TIME-VARYING RISK AVERSION: A DYNAMIC APPLICATION IN INDEX HEDGING

BY

MR. ARAN PHRINGPHRED

A THESIS SUBMITTED IN PARTIAL FULFILMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
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(INTernational Program)
THAMMASAT UNIVERSITY
ACADEMIC YEAR 2016
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FACULTY OF ECONOMICS

THESIS

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MR. ARAN PHRINGPHRED

ENTITLED

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was approved as partial fulfillment of the requirements for the degree of Master of Economics (International Program)

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Degree of risk aversion has recently been claimed as an important factor in determining hedge ratio level since the conventional minimum variance hedge ratio (MVHR) with risk minimization objective can only lead to suboptimal hedge level. By taking into account of investors’ risk attitude through their degree of risk aversion and expected return, risk aversion hedge ratio (RAHR), with the optimal lower number of contracts which lead to lower transaction cost, can help investors reach their utility maximization. This study intended (i) to determine two different types of risk attitude of Thai investors, classified as short and long hedgers, and (ii) to confirm the superior of RAHR to MVHR for the two groups of investors. The generalized autoregressive conditional heteroscedasticity in mean (GARCH-M) model was estimated, using daily data of SET50 Index and SET50 Index Futures during May 2006 to December 2016, to determine time varying risk aversion (TVRA) and classify short and long hedgers. Multivariate GARCH assuming dynamic conditional correlation (MGARCH-DCC) models were then applied, to estimate expected return equation model and conditional variance and covariance models, to determine optimal hedge ratio of RAHR. Then, portfolios based on RAHR and MVHR were formed and evaluated. The results revealed that RAHR portfolio with lower hedge ratio outperformed MVHR portfolio for both short and long hedgers in term of risk adjusted return. Additionally, the positive impact of estimated TVRA on systematic
risk of the SET suggests that TVRA might be an alternative of sentiment index of SET.

**Keywords:** Degree of risk aversion, Hedging, Generalized autoregressive conditional heteroscedasticity (GARCH)-Multivariate GARCH (MGARCH), Dynamic conditional correlation (DCC) Risk management.
ACKNOWLEDGEMENTS

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Aran Phringphred
Thammasat University
July 2017
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CHAPTER 1
INTRODUCTION

1.1 Motivation

Currently, investors face interest rate fluctuations, which affect consumer savings, thereby causing them considerable concern. Thailand’s movement into the globalization changed the financial mechanism. Consequently, the old method of saving was no longer appropriate because this approach provides a low return, and investor behavior has switched toward new channels. Many alternative investments are available to investors who can be flexible to maximize their utility. Accordingly, investments, such as the stock and futures markets, represent an interesting milieu for various sectors to delve into.

The derivatives market an important investment channel, which helps investors or speculators handle risks. Moreover, by using the futures market to diversify their risks, investors can minimize them. The simplest method is a long future contract, which is equal to the amount of the total assets. However, should the stock and futures prices become similar, hedgers will perform impeccably. In fact, the perfect hedging is unattainable because no contract, delivery price, and month for their demand are available. Consequently, one fundamental problem is a basic risk causing inefficiency in the futures contract and fluctuations in commodities.

This study uses the SET50 index futures given the popularity of the index for foreign and local investors. (SET stands for the Stock Exchange of Thailand.) One common concern is that the SET50 futures involves only one contract referred to in the SET in the stock market. The SET50 index futures differs from other underlying contracts because this contract is not substantial and the investor buys or sells with the index. Accordingly, the SET50 futures pays for cash settlements. The apparent advantages of the trading SET50 index futures are as follows. First, portfolio risk management reduces risks by short and long strategies. Second, another beneficial aspect is the low cost that the investor can arbitrage. Third, this index futures is easy to analyze given that an investor can decide to trade using an overview of 50 stocks at once.
Initially, Figure 1.1 represents the volume of the SET 50 index futures. They have significantly grown in the last decade. Overall, the trend witnessed a regular increase from 2009 to 2015. This trend has an enormous impact on the investment and trading opportunities for market participants.

![Figure 1.1](image.png)

Source: Datastream

**Note:** The contract size of the SET50 index futures was changed from 1,000 Baht per index point to 200 Baht per index point from May 6, 2014, onward.

Despite the increase in the volume of the SET50 futures, the investor must remain aware of the fluctuations in volume and price. One investment strategy that occurs from market power is hedging, and information follows the assumption by Copeland (1976) that a group of investors do not simultaneously recognize information. Sellers and buyers will obtain sequential information that commonly causes an incomplete response to the type of information called asymmetric information. This difference leads stock and futures prices to a basis risk that can cause inefficiency in the futures contract. The positive basis shows the market in contango, whereas its opposite indicates a normal backwardation market.
Figure 2 depicts the averages of the stock and futures prices. Prices suggest the negative basis or the normal backwardation market. The SET50 futures also exhibits a significant fluctuation, which is suitable for hedging. Another point to consider is that lead-lag relationship mostly implied that the future price has the leading spot because an investor in the future market can make a decision in the future called “price discovery.” Black (1975) claimed that a trader prefers the futures market over the stock market because of the degrees of leverage or significantly high returns as the futures market tends to adapt substantially quickly to information. This reason prompts hedging in the futures market to reduce volatility in the stock market.

Figure 1.2 shows the motivation of hedging. The problem occurs from the difference between the SET50 index and the SET50 index futures, which Ederington (1979) called the basis risk. This imperfect correlation between the stock index and the futures index leads to the potential for excess benefit or losses in a hedging strategy, thereby adding risk to the position.

---

1 Basis risk is a variation between the hedge/futures/relative price and the cash/spot price of the hedged underlying at any given point of time.
Theoretically, the futures exchange can be distinguished by three different players: the speculators, arbitrageurs, and, hedgers who are trading in the currency market and are prominent players as they can reduce the volatility of the underlying asset to handle the bull and bear markets. Working (1953) explained that traders and hedgers not only pursue risk minimization but also aim to increase profits. This study applies that concept to the Thailand Futures Exchange (TFEX) by classifying investors into three types (local institutions, foreign investors, and local investors) to observe their behaviors.

Figures 1.3 and 1.4 illustrate the quantity of the long and short positions classified into the three investor types in the SET50 index futures. Figure 1.3 shows the number of the buyers in futures. A gradual increase occurred from 2011 to 2013, whereas marked growth transpired from 2014 to 2016. The number of buyers is higher for local investors compared with the other types. Figure 1.4 also indicates that the rate climbed considerably from 2014 to 2016 and that the number of sellers is highest for local investors in comparison with other investors. Overall, the graphs clearly suggest that local investors have the most power in the derivative market.

Figure 1.3

Long volume of the SET50 index futures by investor type from 2011 to 2016

Source: SETSMART
Figures 1.3 and 1.4 demonstrate that the three investor types gradually increased during 2011–2016. Such outcome possibly results from exploration or speculation in the futures market or arbitrage between stock and futures. Interestingly, investors are likely to use hedging strategies during the bust period or uncertainty situation. This growth trend leads to the evaluation of the hedging in SET50 index futures.

Tables 1.1 and 1.2 show the volumes of short and long positions for the foreign investors, local institutions, and local investors. Table 1.1 demonstrates the net volume from 2011 to 2016. In 2016, a sizeable net SET50 future occurred for foreign investors given the profoundly big long position. Both of them gradually increased in the short and the long position from 2011 to 2016 (September). Table 2 shows the net of three investors whose net long position is more than their short position from 2011 to 2016. Compared with the local investors and local institutions, clearly, the long position is a foreign investor behavior. Such data provide support to the result. The finding will be discussed again in Chapter 4.
### Table 1.1
Net investor type in the SET50 index futures classified by group

<table>
<thead>
<tr>
<th></th>
<th>Foreign Investors</th>
<th>Local Institutions</th>
<th>Local Investors</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Volume</td>
<td>%</td>
<td>Volume</td>
<td>%</td>
</tr>
<tr>
<td>Long</td>
<td>16,613,447</td>
<td>20</td>
<td>20,136,826</td>
<td>24.24</td>
</tr>
<tr>
<td>Short</td>
<td>16,512,526</td>
<td>19.87</td>
<td>20,191,825</td>
<td>24.3</td>
</tr>
<tr>
<td>Net</td>
<td>100,921</td>
<td>–</td>
<td>-54,999</td>
<td>–</td>
</tr>
</tbody>
</table>

Source: SETSMART

### Table 1.2
Net investor type in the SET50 index futures classified by group 2012–2016

<table>
<thead>
<tr>
<th>Year</th>
<th>Foreign Investor</th>
<th>Local Institutions</th>
<th>Local Investor</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Volume</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Long Short Net</td>
<td>Long Short Net</td>
<td>Long Short Net</td>
<td>Volume OI</td>
</tr>
<tr>
<td>2016</td>
<td>6,941,501 6,727,136 214,365</td>
<td>6,577,079 6,704,735 -127,656</td>
<td>18,674,404 18,761,113 -86,709</td>
<td>32,192,984 283,692</td>
</tr>
<tr>
<td>2015</td>
<td>5,282,254 5,337,229 -54,975</td>
<td>6,580,764 6,543,451 37,313</td>
<td>14,901,377 14,883,715 17,662</td>
<td>26,764,395 288,560</td>
</tr>
<tr>
<td>2014</td>
<td>2,852,293 2,900,041 -47,748</td>
<td>3,985,531 3,959,748 25,783</td>
<td>7,565,750 7,543,785 21,965</td>
<td>14,403,574 177,704</td>
</tr>
<tr>
<td>2013</td>
<td>996,237 1,014,575 -18,338</td>
<td>1,743,999 1,729,864 14,135</td>
<td>2,948,168 2,943,965 4,203</td>
<td>5,688,404 37,496</td>
</tr>
<tr>
<td>2012</td>
<td>541,162 533,545 7,617</td>
<td>1,249,453 1,254,027 -4,574</td>
<td>2,243,844 2,246,887 -3,043</td>
<td>4,034,459 36,920</td>
</tr>
</tbody>
</table>

Source: SETSMART
1.2 Introduction

Hedging is an essential tool to manage the fluctuation in stock and futures prices. Correspondingly, hedge ratio is the main concern for an hedger who decides on holding the futures contracts because it affects their return. Several studies, including Ederington (1979), Kumar (2008), Floros and Vougas (2011), as well as Hou and Li (2013), affirm the estimation of the optimal hedge ratio by finding the exact number of holding futures contracts. Subsequently, the most crucial process is determining hedge effectiveness, which has become the core measurement of hedging. The traditional hedging framework involves the greatest risk reduction, but this framework fails in terms of utility maximization.

To correspond with the realistic hedging in the futures market, this study intends to show other dimensions about the hedging perspective. Previous research only estimated the risk minimization. Therefore, the alternative approach is to present the actual risk aversion, which leads to utility maximization. Risk aversion is the key factor generating different reactions in investment. This context presents two different strategies: short and long hedgers. Similarly, the coefficient relative of risk aversion (CRRA) is the primary theory to measure the degree of the risk aversion framework as it shows the percentage change in holding the risky asset, which is possibly influenced by the number of futures contracts. However, some studies apply arbitrary values for risk aversion, such as Mehra (1985) as well as Conlon, Cotter, and Gençay (2016). Consequently, shortcomings occur in risk preference because it does not reflect a real attitude to risk. Subsequently, the evaluation of the econometric model facilitates the measurement of the aggregate risk aversion by using generalized autoregressive conditional heteroskedasticity (GARCH)-in-mean. Moreover, the risk aversion parameter between short and long hedges can be constructed as a hedging application to support investors’ aims.

In this study, hedging application is the chief concept for risk minimization and utility maximization. This application can help investors have appreciable portfolio risk management. According to traditional hedging, the application to minimize risk is called the minimum variance hedge ratio (MVHR). Certainly, traditional hedging provides the lowest risk but fails to guarantee investor
satisfaction after hedging given that it has a hedge cost and that the investor is likely to lose their return. Accordingly, the alternative hedging application is expressed by a utility function, which is crucial for determining the hedging perspective by taking the actual risk attitude into account. Furthermore, the alternative hedging application addresses utility rather than risk minimization.

The present research employs quadratic utility because it is an outstanding utility that describes behavior in financial markets. Correspondingly, a popular theory applied a quadratic function based on investor behavior, such as the capital asset pricing model (CAPM). The following are the advantages of quadratic utility: (1) incorporates risk aversion and (2) expects a return to estimate hedge ratio for short and long hedgers. Another useful aspect is that we can measure the utility level through increasing the expected utility, which is the main expectation of the study. However, this work assumes that investor behavior is a quadratic function. Several papers do not consciously examine the difference between maximizing utility and minimizing variance. They assume that the two different hedging applications are similar. Many studies overlook reality by assuming that the stock and futures prices follow the martingale process, which does not allow an excess return and converts risk aversion to infinity. Consequently, deficiency occurs in the hedging framework.

Time-varying and econometric models are also involved in constructing hedging application. In the financial market, investors update their information and make decisions to manage their portfolios. Meanwhile, volatility arises as information and rumors vary over time. These reasons generate time-varying and dynamic relationship features. We hypothesize that the multivariate GARCH dynamic conditional correlation (DCC) provides the efficient hedge ratio. Moreover, the said model combines the vector autoregressive model (VAR), the GARCH, and the DCC method to provide time-varying correlation. Finally, measurement in this study is conducted by using the econometrics model to examine the risk reduction (by variance reduction as an optimal hedge ratio between short and long hedgers) and evaluate the expected utility in and out of the sample for the SET 50 and the SET 50 index futures.
The empirical result corroborates that statically significant distinction exists between minimizing risk and maximizing utility. Moreover, a short hedger tends to be more risk averse than the long hedger in index futures in and out of the sample. The result cannot explain with certainty which hedging applications provide a significant performance. However, the outcome implies that hedgers have various ways for risk evaluation. If they prefer the lowest risk, then they will pursue the MVHR. Should they use the alternative hedge ratio, they may obtain considerably high utility.

The rest of this study is structured as follows. Chapter 2 demonstrates the estimation risk aversion and an econometric model. Chapter 3 discusses about a coefficient relative of risk aversion and mean-variance optimization (which are relevant concepts for linking estimation risk aversion by GARCH-in-mean). Chapters 4 and 5 present the empirical results and the conclusion, respectively.

1.3 Objectives of the Study

1. To estimate and compare the degree of risk aversion of two different groups of investors investing in the SET50 index futures as long and short hedgers.

2. To estimate the hedging ratio through risk minimization as well as utility maximization between short and long hedgers.

3. To compare the hedging performances between the MVHR and the risk aversion hedge ratio (RAHR) in the SET50 index futures.

1.4 Scope of the Study

This study uses the SET50 and the SET50 index future in settlement prices with restriction to only the SET and the TFEX. The main aim of this research is to construct two different hedging applications. Initially, the study defines two different players who are short and long hedgers. Subsequently, the study considers only the quadratic utility as the RAHR. Finally, expected utility is expressed only by a quadratic function that concerns mean and variance.
CHAPTER 2
REVIEW OF LITERATURE

2.1 Hedging Concepts

The definition of the futures market is connected to the hedging and variance reduction specified in several papers. The original idea came from Johnson (1960), who defined that speculation and hedging as the main two activities for trading in the futures market. A speculator can benefit from buying a product from the spot market, holding it until the asset price increases and then making a short position commodity date. They expect the futures price to dominate the spot price. Another activity is the hedgers as “insurance.” They will hedge from the price changes they face and lock the current prices. Stein (1961) also has the same concept that the holding stock creates two alternatives. The first option involves speculators who contract to sell at a stated price and sell either spot or forward. The second option entails hedgers who possibly short position aim to hedge or to unhedge. Hedging or hedging strategies are applied for utility maximization.

