLES

		Page
Table 1.1	Major Malaysia palm oil export destination	3
Table 1.2	Trading volume of FCPO in 2018	5
Table 1.3	5 Years Global Palm Oil Production	9
Table 3.1.1	Variable description	30
Table 3.1.2	Result of unit root test	31
Table 3.2.1	Descriptive statistics of the entire sample	34
Table 3.2.2	Descriptive statistics of the In-sample	35
Table 3.2.3	Descriptive statistics of the Out-of-sample	36
Table 4.1.1.1	Estimated result of the mean equation under Diag- BEKK-GARCH framework	59
Table 4.1.1.2	Estimated result of the variance-covariance equation under Diag-BEKK-GARCH framework	60
Table 4.1.2.1	Estimated result of the mean equation under CCC-GARCH framework	61
Table 4.1.2.2	Estimated result of the variance-covariance equation under CCC-GARCH framework	62
Table 4.1.3.1	Estimated result of the mean equation under DCC-GARCH framework	63
Table 4.1.3.2	Estimated result of the variance-covariance equation under DCC-GARCH framework	64
Table 4.2.1	Descriptive statistic of estimated OHR for spot month future	67
Table 4.2.2	Descriptive statistic of estimated optimal hedge ratio (OHR) for next-two-month futures	68
Table 4.2.3	Descriptive statistic of estimated optimal hedge ratio (OHR) for next-four-month futures	69
Table 4.3.1	Hedging effectiveness for spot month FCPO futures	74
Table 4.3.2	Hedging effectiveness for next-two-month FCPO futures	75
Table 4.3.3	Hedging effectiveness for next-four-month FCPO futures	76

LIST OF FIGURES

		Page
Figure 1.1	Major Malaysia palm oil export destination in 2018	2
Figure 1.2	Global Palm oil Production in 2018	8
Figure 1.3	Monthly Palm Import from China	9
Figure 1.4	Inventory level and Price of CPO in Malaysia	10
Figure 1.5	Productions and Export of CPO in Malaysia	11
Figure 1.6	Monthly statistic of CPO return in Malaysia	12
Figure 2.1	Cost Carrying model and Law of one price	16
Figure 4.3.1	Malaysia CPO Spot and Futures Price for In-sample	71
Figure 4.3.2	Malaysia CPO Spot and Futures Price for Out-of-sample	73

LIST OF ABBREVIATIONS

Akaike information criterion	AIC
Asian financial crisis	AFC
Asymmetric dynamic conditional correlation	ADCC
Augmented dickey fuller	ADF
Autoregressive conditional heteroscedasticity	ARCH
Baba-engle-kraft-kron	BEKK
Bursa malaysia derivative berhad	BMDB
Commodity and Malaysian Monetary Exchange	COMMEX
Constant conditional correlation	CCC
Crude palm oil	CPO
Crude palm oil futures	FCPO
Diagonal-baba-engle-karft-kroner	Diag-BEKK
Dynamic conditional correlation	DCC
Efficient market hypothesis	EMH
Error correction model	ECM
European union	EU
Exponential GARCH	EGARCH
Final prediction error	FPE
Generalized autoregressive conditional heteroscedasticity	GARCH
Generalized Orthogonal GARCH	GO-GARCH
Global financial crisis	GFC
Hannan-Quinn information criterion	HQ
Hedging effectiveness	HE
Kuala lumpur commodity exchange	KLCE
Kuala lumpur composite index	KLCI
Kuala Lumpur futures Index	KLFI
Kuala Lumpur Options and Financial Futures Exchange	KLOFE
Law of One Price	LOP

Malaysia derivative exchange	MDEX
Malaysia palm oil board	MPOB
Malaysian monetary exchange	MME
Multivariate generalized autoregressive conditional heteroscedasticity	MGARCH
Next to four month	FP4
Next to two month	FP2
Optimal hedge ratio	OHR
Ordinary least square	OLS
Phillips-perron	PP
Ringgit malaysia	MYR
Schwarz information criterion	SC
Spot	SP
Spot month	FP0
Value at Risk	VaR
Vector autoregressive	VAR
Vector error correction	VEC
Vector error correction model	VECM

LIST OF APPENDICES

		Page
Appendix 1.1	World's Vegetable Oil Production, Consumption and Ending Stock	89
Appendix 1.2	World's Vegetable Oil Import and Export	90
Appendix 1.3	World's Vegetable Oil Import and Export	91

PREFACE

Recently, the palm oil market is relatively volatile due to several major events such as the adverse palm oil ban from the European Union, restriction of country's trade policy, strong competition between Indonesia and etc. Thus, Malaysia is exploring a serious palm oil price risk that might adversely affect the country's GDP level since palm oil is the major income source from the agriculture aspect. In such a condition, the hedging activities are taking place to mitigate the price risk. However, the hedger is facing a challenge of "How much futures contract needed to achieve the highest risk reduction?". Although the question of the optimal hedge ratio has been widely discussed, but the hedging effectiveness of Malaysia derivative instruments are scare. Thereby, the study is conducted to provide a piece of important information to the hedger and academia.

ABSTRACT

This study examines the hedging effectiveness of Malaysia crude palm oil futures (FCPO) with different time to maturity by employing the static hedging models of naïve, ordinary least square (OLS) and dynamic hedging models of Diagonal-Baba-Engle-Kraft-Kroner (Diag-BEKK GARCH), constant conditional correlation (CCC GARCH) and Dynamic conditional correlation (DCC GARCH). First, the study found that the far month FCPO is not an effective hedging tool for the CPO spot while the hedging performance for near month FCPOs is relatively close to each other regardless of the contract liquidity. Second, the unconditional correlation model of Diag-BEKK GARCH is unable to sustain its performance in out-of-sample and the performance of CCC GARCH model has achieved the highest risk reduction of 45.78% in out-of-sample. Although DCC-GARCH model is unable to achieve the highest variance reduction, but the overall hedging performance is relatively stable and consistent. When the model specification is getting complex, the superiority of DCC-GARCH model will be showed. Lastly, the ignorance of basis effect will result in a lower risk reduction but the directional asymmetric basis effect might not always improve the hedging effectiveness.

CHAPTER 1:
INTRODUCTION

1.0 Overview

In this chapter, the study attempts to introduce the background of the Malaysia palm oil sector as well as the Malaysia crude palm oil futures (FCPO). Subsequently, the problem statement, research objectives, research questions as well as the significance of study is further discussed in section 1.2, 1.3, 1.4 and 1.5 respectively.

1.1 Research Background

1.1.1 Background of Malaysia palm oil sector

In late 1870s, the oil palm species (*Elaeis guineensis*) origin from West Africa was initially introduced to Malaysia as an ornamental plant. Thereafter, the Malaysia's palm oil industry has experienced an incredible growth from the beginning of 54,700 hectares panted area in 1960 to 1.023 million hectares in 1980s, 2.030 million hectares in 1990s, 3.376 million hectares in 2000 and followed by the latest statistics of 5.849 million hectares in 2018. Today, Malaysia remained the second largest palm oil producer after Indonesia and both countries account for 84.58% of the total global CPO production (MPOB, 2018).

In year 2018, Malaysia's palm oil production has attained a 28% or 20.5 million tons out of the global production of 73.58 million metric tons. The average annual palm oil production of Malaysia is approximating to 20 million metric ton while 15% was used for domestic consumption and the remaining 85% is exported (Mohammad Nor & Masih, 2016). The statistic has evidently showed that the Malaysia is highly relying on palm oil exporting activities. However, this situation is relatively adverse against Malaysia as a major palm oil producer. The market power of Malaysia will be diluted since the market is majorly denominated by the international market forces.

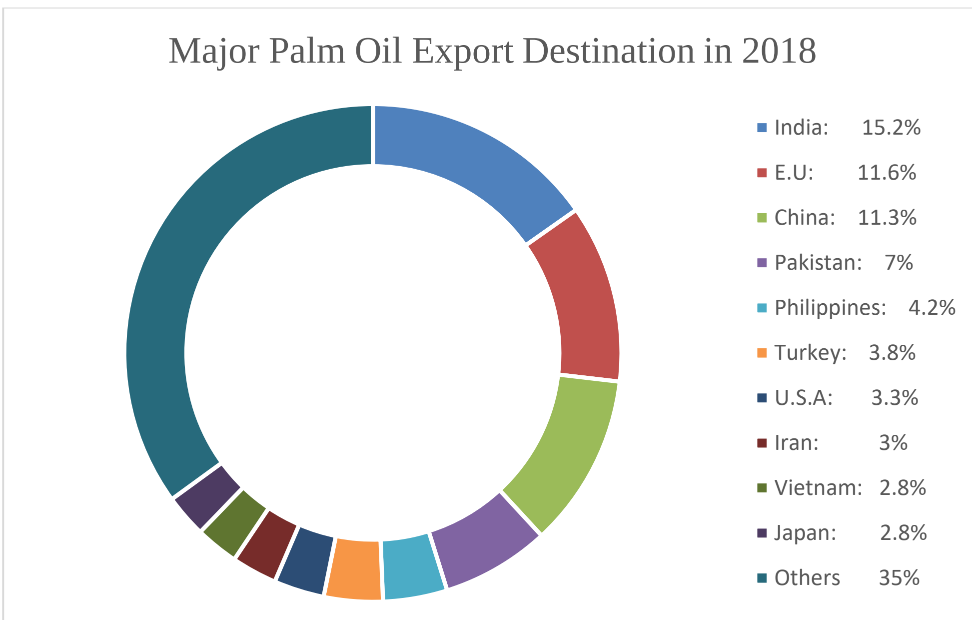

Figure 1.1 Major Malaysia palm oil export destination in 2018

Export Destination	Metric tons	Percentage of Total Palm Oil Export (%)
India	2,514,008	15.25
European Union	1,911,797	11.60
China	1,859,748	11.28
Pakistan	1,161,260	7.04
Philippines	689,238	4.18
Turkey	631,887	3.83
Unite States American	540,509	3.28
Iran	487,923	2.96
Vietnam	461,567	2.80
Japan	458,594	2.78
Others	5,770,171	35.00
Total	16,486,702	100

Table1.1: Major Malaysia palm oil export destination

Sources from MPOB

Based on Figure 1.1 and Table 1.1, the major Malaysia’s palm oil export destinations are India, European Union, China and Pakistan which jointly account about 45.2% of the total palm oil export. According to MATRADE (2019), the palm oil export in year 2018 has contributed a 3.9% or RM 38.63 billion out of the total export revenue.

Furthermore, Palm oil remained the world largest vegetable oil that playing as a crucial ingredients for food producing. In 2018, the global palm oil production has achieved the historical highest of 73.58 million tons or 36% out of the total 203.95 million tons of global vegetable oil production. In addition, soybean is the second largest vegetable oil which account for 28% out of the total vegetable oil production. In term of global vegetable oil consumption, approximate 72.55

million tons of palm oil has been consumed in 2018 and the consumption is projected to achieve a higher of 75.1 million ton in 2020 (Appendix 1.1 & 1.2). The global palm oil export and import in 2018 was recorded as 51.79 million tons and 50.4 million tons respectively. According to USDA (2019), the global vegetable oil stock is projected to have a 10% drop due to a poor global vegetable oil production while the projected growth for global vegetable oil consumption will be slower than past recent years.

1.1.2 Background of Malaysia Crude Palm Oil Futures (FCPO)

Malaysia FCPO contract is having a long history since October 1980 which is initially introduced in Kuala Lumpur Commodity Exchange (KLCE). In November 1988, KLCE was having a merge with Malaysian Monetary Exchange (MME) to establish Commodity and Malaysian Monetary Exchange (COMMEX). Later, COMMEX combined its operation with Kuala Lumpur Options and Financial Futures Exchange (KLOFE) to establish Malaysia Derivative Exchange (MDEX) before restructuring as Bursa Malaysia Derivative Berhad (BMDB) in year 2003, (Bursa Malaysia, 2019). Today, FCPO is being one of the active trading derivative contracts on BMDB and eventually served as a global CPO pricing benchmark. The corresponding FCPO contract specification on BMDB is exhibited in (Appendix 1.3).

Table 1.2: Trading volume of FCPO in 2018

	Average	**Highest**	**Lowest**
Spot month	427	2907	0
Next one month	4475	18485	348
Next two month	17977	37621	3590
Next three month	7462	16551	1531
Next four month	4325	13424	799
Next five month	2721	10992	163

Resource from Bloomberg

Statistic computed by the researcher

Based on table 1.2, the next two month FCPO remained the most active trading contract with an average daily trading volume of 17977 in year 2018. Subsequently, it is followed by the next three month and next one month FCPO of 7462 and 4475 average daily trading volume respectively. In contrast, the spot month FCPO is having the lowest average trading volume of 427 in 2018. This is because when the FCPO contract is approximating to maturity, the spot-futures price will be convergence and result in a lower of price gap. Thereby, the hedgers are more prefer to close their position early in one to three month before maturity. It is the reason to explain the low trading volume of spot month contract.

1.1.3 Background of the Spot-Futures Relationship

Spot market is referred to a place in facilitating the trading activities where the cash is paid for an instant asset delivery, while the futures market provided an alternative contractual trading where the buyer and seller are contractually obligated to buy or sell a specific quantity of an underlying asset based on the predetermined price at a future date (Hull, 2017). The spot price referred to the market price for an instant delivery while the futures price referred to the market price for trading a futures instrument. Over the past few decades, the relationship between spot and futures has been widely examined (Malhotra & Sharma, 2016; Biswal & Barik, 2017; Go & Lau, 2017; Joarder & Mukherjee, 2019).

Theoretically, the commodity futures contract is priced using the cost-carrying model where the storage costs as well as the convenience yield are taken into account. Under a perfect efficient market, the contemporaneous rate of return for spot and futures are symmetrically correlated since the value of the futures contract is derived from the value of the underlying asset. Any up-to-date information should be simultaneously incorporated into both spot and futures price, thereby, the lead-lag relationship between both markets should be eliminated. In other words, the tendency price movement in one market should not be determined by another market. In such condition, a perfect hedge can be realized via the naïve hedging approach in which a parallel inverse position of spot and futures is taken (Biswal & Barik, 2017).

However, in reality, the spot-futures relation is questioned where the information efficiency is difference in both markets. For example, Khediri and Charfeddine (2015) found that the market efficiency for energy spot and futures is changing over time. Ruan, Huang and Jiang (2016) claims that the theoretical spot-futures relationship is no longer hold in gold market due to the existence of asymmetric information and transactions costs.

Joarder and Mukherjee (2019) claimed that the futures market is relatively efficient than spot market as the new relevant information is rapidly compounded in futures price due to the flexibility of short selling, high liquidity, low margin as well as the low transaction costs. Besides, the point is further supported by Rahman, Nawi and Naziman (2012) in finding the lagged FCPO prices is critically affecting the CPO spot price and thus, concluded the Malaysia FCPO contract is an effective price discovery tool. On the other hand, there are some opposite results from (Malhotra & Sharma, 2016; Karabiyik & Naraya, 2018) in claiming the spot is leading the futures price. In general, the existence of lead-lag relation due to the market imperfection might cause the hedge ratio to be changing over time. Thereby, the conditional information is relatively important in affecting the hedging performance.

Hedging is a financial technique to reduce or mitigate the risk of future value changes in assets, currencies, commodities as well as a particular cash flows. According to Speranda and Trsinski (2015), the hedging strategy enable to protect a company from a price fluctuation which may adversely affect the company's performance. In order to minimize the risk exposure, the hedger is required to enter into an opposite futures position against the spot position. Thereby, the losses occur in spot market due to the sudden changes in prices can be offset by the gain in futures.

When constructing a hedging strategy, the determination of hedge ratio is relatively important. The hedge ratio is referred to the proportion of futures contracts needed relative to the spot position to hedge. In addition, the optimal hedge ratio (OHR) is the hedge ratio that enable to provide the highest portfolio risk reduction.

In general, the hedging strategies can be classified as static and dynamic approach. Firstly, the static approach indicated that the optimal hedge ratio is time-invariant where the hedge ratio remained constant over the entire hedging period. In this study, the naïve approach assumed a 1:1 hedging ratio while the ordinary least square (OLS) approach is merely providing an average hedging ratio for the entire period. However, the static approach has been widely criticized that the model is ignoring the conditional information which might critically affect the hedging performance.

Thereby, the dynamic hedging approach is introduced to capture the conditional information at different time period. The dynamic hedging approach suggested that the estimated OHR is time-variant where the hedge ratio is changing over the entire hedging period. For example, the generalized autoregressive conditional heteroscedasticity (GARCH) model is the most popular approach that been used to estimate the dynamic hedge ratio. In this study, MGARCH models with several variance-covariance specification of Diagonal-Baba-Engle-Karft-Kroner (Diag-BEKK), Constant conditional correlation (CCC) and Dynamic conditional correlation (DCC) are employed to estimate the hedge ratio by taking the conditional covariance between spot and futures return into account.

1.2 Problem Statement

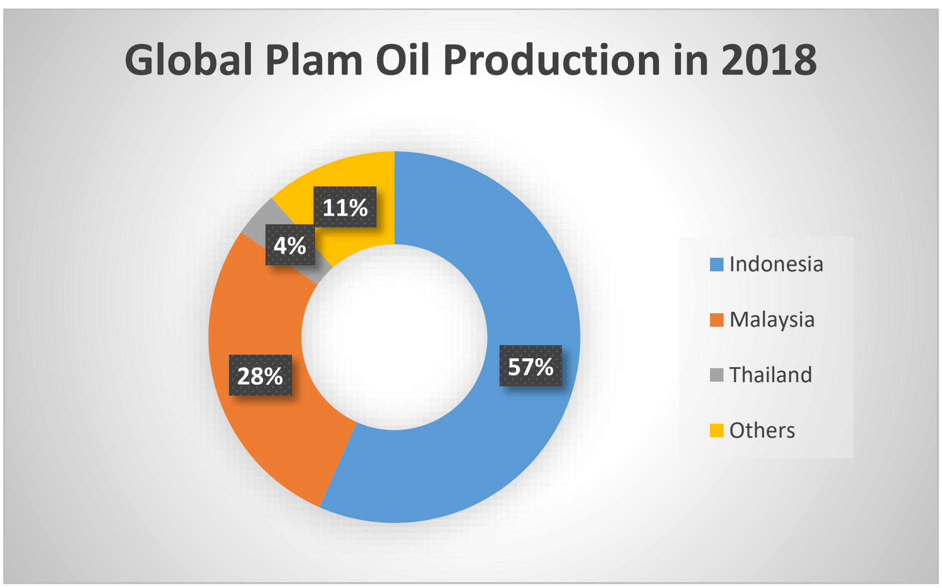

Figure 1.2: Global Palm oil Production in 2018

Sources from Bloomberg

	Palm oil Production				Percentage of Global Production (%)		
	Malaysia	Indonesia	Thailand	World	Malaysia	Indonesia	Thailand
2014	21250	33000	2068	61780	34.00	52.55	3.00
2015	20500	33000	1804	58901	33.00	52.71	3.00
2016	20000	35000	2500	65267	31.01	54.27	3.83
2017	20500	38500	2780	70610	29.57	55.53	3.94
2018	20500	41500	2900	73580	27.97	56.61	3.94

Table 1.3: 5 Years Global Palm Oil Production

Sources from Bloomberg

According to table 1.3, the global CPO market share of Malaysia is gradually decline from the beginning of 34% in year 2014 to 27.97% in year 2018. Relatively, the major competitor, Indonesia has experienced an incredible palm oil production growth from the beginning of 52.55% global production in year 2014 to 56.61% in year 2018. As a matter of fact, the increase of total palm oil supply has eventually intensified the competition between both countries. For example, the third largest Malaysian palm oil importer, China has gradually switching their palm oil demand from Malaysia to Indonesia (Figure 1.3).

