Comparison study of different Value at Risk Models and their effectiveness on the Malaysian Palm Oil Futures (FCPO) market.

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ABSTRACT

Market risk is an important element of derivatives trading and can cause derivatives market participants to suffer substantial amount of loss if not managed properly. Value at Risk (VaR) is a tool that has been used to manage market risk particularly in the developed markets. This research tries to identify which VaR model out of three models namely Historical Simulation, Delta Normal and Age Weighted Historical Simulation that can be effectively used as risk management tool for Malaysian derivatives market particularly the Malaysian Palm Oil Futures (FCPO) market. The back testing process was conducted to study the number of violations of each models produced and the exceptions were tested using Kupiec Proportion of Failure (POF) test to find the most accurate model. The study revealed that the Age Weighted Model was the most effective and robust compared to the other two models. Age Weighted potentially can be a viable alternative method of market assessment along with more complex models such as Monte Carlo Simulation and GARCH.

Keywords: Value at Risk (VaR), Market risk, Back testing, Futures market.

ABSTRAK

Risiko Pasaran merupakan suatu elemen yang penting dalam perdagangan derivatif. Jika risiko pasaran tidak diuruskan secara teliti, ia akan mengakibatkan kerugian yang besar. Risiko pada Nilai atau Value at Risk (VaR) merupakan satu cara yang digunakan untuk menguruskan risiko berkenaan terutamanya di negara-negara maju. Kajian ini menguji nilai dalam kerugian dengan membuat kajian dan mengenal pasti model VaR yang terbaik untuk risiko pasaran ini. Justeru itu tiga model VaR yakni Simulasi Sejarah atau Historical Simulation (HS), Delta Normal (DN) dan Wajaran Hayat Simulasi Sejarah atau Age Weighted Historical Simulation (AWHS) dikaji untuk kegunaan menilai risiko pasaran untuk pasaran hadapan minyak kelapa sawit Malaysia (FCPO). Proses ujian kembali (back test) dibuat untuk mengkaji berapa kali model-model berkenaan gagal untuk meramal kerugian yang berlaku. Perbandingan dan ujian dibuat ke atas bilangan kegagalan yang di catat oleh setiap model. Daripada ujian yang di buat di dapati model Wajaran Simulasi Sejarah (AWHS) paling berkesan dalam menganggar risiko pasaran untuk pasaran hadapan kelapa sawit Malaysia (FCPO). Wajaran Simulasi Sejarah (AWHS) memiliki potensi untuk menjadi model alternatif selain daripada model yang lebih kompleks seperti simulasi Monte Carlo dan GARCH untuk di gunakan di pasaran hadapan berkenaan.

Kata Kunci: Risiko pada nilai, Risiko pasaran, Ujian kembali, Pasaran hadapan.

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GLOSSARY OF TERMS

Basel Committee:	An international organ for banking supervision by providing standards, guidelines and recommendations to financial institution around the world.
Confidence level:	The confidence level is used to indicate the reliability of an estimate.
Kupiec Test:	Statistical test for model validation based on failure rates.
Kurtosis:	Describes the degree of flatness of a distribution.
Normal distribution:	The Gaussian probability distribution.
Risk:	The dispersion of unexpected outcomes owing to movements in financial variables.
Skewness:	Describes departures from symmetry.
Value at Risk (VaR):	The maximum expected loss over a given holding period at a given level of confidence.

LIST OF ACRONYMNS

AWHS:	Age Weighted Historical Simulation.
CaViar:	Conditional Autoregressive Value at Risk.
DN:	Delta Normal.
EGARCH:	Exponential Generalized Autoregressive Conditional Heteroskedasticity.
FCPO:	Futures Crude Palm Oil.
GARCH:	Generalized Autoregressive Conditional Heteroskedasticity.
HS:	Historical Simulation.
I.I.D:	Identically and Independently Distributed.
LR:	Likelihood Ratio.
OTC:	Over the Counter
P&L:	Profit and Loss.
POF:	Proportion of Failure.
TUFF:	Time until First Failure.
VaR:	Value at Risk.

CHAPTER 1

INTRODUCTION

1.1 Background of study

Risk taking is an integral part of any financial institutions and it is important to balance the return that they are willing to accept with the soundness of their financial position. An effective risk management function can help the institutions to manage its risk based on its strategy and risk appetite. Financial institutions face various risks in their day to day activity like operational risk, financial risk, credit risk, regulatory risk and market risk. It is therefore imperative that financial institutions establish a rigorous risk management process of identifying, assessing, controlling and mitigating the risks.

This study is conducted to find the most effective yet a simple risk management tool that can assess the market risk that can be used by derivatives brokers particularly the smaller brokers that do not have sophisticated systems in place due to insufficient resources and expertise. This will allow smaller derivatives broker to assess market risk exposure in a structured and quantitative manner. The study focuses on risk assessment model called Value at Risk (VaR). The objective of the study is to compare three models of VaR and identify which is the most viable method for smaller derivatives brokers to use for assessment of their exposure to market risk.