According to theory of hedging, Johnson (1960), Stein (1961), Ederington (1979), as well as Myers and Thompson (1989) supported that the hedgers would hedge position their contract at y contracts (y as a unit) from the fluctuation of the price risk by short position at y contract to cover all delivery prices at y contract in simultaneously selling. Furthermore, the fundamental problem in hedging is the difference between stock price and futures, which is defined as the basis risk. Hedgers can incur the benefits or losses from the gap between two markets from today as time t and yesterday as time t - 1. Remarkably, in the perfect case, basis risk becomes 0, meaning that no difference\(^1\) between stock and futures the price occurs. Ederington (1979) also defined that the risk from hedging must be less than the unhedging position or that the variance of the hedged be less than the variance of the unhedged position.

\[^1\) No basis risk means \[ (S_t - S_{t-1}) - (F_t - F_{t-1}) \] = 0\]
Furthermore, Markowitz (1952) introduced Modern Portfolio Theory (MPT) to show portfolio selection and allocation with various assets. This investment theory follows the concept of risk (defined as variance) and the benefit from portfolio (defined as expected return) and is called the mean-variance model. Afterward, the motivation of theory of hedging is mentioned by Johnson (1960) and Stein (1961) who studied “price risk.” This concept can consider a reflection of the variance and show it as a probability density function. The variance function is composed of two main parts: first is the number of assets which invested in the portfolio and second is the covariance between the number of each asset. It then applies to the hedge effectiveness, which is measured by a variance reduction. In the same way, Ederington (1979) and Figlewski (1984) also suggested that modern portfolio theory indicates that the risk reduction from hedging should incorporate the price movement. The proportion of the price movement, called hedge ratio. The potential of using the hedge ratio for risk reduction entails showing the hedge effectiveness (risk minimizing), which can be measured by comparing the unhedged position and the hedged position. In other words, the hedge ratio or “beta hedging” is representative of stock and futures price relationship. Investors have to obtain the most suitable hedge ratio to provide the lowest risk in their portfolio.

2.2 Hedging Problem

The motivation to separate short and long hedgers is caused by an asymmetric performance, which is essential for theoretical and practical purposes. Regarding commodity futures, numerous studies affirm that the short hedger perspective surpasses that of long hedgers. Yamey (1971) intended to identify the distinction between short and the long hedgers. Cotter and Hanly (2010) found evidence regarding the two sets of hedgers: short hedgers as the producer (oil companies) whose aim concerns price decrease and long hedger as the oil user whose goal is to pursue price increases. Julia and Titman (2004) demonstrated that, in most futures market cases, the long hedgers (consumers) are more active in price changes than the short hedgers (producers).
The result corroborates that the types of hedgers tend to have different reactions in the portfolio as determined by risk aversion. Following the study, the degree of risk aversion has to differ in the comparison of hedging strategies. Consequentially, they must be considered individually. Demirer, Lien, and Shaffer (2005) defined a hedging problem as short and long strategies demonstrated in the return of the portfolio as follows equation (1) and (2):

\[
R_p = +xR_s - \beta R_f \quad \text{Short Hedger,} \\
R_p = -yR_s + \beta R_f \quad \text{Long Hedger,}
\]

where \( R_p \) is the portfolio return, \( R_s = \log \frac{S_t}{S_{t-1}} \) is the logarithm return of stock price, \( R_f = \log \frac{F_t}{F_{t-1}} \) is the logarithm return of futures price, \( X \) is the number of contracts for the short position; \( Y \) is the number of contracts for the long position; and \( \beta \) is the hedge ratio between the short and long hedgers.

For convenience during the comparison, we allow contracts x and y to be equal to 1. For the short hedgers who long position in a stock asset and short position in a futures asset, the negative return is realized in their portfolio. Conversely, the long hedgers short position in a stock asset and long position in a futures asset, and the positive return is realized in their portfolio.

2.3 Risk Aversion in the Econometric Model

Tobin (1958) and Pratt (1964) claimed that risk premiums have a substantial link to risk aversion based on certainty equivalent, a concept suggesting that investors pay to avoid an arbitrary risk. Cambell (2003) demonstrated the utility function with power utility through a constant relative of risk, proved the relationship between risk premium and risk aversion with asset pricing to explain the equity premium puzzle.
Empirical studies also examined risk aversion using risk premium, risk asset, and risk-free rate by applying an econometric model that supports the degree of risk aversion. Engle, Lilien, and Robins (1987) estimated risk aversion through three different types of bonds. The primary motivation of time-varying risk aversion stemming from the level of uncertainty in asset return was change over time. Consequently, compensation that considers risk aversion from holding the asset has to be varying. Accordingly, increasing the expected rate of returns leads to a significantly high risk. Their research extended the Autoregressive Conditional Heteroskedasticity (ARCH) to Autoregressive Conditional Heteroskedasticity in mean (ARCH-M), which allowed for conditional variance to determine returns. Their result also verifies that conditional variance is significant to explain expected returns but invariant in risk premia. Subsequently, Chou, Engle, and Kane (1992) extended ARCH-M to Generalized Autoregressive Conditional Heteroskedasticity (GARCH-M), and Shrestha (2009) measured risk premium to variance by a single factor of Capital Asset Pricing Model (CAPM). The slope coefficient indicates the linear relationship between excess return and its variance. The GARCH-M method incorporated conditional variance and the risk aversion parameter instead of the unconditional variance. Interestingly, the relationship between risk aversion and excess return must be positive. The finding by Chou et al. (1992) validated that the risk aversion parameter varies with time because of changing risk preference and investment opportunities.

Some studies empirically examined hedge strategies based on the martingale hypothesis. De Goyet, Dhaene, and Sercu (2008) considered the said hypothesis for the futures contract in agriculture together with the hedge ratio. They confirmed that the investor does not exhibit high-risk aversion and that the futures price does not support the martingale hypothesis. Consequently, an enormous difference exists in the degree of risk aversion and the effect on the optimal mean-variance hedge ratio.

A few paper determined the level of risk aversion through an arbitrary value. Mehra (1985) estimated the large size of risk aversion (converge to 1000) to determine equity. Kroner and Sultan (1993) followed the utility function and used the risk aversion parameter from literature, which is equal to 4. Conlon et al. (2016) considered the level of risk aversion that affects the hedge ratio. This process defined
the different levels of risk aversion, such as low, gradual, high, and extremely high-risk aversions, given that the arbitrary value reflected the general risk preferences. The disadvantage of using an arbitrary value of risk aversion is that it is unlikely to contemplate the real risk attitude of those hedgers, leading to the bias of the hedging result.

These papers present risk preference applied to the energy hedging market participants who reflect the hedger perspective. It can show the GARCH-M estimate risk preference. A Coefficient Relative of Risk Aversion (CRRA) explains the outcome of using GARCH-M. The previous studies by Cotter and Hanly (2010) examined three different utility functions. The hedger’s risk aversion describes the tradeoff between risk and expected return. The authors used the time rolling window to allow risk aversion coefficient to vary over time using weekly and monthly data. Their result confirmed strongly positive outcome in the risk aversion parameter for both frequencies. Notably, the finding validates that commodity investors have different risk attitudes depending on the investment horizon. Cotter and Hanly (2010) claimed that risk aversion is the main goal to reflect utility maximizing hedge strategies and that many researchers avoid this framework because they believe that maximal utilities and minimal risk are similar. Using GARCH-M illustrates that a strongly positive relationship also exists between return and its volatility. Furthermore, long hedgers have a longer time horizon (low frequency) that makes them more liable to be risk-averse than short hedging due to their size (which are larger in the futures market).

2.4 Empirical Analysis of Econometric Models

Initially, the naïve econometric model from Ederington (1979) used the Ordinary Least Square (OLS) method to find an appropriate hedge ratio and claimed that R-squared is a representative of hedging effectiveness. Myers and Thompson (1989) affirmed the relationship between stock and futures in the case of estimating OLS. However, their finding is in contrast to that of Yang, School of, and Business Economics Perth (2001) whose estimation of linear regression failed to provide a significant hedge ratio due to ineffective variance reduction. In addition, Herbst, Kare,
and Marshall (1993) criticized the estimation of OLS as it led to ineffective results. The main reason for such outcome is that the optimal hedge ratio can achieve serial autocorrelation in residual. Conversely, Bell and Krasker (1986) confirmed that the expectation of the futures price depends on information and that using OLS leads to bias in the estimator, thereby rendering the data unreliable.

The GARCH family entails the best hedge effectiveness because GARCH is a return asset that fluctuates as a volatility clustering mean. If the prices change more or less, the price will tend to be probably modified more or less. Mandelbrot (1963) affirmed that shocks affect the conditional volatility. That has meant that shock which was in the past was importantly affected to estimate volatility. It has meant like GARCH further. Moreover, Garcia, Roh, and Leuthold (1995) employed Bivariate Generalized Autoregressive Conditional Heteroskedasticity (B-GARCH) and the Random Coefficient Autoregressive (RCAR) process to measure the hedging effectiveness of corn and soy contracts. They corroborated that diagonal VECH (DVECH) from the B-GARCH model provides substantial variance reduction. Therefore, time-varying models are suitable for measuring the hedge ratio.

Several studies empirically examined the variance reduction using econometric models. They concluded that B-GARCH is the best econometric model to reduce variances. A good illustration is that of Floros and Vougas (2011), who compared hedge effectiveness with constant hedge ratio models such as Ordinary Leas Square (OLS), Error Correction Model (ECM), and Vector Error Correction Model (VECM), and the time-varying hedge ratio is B-GARCH (1,1). However, R-squared from estimating OLS does not guarantee a good performance because of variance reduction. Conversely, testing B-GARCH (1,1) offers the best variance reduction. Such method allows the variance to be varied over time and leads to time varying in the hedge ratio. Kumar (2008) examined hedge effectiveness of financial asset and commodities contracts in India derivative markets. The study also included a comparison of the econometric models, including OLS, VAR, VECM, and Vector Autoregressive with Multivariate Generalized Autoregressive Conditional Heteroskedasticity (VAR-MARCH). An examination both in and out sample found that both cases. The result confirms that the calculation of the hedge ratio from VAR-MGARCH provides the best variance reduction. Furthermore, their feature also
allows variance as a component of the hedge ratio, leading to a time-varying hedge ratio. Meanwhile, constant hedge ratio models showed poor performance. Nevertheless, their finding proposes that the VAR-MGARCH model possibly demands a regular shift in hedging. Therefore, hedgers should not only be concerned with the transaction cost but should also subtract some of the benefits from the expenditure.

Pradhan (2011) also examined the S&P CNX Nifty Index, but his findings confirm some contrast to another study by estimating the sample and forecasting out sample data with one, five, ten, and twenty day time horizons to clearly notice the effect. The result corroborates that Vector Error Correction Model - Generalized Autoregressive Conditional Heteroskedasticity (VECM-GARCH) supported risk reduction and became the greatest portfolio due to the generation of the highest portfolio return.

Hou and Li (2013) compared only two different time-varying hedge ratios between Dynamic Conditional Correlation- Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) and Constant Conditional Correlation- Generalized Autoregressive Conditional Heteroskedasticity (CCC-GARCH) by using the CSI 300 stock index futures. Their result affirms that DCC-GARCH is better than CCC-GARCH in short horizon because of a high frequency that fitted to DCC. Moreover, CCC-GARCH outperformed DCC-GARCH in a long time horizon in the sense of hedge effectiveness. Chang, McAleer, and Tansuchat (2011) compared Baba, Engle, Kraft and Kroner (BEKK), CCC, DCC, and Vector Autoregressive Moving Average- Generalized Autoregressive Conditional Heteroskedasticity (VARMA-GARCH) as conditional variance models by using the data of crude oil spot and futures price. Using BEKK, Diagonal BEKK, and DCC suggests that hedgers should hold a spot price to a futures price, whereas CCC and VARMA-GARCH are suggested for a futures price to a spot price. The evidence of hedging effectiveness confirms that hedge ratio from DCC is the best model for variance reduction. Meanwhile, diagonal BEKK had the worst performance.
2.5 Utility Function and Hedge Effectiveness

Starting with Minimum Variance Hedge Ratio (MVHR), a fundamental framework is used to examine risk reduction or variance minimization. A few illustrations of MVHR are extant. Johnson (1960), who defined the hedge ratio, represented a proportion to holding assets between spot and futures as a relationship. However, the relationship has to be less than a perfect case or be equal to 1 given that, in reality, these prices do not converge similarly. Furthermore, capital asset pricing is associated with the hedge ratio framework because the risk is defined as a variance for each asset. H. M. Markowitz (1991) defined risk as a standard deviation that can be applied to measure hedge effectiveness. H. M. Markowitz (1991) extended the concept of Ederington (1979), Johnson (1960), and Stein (1961) about modern portfolio theory. They propose a standard deviation that transforms to variance, also called hedge effectiveness. The objective of hedge effectiveness is to minimize the risk (basis risk). Interpretation of hedge effectiveness is made through the percentage of variance reduction between hedging and unhedged position. Park and Switzer (1995) and Kavussanos and Nomikos (2000) examined hedge effectiveness. A significant hedge ratio is shown if, and only if, a high variance reduction results in substantial performance in hedge effectiveness.

Empirical studies confirm a distinction between in sample and out sample performances in hedge ratio and also hedge effectiveness. Using hedge ratio effectively is an advantage for a hedger who wants to obtain the current and futures performance. For example, Benet (1990) and W. Chen and Ford (2010) investigated potential risk reduction on the ex-ante basis by involving foreign exchanges. The result verifies that some distinction exists between ex-ante and ex-post hedge ratios, leading to the measurement of hedge effectiveness. Moreover, such result also supports the study of Holmes (1995). Floros and Vougas (2011) examined the Greek stock index futures market. They followed previous empirical studies to investigate hedge effectiveness between in and out samples. Different performances between current and futures lead to differences in hedge ratio and variance reduction. Hou and Li (2014) evaluated the CSI300 stock index futures on the short horizon. Their findings confirm that the best variance reduction from in sample and out sample
differs in econometric models. That outcome meant that the study used different strategies to hedge futures contracts.

Moving onto utility function and hedge effectiveness, Hsin, Kuo, and Lee (1994) introduced the mean-variance by the expected quadratic utility based on the CRRA framework. This measurement can be interpreted as the increasing quadratic utility between unhedging and hedging portfolios. The growing utility required high expected return and low volatility. M. Lau, Y. Su, N. Tan, and Z. Zhang (2014) demonstrated the quadratic utility, which is popular in financial asset pricing frameworks, such as CAPM and hedging. Subsequently, they examined the standard mean variance of hedge effectiveness in the Chinese energy oil market. Lahiani and Guesmi (2014), Cotter and Hanly (2014), as well as Chung-Chu Chuanga and Chuang (2015) evaluated the hedge ratio by classifying investors between short and long hedgers and employed hedge performances by using expected utility. Moreover, W. Chen (2009) explained that the main advantage of choosing quadratic utility is that they considered risk aversion term and expected return. However, most of the studies assumed that the futures price follows the martingale process. Kroner and Sultan (1993) as well as M. C. K. Lau, Y. Su, N. Tan, and Z. Zhang (2014) reduced the term of the risk aversion to the MVHR. However, in reality, martingale may not hold; hence, the Risk Aversion Hedge Ratio (RAHR) is deemed as essential to measure by utility increasing gave wealth as w. It meant that variance is minimizing but not equal to utility maximizing.