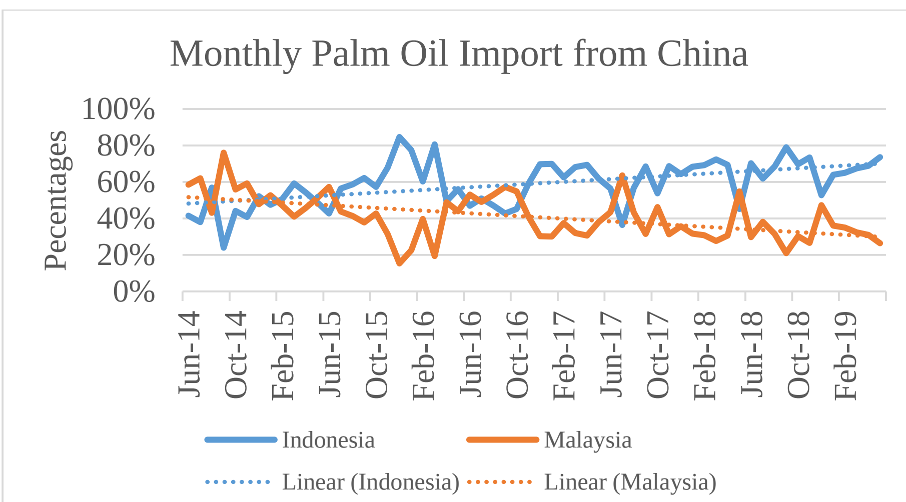

Figure 1.3 Monthly Palm Import from China

Sources from: Bloomberg

However, the case is eventually worsen when Malaysia is highly relying on palm oil exporting activity. According to Mohammad Nor and Masih (2016), approximate 85% of Malaysian total palm oil production is exported and this situation is relatively adverse against Malaysia since the market power will be diluted. In other word, Malaysia will lose its control on CPO prices and the prices is will be driven by the international market forces. Based on figure 1.4, the growth of Malaysia CPO prices has been terminated at the highest of RM 3275 in the earlier 2017 before facing a tremendous decline until the recent day.

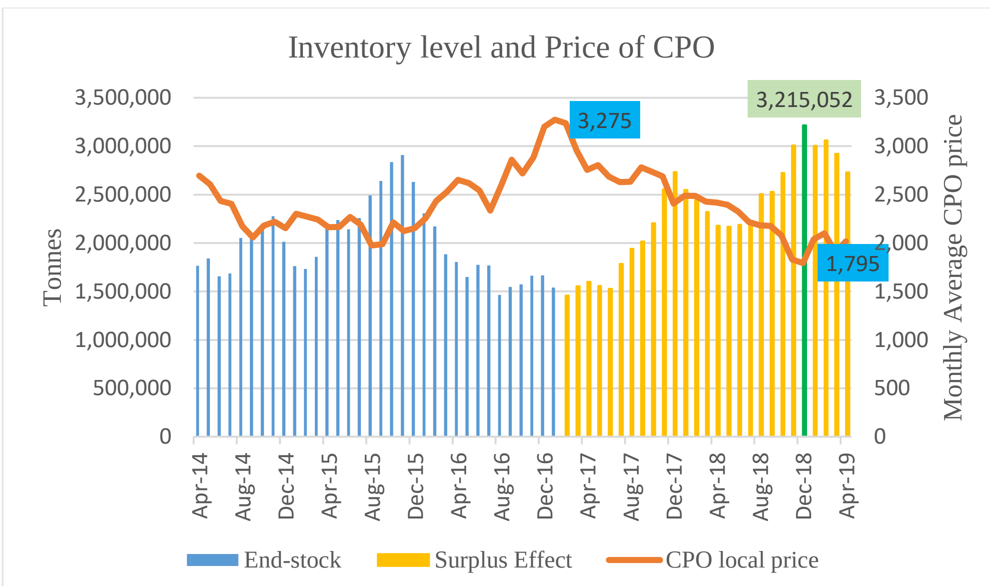

Figure 1.4: Inventory level and Price of CPO in Malaysia

Source from: MPOB

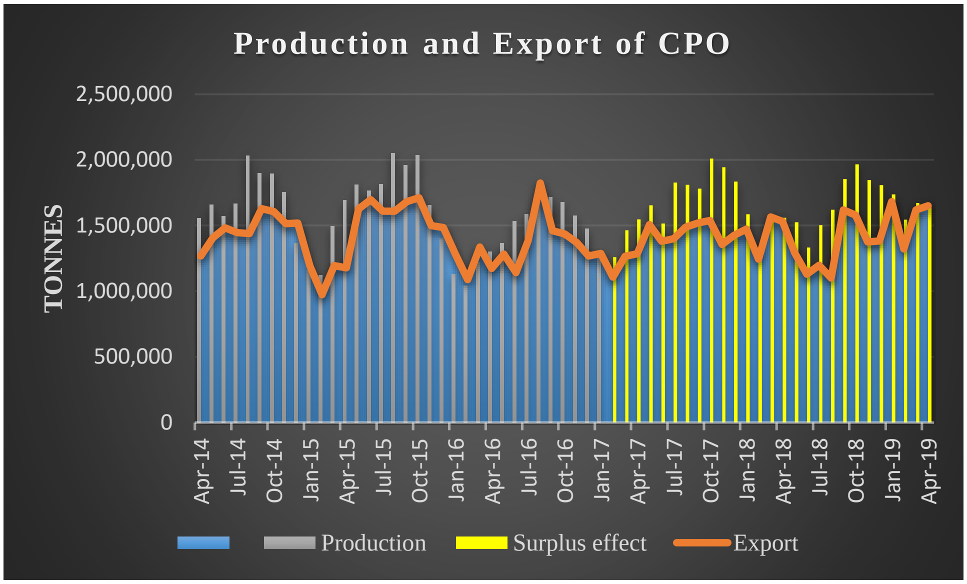

Figure 1.5 Productions and Export of CPO in Malaysia

Source from: MPOB

Since the majority CPO production of Malaysia is exported, thereby, this study assumes the CPO export and production as the proxy of CPO demand and supply respectively. Based on figure 1.5, the CPO production was growing rapidly, however, the export was fluctuating minimally upon a constant. The excess of production over export indicates the surplus issue and the mismatch between CPO demand and supply is getting serious since the earlier 2017.

Based on (Surplus Effect, figure 1.4), the surplus issue was accumulated and eventually boosting the CPO inventory level and lower the CPO prices. In December 2018, the Malaysia's CPO prices has recorded a 5 year low of RM 1795 per metric tons with the highest inventory level of 3.2 million tons. According to Rahman (2012), the CPO export, production, and inventory level is the most important factors in affecting the Malaysia CPO prices. As a consequences, Malaysia total palm oil export revenue has declined from RM46.09 billion in 2017 to RM38.63 billion in 2018. The first quarter palm oil export revenue in 2019 was lower from RM14.25 billion in year 2018 to RM 12.10 billion (MATRADE, 2019).

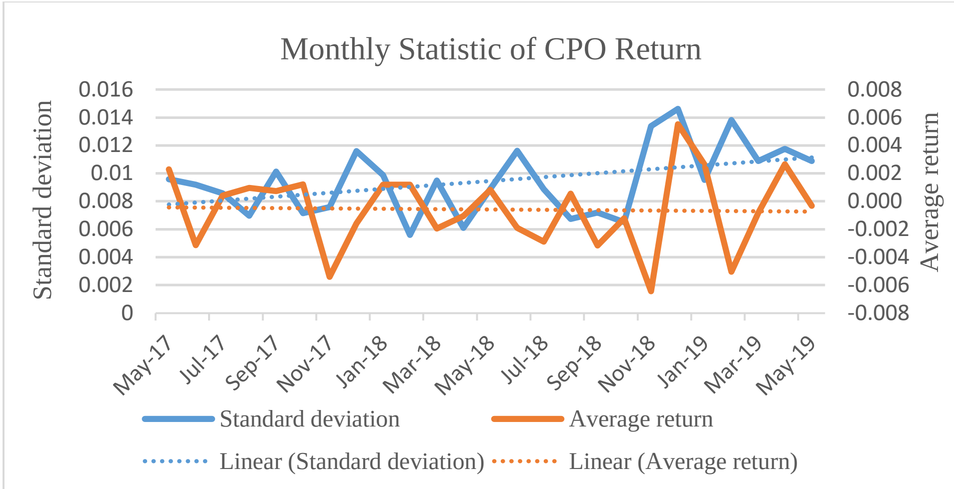

Figure 1.6: Monthly statistic of CPO return in Malaysia

Sources from MPOB, Statistic completed by researcher

On the other hand, based on figure 1.6, the standard deviation of monthly CPO return is having a positive increasing trend while the average CPO return is having a negative declining trend over the past two years. According to Creti, Joets and Mignon (2013), the high standard deviation may result in a greater sensitivity of price changes and higher the price volatility of a particular asset. The instability of CPO return is critical to Malaysia as it remained the major agriculture product that contributing an average of 5% to 7% of Malaysia GDP (Nambiappan et al., 2018).

Besides, European Union (EU), the second-largest palm oil importer of Malaysia accounted for 11.6% of the Malaysia's total palm oil export has classified the palm-oil biofuel as unsustainable in its Delegated Act of 13 March 2019. If the act is passed, the palm-oil biofuel will be gradually phased out from the EU market by 2030 and significantly injure the palm oil demand (European Parliament, 2018). According to Corciolani, Gistri and Pace (2019), several campaigns was raised to criticize the palm oil regarding the issues of deforestation, greenhouse gas emissions as well as human rights violations. Those factors have majorly intensified the fluctuation of global CPO prices in the recent days.

Other than that, Islam (2017) found that several factors including currency exchange rates, rivalry between exporting countries, demand from importing countries, fierce competition among edible oils, and weather affection on future palm oil production are likely to volatile the Malaysia palm-oil price. As mention by Moreira (2014), the higher price fluctuation of a particular commodity might adversely increase the inflationary expectation and decline a country's GDP level.

1.3 Research Objective

General objective

The core objective of this study is to examine the hedging effectiveness of Malaysia Crude Palm Oil Futures (FCPO) with different time to maturity via different hedging strategies of static and dynamic approaches.

Specific objective

1. To determine the most suitable hedging approach that provides the highest variance reduction in Malaysia's CPO spot market.
2. To compare the hedging effectiveness of FCPO with different time to maturities.

1.4 Research Questions

1. Which hedging strategy provides the lowest portfolio variance for Malaysia's CPO spot market?
2. Is the different time to maturities of FCPO matter in affecting the hedging effectiveness?

1.5 Significance of study

The findings of this research are expected to make some crucial contributions to the academia as well as the CPO hedger.

1.5.1 Academia

The past studies regarding the hedging effectiveness of Malaysia derivative instruments are very limited. The recent studies were soundly drawn by (Zainudin et al., 2011; San Ong et al., 2012; Awang at al., 2014; Go & Lau, 2014, 2015; Islam, 2017). Thereby, this study attempts to extend the work of Islam (2017) in examining the hedging effectiveness of FCPO contract. Firstly, Islam (2017) has ignored the symmetric and asymmetric basis effect that might be a crucial variable in affecting hedging effectiveness. Thereby, this study provided an enhancement by introducing the basis effect in examining the hedging effectiveness.

Secondly, this study attempt to provide a new sight in examining the hedging performance of FCPO contract with different time to maturity which encouraged by Islam (2017). Thirdly, this study advanced the methodology by employing the dynamic conditional correlation (DCC)-GARCH model which is yet to be adopted in examining the hedging effectiveness of Malaysia FCPO contract. DCC-GARCH model is employed because it able to take into account of time-varying conditional correlation to ensure the accuracy of variance covariance matrix estimation. In addition, DCC-GARH model has been widely adopted by Kharbanda & Singh (2018), Basher & Sadorsky (2016) and Chen et al. (2016) in examining the hedging effectiveness of different futures contract.

Thus, this study attempts to narrow the gap of knowledge from the previous literature and being a crucial reference for futures researchers.

1.5.2 Hedger

Recently, the CPO price fluctuation remained an uncertainty for most of the CPO market participants. Thereby, the hedger was encouraged to take an opposite futures position to mitigate the price risk. The findings of this study attempt to provide some useful information in determining their hedging strategy. The study attempts to clarify the confusion of hedger by providing an evidence to select the most effective time to maturity FCPO to hedge against the fluctuation of CPO spot price.

CHAPTER 2: LITERATURE REVIEW

2.0 Overview

In this chapter, the study discusses the underlying theory of supporting the spot-futures pricing mechanism such as the theory of storage, cost carry model, efficient market hypothesis as well as the law of one price. Subsequently, the literature about the hedging theory development, review of hedging model specification, empirical of hedging effectiveness in Malaysia as well as the basis effect toward the hedging effectiveness are discussed.

2.1 Underlying theory of spot-futures pricing mechanism

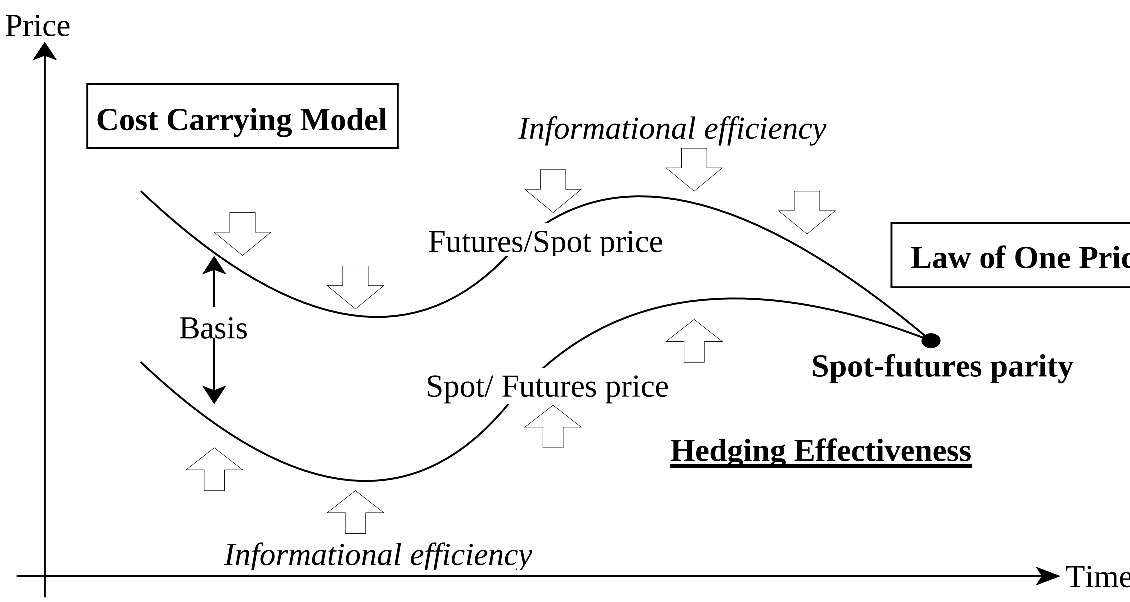

Figure 2.1: Cost Carrying model and Law of one price

Source: Diagram constructed by researcher

2.1.1 Theory of storage and Cost-carry model

According to Fama, Eugene, French and Kenneth (1987), the theory of storage is mainly suggesting the inclusion of storage cost in demonstrating the futures prices. This concept was first stimulated by Working (1953a) in describing the contemporaneous spread between spot and futures prices. Subsequently, it has been widely extended by Kaldor (1939), Brennan (1958), Weymar (1968) and etc. The theory indicated that the particular spot-futures spread is mainly attributed by the financing costs, storage costs, transportation costs, insurance costs and the convenience yield of asset holding. Later, Cornell and French (1983) has developed the cost-carry-model based on the underlying concept. Under the perfect market condition, the spot-futures relation should be defined as below:

$$F_0 = S_0 e^{(r+u-q)T}$$

Where:

F_0 = Present value of futures price

S_0 = Present value of spot price

r = Risk free rate

u = Storage costs

q = Income rate

T= Time to maturity

Theoretically, any price deviation from either spot or futures market should be correctly adjusted to a fair market value throughout the work of arbitrage. Under the condition of $F_0 > S_0 e^{(r+u-q)T}$, the Cash and Carry strategy is suggested by long spot and short futures. In contrary, when $F_0 < S_0 e^{(r+u-q)T}$, a Reverse Cash and Carry strategy is suggested by long futures and short spot. Therefore, a “risk-free profit” can be locked when there is any mispricing in both markets.

2.1.2 Efficient market hypothesis

The theory of EMH was first stimulated by Fama (1970) in describing a prefect market condition where there is an extensive number of rational and profit-maximizing investors are striving themselves in participating the market informational trade. Under the efficient market, investors are enable to rapidly and fully respond to all available information. Therefore, the market prices should be in fair and consistent with the theory (Smart, Gitman & Joehnk, 2017). In the other words, there is neither undervalued nor overvalued of particular assets in the markets. In general, the market efficiency can be classified as strong, semi-strong and weak form. According to Naseer and Tariq (2015), the strong form EMH assumes that the current market prices reflect all relevant information in the aspect of public and private information. In contrast, the current market prices of semi-strong and weak form EMH are merely reflecting the public information and historical market information respectively.

2.1.3 Law of One Price (LOP)

The theory of LOP is a fundamental economic theory that emphasized the price equivalent of an identical good regardless the market location, currency exchange rate, etc. However, LOP is only existed in a free market under a strong assumption of no trade barrier and no transportation costs. In the perspective of international trade, Ardeni (1989) claims that the currency exchange rate can be determined based on the theory of LOP. The theoretical relationship is exhibited as below:

$$\mathrm{P}_D = P_F \times E$$

Where,

P_D : Price of domestic identical good

P_F : Price of foreign identical good

E : Exchange rate

Subsequently, the concept of LOP is further extended to describe the spot-futures pricing mechanism. The futures contract obligated the buyer and seller to buy or sell the underlying asset based on a predetermined price at maturity. Theoretically, the spot and futures instrument is perfectly correlated as an identical good. According to Bowers and Twite (1985), the deviation between the theoretical and actual futures price will be corrected throughout the process of arbitrage. Under an ideal market, the theory of LOP should be held to ensure the prices are fair and consistent between spot and futures markets.

2.2 Empirical Review

2.2.1 Hedging theory development

Over the past decade, the hedging theory was transforming and being developed by voluminous studies. In general, there are a total of three developed theories which known as the conventional hedging theory, Working's hedging theory as well as portfolio hedging theory.