Market Risk is one of the major risks faced by the financial industry and is one of the major factors of the financial crisis of 2008 due to excessive usage of mortgage backed securities and derivatives which are known to have highly complex structures. Market risk is defined by Jorion (2001, p.15) as "the risk that arises from the movement or the volatility of market prices". Jorion (2001) suggested that losses due to market risk can occur through the volatility of the underlying financial variable and the exposure to this source of risk. Market risk can also be referred to, the changes in the value of financial instruments or contracts held by a firm due to unpredictable fluctuations in prices of traded assets and commodities and fluctuations in interest rate, exchange rates, commodity and equity prices risk.

Derivatives brokers are examples of financial institutions that have substantial exposure to market risk as they tend to hold financial instruments that are highly volatile such as futures and options. Derivatives brokers firms act as brokers and assist individuals and corporate clients to buy and sell derivatives products such as futures and options and in exchange charge commissions on their clients. They participate in derivatives exchanges that facilitate the trading of derivatives products. Derivatives markets are usually highly regulated due to the high volatility of the market. The derivatives market is a financial market where individuals and corporations can participate in the transaction of derivatives products. Derivatives products such as Futures and Options are types of secondary asset classes that are derived from the main asset classes such as equity, commodity and bonds. They are primarily used for managing risk and setting prices but are also a popular speculation instruments as it can be highly profitable (Hull, 2009). The derivatives market can be divided into Exchange traded market and Over the Counter (OTC) market; they differ mainly in terms of legal structure. The instruments that are traded in these markets are Futures, Forwards and Options, Swaps, Structured Notes and Inverse Floaters. In Malaysia exchange traded derivatives instruments are traded in the Bursa Malaysia Derivatives Berhad (BMDB) while OTC instruments are only traded between major banks.

Futures are defined as an agreement where one party agrees to buy an asset at a specific price on a specific future date and the other party agrees to make the sale (Brigham & Houstan, 1998). Futures are marked to market on daily basis which means money must be topped up in case of losses that go below a specific amount of margin. Margins are cash that must be paid upfront before a client is allowed to trade. Margins act as buffer to ensure client do not lose more than they can afford to and an important risk mitigation tool of the derivatives industry. The assets that are bought and sold can be physically delivered but are mostly closed out by monetary value before or on the last day of the agreed date of delivery. The Derivatives market in Malaysia started in the 1980s and has shown tremendous growth and is currently a major derivatives market in the ASEAN region. The most popular instrument in the Bursa Derivatives market is the Malaysian Futures Crude Palm Oil (FCPO). FCPO is a commodity based derivatives product and is actively traded by brokers, corporate clients and individuals. Corporate and individual clients can only participate in the market through the derivatives brokers who are the intermediaries between clients and the exchange where the trading takes place. They can place their trades through the brokers who are represented by licensed dealers who are authorized to execute the trades on behalf of their clients. Most of the derivatives brokers in Malaysia are divided into bank or non bank based brokers. CIMB Futures, RHB Futures, Maybank Futures are examples of bank based brokers, while companies such as Oriental Pacific Futures, LT International Futures Sdn. Bhd and Apex Futures Sdn. Bhd are stand alone brokers who are non bank based. The Brokers are regulated by the Securities Commission (SC) and BMDB, and are bound by the Capital Markets Act 2008 and are subjected to rules and regulations of the SC and BMDB.

The brokers have the responsibility to manage the various risks associated with the market such as settlement risk, operational risk and market risk. Derivatives instruments such as Futures, Options and Credit Default Swaps are known to cause substantial financial losses due to their high level of financial risks. For example, in the U.S., corporations such as Enron in 2001, Barings in 1998 and AIG in 2011 have gone into bankruptcy due to inefficient risk management while participating in the derivatives market. The derivatives market can cause systemic risk which is defined by Schwarcz (2008, p.198) as "a situation where a trigger event such as an economic occurrence or an institutional failure causes a chain of bad economic consequences sometime called the domino effect". These consequences of failures can impact financial institutions and the markets. The Barings Banks collapse, which was due to incurring substantial losses in the derivatives market is a classic example of the risk of trading in the futures market. The Barings collapse caused systemic consequences on the financial industry and the overall economy. Among the primary risk factors that can cause systemic risk include market risk, credit risk, and settlement risk. Changes in market conditions increase the volatility of the futures market which in turn causes participants to lose their funds. Losses in the market largely occur due to a condition called “over loss”. Over loss is a situation when clients have lost more than their margin deposited to the broker therefore the broker is now faced with “bad debts” and would find it difficult to recover the money owed by the clients. This in turn will adversely impact the liquidity of the broker. Regulation 602.1 of the Rules of Bursa Malaysia Derivatives specifies all derivatives brokers are required to maintain a minimum financial requirement of an amount of RM500,000 or 10% of aggregate margin whichever is higher at all times. This amount is the buffer in case the broker faces liquidity issues and is closely monitored by SC and BMDB. Failure to maintain the minimum amount may cause the broker’s license to be suspended. Therefore it is vital for the brokers to manage their risks to ensure they are always able to fulfill their obligations and maintain a good standing among the regulators. It is vital for trading participants especially the brokers who represent the clients in the market to understand the market risk and take the necessary steps to manage risk particularly market risk.