Cotter and Hanly (2010) created the dimension that involved hedge effectiveness by adding short and long hedgers. Furthermore, they added three different utility functions (quadratic utility, log utility, and exponential utility) to observe the difference between minimizing variance and various maximizing utility by using the time horizon. Using weekly and monthly data resulted in identifying the short hedgers whose RAHR overshadows the MVHR regarding expected utility. In most cases, the return of using RAHR was significantly high. By contrast, when hedgers consider risk minimization only, the MVHR dominates the RAHR. For long hedgers, the MVHR dominated the RAHR regarding expected utility. However, long hedgers are outperformed in most cases.
CHAPTER 3
RESEARCH METHODOLOGY

This research intends to measure the degree of risk aversion in the SET50 index futures short and long position with the optimal hedge ratio. Subsequently, the research methodology is divided into six fragments. The first section is data description. Second part is the set of variables. This part is where the logarithm form of the stock and future variables are illustrated. Third section is the coefficient of relative risk aversion and the Generalized Autoregressive Heteroskedasticity in mean (GARCH-M), which are applied for the short and long positions. Forth part, Multivariate Generalized Autoregressive Heteroskedasticity with dynamic conditional correlation model (M-GARCH DCC) and receives the optimal hedge. Moreover, econometric models are not enough to obtain the optimal hedge ratio. Fifth part, the study employs not only hedging performance to measure the percentage of the variance reduction of the SET50 index futures but also the increasing expected utility that measures investor behavior for hedging SET50 index futures by incorporating risk aversion. Lastly, the study summarize the methodology by estimation procedure.

3.1 Data Description and Selection Criteria

The data obtain the SET50 futures from the Thailand Futures Exchange (TFEX) and the SET 50 from the Stock Exchange of Thailand (SET). The reason is to focus on the wide perspective on the futures market to be an advantage for the various investors. Accordingly, the research selected the SET50 futures to examine the market regulation, which allows only the SET50 index future contract. Consequently, investors can trade futures by evaluating the market movement in the market overview without analyzing an individual stock. Meanwhile, in comparison of the volume of the SET50 index futures with the single stock futures, Figure 5 shows the advantage of the SET50 index futures, which has more liquidity compared with the single stock futures. Therefore, considering the investor behavior and manipulating the overall stocks are important, owing to the high volume in the SET 50 futures and to all the details mentioned in the study.
Table 3.1
Comparison between the SET50 index futures and the single stock futures

<table>
<thead>
<tr>
<th>Topic</th>
<th>SET50 Index Futures</th>
<th>Single Stock Futures</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asset</td>
<td>SET50 index point</td>
<td>Common stock/Baht per share</td>
</tr>
<tr>
<td>Analysis</td>
<td>Investors easily analyze the trend of all 50 stocks.</td>
<td>The investor has to analyze each stock.</td>
</tr>
<tr>
<td>Liquidity</td>
<td>The change of the mini-SET50 index futures discount to 200 per point aims to inject the volume.</td>
<td>Full payment and separation of the volumes in each company</td>
</tr>
<tr>
<td>Risk</td>
<td>Risk diversification due to the investment in the 50 stock index</td>
<td>Considerable risks due to the consideration of only one stock</td>
</tr>
</tbody>
</table>

Source: The Stock Exchange of Thailand

Figure 3.1
Comparison between the SET50 index future and the Banpu Company weight of volumes during 2010–2016

Source: Datastream
Hedging is defined as the financial instrument to lock the current price. Correspondingly, hedging relieves some uncertainty in the financial market. This study focuses on the index market and employs the two asset types of the SET 50 index and the SET 50 index futures as the risky asset. The full sample of daily data is gathered between 1/5/2006 and 31/10/2016 from the data stream because the research intends to cover the normal period and the financial crisis, which has fluctuated the market. Financial crises, such as Greece’s debt crisis, Brexit, as well as the political instability problem in Thailand call for the use of the hedging strategy as the bear market. Similarly, the research concerns equity premium by taking into account the risk-free rate to use the three-month treasury-bill from 5/2006 to 12/2016 from the Bank of Thailand, but the data set provides only the monthly data. Subsequently, the average monthly data should be calculated as daily data to correspond with the index price. The data are transformed to logarithmic prices because they adjust the variation of the time series and provide the stationary data process.

3.2 Set of Variables

3.2.1 Log return of stock and futures prices

The time series data set is obtained from the close price. Subsequently, this data set is adjusted in the logarithmic return or continuously compounded return in the stock market, and the futures market follows Equation (1) to reduce the variation of the time series due to the pure price that is nonstationary. However, this time series set has to undergo a unit root test to ensure that no trend that shields a spurious problem occurs, thereby making the fitting of the model in question considerably easy.

\[
\Delta S_t = \ln \left( \frac{S_t}{S_{t-1}} \right), \quad \Delta F_t = \ln \left( \frac{F_t}{F_{t-1}} \right),
\]

(1)

where \( \Delta S_t \), \( \Delta F_t \) is the continuously compounded return at period \( t \) of the stock and futures.

\( S_t, F_t \) is the price form of the stock and futures price index at period \( t \).
Given the time series data, the study has to employ the essential process. The unit root test is test for stationary in a time series. For non-stationary we have to first different for solving the problem. Moreover, this study requires the same integrating order to find the cointegration effect between the stock and futures variables. Nevertheless, if the variables are stationary, then they do not need to undergo the unit root test.

3.2.2 Log return portfolio between short and long hedgers

In this study, the author intends to separate the long and short hedge to estimate the difference value of the hedge ratio in the SET 50. Furthermore, the study examines not only the minimized hedge ratio but also the maximized utility as a quadratic utility as an alternative way for hedgers with low-risk averse for hedging. Therefore, the study constructs the hedge ratio to the hedgers as a choice to hedging in their portfolio. Furthermore, the study examines the hedge ratio for in-sample and out-sample to investigate the current and futures performance.

As the study mention about separating between short hedgers and long hedger in the part of review of the literature. Demirer et al. (2005) as well as Cotter and Hanly (2010) showed the short and long hedger frameworks by letting \( r_s \) and \( r_f \) as the logarithmic stock and futures successively and \( \beta \) as the optimal hedge ratio (OHR) and then by constructing a return of portfolio after hedging as referred to equation (2) and (3):

\[
R_p = +xR_s - \beta R_f \quad \text{Short Hedger,} \\
R_p = -yR_s + \beta R_f \quad \text{Long Hedger,}
\]

Subsequently, the calculation of the Minimum Variance hedge Ratio (MVHR) is to be compared with the Risk Aversion Hedge Ratio (RAHR) in case of short hedgers and long hedgers. This equation is mentioned again in the hedging performance (Section 3.5.1).
3.3 Coefficient Relative Risk Aversion (CRRA) with Risk Preference

The first objective is the measurement of risk preference between long and short hedgers in the SET50 index futures. The study employs the main theory to describe certainty equivalent and risk aversion. The Coefficient Relative Risk Aversion (CRRA) is a theory to describe the investors’ attitudes to risk behavior in the portfolio. Consequently, the CRRA is applied in GARCH-M model. We then estimate and compare risk aversion through parameters on two different classes of hedgers to follow which group is significantly active on hedging. Finally, the study will suggest the use of hedging strategy for risk minimization or utility maximization.

Arrow (1974) and Pratt (1964) developed a theory of risk aversion to measure risk aversion expressed by several utility functions, such as quadratic utility, negative exponential utility, and logarithm utility. Subsequently, they divided the measurement into two. First, absolute risk aversion can present the actual amount of dollar for individual investors who hold the risky asset. This measurement can be assessed by the relative change of the solved function of the utility curve. Second, a relative risk aversion is the relative percentage invested from holding risk-free and risky asset. Noticeably, the formula in Equation (4) is similar to absolute risk aversion but possesses some difference in scaling the relative level of wealth. The relative risk aversion can be expressed through:

\[ CRRA = -Wealth \frac{U''(Wealth)}{U'(Wealth)}. \]  

The study employs the CRRA to measure the risk aversion in the SET50 index and the SET50 index futures. Thereafter, GARCH-M is used to identify a degree of risk aversion that is based on the CRRA. Consequently, GARCH-M model can support this process because it is already included in the variance as a volatility into the mean equation. Finally, the CRRA will be the proxy to calculate the hedge ratio formula.

3.3.1 Mean–variance optimization
The study measures the degree of risk aversion by using the mean–variance optimization framework, which concerns mean and variance utility. This derivation leads to GARCH-M. Further, Frankel (1982), Frankel (1983), Frankel (1995), and Frankel (1986) introduced the multicurrency asset-demand equation, in which means and variance are taken to maximize utility by the given end of period wealth. Giovannini and Jorion (1989) developed Frankel’s paper, in which they focused on the conditional expected return and the conditional variance over the maximizing utility of investors. This framework derives from Equations (5)-(14).

\[
\max U[E_t(W_{t+1}), \sigma_t^2(W_{t+1})] \tag{5}
\]

where

\[
E_t(W_{t+1}) = W_t x_1'E_t(R_{t+1}) + W_t (1-x_1')_t R_t', \tag{6}
\]

\[
\sigma_t^2(W_{t+1}) = W_t^2 x_1'E_t\Omega_{t+1} x_1', \tag{7}
\]

Where
- \( W_t \) is the investor’s wealth
- \( R_t' \) is the risk-free rate
- \( 1 \) is a unit vector
- \( x_t \) is the share of a risky asset expressed by a vector
- \( E_t(R_{t+1}) \) is the conditional mean
- \( \Omega_{t+1} \) is the conditional covariance

Thereafter, we differentiate \( x_t' \), the vector of portfolio shares:

\[
\frac{dU}{dx_t} = U_1 \frac{dE(W_{t+1})}{dx_t} + U_2 \frac{d\sigma^2(W_{t+1})}{dx_t} = 0 \tag{8}
\]

Subsequently, the differential utility is shown in Equation (9):

\[
U_tW_tE_t(R_{t+1}) - U_tW_tR_t' + 2U_tW_t^2x_tE_t\Omega_{t+1} = 0. \tag{9}
\]

Thereafter, we rearrange the equation (9) as shown below (Equation (10)):
We have \( x \) that provides a maximized utility

\[
x_t = \frac{U_t(R_t^f - E_t(R_{t+1}))}{2U_2W_2E_t\Omega_{t+1}}. \tag{11}
\]

Assuming that the coefficient relative risk aversion is constant \( \lambda = \frac{-2W_2}{U_2} \), equation (11) then becomes:

\[
x_t = \lambda^{-1} \left( \frac{E_t(R_{t+1}) - R_t^f}{E_t\Omega_{t+1}} \right) \text{ or } x_t = \lambda^{-1} E_t\Omega_{t+1}^{-1}(E_t(R_{t+1}) - R_t^f) \tag{12}
\]

The first order condition provides “Sharpe Ratio”, which is a proportion of risk premium and incorporates risk aversion.

\[
x_t = \frac{(E_t(R_{t+1}) - R_t^f)}{\lambda E_t\Omega_{t+1}} \tag{13}
\]

Equation (12) the Sharpe ratio can be rearranged as equation (14):

\[
\lambda\Omega_{t+1} x_t = E_t(R_{t+1}) - R_t^f. \tag{14}
\]

Given that \( E_t(R_{t+1}) \) is the actual return, an error term appears as follows:

\[
R_{t,t} = R_t^f + \lambda\Omega_{t+1} x_t + \varepsilon_{t+1}, \tag{15}
\]

where \( \varepsilon_{t+1} \) is an error or unexpected return and is orthogonal in rational expectation.

Subsequently, the equation is rearranged in the risk premium framework:

\[
R_{t,t} - R_t^f = \lambda\Omega_{t+1} x_t + \varepsilon_{t+1}. \tag{16}
\]
In equation (16), the variable $\Omega_{t+1}x_t$ is the variance of the portfolio that reduces to $\sigma_{p_t}^2$ and adapts the new equation to (17), which corresponds to GARCH – M model. This hedging framework includes treasury bill as a risk-free return to obtain the excess. The study employs the SET50 index return as a short hedger and the return of the SET50 index futures as a long hedger.

$$R_{p_t} - R_{f_t}^f = \lambda \sigma_{p_t}^2 + \varepsilon_t$$

(17)

3.3.2 Generalized Autoregressive Heteroskedasticity in the mean model (GARCH-M)

In order to determine degree of risk aversion, Engle et al. (1987) and Chou et al. (1992) introduced a degree of risk aversion model, Autoregressive Conditional Heteroskedasticity in mean (ARCH-M), an univariate model, which explains the relationship between return and its variance, supporting the financial theory, such as Capital Asset Pricing Model (CAPM). The volatility model, ARCH-M, leads to Generalized Autoregressive Conditional Heteroskedasticity in mean GARCH-M, which concerns the heteroscedasticity process in the conditional mean. Moreover, variance is a dependent variable.

According to Demirer et al. (2005), to create two difference hedgers, such as short and long hedgers, the market decision-maker should be a producer or a consumer. One example is the asset allocation strategy. An investor possibly decides to a short or strategy which depends on their aim to increase or reduce beta hedging. Another point is an asymmetric performance between short and long positions leading to the different hedging outcomes.

Regarding hedging strategies, the short hedgers who opened a long position in the stock market and operating a short position for futures. It can determine that short hedgers should concern risk aversion through the stock market because they first make a decision to hold an asset in the stock while long hedgers who short position on the stock exchange and operating a long position for futures. Correspondingly, long hedgers should concern risk aversion based on the futures market as they first make a decision to hold an asset in the futures market. Therefore,
short hedgers (Equations (18) and (19)) appropriately measure risk aversion through the SET50 index, whereas long hedgers (Equations (20) and (21)) appropriately measure risk aversion through the SET50 index futures. Using GARCH-M model and variable, the equation will be as follows:

Short hedgers model:

\[ R_{\text{Short Hedger},t} = \lambda \sigma_{i,t}^2 + \varepsilon_{i,t}, \quad (18) \]

\[ (R_{\text{Stock},t} - R_{t-\text{bill},t}) = \lambda \sigma_{i,t}^2 + \varepsilon_{i,t}. \quad (19) \]

Long hedgers model:

\[ R_{\text{Long Hedger},t} = \lambda \sigma_{i,t}^2 + \varepsilon_{i,t}, \quad (20) \]

\[ (R_{\text{Futures},t} - R_{t-\text{bill},t}) = \lambda \sigma_{i,t}^2 + \varepsilon_{i,t}. \quad (21) \]

Distribution of error term and variance equation follow Equations (22) and (23).

\[ [\varepsilon_{i,t}] \Omega_{t-1} \sim N(0, \sigma_{i,t}^2), \quad (22) \]

\[ \sigma_{st}^2 = c_s + \alpha_0 \varepsilon_{s,t-1}^2 + \beta_0 \sigma_{s,t-1}^2, \quad (23) \]

where \( R_{S,L,t} \) is the portfolio return of short and long hedgers,
\( \varepsilon_t \) is the error term or the unexpected return,
\( \sigma_{st}^2 \) is the variance of the hedged portfolio,
\( \lambda \) is the degree of the risk aversion parameter,
\( \Omega_{t-1} \) is the investor information at time \( t - 1 \).

However, Li (2006) defined the investor regarding only the returns through GARCH-M and lambda define as a risk attitude.