First, the conventional hedging theory is also known as the naïve hedging approach which suggesting the spot and futures prices are perfectly correlated since the both futures and spot markets are sharing a common information set (Gupta and Singh, 2009). Under such assumption, the hedger can ideally realize a perfect hedge by taking a parallel inverse position of spot and futures. In other word, every single spot position can be exactly offset by one futures contract which indicated the hedge ratio always equal to 1. However, the perfect hedge is impractical due to the existence of basis risk, market imperfection, cross hedging and etc. which may deviate the spot-futures movement from an ideal condition.

Second, the Working's hedging theory proposed by Working (1961) suggested that the aim of futures hedging is prior to maximize the return instead of minimizing the risk. The theory claimed that the short term discrepancy between the spot and futures price which is known as the basis is providing a profit-making opportunity. Therefore, the hedgers are recommended to anticipate the co-movement between the spot and futures prices. In other words, the basis change has been the main concern in determining the hedging strategy. For instance, when the investor attempts to remain the spot position, the hedging action is suggested in such the basis is expected to fall, otherwise, an unhedged portfolio is preferable (Working, 1961; Castelino, 1992).

Third, the portfolio hedging theory was developed based on the concept of Markowitz (1952) in suggesting the optimum risk-return portfolio rather than only maximizes the return or minimizes the risk. The theory claimed that there is a variety of efficient hedge ratios along with the efficient utility maximization frontier that could be suggested to the hedgers according to their risk preference (Gupta and Singh, 2009). However, the theory is still facing challenges in examining the time-varying spot-futures relationship to determine the efficient utility maximization frontier.

2.2.2 Development of hedging model

In post-1960, the concept of the optimal hedge ratio (OHR) was first proposed by Johnson (1960) in constructing the hedging strategy to minimize the risk of the portfolio. Ideally, the ratio of the covariance of spot-futures return to the variance of futures return was defined as the OHR. Thereafter, the estimation of OHR has further developed by (Stein, 1961; Ederington, 1979; Anderson and Danthine, 1981; Hill and Schneeweis, 1981). Stein (1961) has initially introduced the ordinary least square (OLS) approach to estimate the OHR by assuming the covariance between spot and futures return is time-invariant throughout a simple linear regression. This method has improved the Naïve hedging approach since the spot-futures relation is precisely measured. The hedging effectiveness of the OLS approach is measured via its R-squared while the OHR is determined by its estimated slope coefficient. But, the OLS approach has been widely criticized by numerous studies.

First, the OLS approach was found to be suffered from the autocorrelation problem. Myers and Thompson (1989) attempted to overcome the underlying issue by proposing the bivariate VAR model. However, the co-integration between the spot and futures was omitted for both VAR and OLS methods and consequently lead to a downward bias in hedge ratio (Hill and Scheeweis, 1981; Cecchetti et al., 1988; Ghosh 1993; Lien and Yang, 2016; 2010). Engle and Granger (1987) claimed that the consideration of the co-integration is important since the dynamic disequilibrium error can be adjusted to improve the estimation of the spot-futures relation. Therefore, Ghosh (1995) & Ghosh and Clayton (1996) have adopted the Error Correction Model (ECM) to examine the hedging performance of currency futures and stock index futures respectively. Their results are consistent to claim that the hedging performance of the ECM approach is more superior to OLS since the short term disequilibrium error can be correlated and precisely measure the long term equilibrium of spot and futures.

Thereafter, Koutmas and Tucker (1996), Cecchetti, Cumby, and Figlewski (1988) & Meneu and Torro (2003) claimed that the time-varying distribution between the spot and futures return was not considered by either OLS or ECM models. Both models were critically restricted by their assumption of constant variance and covariance between spot and futures return. Consequently, it may lead to a bias hedging result since the conditional information is not captured and the spot-futures relationship is impractical to remain constant over time. Therefore, these methods were known as static models since they only can provide the average hedging ratio for a certain period.

To overcome the limitation of the static models, Engle (1982) has initially proposed the autoregressive conditional heteroscedasticity (ARCH) model to capture the conditional variance and the model was the origin of the dynamic hedging model. Throughout this model, a time-varying OHR can be realized and providing risk control at different time periods. Later, Bollerslev (1986) has improved the ARCH model by introducing the Generalized ARCH (GARCH) model to ensure the non-negativity variance and persist the parsimony principle. In later studies, the GARCH model has been widely adopted and further improved to ensure the estimation of spot-futures relationship. The studies of Kroner and Sultan (1993) & Yang and Awokuse (2003) attempt to enhance the methodology by introducing the ECM-GARCH model to take the co-integration as well as conditional information into account.

On the other hand, Yang and Song (2017) & Sy, Li and Nguyen (2015) & Tang, Yang and Yu (2018) have justified the presence of the volatility spillover effect between the spot and futures markets of CPO and Treasury bond. Despite the heteroskedasticity as well as the volatility clustering of spot-futures return were considered by the univariate GARCH model but it was limited to take the spillover effect between two markets into account. Therefore, the Multivariate GARCH model was proposed to capture the co-volatility dynamics between spot and futures returns. The first MGARCH model was known as the Vector Error Correction (VEC) model which initialed by Bollerslev, Engle and Wooldridge (1988). However, the VEC approach was criticized by Floros and Vougas (2004) in claiming the computation process was cumbersome since it involved a vast number of parameters and possible to increase the estimation error.

Besides, the MGARH model has to ensure the criterion of the positive-definite of covariance matrix. Therefore, Engle and Kroner (1995) have further introduced the Baba-Engle-Kraft-Kroner (BEKK) specification to attain the requirement. However, Caporin and McAleer (2012) reveal that the BEKK-GARCH model was suffering from the issue of the “curse of dimensionality” where there is a tradeoff between the effectiveness and parsimonious. For example, a parsimonious model with a few parameters might lower the capability in capturing the dynamic covariance matrix, vice versa.

Thereafter, Bollerslev (1990) proposed the Constant Conditional Correlation, CCC specification to reduce the parameter of the variance-covariance matrix from BEKK model of eleven to CCC model of seven. However, the CCC-GARCH model is impractical due to the restriction of the constant conditional correlation (Su & Huang, 2010). Subsequently, Engle (2002) & Tse and Tsui (2002) introduced the Dynamic Conditional Correlation (DCC) GARH model to improve the preciseness of variance-covariance matrix estimation by taking the time-varying conditional correlation into account. As compare to CCC specification, DCC is much more realistic on the varying correlation assumption.

However, Kharbanda and Singh (2018) found that the result obtained from CCC-GARCH was in line with DCC-GARCH although the DCC-GARCH was more advance in capturing the time-varying correlation. Basher and Sadorsky (2016) found that the ADCC model provided the most effective hedge ratio for oil, VIX and bond to hedge against emerging market stock price while the most effective hedge ratio for gold was estimated by GO-GARCH model. The inconsistent outcomes were mainly due to the model appropriateness on various data properties that result from different markets. Therefore, the model specification and data characteristics were significantly affecting the hedging outcome.

Besides, there is voluminous studies have reported that the dynamic model is outperforming the static model. Islam (2017) suggested that the diag-BEKK GARCH model is outperforming the OLS, VAR and VECM in examining the hedging effectiveness of Malaysia's CPO market. Koulis, Kaimakamis & Beneki (2018) found that the time-varying hedge ratio provided a better result in risk reduction as compared to static OLS and ECM in examining the hedging effectiveness of U.S. stock index futures. Chen, Zhuo and Liu (2016) was claiming a similar finding that the dynamic approach is better than the static method in hedging the gold price in China market.

Although the portfolio risk can be significantly reduced by a frequent position adjustment, however, the operation was followed by a high transaction cost. Peng, Tan & Chen (2016) examined the economic value of the dynamic hedging model and found that half of the operation consisted of high economic value while the remaining action was reflecting the higher costs instead of risk reduction. Therefore, the impractical of adjusting the hedge ratio frequently has raised the interest of examining the performance of the static hedging approach.

More recently, several contradictory findings have emerged regarding the model superiority for hedging performance. Awang et al. (2014) claimed that the OLS approach was providing a better hedging performance than the other static and dynamic models such as VECM, EGARCH and bivariate GARCH in examining the hedging effectiveness of Singapore and Malaysian stock index futures market. Besides, there is a similar study from Czekierda and Zhang (2010) claims that the bivariate GARCH failed to outperform the static OLS and naïve approach in their study. Furthermore, Betancourt and Al Azzawi (2013) attempted to compare the hedging performance of BEKK and diagonal VECH-GARCH with OLS and naïve approaches. Their result is consistent with

Gupta and Kaur (2015) & Zhou (2016) in claiming the gap of hedging performance between the static and dynamic models are relatively small. Although the naïve hedging approach has widely criticized as the worse model in estimating the OHR, however, Kaur and Gupta (2018) & Misund and Asche (2016) have obtained a consistent result in claiming the naïve approach was outperforming the other methods.

According to Wang, Wu and Yang (2015), the sophisticated econometrical models do not necessarily improve the hedging performance. The complex model might generate an extent of parameters which might larger the estimation error and not necessarily to describe the dynamic nature of spot and futures return correctly. Overall, these studies highlight the contradict finding between the static and dynamic models in determining the OHR.

2.2.3 Hedging Effectiveness of Malaysia derivatives

However, the empirical study regarding the hedging effectiveness was scarce in Malaysia derivatives markets. The corresponding studies were soundly drawn by (Zainudin et al., 2011; Go & Lau, 2014, 2015; Awang et al., 2014; Ong et al., 2012; Islam, 2017).

Prior studies have extensively examined the hedging performance from different variance specification approach such as BEKK, CCC, DCC and etc. However, the studies were scarce in exploring the effect from the different conditional mean equation, Zainudin and Shahrudin (2011) examined the hedging effectiveness of Malaysian CPO futures market by using BEKK-GARCH model with three different mean specification including the intercept, Vector Autoregressive (VAR) as well as Vector Error Correction Model (VECM) based on the criterion of risk minimization and utility maximization.

In the aspect of risk minimization, a parsimonious model, such as BEKK-GARCH models with intercept and VAR provided a superior hedging performance compared with the sophisticated model, such as BEKK-VECM model. In terms of utility maximization, there was only a minimal discrepancy between the models. In general, they discovered that the hedging effectiveness could be significantly affected by different specifications of the conditional mean equation.

Go and Lau (2014) claimed that the Bivariate-VAR-threshold-GARCH model has effectively captured the volatility spillover between Malaysian spot and futures CPO markets and providing a higher risk reduction compared to conventional GARCH as well as naïve approach. They further concluded that the volatility spillover and asymmetric effect were crucial to be comprised of conditional variance and covariance equations to improve the accuracy of volatility estimation. Subsequently, Go and Lau (2015) found that the CPO spot and futures return was extremely volatile during the world economic recession in 1986, the Asian financial crisis (AFC) in 1997-1998 as well as a global financial crisis (GFC) in 2008-2009. Thereby, they attempted to examine the changes in hedging performance on the CPO futures market during the financial crises in three different periods. By employing eight hedging models with distinct means and variance-covariance specifications, they discovered that the model insisted on the basis term provided a superior result during AFC and GFC while the mean of the hedge ratio was changing across the event. The study further finalized that the basis term was imperative in modeling the joint dynamics of spot and futures returns during crises.

Furthermore, Ong et al (2012) computed a series of monthly hedge ratios by using the OLS approach for Malaysian FCPO. They reported that the hedging effectiveness ranging from the lowest of 19% to the highest of 53%. The low level of hedging performance was mainly due to the stability of CPO spot prices which attributed to the steadiness of petroleum crude oil, recovery of the world economy in 2010, Europe debt crisis as well as a slight impact from earthquake and tsunami in Japan. Ibrahim and Sundarasen (2010) compared the hedging performance of static least square approach and dynamic State Space model (Kalman Filter approach) based on the daily Kuala Lumpur Composite Index (KLCI) and Kuala Lumpur futures Index (KLFI) from April 2005 to March 2008. They found that the least square static hedge ratio was overestimated and probably reflecting a higher hedging cost.

2.2.4 The Basis Effect on Hedging Effectiveness

The basis is referring to the prices different between the spot and futures. As the spot-futures price will be convergence, thus, the basis will be gradually declined and eliminated at the maturity. However, the studies of basis effect on hedging effectiveness were scarce after the studies of (Working 1953a, b, 1961).

Lien and Yang (2006) discovered that the basis is asymmetrically affecting the currency spot-futures markets during the period of 1990 to 2004. Their study concluded that the inclusion of the basis effect has significantly enhanced the dynamic hedging strategy, where the asymmetric basis has evidently provided a higher risk reduction than the symmetric basis. Subsequently, the study is further extended by Lien and Yang (2008a) in examining the hedging performance for ten commodities in the United States during 1980-1999. Their finding suggested that the impact from the positive basis is found to be greater than the negative basis and further emphasized the importance of asymmetric basis. The study justified that the symmetric-basis-model was found to be over-hedged (under-hedged) when the basis is decreasing (increasing). Lien and Yang (2008b) advanced the model used in examining the hedging performance of aluminum and copper futures on Shanghai Futures Exchanges. Their result claimed that the asymmetric bivariate fractionally integrated GARCH model was providing a superior hedging performance since it able to capture the asymmetric basis effect.

Furthermore, the literature of Lien and Yang (2008a) was further extended by Chen et al. (2016). First, Chen et al. (2016) enhanced the former bivariate-GARCH model by adopting the dynamic conditional correlation (DCC) specification to improve the efficiency of parameter estimation. Second, they proposed the Value at Risk (VaR) concept as an alternative to evaluate the hedging performance instead of the conventional variance approach. The prevailing of VaR concept has fulfilled the hedger expectation in concerning the downside risk rather than two-sided risk. Zero-VaR hedging also provided the flexibility for the hedger to adjust the level of risk aversion through the confidence level determination. Their finding suggested that the optimal hedging strategy from the asymmetric BGARCH-DCC model has provided the highest risk reduction in China aluminum and copper markets.

In the study of Lau and Bilgin (2013), the structural change of volatility spillover and the basis effect was taken into account to examine the hedging effectiveness of the China aluminum futures market during 1993-2010. However, the finding suggested that the model properties did not importantly improve the hedging performance of China aluminum futures contracts due to a minimal affection of return and volatility between both London and Shanghai futures markets. The study finalized that the symmetric DCC-GARCH model is the best model for in-sample and out of sample analysis.

CHAPTER 3: METHODOLOGY

3.0 Overview

In this chapter, section 3.1 and 3.2 discuss the data description and data summary of the CPO spot and futures return. This is important to understand the return properties of CPO spot and futures before constructing the hedging strategies. On the other hand, section 3.3.1 is mainly discussed the hedging model specification while the procedure of estimating the hedging effectiveness is discussed in section 3.3.2.

3.1 Data description

In this study, the daily settlement price of CPO spot (SP) and FCPO contracts with different time to maturity of the spot month (FP0), next to two month (FP2) and next to four month (FP4) have been employed to examine the hedging effectiveness. The daily settlement price of the CPO spot is collected from Malaysia Palm Oil Board (MPOB) where the FCPO contract prices are collected from Bloomberg and both prices are denominated in Ringgit Malaysia (MYR).

The entire sample covers the trading days from May 14, 2012 to May 31, 2019 consisting of total observations of 1729. The entire sample is proportionally divided into in-sample and out-of-sample. The in-sample is constituted by 80% of the entire sample which covers from May 14, 2012 to December 27, 2017 and the out-of-sample is constructed based on the remaining 20% of the entire sample which covers from December 28, 2017 to May 31, 2019. The observation for in-sample and out-of-sample are 1383 and 345 respectively.

Subsequently, the corresponding spot and futures prices are transformed into the natural logarithmic return to ensure the return series are stationary. The formula of natural logarithmic return is provided as below:

$$R_t = \frac{Ln\ P_t}{Ln\ P_{t-1}}$$

Where

R_t : Daily return

P_t : Price at t period

P_{t-1} : Price at t-1 period

On the other hand, the FCPO contracts of (FP0), (FP2) as well as (FP4) are used as the futures price of the FCPO contracts. The choice of the following contracts is mainly based on the average trading volume (Table 1.2). In general, the variables used in this study are summarized below:

Table 3.1.1 Variable description

Variables	**Proxy**
Spot price	SP
Spot month futures price	FP0
Next to two month futures price	FP2
Next to four month futures price	FP4
Spot return	SR
Spot month futures return	FR0
Next to two month futures return	FR2
Next to four month futures return	FR4

Source: Bloomberg (2019)

Besides, table 3.1.2 showed the result of the unit root test in terms of Augmented Dickey Fuller (ADF) as well as Phillips-Perron (PP) test. For the entire, in- and out-of-sample, the daily spot-futures returns are diagnosed where the unit root could not be found at 1% of the significant level in all of the cases. Thereby, the study concluded that the daily spot-futures returns are stationary in level form and the spurious regression problem is avoided in this study.

Table 3.1.2 Result of unit root test

Return	**ADF**		**PP**	
	Intercept	**Intercept with Trend**	**Intercept**	**Intercept with Trend**
Entire sample				
Spot	-25.9006***	-25.8948***	-38.3100***	-38.3018***
Spot month	-38.3217***	-38.3122***	-38.3206***	-38.3112***
Next two month	-39.8334***	-39.8246***	-39.8158***	-39.8068***
Next four month	-39.9012***	-39.8928***	-39.8711***	-39.8623***
In-sample				
Spot	-23.1074***	-23.1182***	-34.7342***	-34.7237***
Spot month	-35.1676***	-35.1703***	-35.2130***	-35.2136***
Next two month	-36.0440***	-36.0536***	-36.0463***	-36.0559***
Next four month	-35.8226***	-35.8364***	-35.7999***	-35.8137***
Out-of-sample				
Spot	-15.1836***	-15.1618***	-15.4482***	-15.4264***
Spot month	-15.2171***	-15.1973***	-14.9756***	-14.9514***
Next two month	-16.4830***	-16.4594***	-16.3708***	-16.3439***
Next four month	-17.2168***	-17.1912***	-17.2469***	-17.2167***

Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. The null hypothesis indicates the series is having a unit root.

3.2 Data summary

The descriptive statistic of Malaysia's CPO spot and futures returns are summarized in Table 3.2.1, 3.2.2 and 3.2.3. The results provide insight into the return characteristic of the CPO spot and futures. The result of the mean, standard deviation as well as return distribution will be further discussed below.

First, based on Table 3.2.1, 3.2.2, and 3.2.3, there are common results that showed the negative mean return of Malaysia's CPO spot and futures. However, the negative average spot return of Out-of-sample (-0.0006) is relatively larger than In-sample of (-0.0002). This implied that the prospect of the Malaysia CPO market is unfavorable and the situation is getting worsen. On the other hand, the result showed that the loss incurred in the CPO spot market is relatively higher than the futures market. For FCPO with different time to maturity, the negative average futures return is gradually declined from near month to far month futures. This is because the far month futures might have a greater room of adjustment against the negative impact.

Second, the overall standard deviation of the FCPO futures returns is higher than the CPO spot return regardless of the sample period. This implied that the FCPO futures market is relatively volatile than the spot market. However, for the FCPO futures with different maturity, it is observed that the return volatility of near month futures is higher than the far month futures. This implied that the near-month futures is more sensitive to conditional information.

Third, the Jarque-Bera normality test is employed to examine the normality distribution of spot and futures returns. For the in-sample and the entire sample, the spot-futures distribution is found to be not normally distributed at 1% of the significant level. However, for out-of-sample, the CPO spot and spot-month futures return are not normally distributed at 1% of the significant level, however, the return distribution for the next-two and next-four month futures are found to be normally distributed at 1% of the significant level.

Besides, in comparing the return properties of the in-sample and out-of-sample, the return skewness of the CPO spot is shifting from negative to positive. The positive return skewness of the CPO spot for Out-of-sample might imply the condition of (Mode<Median<Mean). As the corresponding mean return is negative, thereby, it is reasonable to claim that the majority CPO spot returns are negative and the possibility of the extreme positive return is relatively low. Besides, the spot-month futures is found to have the highest kurtosis value. This result implied that the condition of leptokurtic distribution with a fat tail. Thereby, the possibility of having an extreme value is larger. In conclusion, the return distribution of spot is relatively different from the futures contracts.

Table 3.2.1 Descriptive statistics of the entire sample

	Entire Sample			
	Spot	**FCPO**		
		Spot month	**Next to two month**	**Next to four month**
Observations	1729	1729	1729	1729
Mean	-0.000280	-0.00026	-0.000243	-0.000232
Standard deviation	0.011159	0.01398	0.013111	0.012031
Maximum	0.050990	0.09319	0.05011	0.047649
Minimum	-0.076459	-0.09910	-0.088636	-0.057455
Median	0.000000	0.00000	-0.000789	-0.000380
Skewness	-0.301584	0.20713	-0.084841	-0.051853
Kurtosis	6.138414	6.94800	4.350918	3.595397
Jarque-Bera	735.7942***	1135.255***	133.549***	26.313***

Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. The null hypothesis indicates the return series is normally distributed.

Table 3.2.2 Descriptive statistics of the In-sample

	In-Sample			
	Spot	**FCPO**		
		Spot month	**Next to two month**	**Next to four month**
Observations	1383	1383	1383	1383
Mean	-0.0002	-0.00018	-0.00016	-0.00014
Standard deviation	0.01140	0.01406	0.01355	0.01254
Maximum	0.05099	0.09319	0.05011	0.04765
Minimum	-0.0765	-0.09910	-0.08864	-0.05746
Median	0.0000	0.00000	-0.00049	0.00000
Skewness	-0.3604	0.15399	-0.12602	-0.08238
Kurtosis	6.33286	7.06824	4.43252	3.525255
Jarque-Bera	670.0349***	959.1912***	121.9134***	17.46251***

Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. The null hypothesis indicates the return series is normally distributed.

Table 3.2.3 Descriptive statistics of the Out-of-sample

	Out-of-Sample			
	Spot	**FCPO**		
		Spot month	**Next to two month**	**Next to four month**
Observations	345	345	345	345
Mean	-0.000617	-0.00056	-0.00057	-0.00056
Standard deviation	0.010132	0.01367	0.01121	0.00977
Maximum	0.041444	0.06794	0.03249	0.03098
Minimum	-0.041805	-0.05677	-0.03586	-0.02836
Median	-0.000802	-0.00125	-0.00147	-0.00083
Skewness	0.021322	0.43186	0.16444	0.13724
Kurtosis	4.607464	6.39897	2.94327	3.18658
Jarque-Bera	37.17030***	176.796***	1.60112	1.58303

Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. The null hypothesis indicates the return series is normally distributed.

3.3 Methodology

This section attempts to discuss the four-step procedures in estimating the hedging effectiveness of the FCPO contracts via different hedging strategies. First, the study required to estimate the variance-covariance of spot and futures returns throughout the hedging strategies that discussed in section 3.3.2. The second step is to adopt the prior results of the variance-covariance to estimate the optimal hedge ratio (OHR). Based on the computed OHRs, the third step involved the process of estimating the hedged portfolio variance. The formula of OHR and hedged portfolio variance are provided in section 3.3.3.1 and 3.3.3.2 respectively. Finally, the last step is to estimate the hedging effectiveness of different hedging strategies. In addition, for section 3.3.3.3, the log-likelihood function is introduced as the key approach in estimating the variance-covariance of spot-futures return.

3.3.1 Hedging strategies

In this section, the study attempts to introduce the hedging strategies of the static and dynamic hedging approaches. For static hedging approach, the traditional naïve 1:1 hedge ratio as well as the ordinary least square (OLS) approach are employed. However, the dynamic hedging approach is constructed based on four different condition means and three different variance-covariance specifications such as Diag-BEKK, CCC and DCC-GARCH. In other words, there is a total of (3 x 4) 12 dynamic hedging strategies are employed to estimate the hedging effectiveness.

3.3.1.1 Specification of the conditional mean

First, the study begins with the simplest of intercept-model which is only taking the intercept of spot-futures returns into consideration. Second, the vector autoregressive terms are taken into account to improve the intercept-model. The VAR-model of including the lags of the spot and futures return are to examine the past spot-futures return in affecting the hedging effectiveness. Third, the study enhanced the VAR-model by taking the basis effect into account. The basis, B_t is computed based on the formula of $Ln\left(P_{S,t}\right) - Ln\left(P_{F,t}\right)$. However, the symmetrical-basis model assumes the basis effect to be symmetric. In other word, the direction of the basis is excluded. Fourth, the study attempts to incorporate the basis direction. Thereby, the basis, B_t is further decomposed into the positive basis B_{t-1}^{+} ;(max $(B_{t-1}, 0)$) and the negative basis B_{t-1}^{-}. ; min $(B_{t-1}, 0)$). According to Chen et al. (2016), the directional basis of positive and negative effect might able to improve the hedging performance.

3.3.1.2 Specification of the conditional variance-covariance

First, the variance-covariance specification of Diagonal-Baba-Engle-Kraft-Krone (Diag-BEKK) was first introduced by Engle and Kroner (1995) to capture the ARCH effect as well the volatility clustering in return series. The setting of Diag-BEKK is to ensure the criterion of positivity for the covariance matrix. However, the model is limited to capture the conditional correlation into account.

Second, the specification of Constant conditional correlation (CCC) was first introduced by Bollerslev (1990). The CCC specification has provided an improvement on the Diag-BEKK in the terms of taking the conditional correlation into account. CCC-GARCH also enable to ensure the parsimonious principle and effectively lower the estimation error. Besides, the CCC-GARCH model transformed the residuals into standardized residual for spot and futures returns by using formula of $\eta_t = \frac{\varepsilon_t}{\sqrt{h_t}}$. Subsequently, the standardized residual, η_t is further adopted to compute the unconditional correlation between spot and futures. However, the model is restricted by assuming the conditional correlation is constant.

Third, the specification of Dynamic conditional correlation (DCC) was first proposed by Engle (2002) & Tse and Tsui (2002) to enhance the CCC-GARCH model. In practice, the spot-futures relationship is changing according to the conditional information. Thereby, DCC-GARCH model enable to capture the dynamic conditional correlation into account. According to (Ku, Chen and Chen, 2007; Hammoudeh, Yuan and Thompson, 2010; Chen, Leung, Poon and Su, 2016), the estimation of the dynamic conditional variance-covariance matrix of DCC-MGACH model involved a 2 steps procedures. The first step is to compute the symmetric positive definite matrix (matrix Q_t). The second step is to estimate the dynamic conditional correlation coefficient $\rho_{sf,t}$ based on the computed matrix Q_t.

3.3.2 Models specification

3.3.2.1 Static models

The static model assumes that the variance-covariance of spot-futures return are constant over time. These model is adopted since the computation process is relatively simple. However, the time-varying distribution, heteroscedasticity, serial correlation issues has been ignored by the static model. Thereby, the static model is only providing an average hedging ratio for a certain time period.

I. Naïve 1:1 hedging approach

Naïve hedging strategy is the most classic hedging method against spot price risk. This approach assumed that the spot-futures return is perfectly correlated. Every single unit of spot position can be exactly offset by one unit of futures position. The equation is provided as below:

$$S_t = \mathrm{C} + \alpha F_t + \mathcal{E}$$

Where,

S_t : Spot return at time t

C : Intercept

α : 1:1 hedge ratio

F_t : Futures return at time t

Ɛ : Error term

II. Ordinary least square (OLS) model

OLS approach provided a simple linear regression between the spot and futures return. It might provide an average hedging ratio for a certain hedging period. The equation provided as below:

$$S_t = \mathrm{C} + \mathrm{H}\, F_t + \mathcal{E}_t;\ \mathcal{E}_t \sim \text{i.i.d. N } (0, \sigma^2)$$

Where:

S_t : Spot return at time t

C : Intercept

H : Optimal hedge ratio

F_t : Futures return at time t

$\mathcal{E}_t$: Error term which is independently distributed and identically (i.i.d)

3.3.2.2 Dynamic model

The dynamic hedging model is introduced to capture the conditional information that resulted in different periods. It is suggested that the estimated OHR is time-variant. In other word, the hedge ratio might be changing over the entire hedging period. In this study, Diag-BEKK, CCC and DCC-GARCH models are employed as the dynamic hedge approach. Generally, the mean equations are based on the intercept, VAR, Symmetric-basis and Asymmetric-basis. The model specification is provided in the equation of III to XIV.

III. Diag-BEKK-GARCH with intercept

Mean equation:

$$S_t = C_S + \mathcal{E}_{S,t};|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \mathcal{E}_{F,t};|\Phi_{t-1} \sim N(0, H_t)$$

BEKK specification:

$$H_t = CC' + A\mathcal{E}_{t-1}\mathcal{E}'_{t-1}A' + MH_{t-1}M'$$

$$H_t = \begin{bmatrix} H_{SS} & H_{SF} \\ 0 & H_{FF} \end{bmatrix}; C = \begin{bmatrix} C_{SS} & C_{SF} \\ 0 & C_{FF} \end{bmatrix}; A = \begin{bmatrix} A_{SS} & 0 \\ 0 & A_{FF} \end{bmatrix}; M = \begin{bmatrix} G_{SS} & 0 \\ 0 & G_{FF} \end{bmatrix}; \mathcal{E}_t = \begin{bmatrix} \mathcal{E}_{St} \\ \mathcal{E}_{Ft} \end{bmatrix}$$

Conditional variance-covariance equation:

$$H_{SS,t} = C_{SS,t} + {A_{SS}}^2 {\mathcal{E}^2}_{S,t-1} + {G_{SS}}^2 H_{SS,t-1}$$

$$H_{FF,t} = C_{FF,t} + {A_{FF}}^2 {\mathcal{E}^2}_{F,t-1} + {G_{FF}}^2 H_{FF,t-1}$$

$$H_{SF,t} = C_{SF,t} + A_{SS}A_{FF}\mathcal{E}_{S,t-1}\mathcal{E}_{F,t-1} + G_{SS}G_{FF}H_{SS,t-1}H_{FF,t-1}$$

Where,

S	: Spot return at time t
F	: Futures return at time t
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t

$H_{FF,t}$: Conditional variance of futures return at time t

$H_{SF,t}$: Conditional covariance of spot and futures return at time t

IV. Diag-BEKK-GARCH with vector autoregressive term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \mathcal{E}_{S,t}; \mathcal{E}_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \mathcal{E}_{F,t}; \mathcal{E}_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = C_{SS,t} + A_{SS}{}^2 \mathcal{E}^2{}_{S,t-1} + G_{SS}{}^2 H_{SS,t-1}$$

$$H_{FF,t} = C_{FF,t} + A_{FF}{}^2 \mathcal{E}^2{}_{F,t-1} + G_{FF}{}^2 H_{FF,t-1}$$

$$H_{SF,t} = C_{SF,t} + A_{SS} A_{FF} \mathcal{E}_{S,t-1} \mathcal{E}_{F,t-1} + G_{SS} G_{FF} H_{SS,t-1} H_{FF,t-1}$$

S : Spot return

F : Futures return

C : Intercept

Ɛ : Error term

Φ_{t-1} : Past information at t-1

p : Lag number of spot return

q : Lag number of futures return

H_t : Conditional variance-covariance matrix at time t

$H_{SS,t}$: Conditional variance of spot return at time t

$H_{FF,t}$: Conditional variance of futures return at time t

$H_{SF,t}$: Conditional covariance of spot and futures return at time t

V. Diag-BEKK-GARCH with symmetric effect of basis term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \gamma_S B_{t-1} + \mathcal{E}_{S,t}; \mathcal{E}_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \gamma_F B_{t-1} + \mathcal{E}_{F,t}; \mathcal{E}_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = C_{SS,t} + A_{SS}{}^2 \mathcal{E}^2{}_{S,t-1} + G_{SS}{}^2 H_{SS,t-1} + D_{SS} B_{t-1}{}^2$$

$$H_{FF,t} = C_{FF,t} + A_{FF}{}^2 \mathcal{E}^2{}_{F,t-1} + G_{FF}{}^2 H_{FF,t-1} + D_{FF} B_{t-1}{}^2$$

$$H_{SF,t} = C_{SF,t} + A_{SS} A_{FF} \mathcal{E}_{S,t-1} \mathcal{E}_{F,t-1} + G_{SS} G_{FF} H_{SS,t-1} H_{FF,t-1} + D_{SF} B_{t-1}{}^2$$

S	: Spot return
F	: Futures return
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
p	: Lag number of spot return
q	: Lag number of futures return
B_{t-1}	: Basis at time t-1 ; $\left(Ln\left(P_{S,t-1}\right) - Ln\left(P_{F,t-1}\right)\right)$
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
$H_{FF,t}$	: Conditional variance of futures return at time t
$H_{SF,t}$	: Conditional covariance of spot and futures return at time t

VI. Diag-BEKK-GARCH with asymmetric effect of basis term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \delta_S B_{t-1}^{+} + \theta_S B_{t-1}^{-} + \mathcal{E}_{S,t}$$

$$; \mathcal{E}_{S,t} | \Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \delta_f B_{t-1}^{+} + \theta_F B_{t-1}^{-} + \mathcal{E}_{F,t}$$

$$; \mathcal{E}_{F,t} | \Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = C_{SS,t} + {A_{SS}}^2 \mathcal{E}^2{}_{S,t-1} + {G_{SS}}^2 H_{SS,t-1} + P_{SS}(B_{t-1}^{+})^2 + N_{SS}(B_{t-1}^{-})^2$$

$$H_{FF,t} = C_{FF,t} + {A_{FF}}^2 \mathcal{E}^2{}_{F,t-1} + {G_{FF}}^2 H_{FF,t-1} + P_{SS}(B_{t-1}^{+})^2 + N_{FF}(B_{t-1}^{-})^2$$

$$H_{SF,t} = C_{SF,t} + A_{SS} A_{FF} \mathcal{E}_{S,t-1} \mathcal{E}_{F,t-1} + G_{SS} G_{FF} H_{SS,t-1} H_{FF,t-1} + P_{SF}(B_{t-1}^{+})^2 + N_{SF}(B_{t-1}^{-})^2$$

S	: Spot return
F	: Futures return
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
p	: Lag number of spot return
q	: Lag number of futures return
B_{t-1}^{+}	: Positive basis at time t-1 ; max $(B_{t-1}, 0)$
B_{t-1}^{-}	: Negative basis at time t-1 ; min $(B_{t-1}, 0)$
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
$H_{FF,t}$	: Conditional variance of futures return at time t
$H_{SF,t}$	: Conditional covariance of spot and futures return at time t

VII. CCC-GARCH with constant term

Mean equation:

$$S_t = C_S + \varepsilon_{S,t}; |\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \varepsilon_{F,t}; |\Phi_{t-1} \sim N(0, H_t)$$

CCC specification

$$H_t = D_t R D_t$$

$$D_t = diag\{\sqrt{h_{it}}\}$$

$$H_t = Var(\varepsilon_{S,t}, \varepsilon_{F,t} | \Phi_{t-1}) = \begin{bmatrix} H_{SS,t} & H_{SF,t} \\ H_{FS,t} & H_{FF,t} \end{bmatrix}$$

$$= \begin{bmatrix} \sqrt{H_{SS,t}} & 0 \\ 0 & \sqrt{H_{FF,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sqrt{H_{SS,t}} & 0 \\ 0 & \sqrt{H_{FF,t}} \end{bmatrix}$$

Conditional variance-covariance equation:

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

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

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

; given= $E_{t-1}(\eta_t \eta'_t) = D_t{}^{-1} H_t D_t{}^{-1}$; $\eta_t = \frac{\varepsilon_t}{\sqrt{h_t}}$

Where,

S	: Spot return
F	: Futures return
C	: Intercept
ε	: Error term
Φ_{t-1}	: Past information at t-1
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
R	: Unconditional correlation matrix of standardized error terms for daily CPO spot and futures return
$H_{FF,t}$	: Conditional variance of futures return at time t
$H_{SF,t}$	: Conditional covariance of spot and futures return at time t

ρ	: Correlation coefficient between standardized error terms of daily CPO and futures return

VIII. CCC-GARCH with Vector autoregressive term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \mathcal{E}_{S,t}; \mathcal{E}_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \mathcal{E}_{F,t}; \mathcal{E}_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = \omega_{SS} + \alpha_{SS}\mathcal{E}^2{}_{S,t-1} + \beta_{SS}H_{SS,t-1}$$

$$H_{FF,t} = \omega_{FF} + \alpha_{FF}\mathcal{E}^2{}_{F,t-1} + \beta_{FF}H_{FF,t-1}$$

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

$$\text{; given} = E_{t-1}(\eta_t\eta'_t) = D_t{}^{-1}H_tD_t{}^{-1} \text{ ; } \eta_t = \frac{\mathcal{E}_t}{\sqrt{h_t}}$$

Where,

S	: Spot return
F	: Futures return
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
p	: Lag number of spot return
q	: Lag number of futures return
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
$H_{FF,t}$	: Conditional variance of futures return at time t
$H_{SF,t}$	: Conditional covariance of spot and futures return at time t
ρ	: Unconditional correlation coefficient between standardized error terms of daily CPO spot and futures return

IX. CCC-GARCH with symmetric effect of basis term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \gamma_S B_{t-1} + \mathcal{E}_{S,t}; \mathcal{E}_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \gamma_F B_{t-1} + \mathcal{E}_{F,t}; \mathcal{E}_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = \omega_{SS} + \alpha_{SS}\mathcal{E}^2{}_{S,t-1} + \beta_{SS}H_{SS,t-1} + D_{SS}{B_{t-1}}^2$$

$$H_{FF,t} = \omega_{FF} + \alpha_{FF}\mathcal{E}^2{}_{F,t-1} + \beta_{FF}H_{FF,t-1} + D_{FF}{B_{t-1}}^2$$

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

$$;\ \text{given} = E_{t-1}(\eta_t \eta'_t) = {D_t}^{-1} H_t {D_t}^{-1}\ ;\ \eta_t = \frac{\mathcal{E}_t}{\sqrt{h_t}}$$

Where,

S	: Spot return
F	: Futures return
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
p	: Lag number of spot return
q	: Lag number of futures return
B_{t-1}	: Basis at time t-1 ; $\left(Ln(P_{S,t-1}) - Ln(P_{F,t-1})\right)$
${B_{t-1}}^2$	: Basis squared (symmetric effect of basis)
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
$H_{FF,t}$	: Conditional variance of futures return at time t
$H_{SF,t}$	: Conditional covariance of spot and futures return at time t