\( \lambda < 1 \) represents a risk-seeking investor
\( \lambda = 1 \) represents a risk neutral investor
\( \lambda > 1 \) represents a risk averse investor
3.4 Optimal Hedge Ratio and Estimation Technique

The second objective is to compare the hedge ratio between the Minimum Variance Hedge Ratio (MVHR) and the Risk Aversion Hedge Ratio (RAHR). The core of the study is to explain the difference between risk minimization and utility maximization by applying quadratic utility and when its hedge ratio incorporates risk aversion. Therefore, if the RAHR differs from the MVHR, then the former will become the alternative hedge ratio for hedgers. However, in the case of the MVHR and the RAHR as the same hedge ratio, we will just call for the MVHR. In this section, the meaning of the hedge ratio is the size of holding the stock index to hedge with the size of holding the futures contract. The study then employs the time-varying volatility model, which is Multivariate Generalized Autoregressive Heteroskedasticity with dynamic conditional correlation model (MGARCH-DCC). This model provides the time-varying hedge ratio for an investor who chooses to vary the proportion of the hedge ratio over time. Subsequently, apart from estimating the econometric model, the study compares the hedge performance between in-sample and out-sample.

The estimation procedure of MGARCH DCC is to run the log return SET50 index as an independent variable and the log return SET50 index futures as a dependent variable in considering the optimal lag term. In prediction of variances, the research will obtain three different variances, such as the SET50 index variance, the SET50 index futures variance, and the covariance between the SET50 index and index futures. Moreover, a substitution for the construction of the MVHR and the RAHR for both in-sample and out-sample emerges. The study then uses rolling variance by using the fixed length. Then, using time rolling the coefficient for variance and expected return for 784 observations. We calculate variances and covariances into the average of each period and also use them as substitutions. Next session 3.4.1 is shown about quadratic utility which is based on coefficient relative of risk aversion (CRRA). This function will be applied to Minimum Variance Hedge Ratio (MVHR) 3.4.2 and Risk Aversion Hedge Ratio (RAHR) 3.4.3.
3.4.1 Quadratic Utility Function

In financial economics, quadratic utility is the most frequently described investor behavior. Given that the assumption under quadratic utility in the mean-variance framework is optimal, which corresponds with portfolio theory, Markowitz (1952) employed quadratic utility as an instrument in the minimum variance portfolio. Correspondingly, Ederington (1979) employed quadratic utility for optimal hedging as follows:

\[ U(W) = W - aW^2, \quad a > 0. \]  

(24)

For the definition of the quadratic utility function, \( W \) is wealth, and \( a \) is a degree of risk aversion by a positive scalar parameter. The first derivative becomes:

\[ U'(W) = 1 - 2aW. \]

(25)

Subsequently, the second derivative of quadratic utility becomes the following:

\[ U''(W) = -2a. \]

(26)

Arrow-Pratt to the coefficient absolute of risk aversion (CARA):

\[ R(W) = \frac{2aW}{1 - 2aW}. \]

(27)

Arrow-Pratt to the coefficient relative of risk aversion (CRRA):

\[ R(W) = w \left[ \frac{2aW}{1 - 2aW} \right]. \]

(28)

Therefore, Alexander (2008) the quadratic utility function (24) has increasing relative aversion, which implies the absolute risk aversion must also be increasing. Hence a risk averse investor with a quadratic utility will increase the percentage of his wealth (and therefore also the absolute amount) invested in risky assets as his wealth increases. However, there are two the limitation of using quadratic utility, First, Arrow (1974) and Pratt (1964) have shown that such a function implies ever increasing absolute risk aversion, that is, reduced risk taking as wealth increases, which contradicts everyday experience. Second, Sarnat (1974) and Wippern (1971) This function has a well-defined maximum beyond which the marginal utility of money declines, and as a result the range of admissible returns must be restricted.
3.4.2 Minimum Variance Hedge Ratio (MVHR)

Ederington (1979) and Myers and Thompson (1989) introduced the hedging theory whose objective is to minimize variance after hedging. However, the Minimum Variance Hedge Ratio (MVHR) assumes that the level of risk aversion converges to infinity Floros and Vougas (2011) and Basher and Sadorsky (2016) or the price follows the martingale hypothesis. It is calculated using Equation (29):

$$\beta = \frac{\sigma_{sf}}{\sigma_{f}^2},$$

(29)

where $\sigma_{f}^2$ is the variance of the SET50 index futures

$\sigma_{sf}$ is the covariance between the SET50 index and the SET50 index futures.

3.4.3 Risk Aversion Hedge Ratio (RAHR)

This hedge ratio is based on the quadratic utility function or the mean-variance hedge ratio. For example, Hsin et al. (1994), S.-S. Chen, Lee, and Shrestha (2003) defined that the investor has focused on a quadratic form that is a representative for maximizing utility. Cotter and Hanly (2010) as well as Conlon et al. (2016) explained that the futures return does not follow the martingale hypothesis, thereby allowing an excess return in the hedge ratio. Subsequently, the risk aversion hedge ratio can be calculated (30) as follows:

$$\beta = -\frac{E(r_f)}{2\lambda \sigma_{f}^2} + \frac{\sigma_{sf}}{\sigma_{f}^2},$$

(30)

where $E(r_f)$ is the excess return of the SET 50 index futures

$\lambda$ is the coefficient relative risk aversion

$\sigma_{f}^2$ is the variance of the SET50 index futures

$\sigma_{sf}$ is the covariance between the SET50 index and the SET50 index futures.
The right-hand side term shows the minimum variance hedge ratio term under risk minimization, and the left-hand side term displays the utility function, in the event that the price does not follow the martingale hypothesis or fair game (no excess return) under utility maximization. Equation (24), thus, explicitly shows that the degree of risk aversion and the excess return of futures possibly determined the hedge ratio. For example, in the case of high risk aversion, the first term becomes less, and the left-hand side term becomes zero, or we call for the martingale process. As stated in the study of S.-S. Chen et al. (2003), the main problem is that before constructing the risk aversion hedge ratio, we need to estimate the aggregate risk aversion parameter. Moreover, the different hedgers will likely play the different hedge ratios, which depends on the risk aversion value.

### 3.4.3 Multivariate Generalized Autoregressive Heteroskedasticity with dynamic conditional correlation model (M-GARCH DCC)

In order to estimate time-varying variance and covariance which are the composition of equation (29) and (30). Generally, the financial framework believes that the time-varying process is more appropriate than the constant process because of the value obtained from time changes over time from the new information in each period. Subsequently, the study employs the M-GARCH DCC, which is introduced by Engle (2000) and Engle and Sheppard (2001). Correspondingly, a desirable practical feature of the DCC models is that multivariate and univariate volatility forecasts are consistent with one another. Massimiliano and Michael (2013) as well as Boffelli and Urga (2016) capture dynamic correlation of variables to change over time. These features are useful to investigate the hedge ratio.

\[ Y = AX_t + \varepsilon_t \] (31)

where

\[ \varepsilon_t = H_t^{1/2} \nu_t \]

\[ H_t = D_t^{1/2} R_t D_t^{1/2} \]

\[ R_t = \text{diag}(Q_t)^{-1/2} Q_t \text{diag}(Q_t)^{-1/2} \]

\[ Q = (1 - \lambda_1 - \lambda_2) R + \lambda_1 \tilde{\varepsilon}_{t-1} \tilde{\varepsilon}_{t-1} + \lambda_2 Q_{t-1} \]
where \( Y_t \) is the \( m \times 1 \) vector of the dependent variables

\( X_t \) is the \( k \times 1 \) vector of the independent variables

\( A \) is the \( m \times k \) matrix parameters

\( H_t \) is the time-varying conditional variance matrix

\( \nu_t \) is the \( m \times 1 \) vector of normal, which are the independent and identically distributed innovations.

\( D_t \) is the diagonal matrix of the conditional variance

\( R_t \) is a matrix of the conditional quasi-correlations of standardized residuals

\( Q_t \) is a symmetric positive definite matrix

\( \tilde{\varepsilon}_t \) is a \( m \times 1 \) vector of standardized residuals

\( \lambda_1, \lambda_2 \) are the parameters of dynamic conditional quasi-correlations and nonnegative parameters with \( 0 \leq \lambda_t + \lambda_t < 1 \).

\[
D_t = \begin{bmatrix}
\sigma_{11}^2 & 0 & \cdots & 0 \\
0 & \sigma_{22}^2 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & 0 & \sigma_{mm}^2
\end{bmatrix}
\quad \quad \text{and} \quad \quad
R_t = \begin{bmatrix}
1 & \rho_{12t} & \cdots & \rho_{1mt} \\
\rho_{21t} & 1 & \cdots & \rho_{2mt} \\
\vdots & \ddots & \ddots & \vdots \\
\rho_{mt1} & \rho_{mnt} & \cdots & 1
\end{bmatrix}
\]

Subsequently,

\[
\sigma_{tt}^2 = c + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{tt-j}^2.
\]

In the heteroscedasticity case,

\[
\sigma_{tt}^2 = \exp(\delta z_t) + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{tt-j}^2.
\]

where \( z_t \) is the \( p \times 1 \) vector of the independent variables that includes a constant term

\( \delta_{it} \) is the \( 1 \times p \) matrix parameters

\( \alpha_j \) are the parameters of ARCH

\( \beta_j \) are the parameters of GARCH.

Notice that multivariate GARCH or bivariate GARCH with the DCC method is the conditional quasi-maximum likelihood estimation. The conditional log likelihood function for a single observation can be written as follows:
\[ LL = -\left(\frac{1}{2}\right) m \log(2\pi) - 0.5 \log \{\det(R_t)\} - \log \{\det(D_t^{1/2})\} - 0.5 \tilde{e}_t R_t^{-1/2} \tilde{e}_t \] (32)

where \( \tilde{e}_t = D_t^{1/2} e_t \) is the \( m \times 1 \) vector of standardized residuals.

Correspondingly, the computation of the hedge ratio through bivariate GARCH provides time-varying collection between stock and futures. Testing optimal lag length by using AIC shows that the optimal lag length is lag four\(^2\). Consequently, the bivariate GARCH(4,1) of stock and futures are given by Equations (33) and (34):

\[ s_t = 1_t \alpha_1 s_{t-1} + \alpha_{12} f_{t-2} + \alpha_{13} s_{t-3} + \alpha_{14} s_{t-4} + \beta_{12} f_{t-2} + \beta_{13} f_{t-3} + \beta_{14} f_{t-4} + e_{it}, \] (33)

\[ f_t = 2_t \alpha_{21} s_{t-1} + \alpha_{22} s_{t-2} + \alpha_{23} s_{t-3} + \alpha_{24} s_{t-4} + \beta_{21} f_{t-1} + \beta_{22} f_{t-2} + \beta_{23} f_{t-3} + \beta_{24} f_{t-4} + e_{2t}, \] (34)

\[ \psi_{t-1} = \begin{bmatrix} \epsilon_{st} \\ \epsilon_{ft} \end{bmatrix} \sim N(0, H_t), \] (35)

where \( \psi_{t-1} \) is the information at time \( t - 1 \).

Subsequently, the variance equation can be shown as follows:

\[ \sigma^2_{ss,t} = c_{ss} + \alpha_{ss} \epsilon_{s,t-1}^2 + \beta_{ss,j-1}^2 \sigma^2_{ss,j-1}, \] (36)

\[ \sigma^2_{ff,t} = c_{ff} + \alpha_{ff} \epsilon_{f,t-1}^2 + \beta_{ff,j-1}^2 \sigma^2_{ff,j-1}, \] (37)

\[ \sigma^2_{sf,t} = c_{sf} + \alpha_{sf} \epsilon_{s,t-1} \epsilon_{f,t-1} + \beta_{sf,j-1}^2 \sigma^2_{sf,j-1}. \] (38)

The formula for the substitute of the time-varying conditional correlation is

\[ \rho_t = \frac{\sigma_{sf,t}}{\sqrt{\sigma^2_{ss,t} \cdot \sigma^2_{ff,t}}}, i \neq j, \] (39)

Where \( \sigma_{sf,t} \) is the conditional covariance between the stock and futures at time \( t \),

\( \sigma^2_{ss,t} \) is the conditional variance of the stock at time \( t \),

\( \sigma^2_{ff,t} \) is the conditional variance of the futures at time \( t \).
3.5 Hedging Performance

The third objective is to find the hedge performance. Because both type hedge ratios obtained by M-GARCH DCC do not clearly explain about optimal hedging performance. Accordingly, the study has to emphasize that these performances would be Average return, Variance, expected utility, Hedge effectiveness and sharpe ratio to compare between the MVHR and the RAHR to ensure that which one is the best.

3.5.1 Average return

The average returns are the main performance to measure among MVHR, RAHR and Unhedged position (UH). The study tends to transform return as an average return to conveniently interpret it. Evidently, Demirer et al. (2005) and Cotter and Hanly (2010) the beta as the hedge ratio is determined in the portfolio return.

Short hedger (MVHR) \[ R_{\text{ShortHedger}} = +r_s - \beta_{\text{MVHR}} r_f, \] (40)

Long hedger (MVHR) \[ R_{\text{LongHedger}} = -r_s + \beta_{\text{MVHR}} r_f, \] (41)

Short hedger (RAHR) \[ R_{\text{ShortHedger}} = +r_s - \beta_{\text{RAHR}} r_f, \] (42)

Long hedger (RAHR) \[ R_{\text{LongHedger}} = -r_s + \beta_{\text{RAHR}} r_f, \] (43)

Short hedger (UH) \[ R_{\text{ShortHedger}} = +r_s, \] (44)

Long hedger (UH) \[ R_{\text{LongHedger}} = -r_s, \] (45)

where \( R_{s,l} \) is the short and long hedger portfolio returns

\( r_s \) is the log return of the SET50 index

\( r_f \) is the log return of the SET50 index futures

\( \beta_{\text{MVHR}} \) is the minimum variance hedge ratio

\( \beta_{\text{RAHR}} \) is the risk aversion variance hedge ratio
3.5.2 Variance

The return on topic 3.5.1 is transformed to the variance term proposed by Floros and Vougas (2011). The study compares the variance of hedged position (H) among the MVHR, the RAHR, and the unhedged position (UH). Subsequently, the calculation is given as follows:

Hedged position case presented in Equation (46):
\[ \text{Var}(H) = \sigma_s^2 + \beta^{2*}_\text{MVHR}\sigma_f^2 - 2\beta^{*}\sigma_{s,f} \, . \] (46)

Unhedged position case presented in Equation (47)
\[ \text{Var}(UH) = \sigma_s^2 \, . \] (47)

However, the MVHR and the UH between the short and long hedgers are similar. Accordingly, we construct four different kinds of the variance to compare Equation (48) with Equation (53).