ρ : Unconditional correlation coefficient between standardized error terms of daily CPO spot and futures return

X. CCC-GARCH with asymmetric effect of basis term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \delta_S B_{t-1}^{+} + \theta_S B_{t-1}^{-} + \mathcal{E}_{S,t}; \mathcal{E}_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \delta_f B_{t-1}^{+} + \theta_F B_{t-1}^{-} + \mathcal{E}_{F,t}\mathcal{E}_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = \omega_{SS} + \alpha_{SS}\mathcal{E}^2{}_{S,t-1} + \beta_{SS}H_{SS,t-1} + P_{SS}(B_{t-1}^{+})^2 + N_{SS}(B_{t-1}^{-})^2$$

$$H_{FF,t} = \omega_{FF} + \alpha_{FF}\mathcal{E}^2{}_{F,t-1} + \beta_{FF}H_{FF,t-1} + P_{FF}(B_{t-1}^{+})^2 + N_{FF}(B_{t-1}^{-})^2$$

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

; given= $E_{t-1}(\eta_t \eta'_t) = D_t{}^{-1} H_t D_t{}^{-1}$; $\eta_t = \frac{\mathcal{E}_t}{\sqrt{h_t}}$

Where,

S : Spot return

F : Futures return

C : Intercept

$\mathcal{E}$: Error term

Φ_{t-1} : Past information at t-1

p : Lag number of spot return

q : Lag number of futures return

H_t : Conditional variance-covariance matrix at time t

B_{t-1}^{+} : Positive basis at time t-1 ; max $(B_{t-1}, 0)$

B_{t-1}^{-} : Negative basis at time t-1 ; min $(B_{t-1}, 0)$

$H_{SS,t}$: Conditional variance of spot return at time t

$H_{FF,t}$: Conditional variance of futures return at time t

$H_{SF,t}$: Conditional covariance of spot and futures return at time t

ρ : Unconditional correlation coefficient between standardized error terms of daily CPO spot and futures return

XI. DCC-GARCH with constant term

Mean equation:

$$S_t = C_S + \mathcal{E}_{S,t}; |\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \mathcal{E}_{F,t}; |\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_t = D_t R_t D_t$$

$$D_t = diag\{\sqrt{h_{it}}\}$$

$$\text{Var}\left(R_{S,t}, R_{F,t}|\Phi_{t-1}\right) = Var\left(\mathcal{E}_{S,t}, \mathcal{E}_{F,t}|\Phi_{t-1}\right) = H_t = \begin{bmatrix} H_{SS,t} & H_{SF,t} \\ H_{FS,t} & H_{FF,t} \end{bmatrix}$$

$$R_t = \left(diag(Q_t)\right)^{-\frac{1}{2}} Q_t (diag(Q_t))^{-\frac{1}{2}}$$

$$H_{SS,t} = \omega_{SS} + \alpha_{SS}\mathcal{E}^2{}_{S,t-1} + \beta_{SS}H_{SS,t-1}$$

$$H_{FF,t} = \omega_{FF} + \alpha_{FF}\mathcal{E}^2{}_{F,t-1} + \beta_{FF}H_{FF,t-1}$$

$$Q_t = \begin{bmatrix} Q_{SS,t} & Q_{sf,t} \\ Q_{sf,t} & Q_{FF,t} \end{bmatrix} = (1 - K_1 - K_2)\bar{Q} + K_1\mu_{1,t-1}\mu_{2,t-1} + K_2Q_{t-1}; \mu_{i,t} = \frac{\mathcal{E}^2{}_{i,t}}{\sqrt{h_{i,t}}}$$

$$\rho_{sf,t} = \frac{Q_{sf,t}}{\sqrt{Q_{SS,t}Q_{FF,t}}} = \rho_{12,t} = \frac{(1 - K_1 - K_2)\bar{Q}_{12} + K_1\mu_{1,t-1}\mu_{2,t-1} + K_2Q_{12,t-1}}{\sqrt{\pi_{i=1}^2((1 - K_1 - K_2)\bar{Q}_{ii} + K_1\mu_{i,t-1}^2 + K_2Q_{ii,t-1}}}$$

Where,

S	: Spot return
F	: Futures return
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
R_t	: Conditional correlation matrix of standardized error terms for daily CPO spot and futures return
$H_{FF,t}$	: Conditional variance of futures return at time t
$H_{SF,t}$	: Conditional covariance of spot and futures return at time t
$\rho_{sf,t}$	: Conditional Correlation coefficient between standardized error terms for daily CPO spot and futures return
Q_t	: Symmetric positive definite matrix
$\bar{Q}$	: Unconditional covariance matrix of standardized residuals
$\mu_{i,t}$	: Standardized error terms
$(diag(Q_t))^{\frac{1}{2}}$	: Diagonal matrix composed of the square root of the diagonal elements of Q_t

XII. DCC-GARCH with Vector autoregressive term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \varepsilon_{S,t}; \varepsilon_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \varepsilon_{F,t}; \varepsilon_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = \omega_{SS} + \alpha_{SS}\mathcal{E}^2{}_{S,t-1} + \beta_{SS}H_{SS,t-1}$$

$$H_{FF,t} = \omega_{FF} + \alpha_{FF}\mathcal{E}^2{}_{F,t-1} + \beta_{FF}H_{FF,t-1}$$

$$\rho_{sf,t} = \frac{Q_{sf,t}}{\sqrt{Q_{SS,t}Q_{FF,t}}} = \rho_{12,t} = \frac{(1-K_1-K_2)\bar{Q}_{12} + K_1\mu_{1,t-1}\mu_{2,t-1} + K_2Q_{12,t-1}}{\sqrt{\pi_{i=1}^2((1-K_1-K_2)\bar{Q}_{ii} + K_1\mu_{i,t-1}^2 + K_2Q_{ii,t-1}}}$$

Where,

S : Spot return

F : Futures return

C : Intercept

Ɛ : Error term

Φ_{t-1} : Past information at t-1

p : Lag number of spot return

q : Lag number of futures return

H_t : Conditional variance-covariance matrix at time t

$H_{SS,t}$: Conditional variance of spot return at time t

R_t : Conditional correlation matrix of standardized error terms for daily CPO spot and futures return

$H_{FF,t}$: Conditional variance of futures return at time t

$H_{SF,t}$: Conditional covariance of spot and futures return at time t

$\rho_{sf,t}$: Conditional correlation coefficient between standardized error terms for daily CPO spot and futures return

Q_t : Symmetric positive definite matrix

$\bar{Q}$: Unconditional covariance matrix of standardized residuals

$\mu_{i,t}$: Standardized error terms

$(diag(Q_t))^{\frac{1}{2}}$: Diagonal matrix composed of the square root of the diagonal elements of Q_t

XIII. DCC-GARCH with symmetric effect of basis term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \gamma_S B_{t-1} + \mathcal{E}_{S,t}; \mathcal{E}_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \gamma_F B_{t-1} + \mathcal{E}_{F,t}; \mathcal{E}_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = \omega_{SS} + \alpha_{SS}\mathcal{E}^2{}_{S,t-1} + \beta_{SS}H_{SS,t-1} + D_{SS}{B_{t-1}}^2$$

$$H_{FF,t} = \omega_{FF} + \alpha_{FF}\mathcal{E}^2{}_{F,t-1} + \beta_{FF}H_{FF,t-1} + D_{FF}{B_{t-1}}^2$$

$$Q_t = (1 - K_1 - K_2)\bar{Q} + K_1\mu_{t-1}\mu'{}_{t-1} + K_2Q_{t-1} + \varphi \begin{bmatrix} 0 & B\,^2_{t-1} \\ B\,^2_{t-1} & 0 \end{bmatrix}; \mu_{i,t} = \frac{\mathcal{E}^2{}_{i,t}}{\sqrt{h_{i,t}}}$$

$$\rho_{sf,t} = \frac{Q_{sf,t}}{\sqrt{Q_{SS,t}Q_{FF,t}}} = \rho_{12,t} = \frac{(1 - K_1 - K_2)\bar{Q}_{12} + K_1\mu_{1,t-1}\mu_{2,t-1} + K_2Q_{12,t-1}}{\sqrt{\pi_{i=1}^2((1 - K_1 - K_2)\bar{Q}_{ii} + K_1\mu_{i,t-1}^2 + K_2Q_{ii,t-1}}}$$

Where,

S	: Spot return
F	: Futures return
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
p	: Lag number of spot return
q	: Lag number of futures return
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
R_t	: Conditional correlation matrix of standardized error terms for daily CPO spot and futures return
B_{t-1}	: Basis at time t-1

${B_{t-1}}^2$: Basis squared (symmetric effect of basis)

$H_{FF,t}$: Conditional variance of futures return at time t

$H_{SF,t}$: Conditional covariance of spot and futures return at time t

$\rho_{sf,t}$: Conditional Correlation coefficient between standardized error terms for daily CPO spot and futures return

Q_t : Symmetric positive definite matrix

$\bar{Q}$: Unconditional covariance matrix of standardized residuals

$\mu_{i,t}$: Standardized error terms

$(diag(Q_t))^{\frac{1}{2}}$: Diagonal matrix composed of the square root of the diagonal elements of Q_t

XIV. DCC-GARCH with asymmetric effect of basis term

Mean equation:

$$S_t = C_S + \sum_{i=1}^{p} \alpha_{S,i} S_{t-i} + \sum_{i=1}^{q} \beta_{S,i} F_{t-i} + \delta_S B_{t-1}^{+} + \theta_S B_{t-1}^{-} + \mathcal{E}_{S,t}; \mathcal{E}_{S,t}|\Phi_{t-1} \sim N(0, H_t)$$

$$F_t = C_F + \sum_{i=1}^{p} \alpha_{F,i} S_{t-i} + \sum_{i=1}^{q} \beta_{F,i} F_{t-i} + \delta_f B_{t-1}^{+} + \theta_F B_{t-1}^{-} + \mathcal{E}_{F,t}\mathcal{E}_{F,t}|\Phi_{t-1} \sim N(0, H_t)$$

Conditional variance-covariance equation:

$$H_{SS,t} = \omega_{SS} + \alpha_{SS}\mathcal{E}^2{}_{S,t-1} + \beta_{SS}H_{SS,t-1} + M_{SSp}(B_{t-1}^{+})^2 + N_{SSn}(B_{t-1}^{-})^2$$

$$H_{FF,t} = \omega_{FF} + \alpha_{FF}\mathcal{E}^2{}_{F,t-1} + \beta_{FF}H_{FF,t-1} + M_{FFp}(B_{t-1}^{+})^2 + N_{FFn}(B_{t-1}^{-})^2$$

$$Q_t = (1 - K_1 - K_2)\bar{Q} + K_1\mu_{t-1}\mu'{}_{t-1}K_2Q_{t-1}\ \varphi_p \begin{bmatrix} 0 & (B_{t-1}^{+})^2 \\ (B_{t-1}^{+})^2 & 0 \end{bmatrix}$$

$$+\varphi_n \begin{bmatrix} 0 & (B_{t-1}^{-})^2 \\ (B_{t-1}^{-})^2 & 0 \end{bmatrix}; \mu_{i,t} = \frac{\varepsilon^2{}_{i,t}}{\sqrt{h_{i,t}}}$$

$$\rho_{sf,t} = \frac{Q_{sf,t}}{\sqrt{Q_{SS,t}Q_{FF,t}}} = \rho_{12,t} = \frac{(1 - K_1 - K_2)\bar{Q}_{12} + K_1\mu_{1,t-1}\mu_{2,t-1} + K_2Q_{12,t-1}}{\sqrt{\pi_{i=1}^2((1 - K_1 - K_2)\bar{Q}_{ii} + K_1\mu_{i,t-1}^2 + K_2Q_{ii,t-1}}}$$

Where,

S	: Spot return
F	: Futures return
C	: Intercept
Ɛ	: Error term
Φ_{t-1}	: Past information at t-1
H_t	: Conditional variance-covariance matrix at time t
$H_{SS,t}$	: Conditional variance of spot return at time t
p	: Lag number of spot return
q	: Lag number of futures return
R_t	: Conditional correlation matrix of standardized error terms for daily CPO spot and futures return
$H_{FF,t}$	: Conditional variance of futures return at time t
$H_{SF,t}$	: Conditional covariance of spot and futures return at time t
B_{t-1}^{+}	: Positive basis at time t-1 ; max $(B_{t-1}, 0)$
B_{t-1}^{-}	: Negative basis at time t-1 ; min $(B_{t-1}, 0)$
$\rho_{sf,t}$	: Conditional Correlation coefficient between standardized error terms for daily CPO spot and futures return
Q_t	: Symmetric positive definite matrix
$\bar{Q}$	: Unconditional covariance matrix of standardized residuals
$\mu_{i,t}$	: Standardized error terms
$(diag(Q_t))^{\frac{1}{2}}$	: Diagonal matrix composed of the square root of the diagonal elements of Q_t

3.3.3 Procedure of Estimating the Hedging Effectiveness

3.3.3.1 Optimal hedge ratio

The optimal hedge ratio (OHR) is referred to the number of futures contract needed relative to a spot position to achieve the highest portfolio risk reduction. The formula is provided as below:

$$\mathrm{H}|\Phi_{t-1} = \left(\frac{h_{SF,t}}{h_{FF,t}}\right)|\Phi_{t-1}$$

Where,

H : Optimal hedge ratio

$h_{SF,t}$: Conditional covariance between spot and futures return

$h_{FF,t}$: Conditional variance of futures return

3.3.3.2 The unhedged and hedged of portfolio variance

The variance of the unhedged portfolio indicated the initial portfolio risk without any hedging action. In contrary, the variance of hedged portfolio indicated the portfolio risk after hedged via different optimal hedge ratio that estimated from different hedging strategies. The formula of variance of unhedged and hedged portfolio is provide as below:

$$Var_u = h_{SS,t}$$

$$Var_h = h_{SS,t} + (h_t|\Phi_{t-1})^2 h_{FF,t} - 2(h_t|\Phi_{t-1}) h_{SF,t}$$

Where,

Var_u : Variance of unhedged portfolio

Var_h : Variance of hedged portfolio

$h_{SS,t}$: Variance of spot return at time t

$(h_t|\Phi_{t-1})$: Optimal hedge ratio at time t-1

$h_{FF,t}$: Conditional variance of futures return at time t

$h_{SF,t}$: Conditional covariance between spot-futures return in time t

3.3.3.3 Hedging effectiveness

Hedging effectiveness is an indicator in determining the hedging performance of various hedging strategies. The higher value of HE indicated a higher portfolio risk reduction. The formula is of hedging effectiveness is provided as below:

$$\text{HE} = \frac{Var_h - Var_u}{Var_u}$$

Where,

HE : Hedging effectiveness

Var_u : Variance of unhedged portfolio

Var_h : Variance of hedged portfolio

3.3.3.4 Log-likelihood

The Maximum likelihood is a crucial method to be employed in the process of model estimation. Throughout this method, the key element of $\rho_{sf,t}$;$\sqrt{H_{SS,t}}$ and $\sqrt{H_{FF,t}}$ can estimated before the optimal hedge ratio calculation. The Maximum log likehood function was exhibited as below:

$$L = -\frac{1}{2}\sum_{t-1}^{T}\{2\log(2\pi) + 2log|D_t| + log|R_t| + Z'_t R_t^{-1} Z_t\}$$

CHAPTER 4: RESULTS

4.0 Overview

In this chapter, the estimation results of Diag-BEKK, CCC and DCC-GARCH with different conditional means are discussed in section 4.1. Subsequently, the descriptive statistics of the optimal hedge ratio (OHR) are discussed in section 4.2. For the last section of 4.3, the study attempts to evaluate the hedging effectiveness of different hedging strategies. Generally, the result will be analyzed in three different perspective of the In-sample, Out-of-sample as well as the time to maturity effect.

4.1 Result of Diag-BEKK, CCC, and DCC-GARCH

First of all, the estimated results of Diag-BEKK, CCC as well as DCC-GARCH models with distinct means and variance-covariance specifications are summarized in Table 4.1.1, Table 4.1.2 and Table 4.1.3 respectively.

Based on Table 4.1.1.2, the coefficient of the past squared residual (A_{SS} and A_{FF}) as well as the past variance (G_{SS} and G_{FF}) under Diag-BEKK framework are highly significant at 1% of the significant level in all of the cases. It indicated that the variances of CPO spot-futures return are highly affected by their past own shock and volatility respectively. Besides, the lagged one of symmetric and asymmetric basis are insignificant in affecting the variances of CPO spot-futures return in most of the cases.

Furthermore, according to table 4.1.2.2 of CCC framework, the next-two-month futures is found to have the strongest constant condition correlation, ρ between the standardized residual of CPO spot and futures return while the correlations for next-four-month futures is the weakest. The results indicated that the CPO spot return is having a strong direct interconnections with Next-two-month futures return. The result of constant conditional correlation of next-two-month and next-four-month are ranging from (0.5622-0.6250) and (0.5502-0.6016) respectively.

On the other hand, the ARCH and GARCH terms of the conditional variance equation is to capture the short-run and long-run volatility persistence respectively. In other words, it measures the sensitivity of its past short-run shock and historical volatility in affecting the current conditional volatility. Based on Table 4.1.2.2 and Table 4.1.3.2, the ARCH coefficient of (α_{SS} and α_{FF}) and GARCH coefficient of (β_{SS} and β_{FF}) are highly significant at 1% of the significant level in all of the cases of CCC and DCC-GARCH respectively. The (GARCH term + ARCH term) for CCC and DCC-GARCH is highly close to one in most of the cases. This might result in the existence of high volatility persistence in the conditional volatility.

For DCC framework shown in Table 4.1.3.2, the overall result for the non-negative scalar parameters of (K_1 and K_2) has satisfied the model restriction of ($K_1 + K_2 < 1$) in all of the cases which implies that the DCC-GARCH model is applicable. The overall result of (K_1 + K_2) are ranging from (0.949-0.961 < 1) which indicated that the conditional correlation process is mean reverting. In other words, the conditional correlation will reverse to its long-run unconditional level in time after a shock happens. On the other hand, the basis effects under DCC framework are insignificant and highly close to 0 in all of the cases which implied the conditional variances are highly unaffected by the basis terms.

However, there are some common results of conditional mean for Diag-BEKK, CCC and DCC-GARCH models. Firstly, the futures return are insignificantly affected by its own lagged one term but it found to have a crucial effect on the CPO spot return in all of the cases. Secondly, for the Next four month futures, the lagged one of spot and its own futures return are insignificant in affecting its futures prices.

Table 4.1.1.1: Estimated result of the mean equation under Diag-BEKK-GARCH framework

	Spot Month Futures				Next to Two Month Futures				Next to Four Month Futures			
	Without Basis Term		With Basis Term		Without Basis Term		With Basis Term		Without Basis Term		With Basis Term	
	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric
Mean equation of Diag-BEKK-GARH model												
C_S	-1.31E-05	-3.82E-05	-0.00107***	-0.000697*	-6.12E-05	-8.17E-05	-0.000220	-0.000116	-9.66E-05	-0.000102	-0.000273	-6.75E-05
	(0.0003)	0.000269	(0.000298)	(0.000377)	(0.000297)	(0.000266)	(0.000269)	(0.000376)	(0.000296)	(0.000267)	(0.000254)	(0.000375)
α_{S1}		-0.1523***	-0.11475***	-0.11319***		-0.17521***	-0.17479***	-0.17592***		-0.15425***	-0.13914***	-0.1548***
		0.027500	(0.027721)	(0.029178)		(0.026513)	(0.026499)	(0.026791)		(0.027388)	(0.027761)	(0.030648)
β_{S1}		0.3930***	0.296981***	0.293285***		0.420064***	0.397665***	0.397887***		0.419098***	0.39225***	0.405519***
		0.020592	(0.025122)	(0.026023)		(0.022144)	(0.022068)	(0.022861)		(0.024287)	(0.024007)	(0.025581)
γ_S			-0.15806***				-0.03023***				-0.011568**	
			(0.017253)				(0.006444)				(0.004859)	
δ_S				-0.25282***				-0.03339***				-0.017729*
				(0.053562)				(0.012056)				(0.010146)
θ_S				-0.13204***				-0.02796***				-0.011160
				(0.020992)				(0.009774)				(0.009152)
C_F	5.51E-05	-1.05E-05	0.000259	-0.000675	5.27E-07	-2.91E-05	-8.19E-05	0.000164	-1.94E-05	-2.68E-05	-0.000173	0.000153
	(0.0003)	0.000333	(0.000383)	(0.000437)	(0.000337)	(0.000340)	(0.000347)	(0.000479)	(0.000321)	(0.000322)	(0.000321)	(0.000453)
α_{F1}		0.176998***	0.146773***	0.143584***		0.067373**	0.064121*	0.064941*		0.036872	0.018592	0.034437
		0.035078	(0.037602)	(0.034734)		(0.033239)	(0.033420)	(0.033678)		(0.031783)	(0.031537)	(0.032542)
β_{F1}		-0.020731	0.020829	0.024270		0.017922	0.010674	0.010755		0.028890	0.025789	0.022376
		0.030850	(0.036019)	(0.032830)		(0.033615)	(0.033551)	(0.033860)		(0.033869)	(0.032911)	(0.033960)
γ_F			0.077717***				-0.009535				-0.002527	
			(0.025424)				(0.008494)				(0.005388)	
δ_f				0.237194***				-0.018475				-0.014157
				(0.062246)				(0.017115)				(0.011242)
θ_F				0.034488				-0.001564				0.001566
				(0.027591)				(0.012777)				(0.009194)

1. Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. 2. The estimation error of the parameters are presented in the parentheses. The model specification of Diag-BEKK-GARCH with intercept, vector autoregressive (VAR), symmetric-basis and asymmetric basis are presented by the equation III, IV, V and VI respectively in section 3.3.2.2.

Table 4.1.1.2: Estimated result of the variance-covariance equation under Diag-BEKK-GARCH framework

	Spot Month Futures				Next to Two Month Futures				Next to Four Month Futures			
	Without Basis Term		With Basis Term		Without Basis Term		With Basis Term		Without Basis Term		With Basis Term	
	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric
Variance-covariance equation of Diag-BEKK-GARCH												
C_{SS}	2.25E-06***	1.58E-06***	1.72E-06***	1.25E-06**	2.19E-06***	1.48E-06***	2.24E-06***	2.37E-06***	2.23E-06***	1.50E-06***	1.61E-06***	2.29E-05***
	(5.85E-07)	(4.43E-07)	(5.48E-07)	(5.06E-07)	(5.60E-07)	(3.64E-07)	(5.84E-07)	(6.01E-07)	(5.55E-07)	(3.72E-07)	(4.72E-07)	(6.34E-06)
A_{SS}	0.1550***	0.1468***	0.150350***	0.165777***	0.134144***	0.145739***	0.154204***	0.156059***	0.145079***	0.149410***	0.182890***	0.262784***
	(0.0146)	(0.014751)	(0.015940)	(0.013308)	(0.013828)	(0.013040)	(0.014078)	(0.014302)	(0.013225)	(0.012140)	(0.014103)	(0.030891)
G_{SS}	0.9790***	0.9816***	0.980161***	0.976559***	0.982086***	0.982076***	0.976963***	0.975649***	0.980451***	0.981693***	0.975100***	0.805182***
	(0.0040)	(0.003806)	(0.004843)	(0.004240)	(0.00364)	(0.003158)	(0.004625)	(0.004748)	(0.003579)	(0.003048)	(0.004400)	(0.053694)
D_{SS}			-0.000112				-1.97E-05				1.00E-06	
			(0.000335)				(6.25E-05)				(3.57E-05)	
P_{SS}				0.000168**				-8.28E-07				9.97E-05
				(6.77E-05)				(8.98E-06)				(6.32E-05)
N_{SS}				-3.47E-05				-2.32E-06				-0.00026***
				(2.42E-05)				(8.16E-06)				(7.60E-05)
C_{FF}	9.09E-06***	6.97E-06***	9.73E-06***	1.10E-06***	1.19E-05***	8.71E-06***	1.21E-05***	1.24E-05***	9.35E-06***	7.90E-06***	4.49E-06***	1.12E-05***
	(1.96E-06)	(1.39E-06)	(2.16E-06)	(1.03E-07)	(2.97E-06)	(2.22E-06)	(3.12E-06)	(3.28E-06)	(2.64E-06)	(2.12E-06)	(1.43E-06)	(2.98E-06)
A_{FF}	0.2777***	0.2556***	0.249377***	0.089650***	0.289825***	0.257770***	0.254772***	0.256170***	0.268210***	0.250230***	0.222566***	0.217590***
	(0.0157)	(0.016103)	(0.016393)	(0.004954)	(0.019356)	(0.017576)	(0.019305)	(0.020315)	(0.025158)	(0.023115)	(0.020975)	(0.024050)
G_{FF}	0.9378***	0.9488***	0.938715***	1.000322***	0.923411***	0.940800***	0.928508***	0.925440***	0.932021***	0.941150***	0.958509***	0.933279***
	(0.0083)	(0.006294)	(0.008671)	(1.13E-06)	(0.011913)	(0.009189)	(0.012405)	(0.012824)	(0.012974)	(0.010629)	(0.008195)	(0.013941)
D_{FF}			0.004075	-0.00043***			0.000460				1.00E-06	
			(0.002532)	(3.82E-05)			(0.000334)				(6.97E-05)	
P_{FF}				0.000173***				3.95E-05				8.76E-06
				(1.35E-05)				(4.26E-05)				(2.37E-05)
N_{FF}								-4.91E-05				-4.03E-05
								(4.13E-05)				(2.59E-05)
C_{SF}	3.48E-06***	2.67E-06***	3.73E-06***	1.21E-06***	4.77E-06***	3.19E-06***	4.72E-06***	5.34E-06***	3.72E-06***	2.89E-06***	1.58E-06***	1.46E-05***
	(6.85E-07)	(5.03E-07)	(8.10E-07)	(3.31E-07)	(1.03E-06)	(7.38E-07)	(1.10E-06)	(1.22E-06)	(9.37E-07)	(7.27E-07)	(4.97E-07)	(3.78E-06)
D_{SF}			-0.000502				-0.000247*				1.00E-06	
			(0.000581)				(0.000134)				(4.50E-05)	
P_{SF}				-7.22E-05*				-3.75E-05*				-5.47E-05
				(3.70E-05)				(2.14E-05)				(4.11E-05)
N_{SF}				3.13E-05***				1.89E-05				-2.80E-05
				(1.04E-05)				(1.59E-05)				(3.07E-05)
L	8497.798	8685.731	8759.267	8764.701	8559.464	8746.414	8768.739	8771.177	8642.651	8793.958	8796.439	8817.159

1. Notes: *, **, and *** denote the significance of 10%, 5%, and 1% respectively. 2. The value of L represented the estimation of log-likehood function that provided in section 3.3.3.4.

Table 4.1.2.1: Estimated result of the mean equation under CCC-GARCH framework

	Spot Month Futures				Next to Two Month Futures				Next to Four Month Futures			
	Without Basis Term		With Basis Term		Without Basis Term		With Basis Term		Without Basis Term		With Basis Term	
	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric
Mean equation of CCC-GARCH model												
C_S	1.36E-05 (0.000299)	-2.68E-05 (0.000269)	-0.00100*** (0.000292)	-0.000686* (0.000380)	-1.08E-05 (0.000303)	-0.000171 (0.000265)	-0.000338 (0.000256)	-0.000168 (0.000358)	4.39E-06 (0.000306)	-6.00E-06 (0.000275)	-5.46E-05 (0.000275)	-7.13E-05 (0.000376)
α_{S1}		-0.16228*** (0.027474)	-0.12787*** (0.028455)	-0.12170*** (0.028956)		-0.16886*** (0.026333)	-0.16528*** (0.026067)	-0.18974*** (0.030286)		-0.15831*** (0.027427)	-0.17252*** (0.032220)	-0.13958*** (0.029382)
β_{S1}		0.395577*** (0.021357)	0.307768*** (0.026443)	0.293613*** (0.025734)		0.402129*** (0.022165)	0.388935*** (0.021975)	0.412663*** (0.024269)		0.413126*** (0.024363)	0.415605*** (0.026161)	0.391895*** (0.025966)
γ_S			-0.15627*** (0.020713)				-0.02033*** (0.006791)				-0.012934** (0.006486)	
δ_S				-0.24163*** (0.051953)				-0.025339 (0.015481)				-0.017197* (0.009715)
θ_S				-0.12757*** (0.021211)				-0.026087** (0.012740)				-0.007661 (0.008347)
C_F	3.37E-05 (0.000334)	-7.03E-06 (0.000337)	0.000345 (0.000372)	-0.000465 (0.000444)	1.29E-05 (0.000342)	-0.000163 (0.000341)	-0.000186 (0.000344)	9.57E-07 (0.000458)	3.76E-05 (0.000317)	2.39E-05 (0.000319)	6.01E-06 (0.000319)	0.000129 (0.000441)
α_{F1}		0.159326*** (0.034998)	0.140305*** (0.036922)	0.152583*** (0.035039)		0.042205 (0.034590)	0.042704 (0.035011)	0.038724 (0.035480)		0.023968 (0.032481)	0.013951 (0.033757)	0.017939 (0.033186)
β_{F1}		-0.011390 (0.030760)	0.026028 (0.037075)	0.019036 (0.032822)		0.010780 (0.034069)	0.008937 (0.034948)	0.029430 (0.035303)		0.028138 (0.034257)	0.036221 (0.035376)	0.025257 (0.034765)
γ_F			0.057827** (0.028137)				-0.002840 (0.008550)				-0.003361 (0.006454)	
δ_f				0.214712*** (0.066889)				-0.006972 (0.019585)				-0.010924 (0.011312)
θ_F				0.024983 (0.028372)				-0.003961 (0.014182)				0.003301 (0.008823)

1. Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. 2. The estimation error of the parameters are presented in the parentheses. 3. The model specification of CCC-GARCH with intercept, vector autoregressive (VAR), symmetric-basis and asymmetric basis is presented by the equation VII, VIII, IX and X respectively in section 3.3.2.2.

Table 4.1.2.2: Estimated result of the variance-covariance equation under CCC-GARCH framework

	Spot Month Futures				Next to Two Month Futures				Next to Four Month Futures			
	Without Basis Term		With Basis Term		Without Basis Term		With Basis Term		Without Basis Term		With Basis Term	
	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric
Variance-covariance equation of CCC-GARCH model												
ω_{SS}	1.87E-06***	1.14E-06***	2.28E-06***	7.93E-07**	2.40E-06***	1.14E-06***	9.42E-07***	7.84E-06***	2.65E-06***	1.68E-06***	7.14E-06***	1.66E-06***
	(5.68E-07)	(4.08E-07)	(6.87E-07)	(3.93E-07)	(6.49E-07)	(3.34E-07)	(3.29E-07)	(2.03E-06)	(6.87E-07)	(4.67E-07)	(1.81E-06)	(5.38E-07)
α_{SS}	0.025841***	0.021801***	0.032848***	0.026934***	0.028875***	0.028178***	0.027652***	0.071214***	0.032043***	0.029232***	0.061296***	0.034127***
	(0.004834)	(0.004490)	(0.008228)	(0.005900)	(0.005483)	(0.003963)	(0.003994)	(0.014593)	(0.005763)	(0.004435)	(0.011630)	(0.005416)
β_{SS}	0.959281***	0.967172***	0.938925***	0.963416***	0.952022***	0.961072***	0.964263***	0.811531***	0.947074***	0.955257***	0.854388***	0.948323***
	(0.008134)	(0.007436)	(0.015189)	(0.009552)	(0.009178)	(0.006047)	(0.006321)	(0.038248)	(0.009653)	(0.007699)	(0.029855)	(0.010089)
D_{SS}			0.002031**				-4.75E-05				0.000674***	
			(0.000890)				(3.73E-05)				(0.000189)	
P_{SS}				8.43E-05				0.000127***				5.40E-06
				(5.49E-05)				(3.97E-05)				(5.22E-06)
N_{SS}				-6.47E-06				-0.00018***				-6.94E-06
				(2.14E-05)				(4.44E-05)				(5.89E-06)
ω_{FF}	2.85E-06***	3.07E-06***	4.76E-06***	1.33E-06***	6.39E-06***	4.32E-06***	5.24E-06***	9.62E-06***	6.69E-06***	7.46E-06***	9.29E-06***	4.62E-06**
	(7.56E-07)	(7.84E-07)	(1.13E-06)	(1.12E-07)	(2.15E-06)	(1.46E-06)	(1.77E-06)	(3.09E-06)	(2.56E-06)	(2.65E-06)	(3.05E-06)	(1.92E-06)
α_{FF}	0.042322***	0.041210***	0.044946***	0.006507***	0.057518***	0.050728***	0.054086***	0.062400***	0.057014***	0.060463***	0.064270***	0.049559***
	(0.005481)	(0.005464)	(0.006142)	(0.001114)	(0.009704)	(0.008225)	(0.009255)	(0.012024)	(0.013350)	(0.013965)	(0.014930)	(0.011818)
β_{FF}	0.943193***	0.942512***	0.923736***	1.002222***	0.906035***	0.924486***	0.913719***	0.857719***	0.898185***	0.889804***	0.863409***	0.915987***
	(0.007834)	(0.007805)	(0.010983)	(2.05E-06)	(0.019310)	(0.014151)	(0.018049)	(0.029683)	(0.026537)	(0.027434)	(0.032090)	(0.022955)
D_{FF}			0.003798*				0.000198				0.000482***	
			(0.002052)				(0.000186)				(0.000176)	
P_{FF}				-0.00047***				0.000153***				5.88E-06
				(4.53E-05)				(4.98E-05)				(1.07E-05)
N_{FF}				0.000187***				-0.00015***				-1.52E-05
				(1.49E-05)				(5.23E-05)				(1.53E-05)
ρ	0.534978***	0.579948***	0.613507***	0.610242***	0.562211***	0.611025***	0.612581***	0.624955***	0.550201***	0.582637***	0.601557***	0.585573***
	(0.016796)	(0.015742)	(0.015634)	(0.016072)	(0.016144)	(0.015113)	(0.016254)	(0.015867)	(0.016886)	(0.015954)	(0.016186)	(0.017365)
L	8489.499	8674.232	8741.670	8749.069	8555.589	8733.945	8746.229	8762.032	8644.510	8789.085	8810.141	8798.929

1. Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. 2. The value of L represented the estimation of log-likehood function that provided in section 3.3.3.4.

Table 4.1.3.1: Estimated result of the mean equation under DCC-GARCH framework

	Spot Month Futures				Next to Two Month Futures				Next to Four Month Futures			
	Without Basis Term		With Basis Term		Without Basis Term		With Basis Term		Without Basis Term		With Basis Term	
	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric
Mean equation of DCC-GARCH model:												
C_S	-0.000100	-0.000163	-0.00117***	-0.000772**	-0.000100	-0.000171	-0.000338	-0.000256	-0.0001	-0.00017	-0.000273	-0.0000713
	(0.000285)	(0.000279)	(0.0003105)	(0.000392)	(0.000285)	(0.00028)	(0.000284)	(0.0003981)	(0.000285)	(0.000284)	(0.000286)	(0.000401)
α_{S1}		-0.15183***	-0.12333***	-0.12112***		-0.16886***	-0.16528***	-0.16542***		-0.14180***	-0.13914***	-0.13958***
		(0.0289571)	(0.0287602)	(0.028772)		(0.02981)	(0.02972)	(0.0297359)		(0.029865)	(0.029827)	(0.029838)
β_{S1}		0.38504***	0.3123***	0.304609***		0.402132***	0.388938***	0.388878***		0.400195***	0.39225***	0.391895***
		(0.0234792)	(0.0253248)	(0.025727)		(0.02508)	(0.02532)	(0.025327)		(0.027163)	(0.027297)	(0.027306)
γ_S			-0.12033***				-0.02033***				-0.01157**	
			(0.0172376)				(0.00623)				(0.004621)	
δ_S				-0.20821***				-0.023532*				-0.017197*
				(0.0553664)				(0.012518)				(0.009074)
θ_S				-0.10328***				-0.0182418*				-0.007661
				(0.020021)				(0.009417)				(0.00712)
C_F	-0.000097	-0.000153	0.000326	-0.00063	-0.000138	-0.000163	-0.00019	-0.0000428	-0.000132	-0.00015	-0.000173	0.0001287
	(0.000359)	(0.000375)	(0.0004237)	(0.00053)	(0.000335)	(0.00036)	(0.00037)	(0.000519)	(0.000313)	(0.000337)	(0.000341)	(0.000477)
α_{F1}		0.166646***	0.153120***	0.147853***		0.042202	0.04270	0.0424675		0.01801	0.01859	0.017939
		(0.0388951)	(0.0392234)	(0.039157)		(0.03869)	(0.03873)	(0.038743)		(0.035441)	(0.035473)	(0.035483)
β_{F1}		-0.017232	0.017281	0.0357153		0.010782	0.00894	0.0088356		0.02752	0.02579	0.025257
		(0.0315372)	(0.0345381)	(0.035013)		(0.03255)	(0.03299)	(0.032999)		(0.032235)	(0.032464)	(0.032472)
γ_F			0.057115**				-0.00284				-0.00253	
			(0.0235087)				(0.00811)				(0.005495)	
δ_f				0.267022***				-0.008417				-0.010924
				(0.075351)				(0.01631)				(0.010791)
θ_F				0.0164109				0.000788				0.003301
				(0.02725)				(0.012269)				(0.008471)

1. Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. 2. The estimation error of the parameters are presented in the parentheses. 3. The model specification of DCC-GARCH with intercept, vector autoregressive (VAR), symmetric-basis and asymmetric basis is presented by the equation XI, XII, XIII and XIV respectively in section 3.3.2.2.