Short hedger (MVHR)
\[ \sigma_s^2 + \beta^{2*}_{\text{MVHR}}\sigma_f^2 - 2\beta^{*}_{\text{MVHR}}\sigma_{s,f} \, , \] (48)

Long hedger (MVHR)
\[ \sigma_s^2 + \beta^{2*}_{\text{MVHR}}\sigma_f^2 - \beta h^{*}_{\text{MVHR}}\sigma_{s,f} \, , \] (49)

Short hedger (RAHR)
\[ \sigma_s^2 + \beta^{2*}_{\text{RAHR}}\sigma_f^2 - 2\beta^{*}_{\text{RAHR}}\sigma_{s,f} \, , \] (50)

Long hedger (RAHR)
\[ \sigma_s^2 + \beta^{2*}_{\text{RAHR}}\sigma_f^2 - 2\beta^{*}_{\text{RAHR}}\sigma_{s,f} \, , \] (51)

Short hedger (UH)
\[ \sigma_s^2 \, , \] (52)

Long hedger (UH)
\[ \sigma_s^2 \, , \] (53)

where \( \sigma_s^2 \) is a variance of the stock return,
\( \sigma_f^2 \) is a variance of the futures return,
\( \sigma_{s,f} \) is a covariance between stock and future returns
\( \beta_{\text{MVHR}} \) is the MVHR
\( \beta_{\text{RAHR}} \) is the risk aversion variance hedge ratio
3.5.3 Hedge effectiveness of variance minimization

According to Yuan-Hung Hsu, Ho-Chyuan, and Kuang-Hua (2007), to construct and effectively utilize an accurate model, we have to obtain the efficiency conditional volatility. Consequently, a superior model brings about a high hedge. This approach is the efficiency of the minimum-variance presented by Ederington (1979), Yang et al. (2001) whose objective is to compare the effectiveness in the simple hedge ratio and the alternative hedge ratio. Subsequently, the study compares the current period (in-sample) and forecast the future (out-sample). Accordingly, hedge effectiveness can be measured in the percent of variance reduction of hedge portfolio compared with the unhedged portfolio. Hedged Effectiveness (HE) can be expressed as follows:

\[
Hedge\,\,Effectiveness(HE) = 1 - \frac{\text{Variance(Hedged)}}{\text{Variance(Unhedged)}},
\]

\[
Hedge\,\,Effectiveness(HE) = 1 - \left( \frac{\sigma_s^2 + h_s^2 \sigma_f^2 - 2h_s^* \sigma_{s,f}}{\sigma_s^2} \right). \tag{55}
\]

Subsequently, we construct four different kinds of hedge effectiveness to compare the following equations (Equations (56)–(61)):

Short hedger (MVHR)  
\[
1 - \frac{\left( \sigma_s^2 + h_{MVHR}^2 \sigma_f^2 - 2h_{MVHR}^* \sigma_{s,f} \right)}{\sigma_s^2}, \tag{56}
\]

Long hedger (MVHR)  
\[
1 - \frac{\left( \sigma_s^2 + h_{MVHR}^2 \sigma_f^2 - 2h_{MVHR}^* \sigma_{s,f} \right)}{\sigma_s^2}, \tag{57}
\]

Short hedger (RAHR)  
\[
1 - \frac{\left( \sigma_s^2 + h_{RAHR}^2 \sigma_f^2 - 2h_{RAHR}^* \sigma_{s,f} \right)}{\sigma_s^2}, \tag{58}
\]

Long hedger (RAHR)  
\[
1 - \frac{\left( \sigma_s^2 + h_{RAHR}^2 \sigma_f^2 - 2h_{RAHR}^* \sigma_{s,f} \right)}{\sigma_s^2}, \tag{59}
\]

Short hedger (UH)  
\[
equal{0}, \tag{60}
\]

Long hedger (UH)  
\[
equal{0}. \tag{61}
\]
where $\sigma_s^2$ is a variance of the stock return

$\sigma_f^2$ is a variance of the futures return

$\sigma_{s,f}$ is a covariance between stock and futures returns

$\beta_{MVHR}$ is the MVHR

$\beta_{RAHR}$ is the risk aversion variance hedge ratio

Hedge effectiveness can be measured in the percent of variance reduction of the hedge portfolio compared with the unhedged portfolio. Its objective is to compare the hedge effectiveness between the MVHR and the RAHR. Hedge effectiveness that is equal to 1 means that we can obtain 100% absolute reduction in the variance. On the other hand, if hedge effectiveness is equal to 0, then the futures contract can reduce the risk. Accordingly, a large percentage indicates a good hedging performance.

Finally, the optimal hedge ratio that we measure with hedging effectiveness is aware of the posting sample period because the real aim to foresee the optimal hedge ratio with the best econometric model provides the most reduction in variance in the futures in the SET50 futures.

3.5.4 Hedge effectiveness of utility maximization

Hsin et al. (1994), Cotter and Hanly (2010), Cotter and Hanly (2012), as well as Cotter and Hanly (2014) assumed that hedgers’ behavior is a quadratic utility. Therefore, hedging decision depends on a mean-variance framework to maximize their expected utility. In this process, hedge effectiveness in the sense of utility is measured by the percentage of increasing their quadratic utility. However, the study tends to compare the increasing utility between the MVHR and the RAHR to find the distinction between two different hedge ratios.
Hedge Effectiveness = \( V(E(r_{pt}), \sigma_{pt}; \lambda_0) \), \hspace{1cm} (62)

Or

\[
\operatorname{Max}_{w_f} V(E(r, \sigma; \lambda)) = E(r_{pt}) - 0.5 \lambda \sigma_{\mu}^2,
\]

(63)

Where \( E(r_{pt,s}) \) is the expected return of short and long hedgers and stocks

\( \sigma_{pt}^2 \) is the variance of both short and long hedgers and stocks

\( \lambda \) is the degree of risk aversion that is estimated from GARCH-M.

Subsequently, we construct six different kinds of increasing utility to compare one another following Equations (64)–(69):

Short hedger (MVHR) \( E(r_{\text{ShorthedgerMVHR}}) - 0.5 \lambda_{\text{Shorthedger}} \sigma_{\text{MVHR}}^2 \) \hspace{1cm} (64)

Long hedger (MVHR) \( E(r_{\text{LonghedgerMVHR}}) - 0.5 \lambda_{\text{Longhedger}} \sigma_{\text{MVHR}}^2 \) \hspace{1cm} (65)

Short hedger (RAHR) \( E(r_{\text{ShorthedgerSRAHR}}) - 0.5 \lambda_{\text{Shorthedger}} \sigma_{\text{SRAHR}}^2 \) \hspace{1cm} (66)

Long hedger (RAHR) \( E(r_{\text{LonghedgerLRAHR}}) - 0.5 \lambda_{\text{Longhedger}} \sigma_{\text{LRAHR}}^2 \) \hspace{1cm} (67)

Short hedger (UH) \( E(r_{\text{ShorthedgerUH}}) - 0.5 \lambda_{\text{Shorthedger}} \sigma_{S}^2 \) \hspace{1cm} (68)

Long hedger (UH) \( E(r_{\text{LonghedgerUH}}) - 0.5 \lambda_{\text{Longhedger}} \sigma_{S}^2 \) \hspace{1cm} (69)

The utility of hedge effectiveness is typically measured as the certainty equivalent return of the hedged position to compare with the unhedged position. Furthermore, the advantages of the measurement it incorporates expected a return and risk aversion. The result can show whether positive or negative utility. Hsin et al. (1994) pointed out that the hedging effectiveness of using the MVHR (risk minimization) is not likely to produce scores as good as using the risk aversion hedge ratio (utility maximizing) because the MVHR does not consider the return, which is the fundamental framework of the stock and futures markets.
3.5.5 Sharpe ratio

In order to compare the risk management performance between two difference hedge ratio. The sharpe ratio (Sharpe (2007)) is a measurement of investment performance by concerning the risk-adjusted return. The sharpe ratio is formulated by using the excess portfolio return over the risk-free rate relative to its standard deviation or variance. Sharpe ratio’s criterion is a portfolio in which the higher the sharpe ratio, the more return the hedger receives per unit. In another case, if two hedging applications offer the same returns, then the one with a low standard deviation will have a high sharpe ratio. Equation (70) shows the sharpe ratio:

\[
Sharpe\text{ ratio} = \frac{(R_{m} - R_{f})}{\sigma}, \quad (70)
\]

Subsequently, the study is compared with which one provides a high sharpe ratio between in-sample and out-sample performances. These are demonstrated in Equations (71)–(76).

1. Short hedger (MVHR)
\[
Sharpe\text{ ratio} = \frac{(R_{sp} - R_{f})}{\sigma_{MVHR}}, \quad (71)
\]

2. Long hedger (MVHR)
\[
Sharpe\text{ ratio} = \frac{(R_{lp} - R_{f})}{\sigma_{MVHR}}, \quad (72)
\]

3. Short hedger (RAHR)
\[
Sharpe\text{ ratio} = \frac{(R_{sp} - R_{f})}{\sigma_{RAHR}}, \quad (73)
\]

4. Long hedger (RAHR)
\[
Sharpe\text{ ratio} = \frac{(R_{lp} - R_{f})}{\sigma_{RAHR}}, \quad (74)
\]

5. Short hedger (UH)
\[
Sharpe\text{ ratio} = \frac{(R_{sp} - R_{f})}{\sigma_{UH}}, \quad (75)
\]

6. Long hedger (UH)
\[
Sharpe\text{ ratio} = \frac{(R_{lp} - R_{f})}{\sigma_{UH}}, \quad (76)
\]
where

\[ R_{sp} \] is a portfolio return of short hedgers
\[ R_{lp} \] is a portfolio return of long hedgers
\[ R_f \] is a risk-free rate return
\[ \sigma_{MVHR} \] is a standard deviation of using the MVHR
\[ \sigma_{SRAHR} \] is a standard deviation of using the RAHR for short hedgers
\[ \sigma_{SRAHR} \] is a standard deviation of using the RAHR for long hedgers
\[ \sigma_{UH} \] is a standard deviation of the unhedged position.

In this study, the sharpe ratio will be compared with three different types of hedging application such as, the MVHR, the RAHR, and the UH. The portfolio using a return of the SET50 index futures and risk-free rate return will be a three-month treasury bill. Similarly, a standard deviation of using the MVHR between short and long hedgers is the same, whereas a standard deviation of the unhedged position is represented as the variance of stock (3.5.2).

3.6 Estimation Procedure

To summarize the methodology 1. The first objective is to estimate time-varying risk aversion by using GARCH-M and obtaining \( \lambda \) as a degree of risk aversion. This study tries to separate short and long hedgers by following the concept of Demirer et al. (2005), for the reason that the proposed exogenous decision, which depends on market condition and asset allocation, uses this strategy to determine if it increases or decreases beta. Therefore, the study defines that short hedgers concern risk aversion through the SET50 index because they first made a decision to hold an asset in the stock. Meanwhile, long hedgers concern their risk aversion through the SET50 index futures first. Subsequently, time-varying risk aversion between short and long hedgers are applied by the time rolling window, which, in the study, keeps the length unchanged at 2003 window length, resulting in 784 observations. This light contains three years between 2014 and 2016.
2. The second objective has two parts. The first part is called the in-sample (time t). The M-GARCH DCC predicts variance, covariance, and return construct in-sample hedge ratio. Thereafter, time rolling window keeps 2003 window length and rolls forward for 783 observations for time t. Subsequently, these variables are kept as a mean value for the 1-period. The second set of the hedge ratio is called the out-sample. The study used one step ahead forecast in period t+1 by looking forward to 100 observations for variance, covariance, and return. After prediction, we calculate them as a mean for one period. Subsequently, repeat the in-sample step by rolling forward 783 periods. Therefore the study receives variance, covariance, and return of out-sample. The objective is to compare the current and future performances of the hedge ratio. Note that both in-sample and out-sample use the same time-varying risk aversion, which is estimated from the first objective.
CHAPTER 4
EMPIRICAL RESULT

Chapter 4 presents all the empirical results. To understand the mechanism of time-varying risk aversion, the study divided the latter into six parts. The first part displays descriptive statistics during 2006–2016. The next two parts present the unit root test. The study strictly requires the stationary process and estimation procedure, which mainly describe how to estimate degree of risk aversion between short and long hedgers. The last three sections illustrate a time-varying risk aversion parameter between short and long hedgers, estimated by GARCH in mean (GARCH-M) and time rolling windows. Subsequently, the variance–covariance and expected return of the two difference hedgers are predicted by Multivariate-GARCH DCC (M-GARCH DCC) to construct the MVHR and the RAHR. The last part represents the comparison of the hedging performance between the MVHR and the RAHR.

4.1 Descriptive Statistical Result

Starting with Table 4.1., From Panel A to Panel D, most of the periods display positive return, negative skewness, and excess kurtosis (implies Leptokurtic), with the exception of the financial crisis. Subsequently, the Bera–Jarque (B–J) test indicates significance at the 5% levels whose distributions are non-normal for return stock and futures. Panel A shows the full sample, and the study is then separated into four periods to observe the statistic value. Noticeably, Panel C provides negative return due to the financial crisis (subprime crisis), which has an impact on the SET index. Furthermore, this panel has a lower kurtosis than the normal period (Panels A and B), which means additional swing prices. Subsequently, the financial crisis is presented in Panel D, whose return becomes positive but still displays low kurtosis. This scenario implies that after the financial crisis, the investor has faced a high price fluctuation while the pattern of the daily SET50 index futures price series can be seen in Figure.1. Consequently, shock and fluctuation are motivations for this study to examine whether hedging would be effective over such uncertain situation.
Table 4.1
The descriptive statistics of the SET index and futures as an annualized return

Panel A: Full Sample Data (1/05/2006–31/12/2016)

<table>
<thead>
<tr>
<th></th>
<th>Bond</th>
<th>Stock Return</th>
<th>Futures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>0.0166</td>
<td>0.0359</td>
<td>0.0344</td>
</tr>
<tr>
<td><strong>S.D.</strong></td>
<td>0.0004</td>
<td>0.2268</td>
<td>0.2483</td>
</tr>
<tr>
<td><strong>Skewness</strong></td>
<td>0.7061</td>
<td>-0.8549</td>
<td>-0.3616</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td>2.9108</td>
<td>17.7698</td>
<td>10.7159</td>
</tr>
<tr>
<td><strong>Jarque–Bera Test</strong></td>
<td>10.6787***</td>
<td>25653.3786***</td>
<td>6969.2456***</td>
</tr>
<tr>
<td><strong>Observation</strong></td>
<td>127</td>
<td>2,784</td>
<td>2,784</td>
</tr>
</tbody>
</table>

Panel B: Before Financial Crisis (1/05/2006–30/12/2007)

<table>
<thead>
<tr>
<th></th>
<th>Bond</th>
<th>Stock Return</th>
<th>Futures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>0.0274</td>
<td>0.0947</td>
<td>0.0929</td>
</tr>
<tr>
<td><strong>S.D.</strong></td>
<td>0.0004</td>
<td>0.2539</td>
<td>0.2496</td>
</tr>
<tr>
<td><strong>Skewness</strong></td>
<td>-0.1825</td>
<td>-1.9806</td>
<td>-0.8187</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td>1.1819</td>
<td>37.5309</td>
<td>11.2628</td>
</tr>
<tr>
<td><strong>Jarque–Bera Test</strong></td>
<td>2.8656***</td>
<td>21946.6806***</td>
<td>1289.0148***</td>
</tr>
<tr>
<td><strong>Observation</strong></td>
<td>19</td>
<td>435</td>
<td>435</td>
</tr>
</tbody>
</table>

Panel C: During Financial Crisis (01/01/2008–31/12/2008)

<table>
<thead>
<tr>
<th></th>
<th>Bond</th>
<th>Stock Return</th>
<th>Futures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>0.0217</td>
<td>-0.6502</td>
<td>-0.6922</td>
</tr>
<tr>
<td><strong>S.D.</strong></td>
<td>0.0002</td>
<td>0.3750</td>
<td>0.4216</td>
</tr>
<tr>
<td><strong>Skewness</strong></td>
<td>-0.5975</td>
<td>-0.6395</td>
<td>-0.2611</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td>3.2846</td>
<td>8.3740</td>
<td>7.5599</td>
</tr>
<tr>
<td><strong>Jarque–Bera Test</strong></td>
<td>0.8174***</td>
<td>334.4014***</td>
<td>230.8415***</td>
</tr>
<tr>
<td><strong>Observation</strong></td>
<td>12</td>
<td>262</td>
<td>262</td>
</tr>
</tbody>
</table>

Panel D: After Financial Crisis (01/01/2009–30/12/2016)

<table>
<thead>
<tr>
<th></th>
<th>Bond</th>
<th>Stock Return</th>
<th>Futures</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean</strong></td>
<td>0.0137</td>
<td>0.1319</td>
<td>0.1357</td>
</tr>
<tr>
<td><strong>S.D.</strong></td>
<td>0.0003</td>
<td>0.1932</td>
<td>0.2162</td>
</tr>
<tr>
<td><strong>Skewness</strong></td>
<td>0.3720</td>
<td>-0.0863</td>
<td>0.0032</td>
</tr>
<tr>
<td><strong>Kurtosis</strong></td>
<td>1.8560</td>
<td>6.2688</td>
<td>6.7501</td>
</tr>
<tr>
<td><strong>Jarque-Bera Test</strong></td>
<td>7.5267***</td>
<td>932.1914***</td>
<td>1223.5063***</td>
</tr>
<tr>
<td><strong>Observation</strong></td>
<td>96</td>
<td>2,087</td>
<td>2,087</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation

Note: *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.
Figure 4.1
Daily index, return, and volatility of the SET50 index futures during 2006–2016
Time-varying volatility of the SET50 index futures from fitting GARCH (1,1)

Source: Author’s Calculation
4.2 Unit Root Test

In time series data, the occurrence of a non-stationary process, which is spurious problem. Therefore, the augmented Dickey–Fuller’s test (ADF) illustrates the stationary process for time series data. According to the stock index and the futures index, the ADF shows that it cannot reject null hypotheses. Subsequently, the study transforms the stock and futures returns by including trend, intercept, and lag in the model. The null hypothesis is rejected under the ADF and is significant at the 0.05% level. Therefore, the result corroborates that log returns are a stationary process.