Table 4.1.3.2: Estimated result of the variance-covariance equation under DCC-GARCH framework

	Spot Month Futures				Next Two Month Futures				Next to Four Month Futures			
	Without Basis Term		With Basis Term		Without Basis Term		With Basis Term		Without Basis Term		With Basis Term	
	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric	Intercept	VAR	Symmetric	Asymmetric
Variance-covariance equation of DCC-GARCH model												
ω_{SS}	0.000002**	0.000001***	0.000001	0.000001	0.000002**	0.000001*	0.000001	0.000001	0.000002**	0.000001**	0.000001**	0.000001
	(0.000001)	(0.000000)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000003)
α_{SS}	0.030539***	0.028612***	0.026553***	0.028375***	0.030532***	0.029008***	0.028541***	0.030596***	0.030539***	0.029874***	0.029924***	0.031278***
	(0.007320)	(0.005729)	(0.007013)	(0.007430)	(0.007335)	(0.007505)	(0.007704)	(0.004423)	(0.007321)	(0.007826)	(0.007972)	(0.003387)
β_{SS}	0.953622***	0.959367***	0.962327***	0.961237***	0.953631***	0.959905***	0.960439***	0.958388***	0.953622***	0.958072***	0.958130***	0.956716***
	(0.005491)	(0.005198)	(0.009621)	(0.013959)	(0.005489)	(0.006851)	(0.008450)	(0.006020)	(0.005477)	(0.007282)	(0.008082)	(0.013224)
D_{SS}			0.000000				0.000000				0.000000	
			(0.000897)				(0.000108)				(0.000053)	
P_{SS}				0.000000				0.000000				0.000000
				(0.000097)				(0.000008)				(0.000015)
N_{SS}				0.000000				0.000000				0.000000
				(0.000065)				(0.000010)				(0.000036)
ω_{FF}	0.000003	0.000003	0.000003	0.000002	0.000004	0.000004	0.000003	0.000003	0.000003	0.000003	0.000003*	0.000003
	(0.000003)	(0.000003)	(0.000023)	(0.000002)	(0.000005)	(0.000003)	(0.000003)	(0.000003)	(0.000003)	(0.000002)	(0.000002)	(0.000002)
α_{FF}	0.048323***	0.046512**	0.046327	0.037938***	0.048140***	0.048028***	0.047803***	0.047747***	0.044930***	0.044718***	0.044021***	0.044352***
	(0.017811)	(0.021030)	(0.097309)	(0.013227)	(0.017648)	(0.015268)	(0.015407)	(0.015883)	(0.013174)	(0.011791)	(0.011537)	(0.012529)
β_{FF}	0.934811***	0.938154***	0.938569***	0.956740***	0.931712***	0.932265***	0.932877***	0.933241***	0.933798***	0.934346***	0.936098***	0.935165***
	(0.019045)	(0.025076)	(0.174204)	(0.018932)	(0.012269)	(0.013058)	(0.019193)	(0.019487)	(0.009476)	(0.010010)	(0.012924)	(0.018080)
D_{FF}			0.000000				0.000000				0.000000	
			(0.015804)				(0.000257)				(0.000084)	
P_{FF}				0.000014				0.000000				0.000000
				(0.000275)				(0.000033)				(0.000024)
N_{FF}				0.000071				0.000000				0.000000
				(0.000076)				(0.000025)				(0.000018)
K_1	0.033282***	0.034887***	0.036825***	0.036388***	0.018046**	0.027263***	0.027687***	0.028762***	0.016660**	0.022993***	0.023222***	0.025210***
	(0.012699)	(0.010742)	(0.012787)	(0.011692)	(0.009248)	(0.008221)	(0.008119)	(0.008663)	(0.008004)	(0.007662)	(0.007572)	(0.008169)
K_2	0.915980***	0.922737***	0.919634***	0.922769***	0.939705***	0.930653***	0.930245***	0.930732***	0.942325***	0.936889***	0.936717***	0.935884***
	(0.023242)	(0.015258)	(0.018412)	(0.014065)	(0.011508)	(0.012580)	(0.012885)	(0.012298)	(0.011727)	(0.011347)	(0.011537)	(0.011287)
$K_1 + K_2$	0.949262	0.957624	0.956459	0.959157	0.957751	0.957916	0.957932	0.959494	0.958985	0.959882	0.959939	0.961094
L	8499.992	8691.142	8707.318	8769.697	8558.226	8749.688	8749.863	8762.151	8644.222	8799.757	8799.848	8807.724

1. Notes: *, **, and *** denote as the significance level of 10%, 5%, and 1% respectively. 2. The value of L represented the estimation of log-likehood function that provided in section 3.3.3.4.

4.2 Descriptive statistic of optimal hedge ratio

First and foremost, the overall Table 4.2 exhibited the descriptive statistics of the estimated OHR for FCPO with different time to maturity. The mean and standard deviation of OHR for different futures maturity of spot month, next-two-month and next-four-month are computed for the in-sample and out-of-sample respectively. Subsequently, the result will be analyzed in 3 different perspectives included In-sample, Out-of-sample as well as the maturity effect.

4.2.1 Maturity effect

Based on the estimated result showed in Table 4.2, the study discovered that the mean of OHR is relatively higher when the time to maturity of FCPO is getting larger regardless of In-sample and Out-of-sample. On average, the In-sample OHR for spot-month, Next-two month and Next-four-month are ranging from (0.431-0.457), (0.431-0.478) and (0.473-0.515) respectively. This result indicated that the relationship between the spot and far month futures is weakening, thereby the investor has to maintain a higher hedge ratio for far month futures in hedging the physical CPO spot price. The weak correlation between the spot and far-month futures has implied a poor information transmission between the markets.

On the other hand, the study found that the standard deviation of OHR for the Next-two month is relatively lower than the others for both In- and Out-of-sample respectively. This result showed that the OHR for next two month futures is less volatile and more stable than the others. The highest trading volume of the next-two-month futures has resulted in high liquidity that might narrow the futures price fluctuation gap, stabilize the spot-futures relationship and ultimately lower the volatility of OHR.

4.2.2 In sample analysis

For in-sample, the mean of OHR exhibited a minor different between Diag-BEKK, CCC and DCC GARCH. However, the standard deviation of Diag-BEKK is the highest and followed by DCC and CCC. This result has contradicted with the theory that claiming the OHR of DCC is the most changing due to the model properties in capturing the dynamic conditional correlation. In the perspective of static model, the standard deviation of Naïve and OLS are relatively lower than the MGARCH models as the conditional information is captured to compute the time-varying OHR.

4.2.3 Out-of-sample analysis

On the other hand, the study found that the average OHR for spot-month futures is higher than in-sample but average OHR for the next-two and next-four month futures are lower than the in-sample. This implied that the hedger required to adopt lesser spot month futures or more far-month futures to hedge against the CPO spot. The spot-futures relationship is obviously stronger for spot-month futures but weaken for the far-month futures.

As the spot-month futures is relatively efficient, thus, it might contained important information to adjust the OHR frequently and result in a high standard deviation of OHR. However, for far month futures, the result is relatively different as compare to in-sample. The low standard deviation of OHR under Diag-BEKK framework indicated that the OHR adjustment is relatively minimal. On the other hand, for CCC and DCC-GARCH models, the standard deviations of OHR are relatively higher. The high adjustment of OHR implied that the condition correlation is important to be considered as it may precisely captured the spot-futures relationship.

Table 4.2.1: Descriptive statistic of estimated optimal hedge ratio (OHR) for spot month futures

Hedging strategy	In sample		Out of sample	
	Mean	SD	Mean	SD
Spot Month				
Static hedge approach				
Naïve hedge	1.00	N/A	1.00	N/A
OLS hedge	0.4319	0.0185	0.3843	0.0342
Dynamic hedge approach				
Intercept-Diag-BEKK-GARCH	0.4530	0.1056	0.4316	0.1162
VAR-Diag-BEKK-GARCH	0.4478	0.0882	0.3904	0.1290
Symmetric-Basis-Diag-BEKK-GARCH	0.4576	0.1101	0.3787	0.1415
Asymmetric-Basis-Diag-BEKK-GARCH	0.4509	0.0874	0.3776	0.1275
Intercept-CCC-GARCH	0.4413	0.0444	0.4165	0.0841
VAR-BEKK-CCC	0.4390	0.0407	0.3666	0.0912
Symmetric Basis-CCC-GARCH	0.4552	0.0397	0.3794	0.0665
Asymmetric-Basis-CCC-GARCH	0.4518	0.0719	0.3814	0.0683
Intercept-DCC-GARCH	0.4429	0.0821	0.4072	0.0848
VAR-DCC-GARCH	0.4397	0.0738	0.3726	0.1390
Symmetric Basis-DCC-GARCH	0.4383	0.0741	0.3582	0.0906
Asymmetric-Basis-DCC-GARCH	0.4536	0.0746	0.3784	0.1276

Note: SD denotes as standard deviation of OHR. The SD of Naïve hedge is not available (N/A) since the ratio remains unchanged over time. The formula of OHR is presented in section 3.3.3.1.

Table 4.2.2: Descriptive statistic of estimated optimal hedge ratio (OHR) for next-two-month futures

Hedging strategy	In sample		Out of sample	
	Mean	SD	Mean	SD
Next Two Month				
Static hedge approach				
Naïve hedge	1	N/A	1	N/A
OLS hedge	0.4754	0.0187	0.5048	0.0405
Dynamic hedge approach				
Intercept-Diag-BEKK-GARCH	0.4776	0.0746	0.5274	0.0252
VAR-Diag-BEKK-GARCH	0.4652	0.0748	0.4890	0.0717
Symmetric-Basis-Diag-BEKK-GARCH	0.4516	0.1029	0.4541	0.0541
Asymmetric-Basis-Diag-BEKK-GARCH	0.4307	0.1200	0.4338	0.0433
Intercept-CCC-GARCH	0.4625	0.0352	0.5120	0.0903
VAR-BEKK-CCC	0.4631	0.0375	0.4750	0.1093
Symmetric Basis-CCC-GARCH	0.4779	0.0425	0.4782	0.0971
Asymmetric-Basis-CCC-GARCH	0.4718	0.0448	0.4902	0.0891
Intercept-DCC-GARCH	0.4746	0.0572	0.5056	0.0865
VAR-DCC-GARCH	0.4657	0.0671	0.4684	0.0805
Symmetric Basis-DCC-GARCH	0.4659	0.0672	0.4662	0.1263
Asymmetric-Basis-DCC-GARCH	0.4638	0.0722	0.4706	0.0840

Note: SD denotes as standard deviation of OHR. The SD of Naïve hedge is not available (N/A) since the ratio remains unchanged over time. The formula of OHR is presented in section 3.3.3.1.

Table 4.2.3: Descriptive statistic of estimated optimal hedge ratio (OHR) for next-four-month futures

Hedging strategy	In sample		Out of sample	
	Mean	SD	Mean	SD
Next Four Month				
Static hedge approach				
Naïve hedge	1	N/A	1	N/A
OLS hedge	0.5021	0.0204	0.5591	0.0471
Dynamic hedge approach				
Intercept-Diag-BEKK-GARCH	0.5059	0.0770	0.5587	0.0346
VAR-Diag-BEKK-GARCH	0.4938	0.0859	0.5490	0.0807
Symmetric-Basis-Diag-BEKK-GARCH	0.4734	0.1157	0.5375	0.0672
Asymmetric-Basis-Diag-BEKK-GARCH	0.4557	0.1205	0.5112	0.0269
Intercept-CCC-GARCH	0.4937	0.0450	0.5794	0.1222
VAR-BEKK-CCC	0.4950	0.0458	0.5555	0.1280
Symmetric Basis-CCC-GARCH	0.5148	0.0539	0.5505	0.1281
Asymmetric-Basis-CCC-GARCH	0.5077	0.0539	0.5498	0.0727
Intercept-DCC-GARCH	0.4995	0.0590	0.5509	0.1051
VAR-DCC-GARCH	0.4889	0.0702	0.5242	0.1418
Symmetric Basis-DCC-GARCH	0.4894	0.0705	0.5289	0.1526
Asymmetric-Basis-DCC-GARCH	0.4872	0.0764	0.5260	0.1034

Note: SD denotes as standard deviation of OHR. The SD of Naïve hedge is not available (N/A) since the ratio remains unchanged over time. The formula of OHR is presented in section 3.3.3.1.

4.3 Result of the hedging effectiveness

4.3.1 Comparison between Static and Dynamic models

Based on the table 4.3.1, 4.3.2 and 4.3.3, the overall hedging performance of dynamic models such as Diag-BEKK, CCC and DCC-GARCH are outperforming the static model of Naïve and OLS approach regardless of in-sample or out-of-sample. Interestingly, the study discovered that the hedging performance of Naïve approach is getting better when adopting the far-month futures to hedge. However, the OLS approach showed a better hedging result in Next-two-month futures for both in- and out of sample. For static approach, the highest risk reduction is performed by OLS of (31.89%) while the worse performance is Naïve of (-42.11%) regardless of in and out of sample.

4.3.2 Comparison between different of time to maturity FCPO

For the overall results of in-sample and out-of-sample, the study found that the hedging performance of Next four month futures is relatively worse than the others regardless of the models used. The spot month futures provided the highest risk reduction of (51.32%) while the Next-four-month futures provided the lowest hedging result of (44.45%). Although the Next-two-month futures is unable to sustain the highest variance reduction but the overall performance is more superior to the spot-month-futures. The best hedging result has only a minor different between the highest risk reduction for next-two-month (50.83%) and the spot month (51.32%).

4.3.3 In sample analysis

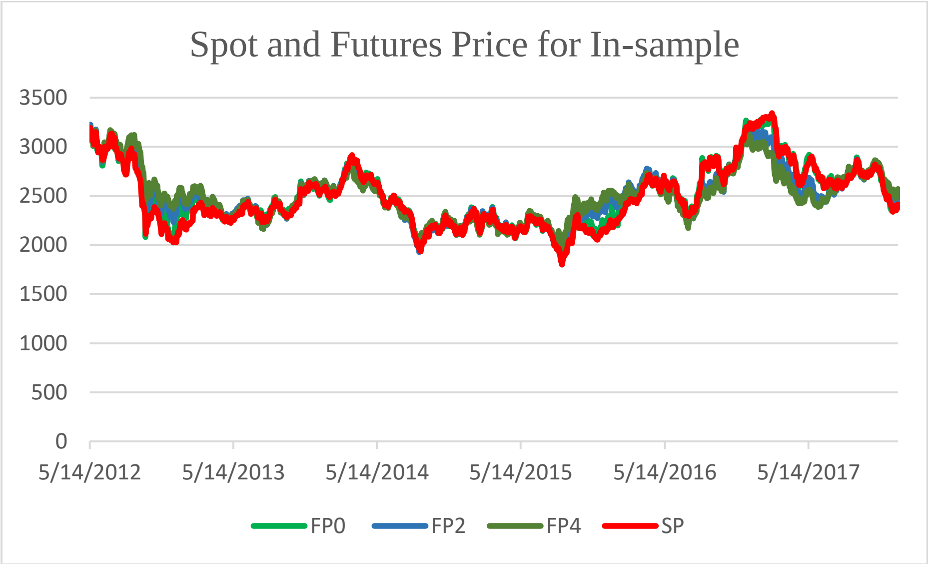

Figure 4.3.1 Malaysia CPO Spot and Futures Price for In-sample

Source from: MPOB and Bloomberg

For in-sample, the estimated result is surprised as the Diag-BEKK-GARH approach provided a better hedging performance than CCC and DCC-GARCH models regardless of the maturity of the futures. The study found that the intercept-GARCH models are underperformed as compared to the VAR-GARCH models in all of the cases. This explained that the past information is having a crucial effect on the current spot-futures return. Furthermore, the GARCH models with the inclusion of basic terms showed a better hedging performance than VAR-GARCH models. The results are consistent with Lien and Yang (2008a); Go and Lau (2015) and Chen et al. (2016) in claiming the importance of basis effect toward the hedging effectiveness. In the study, the symmetric and asymmetric basis effects are examined. However, the results remained inconclusive to claim that the asymmetric basis effect might enhance the hedging performance. Based on figure 4.3.1, the longer of hedging period, the spot-futures prices will likely to be equilibrium. Thereby, the effect between unconditional model of Diag-BEKK and conditional model of CCC and DCC-GARCH is not obviously showed.

4.3.4 Out-of-sample analysis

For out-of-sample, the results are relatively different as compared to in-sample. Firstly, the Diag-BEKK-GARCH models are unable to sustain its superior performance as in-sample regardless of the futures maturity. The GARCH models under CCC framework are providing the highest risk reduction among the others. The overall hedging performance is declining as compare to in-sample.

Furthermore, the study found that the inclusion of asymmetric basis terms is positively affecting the hedging performance of the spot-month futures, but negatively affecting the performance of the next two months and next four-month futures. The hedging effectiveness of the Asymmetric-Basis-Diag-BEKK and CCC GARCH models are having a sharp drop to (-12.15%) and (22.67%) respectively in the next-two-month futures and the results are more worsen in next-four-month futures which are (-20.40%) and (12.66%) respectively.

The negative impact of asymmetric basis are critical to Diag-BEKK and CCC-GARCH models, however, the DCC-GARCH model enables to sustain its performance in all of the cases. Although DCC-GARCH models are unable to achieve the highest variance reduction, but the overall hedging performance is stable and consistent. As the DCC-GARCH model is taking the dynamic conditional correlation into account, thus, the asymmetric basis effect can be precisely measured and improve the demonstration of spot-futures relationship. However, there is a question remained regarding the effect of asymmetric basis is positive toward spot-month futures but negative against far month futures.

As the spot-futures price will theoretically convergence at the maturity, thus, the basis is minimized and reflect a strong information transmission between the CPO spot and spot-month futures. Thereby, the asymmetric basis of spot-month futures might contain important information to enhance the hedging performance. On the other hand, based on Figure 1.4, the out-of-sample is located within the CPO surplus period. The mismatch of demand-supply for CPO is causing a sharp drop in the CPO spot price and build-up the inventory level. It indicated that the storage costs might go beyond the convenience yield and results in high futures prices. As the futures price is overwhelming the CPO spot price, it might result in a one-sided of negative basis which implying the strong contango.

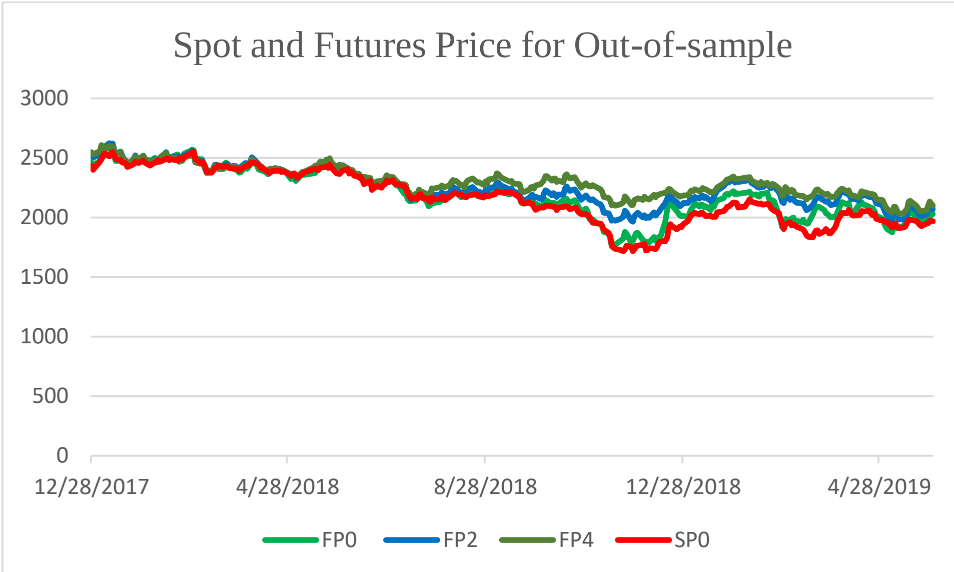

Figure 4.3.2 Malaysia CPO Spot and Futures Price for Out-of-sample

Source from: MPOB and Bloomberg

According to Go & Lau (2017), during strong contango, investor demand on the futures is the less correlated with the spot and futures prices. The strong futures demand might eventually larger the price gap between the CPO spot and futures (Figure 4.3.2). The correlation between the CPO spot and futures will be weaken and result in a poor information transmission in the futures market. Thereby, distinguishing the basis into positive and negative might result in a sophisticated model and the increases of the parameter estimation might larger the estimation error (Wang, Wu, and Yang, 2015). Furthermore, the weak performance of the Asymmetric-Basis-Diag-BEKK and CCC GARCH models is because of the conditional correlation is not taken into account for Diag-BEKK-GARCH and the CCC-GARCH model assumed the conditional correlation is constant.

Table 4.3.1: Hedging effectiveness for spot month FCPO futures

Hedging strategy	In sample		Out of sample	
	Variance Portfolio	Variance Reduction (%)	Variance Portfolio	Variance Reduction (%)
Unhedged portfolio	1.30E-04		1.03E-04	
Hedged portfolio				
Spot Month				
Static Hedge Approach				
Naïve hedge	1.57E-04	-20.70	1.46E-04	-42.11
OLS hedge	9.32E-05	28.35	7.51E-05	26.88
Dynamic Hedge Approach				
Intercept-Diag-BEKK-GARCH	8.91E-05	31.46	7.69E-05	25.05
VAR-Diag-BEKK-GARCH	6.88E-05	47.07	6.07E-05	40.84
Symmetric Basis-Diag-BEKK-GARCH	6.33E-05	51.32	6.06E-05	40.99
Asymmetric-Basis-Diag-BEKK-GARCH	6.76E-05	47.99	5.78E-05	43.73
Intercept-CCC-GARCH	9.17E-05	29.47	7.80E-05	24.02
VAR-BEKK-CCC	7.09E-05	45.45	6.30E-05	38.63
Symmetric Basis-CCC-GARCH	6.62E-05	49.13	5.73E-05	44.15
Asymmetric-Basis-CCC-GARCH	6.64E-05	48.96	5.57E-05	45.78
Intercept-DCC-GARCH	9.09E-05	30.10	7.39E-05	28.01
VAR-DCC-GARCH	7.05E-05	45.82	6.28E-05	38.80
Symmetric Basis-DCC-GARCH	6.86E-05	47.26	6.16E-05	40.04
Asymmetric-Basis-DCC-GARCH	6.42E-05	50.65	5.80E-05	43.55

Note: The formula of variance of unhedged portfolio, hedge portfolio and hedging effectiveness are presented in section 3.3.3.2 and 3.3.3.3 respectively.

Table 4.3.2: Hedging effectiveness for next-two-month FCPO futures

Hedging strategy	In sample		Out of sample	
	Variance Portfolio	Variance Reduction (%)	Variance Portfolio	Variance Reduction (%)
Next to Two Month				
Static Hedge Approach				
Naïve hedge	1.39E-04	-6.96	1.01E-04	1.17
OLS hedge	8.86E-05	31.89	7.06E-05	31.20
Dynamic Hedge Approach				
Intercept-Diag-BEKK-GARCH	7.80E-05	40.00	7.43E-05	27.67
VAR-Diag-BEKK-GARCH	6.43E-05	50.54	6.26E-05	38.99
Symmetric-Basis-Diag-BEKK-GARCH	6.40E-05	50.83	5.86E-05	42.96
Asymmetric-Basis-Diag-BEKK-GARCH	6.59E-05	49.30	1.15E-04	-12.15
Intercept-CCC-GARCH	8.01E-05	38.39	7.20E-05	29.90
VAR-BEKK-CCC-GARCH	6.53E-05	49.79	6.15E-05	40.08
Symmetric Basis-CCC-GARCH	6.61E-05	49.17	5.67E-05	44.73
Asymmetric-Basis-CCC-GARCH	6.48E-05	50.14	7.94E-05	22.67
Intercept-DCC-GARCH	8.75E-05	32.69	7.02E-05	31.62
VAR-DCC-GARCH	6.77E-05	47.98	5.81E-05	43.38
Symmetric Basis-DCC-GARCH	6.76E-05	48.04	5.71E-05	44.38
Asymmetric-Basis-DCC-GARCH	6.69E-05	48.59	5.73E-05	44.19

Note: The formula of variance of unhedged portfolio, hedge portfolio and hedging effectiveness are presented in section 3.3.3.2 and 3.3.3.3 respectively.

Table 4.3.3: Hedging effectiveness for next-four-month FCPO futures

Hedging strategy	In sample		Out of sample	
	Variance Portfolio	Variance Reduction (%)	Variance Portfolio	Variance Reduction (%)
Next to Four month				
Static Hedge Approach				
Naïve hedge	1.29E-04	0.52	9.14E-05	10.99
OLS hedge	9.04E-05	30.47	7.28E-05	29.05
Dynamic Hedge Approach				
Intercept-Diag-BEKK-GARCH	7.99E-05	38.57	7.56E-05	26.36
VAR-Diag-BEKK-GARCH	7.00E-05	46.20	6.67E-05	35.06
Symmetric Basis-Diag-BEKK-GARCH	7.22E-05	44.49	6.27E-05	38.96
Asymmetric-Basis-BEKK-GARCH	7.10E-05	45.38	1.24E-04	-20.40
Intercept-CCC-GARCH	8.19E-05	37.01	7.36E-05	28.32
VAR-BEKK-CCC	7.06E-05	45.70	6.56E-05	36.06
Symmetric Basis-CCC-GARCH	7.26E-05	44.15	6.14E-05	40.16
Asymmetric-Basis-CCC-GARCH	7.01E-05	46.11	8.97E-05	12.66
Intercept-DCC-GARCH	8.96E-05	31.07	7.20E-05	29.88
VAR-DCC-GARCH	7.26E-05	44.14	6.57E-05	36.02
Symmetric Basis-DCC-GARCH	7.28E-05	44.03	6.27E-05	38.95
Asymmetric-Basis-DCC-GARCH	7.22E-05	44.45	6.28E-05	38.87

Note: The formula of variance of unhedged portfolio, hedge portfolio and hedging effectiveness are presented in section 3.3.3.2 and 3.3.3.3 respectively.

CHAPTER 5: CONCLUSION

5.1 Major finding

As stated in the problem statement, this study discovered that the standard deviation of the monthly CPO spot return is increasing where the average return is declining. The negative EU's policy impact and the strong competition between Indonesia had caused the CPO to be surplus. As the palm oil remained the primary agricultural income of Malaysia, the instability of CPO market is critical and impactful. Thereby, this study attempts to examine the hedging effectiveness of FCPO with different maturity throughout the static and dynamic hedging approach. Firstly, the dynamic hedging strategy has eventually outperforming the static approach. This result is not surprised and consistent with Chen, Zhuo and Liu (2016); Islam (2017); and Koulis, Kaimakamis & Beneki (2018) in claiming that the static model has ignoring the conditional information since it assumes the spot-futures relationship to be constant over time.

Secondly, the study found that the far month futures is not an effective hedging tool for CPO spot. It justified that the CPO spot and Next-four-month futures is having the weakest correlation as comparing to the near-month futures. This indicated that the far month futures market is inefficient and the information transmission is weak, thus, resulting in a poor hedging performance. Although next-two-month futures is the most liquid contract, however, the hedging performance is relatively close to the spot-month futures. This result is consistent with Islam (2017) in claiming that the near-month-futures is an affective hedging tool for CPO spot market.

Thirdly, this study discovered that the unconditional correlation model of Diag-BEKK-GARCH is outperforming the conditional correlation model of CCC and DCC-GARCH when the market is equilibrium within a long hedging period for in-sample. This result is consistent with Nawawi, Radzali, Hussin & Mohd (2016) and Islam (2017). On the other hand, for out-of-sample, the result is surprised to discover that the Diag-BEKK-GARCH model is unable to sustain its superior performance as in-sample and the CCC GARCH model provided the highest risk reduction among the others. Despite Diag-BEKK provided the highest risk reduction in in-sample but the different of hedging effectiveness between Diag-BEKK, CCC and DCC GARCH is relatively minimal. Thus, the study may claimed that the CCC-GARCH model is more practical and reliable.

Fourthly, the study found that the ignorance of basis effect will result in a lower risk reduction. However, the asymmetric basis effect might not always improve the hedging effectiveness. The directional basis effects of positive and negative might eventually complicated the model, thus, the estimated parameter will be increased and higher the estimation error (Wang, Wu, and Yang, 2015). According to Go and Lau (2017), during strong contango, the futures demand is weakly driven by the spot and futures prices and result in a weak market's information transmission, thus, disrupting the futures market efficiency.

As the CPO surplus resulting the strong one-sided of negative basis, the incorporation of asymmetric basis might mislead the spot-futures relation especially for Diag-BEKK and CCC models. This is because of the Diag-BEKK-GARCH model did not take the conditional correlation into account while the CCC-GARCH model assumes the conditional correlation is constant. On the other hand, although DCC-GARCH models are unable to achieve the highest variance reduction, but the overall hedging performance is relatively stable and consistent. When the model specification is getting complex, the superiority of DCC-GARCH model will be obviously showed. For example, the model allowed to capture the dynamic conditional correlation and precisely measure the relation between spot and futures. Thus, with the complex of asymmetric basis setting, the performance of DCC-GARCH model is sustained but the others are not.

Lastly, for spot month futures, the asymmetric basis is encouraged to be incurred. It is because of the spot-futures price will theoretically convergence at maturity, thus minimize the basis and reflect a strong information transmission between CPO spot and spot-month futures. The asymmetric basis of spot-month futures might contain important information to enhance the hedging performance.

5.2 Implication

The primary focus of this study is to determine the hedging strategy that provides the highest hedging effectiveness in Malaysia CPO spot market. As the Malaysia CPO spot market is relatively volatile, the finding of this study is valuable for the hedger to construct an effective hedging strategy in mitigating the market risk.

Firstly, the conditional correlation model of CCC-GARCH has achieved the highest hedging performance for out-of-sample. Despite Diag-BEKK GARCH is outperformed in in-sample, but its performance is unable to hold and the different of hedging effectiveness between Diag-BEKK and CCC-GARCH is relatively minimal for in-sample. It is obvious that the hedging strategy under CCC-GARCH is more practical and reliable as compare to Diag-BEKK-GARCH. Thereby, the hedger is suggested to take the conditional correlation into account when constructing the hedging strategies. Besides, although DCC-GARCH model is unable to provide the highest variance reduction, but the overall hedging performance is stable and consistent. The properties of capturing the dynamic conditional correlation might precisely measure the spot-futures relation and thus, mitigate the negative impact of asymmetric basis.

Secondly, during strong contango, the incorporation of the asymmetric basis effect might negatively affecting the hedging performance for far-month futures. When the basis is further distinguishing into positive and negative, the parameter estimation will be increases and result in a complex model which might larger the estimation error. Thereby, the hedger is recommended to omit the asymmetric basis effect due to the instability of hedging performance. Also, the different of hedging effectiveness between asymmetric and symmetric is relatively minimal.

Lastly, the hedgers are suggested to adopt the near-month futures as their primary hedging tools against the Malaysia CPO spot market. In overall, the next-two month futures provided the highest risk reduction as compare to others. The highest correlation between next-two month futures and CPO spot indicated the information transmission is strong and result in an efficient futures market.

The high liquidity of next two month futures might ensure the fairness of the price and alleviate the price fluctuation.

5.3 Limitation

As the hedging performance might be affected by the setting of the conditional mean, thus, this study adopted the vector autoregressive (VAR) approach in examining the hedging effectiveness. Theoretically, the determination of the number of lag length is based on the lowest criterion of Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ). However, for simplicity, this study is only consider the lag length of 1 for the entire model estimation. Furthermore, as the palm oil remained the seasonal agricultural crop, thereby, the seasonal effect might contains some important information to demonstrate the spot-futures relationship. This study is limited to capture the CPO seasonal effect which might affecting the hedging performance.

5.4 Recommendation

Firstly, the future researcher is required to enhance the VAR-model by taking the optimal lag length into consideration throughout the standard procedure. This might increase the preciseness of demonstrating the spot-futures relationship. As the CPO return might be influenced by the palm oil cropping season, thus, future researchers are recommended to take the seasonal effect into account via the dummy variable setting.

Secondly, the model evaluation criteria in this study was based on the highest variance reduction; however, it does not fulfill the hedger's expectation in the practice. In fact, the hedger is more concerning the downside risk instead of two-sided risk, thus, the Value at Risk (VaR) approach is recommended as it may reflect the maximum possible loss based on the given particular confidence level within a time period. It also enables the hedger to adjust their level of risk aversion throughout the confidence level setting.

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Appendix

Appendix 1.1: World's Vegetable Oil Production, Consumption & Ending Stock

Production (Million tonnes)	**2015/16**	**2016/17**	**2017/18**	**2018/19**	**2019 /20**
Oil, Coconut	3.31	3.39	3.66	3.67	3.58
Oil, Cottonseed	4.30	4.43	5.18	5.17	5.32
Oil, Olive	2.13	2.48	3.26	3.09	3.36
Oil, Palm	58.90	65.27	70.61	73.58	75.51
Oil, Palm Kernel	7.01	7.64	8.34	8.59	8.81
Oil, Peanut	5.42	5.77	5.95	5.66	5.86
Oil, Rapeseed	27.34	27.54	28.09	27.99	28.14
Oil, Soybean	51.56	53.81	55.17	56.51	57.67
Oil, Sunflowerseed	15.39	18.16	18.51	19.69	19.90
Total	176.35	188.48	198.77	203.95	208.14
Consumption (Million tonnes)	**2015/16**	**2016/17**	**2017/18**	**2018/19**	**2019 /20**
Oil, Coconut	3.23	3.07	3.39	3.48	3.54
Oil, Cottonseed	4.41	4.39	5.12	5.09	5.25
Oil, Olive	2.81	2.59	2.87	3.07	3.24
Oil, Palm	59.70	61.64	66.31	72.55	75.10
Oil, Palm Kernel	6.82	7.22	7.82	8.17	8.43
Oil, Peanut	5.40	5.64	5.96	5.61	5.86
Oil, Rapeseed	28.18	28.91	28.95	28.29	28.59
Oil, Soybean	52.19	53.41	54.63	56.17	57.44
Oil, Sunflowerseed	15.22	16.54	17.15	18.02	18.47
Total	177.96	183.40	192.20	200.44	205.91
Ending Stocks	**2015/16**	**2016/17**	**2017/18**	**2018/19**	**2019 /20**
Oil, Coconut	0.47	0.39	0.64	0.70	0.75
Oil, Cottonseed	0.1	0.11	0.13	0.14	0.14
Oil, Olive	0.53	0.34	0.62	0.58	0.61
Oil, Palm	8.26	8.83	10.88	10.53	9.62
Oil, Palm Kernel	0.68	0.69	0.88	0.91	0.92
Oil, Peanut	0.26	0.34	0.31	0.33	0.31
Oil, Rapeseed	5.64	4.17	3.20	2.74	2.26
Oil, Soybean	3.75	3.79	3.54	3.62	3.52
Oil, Sunflowerseed	1.67	1.75	1.90	2.00	2.03
Total	21.36	20.41	22.09	21.53	20.16

Sources from Bloomberg

Appendix 1.2: World's Vegetable Oil Import and Export

Import (Million tonnes)	**2015/16**	**2016/17**	**2017/18**	**2018/19**	**2019 /20**
Oil, Coconut	1.61	1.5	1.71	1.72	1.80
Oil, Cottonseed	0.06	0.05	0.06	0.05	0.05
Oil, Olive	0.79	0.79	0.92	0.90	1.01
Oil, Palm	42.84	45.93	46.29	50.40	52.12
Oil, Palm Kernel	2.64	2.69	2.78	2.82	2.91
Oil, Peanut	0.25	0.23	0.24	0.24	0.28
Oil, Rapeseed	4.13	4.39	4.49	4.86	5.02
Oil, Soybean	11.69	10.97	9.72	10.95	11.43
Oil, Sunflowerseed	7.02	8.88	8.53	8.60	8.84
Total	71.02	75.41	74.72	80.53	83.44
Exports	**2015/16**	**2016/17**	**2017/18**	**2018/19**	**2019/20**
Oil, Coconut	1.59	1.91	1.73	1.85	1.78
Oil, Cottonseed	0.07	0.08	0.10	0.12	0.12
Oil, Olive	0.87	0.88	1.02	0.96	1.10
Oil, Palm	43.84	48.99	48.53	51.79	53.54
Oil, Palm Kernel	3.02	3.08	3.12	3.2	3.28
Oil, Peanut	0.25	0.27	0.26	0.27	0.3
Oil, Rapeseed	4.17	4.49	4.6	5.02	5.04
Oil, Soybean	11.77	11.33	10.51	11.21	11.75
Oil, Sunflowerseed	8.11	10.42	9.73	10.18	10.23
Total	73.68	81.44	79.61	84.59	87.15

Sources from Bloomberg

Appendix 1.3: FCPO contract specification

Underlying asset	Crude Palm Oil
Contract size	25 metric tons
Minimum price fluctuation	RM1 per metric ton
Contract Months	Spot month and the next 11 succeeding months, alternate months up to 36 months ahead
Contract grade and delivery points	Crude Palm Oil of good merchantable quality, in bulk, unbleached, in Port Tank Installations approved by the Exchange located at the option of the seller at Port Kelang, Penang/Butterworth and Pasir Gudang (Johor). Free Fatty Acids (FFA) of palm oil delivered into Port Tank Installations shall not exceed 4% and from Port Tank Installations shall not exceed 5%. Moisture and impurities shall not exceed 0.25%. Deterioration of Bleachability Index (DOBI) value of palm oil delivered into Port Tank Installations shall be at a minimum of 2.5 and of palm oil delivered from Port Tank Installations shall be at a minimum of 2.31.
Delivery unit	25 metric tons, plus or minus not more than 25 per cent. Settlement of weight differences shall be based on the simple average of the daily Settlement Prices of the delivery month from: (a) the 1st Business Day of the delivery month to the day of tender, if the tender is made before the last trading day of the delivery month; or (b) the 1st Business Day of the delivery month to the last day of trading, if the tender is made on the last trading day or thereafter.
Speculative position limits	The maximum number of net long or net short positions which a client or a participant may hold or control is: • 1500 contracts for the spot month • 20,000 contracts for any one contract month except for spot month • 30,000 contracts for all months combined

Sources from Bursa Malaysia