4.3 Estimation of Risk Aversion in the SET50 Index and Futures

Table 4.2
Risk aversion between short and long hedgers by full sample 2006–2016

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Short Hedgers</td>
<td>(1.3563)**</td>
<td>3.6666</td>
<td></td>
</tr>
<tr>
<td>Long Hedgers</td>
<td>(1.1869)**</td>
<td>2.9560</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Short Hedger</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Long Hedger</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: Author’s Calculation
Note: *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively. Data in parentheses are t-statistics.

Table 4.3
Time rolling window of risk aversion between short and long hedgers

<table>
<thead>
<tr>
<th>Daily Data</th>
<th>Coefficient Relative of Risk Aversion</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short Hedgers</td>
<td>Long Hedgers</td>
</tr>
<tr>
<td>Observations</td>
<td>783</td>
<td>783</td>
</tr>
<tr>
<td>Mean</td>
<td>3.7999</td>
<td>2.9569</td>
</tr>
<tr>
<td>Min</td>
<td>2.6955</td>
<td>2.0199</td>
</tr>
<tr>
<td>Max</td>
<td>6.1296</td>
<td>5.0187</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.8978</td>
<td>0.7923</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation
Note: *, **, and *** denote significance by using t-test at the 1%, 5%, and 10% levels, respectively.
Table 4.4
Test the difference of risk aversion between 2015 and 2016 for short hedgers by t-test

<table>
<thead>
<tr>
<th></th>
<th>Coefficient Relative of Risk Aversion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2015</td>
</tr>
<tr>
<td>Daily Observations</td>
<td>261</td>
</tr>
<tr>
<td>Mean</td>
<td>3.1722</td>
</tr>
<tr>
<td>Min</td>
<td>2.8041</td>
</tr>
<tr>
<td>Max</td>
<td>3.5976</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.2014</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation

Note: *, **, and *** denote significance by using t-test at the 1%, 5%, and 10% levels, respectively.

Table 4.5
Test the difference of risk aversion between 2015 and 2016 for long hedgers by t-test

<table>
<thead>
<tr>
<th></th>
<th>Coefficient Relative of Risk Aversion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2015</td>
</tr>
<tr>
<td>Daily Observations</td>
<td>261</td>
</tr>
<tr>
<td>Mean</td>
<td>2.4049</td>
</tr>
<tr>
<td>Min</td>
<td>2.1306</td>
</tr>
<tr>
<td>Max</td>
<td>2.7172</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.1449</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation

Note: *, **, and *** denote significance by using t-test at the 1%, 5%, and 10% levels, respectively.
In this section, the estimation of risk aversion is the crucial part for applying the RAHR, which is represented by quadratic utility. The relative risk aversion between short and long hedgers is measured through the SET50 index and the SET50 index futures, respectively. Moreover, the degree of risk aversions is allowed but varies over time because information changes in the financial market every day. Consequently, the time-varying risk aversion (TVRA) of both sets of hedgers possibly changes over time, denoting that the aggregate compensation, which is demanded by investors’ risk aversion for risk bearing, is inconsistent.

The GARCH-M is employed to observe the degree of risk aversion between short and long hedgers to estimate the characteristic of risk aversion. Correspondingly, time rolling window provides the TVRA to construct the time-varying hedge ratio (TVHR). Table 4.2 shows a significant risk aversion parameter between two different hedgers for a full sample estimation to check whether a representative is good before employing time rolling window. The results display that

**Figure 4.2**

Time-varying risk aversion between short and long hedgers during 2014-2016

![Graph showing time-varying risk aversion between short and long hedgers during 2014-2016 with key events: Brexit, Coup d’état, Protestation, and Mourning period for the Majesty.]

Source: Author’s Calculation
it is statistically significant to keep short and long hedgers at the 5% level. For the interpretation of the risk aversion parameter, short hedgers are equal to 3.7%, and if risk increases by 1 percent, then short hedgers require a return of 3.7%. As for relative risk aversion, if wealth increases by 1%, then the proportion invested in risky assets (SET50 index) will increase by 3.7%. Meanwhile, the estimation of risk aversion in long hedgers is equal to 3%, and if risk increases by 1%, then long hedgers require a return of 3%. Relative risk aversion indicates that, if wealth increases by 1%, the proportion invested in risky assets (SET50 index futures) will increases by 3% as well. Intuitively, CRRA shows that short and long hedgers are strongly positive. This scenario implies a positive relationship between risk and expected return and can be explained that, if an investor takes risks, they can require a high return.

Moving on to the time rolling risk aversion parameter, this section provides varied degrees of risk aversion for over three years. Table 4.3 demonstrates mean, maximization, minimization, and standard deviation. The results affirmed that the average risk aversion for short and long hedgers are approximately 3.8% and 2.9%. These results are consistent with Engle et al. (1987), Chou et al. (1992), as well as Cotter and Hanly (2014) who found the evidence of the risk aversion parameter in the range of 0–4 by using GARCH-M. Subsequently, to test the difference between short and long hedgers, the study uses pair t-test to ensure that short and long hedgers can be applied in the optimal hedging strategy. The result demonstrates that short and long hedgers at the 5% level have statistically significant differences, implying that the difference in the degree of risk aversion for short and long hedgers brings different hedging strategies, which are the second objective.

In comparison with the degrees of risk aversion between short and long hedgers, evidently, short hedgers tend to be more risk-averse than long hedgers. The results affirmed that short hedgers react to price change, whereas long hedgers react to price inelasticity. However, this is consistent in Thailand’s financial market; for example, short hedgers can be local investors or local institutions, whereas long hedgers can be foreign investors. By contrast, Demirer et al. (2005) and Cotter and Hanly (2010) confirmed that consumers react more than producers when it comes to hedging. In addition, several reasons to support this contrast emerge. First, these market structures differ because of studies that focus on the commodity market,
whereas this study concerns the index market. Second, the study applies daily data while they concern weekly and monthly data leading to a different outcome Cotter and Hanly (2014). Third, referring to Table 1.1 and 1.2, the investor size on foreign investor (long hedgers) is overshadowed by local investors and local institutions (short hedgers). Consequently, it influences the different degrees of risk aversion for both different hedgers.

Figure 4.2 shows that the risk aversion parameter was low in 2014 due to coup d’état after the protestation of Yingluck Shinawatra. This situation boosted the confidence of investors to invest in the stock and futures markets. The risk aversion parameter improved in 2016. Risk aversion increased by almost twofold. After t-test, short and long hedgers are demonstrated to be statically different (Tables 4.4 and 4.5). For short hedgers, the mean value of the risk aversion parameter was 3.17 in 2015 and 4.52 in 2016, whereas for long hedgers, the mean value of the risk aversion parameter was 2.4 in 2015 and 3.61 in 2016 both at the 5% level. The high risk aversion during 2016 was caused by Brexit in June and the demise of the King in October. This scenario indicates that, during economic recession, risk aversion increases and that, during economic progress, risk aversion diminishes. Therefore, TVRA has an opposite relationship with the business cycle, called countercyclical. These findings correspond with Brandt and Wang (2003), Kim (2014), as well as Cohn, Engelmann, Fehr, and Maréchal (2015) who proposed that risk aversion parameters are countercyclical and given by boom and bust scenarios.

After the study obtained the degree of risk aversion between short and long hedgers. They is taken into the risk aversion hedge ratio (RAHR). It means that RAHR is divided into short hedgers hedge ratio and long hedgers hedge ratio while Minimum Variance Hedge Ratio does not divided as same as RAHR.
### 4.4 Optimal Hedging Strategies

#### Table 4.6

<table>
<thead>
<tr>
<th>Daily</th>
<th>Panel 1: Short Hedgers</th>
<th>Panel 2: Long Hedgers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RAHR</td>
<td>MVHR</td>
</tr>
<tr>
<td>Obs</td>
<td>783</td>
<td>783</td>
</tr>
<tr>
<td>Mean</td>
<td>0.4706</td>
<td>0.8676</td>
</tr>
<tr>
<td>Min</td>
<td>0.2572</td>
<td>0.8038</td>
</tr>
<tr>
<td>Max</td>
<td>0.6461</td>
<td>0.8750</td>
</tr>
<tr>
<td>Stdev</td>
<td>0.0791</td>
<td>0.0071</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation

Note: *, **, and *** denote significance by using t-test at the 1%, 5% and 10% levels, respectively.

#### Table 4.7

<table>
<thead>
<tr>
<th>Daily</th>
<th>Panel 1: Short Hedgers</th>
<th>Panel 2: Long Hedgers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RAHR</td>
<td>MVHR</td>
</tr>
<tr>
<td>Obs</td>
<td>783</td>
<td>783</td>
</tr>
<tr>
<td>Mean</td>
<td>0.4691</td>
<td>0.8677</td>
</tr>
<tr>
<td>Min</td>
<td>0.2547</td>
<td>0.8459</td>
</tr>
<tr>
<td>Max</td>
<td>0.6458</td>
<td>0.8746</td>
</tr>
<tr>
<td>Stdev</td>
<td>0.0794</td>
<td>0.0065</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation

Note: *, **, and *** denote significance by using t-test at the 1%, 5% and 10% levels, respectively.
Figure 4.3
Comparison between the MVHR and the RAHR for short and long hedgers
(in-sample)

Source: Author’s Calculation

Figure 4.4
Comparison between the MVHR and the RAHR for short and long hedgers
(out-sample)

Source: Author’s Calculation
Figure 4.5
The relationship between the risk aversion and the RAHR, which is expressed by short hedgers (in-sample)

Source: Author’s Calculation

Figure 4.6
The relationship between risk aversion and the RAHR, which is expressed by long hedgers (in-sample)

Source: Author’s Calculation
Figure 4.7
The relationship between risk aversion and the RAHR, which is expressed by short hedgers (out-sample)

Source: Author’s Calculation

Figure 4.8
The relationship between risk aversion and the RAHR, which is expressed by long hedgers (out-sample)

Source: Author’s Calculation
The second objective is to divide the study into two main parts. The first part is the comparison between the MVHR and the RAHR. The RAHR incorporates the risk aversion parameter from the first objective based on quadratic utility in- and out-sample. Another part examines the statistical difference between risk minimization and utility maximization using a t-test to ensure that the RAHR can be an alternative hedging concept.

The first part is Table 4.6 which exhibits two different hedge ratios in-sample. To construct time-varying hedge ratio (TVHR), the study predicts variance and covariance by using dynamic conditional correlation (DCC) in order to applied MVHR and RAHR. For short hedgers, the MVHR ranges between 0.80 and 0.88 with the average at 0.87. Therefore, if short hedgers hold the SET50 index for 1 index, then they will on average sell the SET50 index futures at 0.87. For the usage of the RAHR, the range is from 0.26 to 0.65 with the mean at 0.47. Accordingly, if short hedgers hold the SET50 index for 1 index, then they will on average sell the SET50 index futures at 0.47. On the other hand, for long hedgers, the RAHR ranges from 0.09 to 0.6 with a mean value of 0.35. Each index from holding SET50 index, long hedger buy the SET50 index futures at an average of 0.35 by using RAHR while MVHR interpreted as same as the short hedger because it assumes risk aversion converge to infinity.

Table 4.7 provides a summary for the hedge strategies from out-sample. The reason of construction out-sample is considerable with future performance. Accordingly, one-step advance forecast for 100 observations is applied to the study. The range of MVHR is between 0.85 and 0.87 with the mean average at 0.87. For short hedgers, the RAHR ranges from 0.25 to 0.65 with the mean at 0.47. For long hedgers, the RAHR ranges from 0.25 to 0.65 with the mean average at 0.47. The results from in-sample and out-sample confirm that the RAHR and MVHR ranges are close. Both sample periods consistently report the outcome that short hedgers have higher risk aversion than long hedgers and possibly has a higher hedge ratio in their portfolio in using the RAHR, whereas the MVHR does not make the distinction between the two different hedgers. However, this objective has clearly implied that conducting a TVRA influences the optimal hedging strategies by using the RAHR.
Figures 4.3 and 4.4 depict the comparison among the MVHR, RAHR (short), and RAHR (long) for in-sample and out-sample for 783 observations. It can be seen as a figure 4.2, a negative financial situation affected the Thailand stock and futures markets. Consequently, risk aversion increased and forced hedgers to use a high RAHR in 2016, whereas the MVHR remained stable for the whole period. In the recession period, hedgers tend to use high hedge ratios, whereas in the recovery period, they use low hedge ratios, which leads to the context of figure 4.3 and 4.4. These charts provide the scatter plots for the relationship of CRRA and the RAHR between short and long hedgers in-sample, figure 4.5, 4.6 and out-sample, figure 4.7, 4.8. The scatter plots indicate the positive relationship between risk aversion and hedge ratios. Therefore, all cases imply that increase in risk aversion results to significant more hedge ratio. Noticeably, a very high RAHR creates possibility of merging toward the MVHR line.

The second part is t-test is employed to explain the difference between hedging strategies, Table 4.2 and 4.3. The result affirms that, at the 0.05% level, statistically significant differences occur between risk minimization (MVHR) and utility maximization (short and long RAHR) for in-sample and out-sample and shows the substantial difference of using two different hedge ratios. Therefore, investors can utilize two different hedge ratios depending on their situation. Consequently, if an investor wishes to provide the lowest risk, then the MVHR may work. However, if an investor needs to receive sanctification, then the RAHR may be good for hedgers. Nonetheless, all cases of the RAHR are lower than those of the MVHR, which can be explained that the actual risk averse is taken into account. The RAHR for short and long hedgers will exhibit reality of using hedge ratios compared with the MVHR because the RAHR is based on actual aggregate risk aversion, whereas the MVHR assumes that risk aversion converts to infinity. Results in the MVHR may create a sense of cost advantage which is explained in the next topic. Therefore, the estimation of relative risk aversion from GARCH in mean provides the suitable variable to construct the RAHR whose concept does not follow the martingale hypothesis and leads to the allowance of excess return and risk aversion to the formula. After the study obtains two difference hedge ratio (MVHR, RAHR). They are compared by the hedging performance in section 4.5.
### 4.5 Hedging Performance

#### Table 4.8

<table>
<thead>
<tr>
<th></th>
<th>Panel 1: Short Hedgers</th>
<th>Panel 2: Long Hedgers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(×10^4)</td>
<td>(×10^4)</td>
</tr>
<tr>
<td>RAHR</td>
<td>0.3010</td>
<td>0.0046</td>
</tr>
<tr>
<td>MVHR</td>
<td>0.6685</td>
<td>0.2273</td>
</tr>
<tr>
<td>Unhedged</td>
<td>4.1968</td>
<td>1.0456</td>
</tr>
<tr>
<td>ER</td>
<td>2.9265</td>
<td>0.6138</td>
</tr>
<tr>
<td>EU</td>
<td>(×10^4)</td>
<td>(×10^4)</td>
</tr>
<tr>
<td>SR</td>
<td>0.0088</td>
<td>0.0100</td>
</tr>
<tr>
<td>HE</td>
<td>70.37%</td>
<td>89.90%</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation

Note: Mean, variance, expected return (ER), expected utility (EU), sharpe ratio (SR), and hedging effectiveness (HE) are displayed for the RAHR, the MVHR, and a No hedge position.

#### Table 4.9

<table>
<thead>
<tr>
<th></th>
<th>Panel 1: Short Hedgers</th>
<th>Panel 2: Long Hedgers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(×10^4)</td>
<td>(×10^4)</td>
</tr>
<tr>
<td>RAHR</td>
<td>0.2996</td>
<td>0.0044</td>
</tr>
<tr>
<td>MVHR</td>
<td>0.6772</td>
<td>0.2279</td>
</tr>
<tr>
<td>Unhedged</td>
<td>4.2234</td>
<td>0.9776</td>
</tr>
<tr>
<td>Return</td>
<td>2.9370</td>
<td>0.5446</td>
</tr>
<tr>
<td>Variance</td>
<td>(×10^4)</td>
<td>(×10^4)</td>
</tr>
<tr>
<td>SR</td>
<td>0.0099</td>
<td>0.0098</td>
</tr>
<tr>
<td>HE</td>
<td>69.88%</td>
<td>89.84%</td>
</tr>
</tbody>
</table>

Source: Author’s Calculation

Note: Mean, variance, expected return (ER), expected utility (EU), sharpe ratio (SR), and hedging effectiveness (HE) are displayed for the RAHR, the MVHR, and a No hedge position.
The third objective illustrates among six hedging performances, namely, return, variance, expected return, expected utility, sharpe ratio, and hedge effectiveness, which are based on quadratic utility. Subsequently, the MVHR, the RAHR, and the UH are compared through those performances. Nevertheless, time-varying risk aversion (TVRA) which provides 784 values for the result. Therefore, Tables 4.8 and 4.9 are exhibited as the average value.

Table 4.8 displays in-sample performance and clearly shows that short hedgers have a good performance in terms of the RAHR. For the mean of return, short hedgers receive a high rate in the RAHR with 0.003%, whereas the MVHR provides 0.00004%. The result confirms a trade-off between risk and return if investors pursue to minimize risk; they have to accept the low return from using the MVHR. Next is variance, UH performs the highest variance compared to MVHR and RAHR. Looking at MVHR provides the lowest variance compared with RAHR and UH. Interestingly, the performance of expected utility which is the main aim of the study shows that using RAHR provides higher utility than using MVHR. The RAHR offers increasing utility at 0.0029% whereas MVHR gives 0.000098%. Apparently, investors are more satisfied when they choose RAHR to hedges SET50 index futures.

However, sharpe ratio performance demonstrates that MVHR is superior in term of managing risk to RAHR because the average sharpe ratio of MVHR, Short RAHR are 0.01, 0.088, respectively. It can be interpreted that for every point of return, short hedgers are shouldering 1 risk unit while long hedgers are shouldering 0.9 units of risk and long hedgers are shouldering 0.88 units of risk. For hedge effectiveness, MVHR achieves the lowest risk at 89.9% risk reduction. The reason MVHR has the highest sharpe ratio is due to MVHR which requires only risk minimization so it may better risk management while RAHR regards hedger utility as a higher return. Noticeably, although MVHR has a higher level of the risk management than RAHR, their sharpe ratio is close each other.

For long hedgers, reports contrast result to short hedgers. It shows that in all performance MVHR plays the better role than RAHR. Moving for detail, the mean return of MVHR is -0.0046% and RAHR is -0.3225% in which MVHR provides a higher return than using RAHR. For variance, MVHR exhibits a lower variance than RAHR whereas UH still has the highest variance of 0.0231%. For sharpe ratio MVHR
exhibits higher than RAHR, 0.01, 0.09, respectively. The expected utility for this case depicts that MVHR has higher expected utility than RAHR as shown by a negative return. As for hedge effectiveness, the MVHR has the lowest risk at 89.9% reduction. In long hedgers’ perspective, RAHR variance reduction risk is 56.73%. Therefore, long hedgers prefer to use MVHR in hedging than RAHR.

Table 4.9 focuses on out-sample performance. Comparison between RAHR and MVHR are almost consistent result to in-sample. Result displays that MVHR is still eclipsed by RAHR for short hedgers. In RAHR’s mean of return performance, short hedgers have a rate of return at -0.0032% while MVHR is -0.0044%. For variance, MVHR still performs with the lowest variance compared with RAHR and UH. Sharpe ratio illustrates that RAHR is higher than MVHR because of the average sharpe ratio of Long RAHR, Short RAHR and MVHR are 0.01, 0.0099, and 0.0098 respectively. Accordingly, out sample of RAHR provides every point of return on bearing units of risk which is higher when MVHR is used. In the same way expected quadratic utility for RAHR is increasing at 0.0294% and MVHR increases lower than RAHR at 0.0054%. Subsequently, hedge effectiveness provides the lowest risk for MVHR at 89.8% reduction whereas RAHR plays a risk reduction at 69.9%. Overall, short hedgers perform better in RAHR than MVHR. For long hedgers, the result exhibits the same as in the sample. If long hedgers intend to measure the futures performance, they still prefer to use MVHR to hedging than RAHR.

Both in-sample and out-sample show such the interesting results that short hedgers tend to have the better performance than long hedgers. Noticeably, in the in-sample and out-sample of Unhedged position, although it precisely provides higher utility than RAHR, it obtains the higher risk which corresponds with the high-risk=high return belief. Another point is unhedged position which is only invest in stock market (SET50 index) and not concern the relationship between two difference market so there are not related in the hedging framework. However, both strategies implied that RAHR is potentially weightier on utility and risk whereas MVHR focuses only in minimizing risk. Otherwise, there is still uncertainty on determining which strategy will perform better, we could follow the cue that for short hedgers RAHR may work same as long hedger prefer to hedge with MVHR.
CHAPTER 5
CONCLUSION

5.1 Conclusion

The combination of price volatility and unexpected situation causes hedging strategies in the index market. This study introduces alternative hedging applications for hedgers who demand to match their objective (i.e., short and long positions). Similarly, maximizing utility is highlighted in hedging application based on risk preference in the index market with two different hedgers. Consequently, the degree of risk aversion is vital in introducing alternative hedge ratio through the quadratic utility (i.e., RAHR). Attitude to risk is also applied to the hedging framework in order to reflect the hedger’s risk preference by using GARCH in the mean. Thus, time-varying risk aversion (TVRA) is a proxy to time-varying hedge ratio, which means that hedgers will receive significant information to make a new decision under their portfolio.

In this study, GARCH-M is employed and derived from the mean–variance optimization framework and estimates the relationship between risk and variance. The attitudes of short and long hedgers toward risk is also explained by CRRA. Time rolling window is then used as proxies to ensure a stable coefficient. Thereafter, two types of hedge ratio are constructed using the variance and covariance and are predicted in multivariate GARCH-DCC. In addition, testing current performance (in-sample) and forecasting future performance (out-sample) provide the present attitude of hedgers against futures attitude.

Empirical findings show that short hedgers tend to react more to risk preference than long hedgers because the current stock market is more volatile than futures which influence the determination of hedging strategies. When scattering plot, RAHR presents the positive relationship between the degree of risk aversion and hedge ratio, which means that when facing high risk aversion, hedgers tend to spend more hedge ratio. Significant statistical and economical difference exist between RAHR and MVHR. When actual risk aversion is incorporated into the hedge ratio, a lower hedge ratio is observed than the assumed infinity risk which affects the cost.
Furthermore, the risk preferences of the hedger change over time which is especially veritable in the recent timeframe. The risk aversion of the two hedgers decreased in 2014 and increased over twofold in 2016 which can be a sentiment index for investors.

For hedging performance, this study proposed an average risk aversion parameter as this appropriately represents the mean expected utility. These findings present short hedgers as superior to long hedgers in terms of portfolio return, risk, hedge effectiveness, and utility when using RAHR. In the expected utility performance for short hedgers, RAHR is greater than MVHR, whereas for long hedgers, RAHR is overshadowed by MVHR both in in- and out-samples. The comparison between in- and out-samples of short hedgers explains that the in-sample possibly performs better than the out-sample, whereas the long hedger out-sample tends is better than the in-sample. The empirical findings indicate that the degree of risk aversion is an essential input that clearly affects the choice of index hedging strategy.

The overall comparison of two different hedge ratios show that the advantages from using RAHR are as follows: First, RAHR incorporates a degree of risk aversion. This phenomenon means that hedge ratio, based on actual investor risk aversion, varies in the Thailand economy, whereas that of MVHR assumes that risk aversion converges to infinity, leading to a constant and suboptimal hedging framework. Second, RAHR can hold the concept of hedging strategies between short and long hedgers, whereas MVHR ignores the variations in types of hedgers with different risk attitudes.

5.2 Discussion

Based on CRRA, results show a strong positive relationship which means that when investors face higher risk, they will require more returns. Interestingly, the crucial part of the study is that risk aversion parameter varied over time as supported by Engle et al. (1987), Chou et al. (1992), and Ann and Shrestha (2009), who explained that changing economic structures, market imperfections, and incomplete information affect the attitude of investors toward risk. Consequently, Cotter and
Hanly (2010) explained that TVRA causes an inconstant risk bearing among investors. Moreover, TVRA has a contradictory relationship with the Thailand business cycle. These findings correspond with those by Brandt and Wang (2003), Kim (2014), and Cohn et al. (2015), who found that risk aversion parameter is counter-cyclical and provided by a boom and bust scenario.

The significant differences between RAHR and MVHR have economic importance; subsequently, when explicit risk aversion is considered, expected utility and risk minimizing are substantially different. Another finding is that the estimation of RAHR is generally lower than MVHR because the latter is under the assumption of risk aversion, which converges to infinity. This finding is consistent with the actual situation wherein investors do not need to receive high-risk aversion because it causes cost disadvantage, which further corresponds with the results by Cotter and Hanly (2010). Although a minimum variance hedge ratio is provided to minimize risk, it is costly for hedgers. Therefore, this finding lets RAHR discuss the net benefit. Similarly, Thailand's financial market has a short period of shock; thus, RAHR, which is based on actual risk aversion, may be suitable for hedgers. Therefore, the measurement of expected utility by Hsin et al. (1994) and W. Chen (2009) led to the advantages of using RAHR, which reflect hedger disapproval in demanding high hedge ratios. Finally, hedgers are satisfied because they receive high net benefits.

5.3 Policy Implication

Several sectors, such as Stock Exchange of Thailand (SET), Researcher, Policymakers, Securites Company, and the Securities and Exchange Commission (SEC), provide guidance considering the degree of risk aversion and risk aversion hedge ratio. To understand investor’s risk preference (risk aversion), SET should implement a domestic degree of risk aversion as an investor sentiment index to decide between economic recession and recovery. Similarly, researchers ought to develop and extend the knowledge on hedging application. For example, researchers may develop the efficiency method (econometric model or simulation) to estimate the actual risk aversion parameter. In addition, policymakers can persuade investors by using the alternative hedging application RAHR whether situated in a short or long...
position during the normal period. During the bust period, policymakers may offer MVHR to investors in order to ensure minimal risk or use bond to decrease risk during the uncertainty period because bonds are considered as a risk-free asset. Moreover, investors should be coupled with a diversified portfolio to decrease volatility that reduces portfolio damage. Subsequently, the broker and fund manager (securities company) should consider degree of risk aversion to inform the appropriate hedge ratio to a hedger. This finding is a significant advantage because when hedgers experience convenience and obtain updated information, they demand increase service. Consequently, the SEC office should reveal and regulate correct information about an alternative hedging technique (RAHR) before informing investors because market anomalies, such as manipulation, holiday effect, and January effect, sometimes occur leading to bias estimation in the degree of risk aversion. Therefore, symmetric information is essential for investors. Furthermore, SEC should enforce a policy that limits the access of internal people on confidential information to avoid exploitation of this information in exchange for profit. Additionally, SEC should accentuate transparent information in the financial instrument and ensure that investor information are considered correctly in hedging.

5.4 Recommendation for Investors

The examination of hedging performance using SET50 index futures shows an effective portfolio in variance reduction. Although MVHR possibly reduces risk by more than 80%, it offers low returns due to a tradeoff between risk and return. Therefore, RAHR may relieve this problem because it not only separates short and long strategies but also performs better than MVHR in compensating the net return and cost reduction. Additionally, the need to hedge of investors is generally costly. The number of users present in the contract determines how high the cost will be. Consequently, MVHR may cause the cost to hedger, and new hedging application (RAHR) can exacerbate this problem. Other considerable issues are news, shock, and trend.
5.5 Limitation

This study examines the effect of risk aversion by obtaining TVRA, based on hedge ratio with quadratic utility framework. This function is vital to come up with descriptions that are mathematical and economical because these features are slowly diminishing. However, there are numerous utility functions and other information which can describe the investor’s behavior such as logarithmic utility or exponential utility. Therefore, for further study, we will have more concern about other utility function forms which beneficially describe hedger in stock index and futures index market.

Another point is the data frequency; we concern the standard data which is daily data, SET50 index, and SET50 index futures. Meanwhile, the time horizon which is an examination of different frequency to observe investor behavior is an interesting part but for this study. However, we cannot test if the observation in the data stream is sufficient to run the series model for a couple of times. For example, weekly and monthly examinations are limited at ten years (The first opened in Thailand Futures Exchange) and contain around 100–500 observations. Thus, it shows insignificance in time series data while other markets opened more than ten years, giving them enough data to examine time horizon. For further studies or possibly application, other high frequency data such as hourly intraday 30-minute data should be gathered but cost for access is high.
REFERENCE

Books


Article


APPENDICES
APPENDIX A

A. ASSET PRICING WITH CRRA

This derivation is to illustrate the relationship between risk premium and risk aversion. In microeconomic framework, showing that certainty equivalent is a guaranteed return of investor accept and avoid to holding the risky asset. However, if investor increases their certainty equivalent, it has meant that they are a high-risk aversion. Hence, the study now shows in the mathematical term by providing three assumptions.

1. The growth of Consumption is i.i.d.

\[
\log \frac{C_{t+1}}{C_t} = u_c + \varepsilon_{c,t+1} - \frac{\sigma^2_c}{2}
\]  

(1)

2. Return are log-normally distribution

\[
(1 + r_{i,t+1}) = (1 + \bar{r}) \exp \left\{ \varepsilon_{i,t+1} - \frac{\sigma^2}{2} \right\}
\]  

(2)

3. Determining utility function

\[
U(C) = \frac{C^{1-\gamma}}{1-\gamma} \text{ (CRRA Utility)}
\]  

(3)

Mehra (1985) the original study which presented the equity premium puzzle. It assumed that agent is maximized a time-separable with CRRA utility function and \( C_t \) is defined as an aggregate consumption.

\[
U(C) = \frac{C^{1-\gamma}}{1-\gamma} \text{ (CRRA Utility)}
\]  

(4)

Where \( \gamma \) is the coefficient of relative risk aversion (CRRA).
Cambell (2003) the advantage of power utility is scale-invariant. The constant term of return, risk premium, and its distribution keep unchanged as aggregate wealth and the scale of economy growth. This issue is essential on account of past two centuries that consumption and wealth have raised many times. Nevertheless, risk premium and risk-free interest rate do not experience to have an increase or decrease trend. The CRRA utility function is the one utility which is corresponding in fact. Nonetheless, Epstein and Zin (1991) have theoretically presented more specification CRRA utility by they separate between CRRA and intertemporal substitution.

Set Euler equation

$$1 = \beta E_t \left[ (1 + r_{t+1}^i) \frac{U'(C_{t+1})}{U'(C_t)} \right], \quad \forall \in \{s, b\} \tag{5}$$

From Euler equation suppose that $U(C) = \frac{C^{\gamma}}{1 - \gamma}$

$$1 = \beta E_t \left[ (1 + r_{t+1}^i) \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \right] \tag{6}$$

Then, antilog becomes exponential function

$$1 = \beta E_t \left[ (1 + r_{t+1}^i) \exp \left( -\gamma \log \left( \frac{C_{t+1}}{C_t} \right) \right) \right] \tag{7}$$

$$1 = \beta E_t \left[ (1 + r_{t+1}^i) \exp \left( -\gamma \log \left( u_c + \varepsilon_{c,t+1} - \frac{\sigma_i^2}{2} \right) \right) \right] \tag{8}$$

$$1 = \beta E_t \left[ (1 + r_{t+1}^i) \exp \left( \frac{\sigma_i^2}{2} \right) \exp \left( -\gamma \log \left( u_c + \varepsilon_{c,t+1} - \frac{\sigma_i^2}{2} \right) \right) \right] \tag{9}$$

$$1 = \beta E_t \left[ (1 + r_{t+1}^i) \exp \left( \varepsilon_{i,t+1} - \frac{\sigma_i^2}{2} \right) \exp \left( -\gamma \log \left( u_c + \varepsilon_{c,t+1} - \frac{\sigma_i^2}{2} \right) \right) \right] \tag{10}$$
\[
0 = \log \beta + \log E_t \left[ \exp \left\{ \log(1 + r_{i,t+1}) \right\} \right]
\]
\[
\exp \left\{ \varepsilon_{i,t+1} - \frac{\sigma_i^2}{2} - \gamma \left( \mu_c + \varepsilon_{c,t+1} - \frac{\sigma_c^2}{2} \right) \right\}
\]

(11)

We know that
\[
\log(1 + \bar{r}^i) \approx \bar{r}^i \quad \text{and} \quad \varepsilon_i \sim N(\mu, \sigma_i^2)
\]
\[
\log E[\exp \{ \varepsilon_i \}] = \mu + \frac{\sigma_i^2}{2}
\]

(12)

We also assume that
\[
\varepsilon_{i,t+1} \sim N(0, \sigma_i^2)
\]
\[
\varepsilon_{c,t+1} \sim N(0, \sigma_c^2)
\]

(13)

and
\[
\log E[\exp \{ \varepsilon_i \}] = \mu + \frac{\sigma_i^2}{2}
\]

(14)

then
\[
0 = \log \beta + \bar{r}^i + \frac{\sigma_i^2}{2} - \gamma u_c - \frac{\gamma^2 \sigma_c^2}{2} - \frac{2\gamma}{2} \text{cov}(\varepsilon_{i,t+1}, \varepsilon_{c,t+1})
\]

(15)

\[
\bar{r}^i = -\log \beta + \gamma u_c + \frac{\gamma(\gamma - 1)}{2} \sigma_c^2 + \gamma \text{cov}(\varepsilon_i, \varepsilon_c)
\]

(16)

The equation (16) is a comovement between return asset and consumption.

We assume that Bond as a risk-free rate the equation (16) become the equation (17)

\[
\bar{r}^f = -\log \beta + \gamma u_c + \frac{\gamma(\gamma - 1)}{2} \sigma_c^2
\]

(17)

\[
\bar{r}^f = -\log \beta + \gamma u_c + \frac{\gamma(\gamma - 1)}{2} \sigma_c^2 + \gamma \text{cov}(\varepsilon_s, \varepsilon_c)
\]

(18)

Use the equation (17) subtract equation (18) becomes

\[
\bar{r}^b - \bar{r}^f = \gamma \text{cov}(\varepsilon_s, \varepsilon_c)
\]

(19)

The risk premium show as logarithm which is the CRRA multiplied by the covariance of the asset return with consumption growth. Hence, risk aversion is influenced by the risk premium.
APPENDIX B

B. DERIVATION OF THE MINIMUM VARIANCE HEDGE RATIO (MVHR)

The hedged portfolio of short strategy is taken to MVHR due to convenience. However, MVHR formula of short and long hedgers is similar.

\[ R_p = r_s - \beta r_f \]

Where \( R_s \) is the stock return.
\( R_f \) is the futures return.
\( \beta \) is hedge ratio

Then, transform to variance term

\[ Var(R_{p,t}) = Var(R_{s,t}) - 2\beta COV(r_{s,t}, r_{f,t}) + \beta^2 Var(r_{f,t}) \]

First order condition to provide optimal hedge ratio:

\[ \frac{d(Var(R_p))}{d\beta} = -2COV(r_{s,t}, r_{f,t}) + 2\beta Var(r_{f,t}) \]

Then, find the critical value of beta by rearranging:

\[ \beta = \frac{COV(r_{s,t}, r_{f,t})}{Var(r_{f,t})} \]

\[ \beta = \frac{\sigma_{sf}}{\sigma_{f}} \]

Where \( COV(r_{s,t}, r_{f,t}) \) is covariance between stock and futures
\( Var(r_{f,t}) \) is a variance of futures
APPENDIX C

C. DERIVATION OF THE RISK AVERSION HEDGE RATIO (RAHR)

\[ R_p = r_s - \beta r_f \] (1)

Where  
- \( R_s \) is the stock return.  
- \( R_f \) is the futures return.  
- \( \beta \) is hedge ratio.

Rearranging in quadratic utility function becomes:

\[ EU(R_p) = E(r_p) - \lambda \text{Var}(r_p) \] (2)

Then, substitute equation (1) in equation (2) becomes:

\[ \text{Max } E(U(R_p)) = \text{Max}[(E(r_p) - \beta E(r_f)) - \lambda(\text{Var}(r_f) + \beta^2 \text{Var}(r_f) - 2\beta \text{COV}(r_s, r_f))] \] (3)

First order condition to provide optimal hedge ratio:

\[ \frac{d\left( \text{Var}(R_p) \right)}{d\beta} = -E(r_f) - \lambda 2\beta \text{Var}(r_f) + 2\lambda \text{COV}(r_s, r_f)) \] (4)

\[ \beta = \frac{-E(r_f) + 2\lambda \sigma_{sf}}{2\lambda \sigma_{ft}^2} \] (5)

\[ \beta = -\frac{E(r_f)}{2\lambda \sigma_{ft}^2} + \frac{\sigma_{sf}}{\sigma_{ft}^2} \] (6)

Where \( E(r_f) \) is the excess return of futures.  
- \( \lambda \) is the coefficient of risk aversion (CRRA).  
- \( \sigma_{sf}^2 \) is the variance of futures.  
- \( \sigma_{sf} \) is the covariance between stock and futures.
APPENDIX D

D. ROBUSTNESS CHECK

This part is shown in Table D.1 which check that time-varying risk aversion is stability over the situation. First and Foremost, before financial crisis period, the risk aversion of short hedgers is 2.8183 while long hedgers are 3.4995. However, during the financial crisis is shown the negative relationship between risk and return which short hedger is -0.1663 and long hedgers is -1.0649. It can be seen that that index investor was prepared to accept a lower expected return for a given level of risk. Noticeably, both before and during the financial crisis is insignificant because the number of data is insufficient to describe the model. Turning on to after financial crisis is significant at 5% level. The degree of risk aversion is higher because it is an experience for investor during the financial crisis.

Table D.1
Risk aversion parameter by separation for four periods.

<table>
<thead>
<tr>
<th>Panel A : Full sample data (1/05/2006 – 31/12/2016)</th>
<th>Short Hedgers</th>
<th>Long Hedgers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk aversion</td>
<td>(2.70)***</td>
<td>(2.49)**</td>
</tr>
<tr>
<td></td>
<td>3.6618</td>
<td>2.9562</td>
</tr>
<tr>
<td>Panel B : Before financial crisis (1/05/2006 to 30/12/2007)</td>
<td>Short Hedgers</td>
<td>Long Hedgers</td>
</tr>
<tr>
<td>Risk aversion</td>
<td>(0.77)</td>
<td>(1.07)</td>
</tr>
<tr>
<td></td>
<td>2.8183</td>
<td>3.4995</td>
</tr>
<tr>
<td>Panel C : During financial crisis (01/01/2008 to 31/12/2008)</td>
<td>Short Hedgers</td>
<td>Long Hedgers</td>
</tr>
<tr>
<td>Risk aversion</td>
<td>(-0.06)</td>
<td>(-0.47)</td>
</tr>
<tr>
<td></td>
<td>-0.1663</td>
<td>-1.0649</td>
</tr>
<tr>
<td>Panel D : After financial crisis (01/01/2009 to 30/12/2016)</td>
<td>Short Hedgers</td>
<td>Long Hedgers</td>
</tr>
<tr>
<td>Risk aversion</td>
<td>(3.22)***</td>
<td>(2.85)***</td>
</tr>
<tr>
<td></td>
<td>5.4735</td>
<td>4.4005</td>
</tr>
</tbody>
</table>

Source : Author’s Calculation
Note : *, **, *** denote significance at the 1%, 5% and 10% levels, respectively.
Data in parenthesis are t-statistics.
APPENDIX E

E.OPTIMAL LAG LENGTH

Estimation Multivariate-GARCH is included VAR model, so optimal lag length is the essential process to generate VAR. In order to provide the efficient in variables (stock, futures), so the study purpose to choose the minimum information criteria (IC) will be the optimal lag in VAR model. Table E.1 demonstrated the optimal lag length for the SET50 index (rprestock), SET50 index futures (rprefutures). The minimum AIC presented in lag 4 while SBIC provides lag 10 (AIC=-13.6378, SBIC=-13.5707). In order to provide the consistent in information criteria, numerous economics study prefers SBIC than AIC. Therefore, the study decided to use lag 4 as an optimal lag to apply with Multivariate GARCH-DCC.

Figure E.1
Optimal lag length for max lag 10 lags

```
varsoc rprestock rprefutures , maxlag(10)
Selection-order criteria
Sample:  12 - 2785                           Number of obs      =      2774
+---------------------------------------------------------------------------+
|lag |    LL      LR      df    p      FPE       AIC      HQIC      SBIC    |
|----+----------------------------------------------------------------------|
|  0 |  18580.7                      5.2e-09  -13.3949  -13.3934  -13.3906  |
|  1 |  18767.8  374.16    4  0.000  4.6e-09  -13.5269  -13.5223  -13.5141  |
|  2 |  18808.5  81.378    4  0.000  4.5e-09  -13.5534  -13.5456  -13.532  |
|  3 |  18877.3  137.58    4  0.000  4.3e-09  -13.6001  -13.5893  -13.5702  |
|  4 |  18893.9  33.107    4  0.000  4.2e-09  -13.6091  -13.5952  -13.5707* |
|  5 |  18903.4  18.99     4  0.001  4.2e-09  -13.6131  -13.5961  -13.5661  |
|  6 |  18911.3  15.871    4  0.003  4.2e-09  -13.6159  -13.5959  -13.5604  |
|  7 |  18930.4  38.231    4  0.000  4.1e-09  -13.6268  -13.6037  -13.5627  |
|  8 |  18938.3  15.859    4  0.003  4.1e-09  -13.6297  -13.6034  -13.5557  |
|  9 |  18952  27.302    4  0.000  4.1e-09  -13.6366  -13.6073* -13.5554  |
| 10 |  18957.6  11.312*   4  0.023  4.1e-09* -13.6378* -13.6054  -13.5481  |
+---------------------------------------------------------------------------+

Endogenous:  rprestock rprefutures
Exogenous:  _cons
Source : Authors Calculation
```
APPENDIX F

F. IN SAMPLE AND OUT SAMPLE COMMAND

F.1 Predict return in sample command

```plaintext
mat re_turn=[9999, 9999]
set more off
forv start= 0/784 {
    local end = `start' + 2004
    if t> `start' & t< `end', arch(1) garch(1) nolog
    predict R*,xb
    *R_rprestock and R_rprefutures
    egen mean_ss_`start' `end'=mean(R_rprestock)
    egen mean_ff_`start' `end'=mean(R_rprefutures)
    su mean_ss_`start' `end', meanonly
    mat a1=r(mean)
    su mean_ff_`start' `end', meanonly
    mat a2=r(mean)
    mat re_turn= [re_turn\ a1, a2]
    drop R* mean*)
}
mat2txt2 re_turn using D:\result\re_turn.xls, replace matname
```
F.2 Predict return out sample command

mat re_turn=[9999, 9999]
set more off
tsappend, add(100)
forv start= 0/784 {
    local end = `start' + 2004

    if t> `start' & t< `end', arch(1) garch(1) nolog
        predict R*,xb dynamic(2782)

    *R_rprestock and R_rprefutures
        egen mean_ss `start' `end'=mean(R_rprestock)
        egen mean_ff `start' `end'=mean(R_rprefutures)

        su mean_ss `start' `end', meanonly
        mat a1=r(mean)
        su mean_ff `start' `end', meanonly
        mat a2=r(mean)
        mat re_turn= [re_turn \\ a1, a2]
        drop R* mean*
}

mat2txt2 re_turn using D:\result\re_turn.xls, replace matname
F.3 Predict variance in sample command

```stata
mat var_cov=[9999, 9999, 9999]
set more off
forv start= 0/784 {
    local end = `start' + 2004

    if t> `start' & t< `end', arch(1) garch(1) nolog
    predict H*, variance

    *H_rprestock_rprestock H_rprefutures_rprestock H_rprefutures_rprefutures
    egen mean_ss_`start'`end'=mean(H_rprestock_rprestock)
    egen mean_fs_`start'`end'=mean(H_rprefutures_rprestock)
    egen mean_ff_`start'`end'=mean(H_rprefutures_rprefutures)

    su mean_ss_`start'`end', meanonly
    mat a1=r(mean)
    su mean_fs_`start'`end', meanonly
    mat a2=r(mean)
    su mean_ff_`start'`end', meanonly
    mat a3=r(mean)
    mat var_cov= [var_cov\ a1, a2, a3]
}
drop H* mean*

mat2txt2 var_cov using D:\result\varcov.xls, replace matname
```
F.4 Predict variance out sample command

mat var_cov=[9999, 9999, 9999]
set more off
tsappend, add(100)
forv start= 0/784 {
    local end = `start' + 2004

    if t> `start' & t< `end', arch(1) garch(1) nolog
        predict H*, variance dynamic(2786)

    *H_rprestock_rprestock H_rprefutures_rprestock H_rprefutures_rprefutures
    egen mean_ss `start' `end'=mean(H_rprestock_rprestock)
    egen mean_fs `start' `end'=mean(H_rprefutures_rprestock)
    egen mean_ff `start' `end'=mean(H_rprefutures_rprefutures)

    su mean_ss `start' `end', meanonly
    mat a1=r(mean)
    su mean_fs `start' `end', meanonly
    mat a2=r(mean)
    su mean_ff `start' `end', meanonly
    mat a3=r(mean)
    mat var_cov= [var_cov\ a1, a2, a3]

    drop H* mean*)

    mat2txt2 var_cov using D:\result\varcov.xls, replace matname
BIOGRAPHY

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