The management of market risk by the larger bank based brokers is rather more analytical and structured as they have the expertise and the system in place compared to the smaller brokers who are less strong financially. The Malaysian Derivatives brokers especially the smaller organizations rarely use statistical tools to gauge the market risk. Smaller broking houses generally rely on the experience and gut feeling of the managers or the Head of Dealing Department to assess market risk (Sinnasamy, personal interview, March 12 2013).

The control tools used to mitigate the impact of adverse market movement is through the use of margins and collaterals. In order to better manage the risk, brokers use more structured quantitative or qualitative methods such as VaR, Scenario Analysis, Stress testing, and others.

The fundamental problem that impedes smaller brokers to implement a structured market risk management tools is the perception that market risk management tools are expensive and complex. Although there are tools that can be expensive and complex such as Monte Carlo Simulation; there are tools which are less expensive and easy to use such as VaR. Among the various market risk management tools that are being used, the VaR is probably the most popular. The VaR is recommended by the Basel Committee to be used to gauge market risk for commercial and investment banks (Jorion, 2006).

The aim of the dissertation is to help identify a viable VaR model that can be used by small derivatives brokers without the need for complicated and expensive models to assess their exposure to market risk which in turn will help the brokers to make informed decision on controlling and mitigating the risk.

1.2 Problem Statement

Predicting the probability of losses is an important component of risk management. Investment and trading participants are always looking for better and more effective risk tools to assess market losses. It is observed that many of the smaller brokers of the FCPO market do not have a standard method of assessing and calculating the market risk. As confirmed by the ex CEO of LT International Futures who has more than 25 years of experience in the derivatives industry that majority of smaller derivatives brokers do not have a formal methodology to asses market risk and do not use any formal risk management tools to gauge the market risk but rather tend to rely on instincts and judgment of the dealers (Narayanasamy, personal communication, December 13, 2013).

Smaller brokers tend to rely on the dealers who monitor the markets to asses and control effects of the market. Although with experience and good judgment, dealers at times can predict the movement of the market and take the necessary steps to control the effect of adverse movement in the market; this lacks scientific methodology and structure to assess market risk and relies too much on human instinct. In a special report done by McLaughlin (2009) suggested that risk managers must integrate analytics, intuition and experience to make objective decisions and relying solely on either experience or intuition is a risk in itself. He believes that it would be difficult for dealers to validate their intuition without consulting fact based empirical way of thinking about risk. He gives an example of California Energy market crisis which spiraled due to deregulation of the market. Traders and brokers were accustomed to using instinct during period of regulated market but were caught off guard when the market was deregulated. The impact would not have been high if they had used analytics to foresee the price hikes that was imminent in the market. Solely relying on instincts may have caused the crisis and the bankruptcy of the energy companies.

Ideally, smaller brokers can look at VaR as a useful tool to assess and predict the market risk of the futures market, and with the information obtained from VaR they can use their judgement based on their experience and intuition to predict the market risk. It would be important to gauge the effectiveness of VaR before it can be used in the Malaysian markets particularly the FCPO market.

Although there is an abundance of research papers related to VaR and market risk measurement and management, all of the existing research on VaR models were developed and tested in matured, developed and liquid equity markets such as the US, Japan and Europe (Manganelli & Engle, 2001; Lee & Saltoglu, 2001). Although there are several studies on the Malaysian stock market, the focus was on more advanced VaR Models such as Monte Carlo Simulation GARCH and EGARCH models. For example, Karamah, Ahmad and Salamudin (2012) concluded that Kupiec test done on three different sectors of the Malaysian stock market has shown that all of the VaR models applied in the Malaysian market is found to be accurate at 95% level of confidence. In a more recent study, Karamah (2013) examined the effectiveness of one of the three models of Historical Simulation, a type of VaR model using different time periods and confidence level. The research shows the importance of parameters in quantifying the VaR of the Malaysian stock market. It is important that the effectiveness of the VaR models in the Malaysian derivatives model is gauged before it can be recommended to be implemented by the brokers. Since there are lack of studies conducted on the effectiveness of basic VaR models in the Malaysian Derivatives market, this study will try to fill in the gap.

1.3 Research Questions

1. Which of the three models of VaR namely Historical Simulation (HS), Age Weighted Historical Simulation (AWHS) or Delta Normal (DN) is the best model to predict FCPO market loss?

1.4 Research Objectives

1. To determine which of the three VaR models is the best predictor of losses of the FCPO market for a given observation period.
2. To identify the robustness of the model when the number of observation period changes.

1.5 Significance of study

The findings of this study can be used by industry players and researchers as a basis to understand the various VaR models particularly the DN, HS and AWHS models in assessing the market risk of the FCPO market. The study also hopes to help in comparing the VaR models as well as their strengths and weaknesses.

The study hopes to allow researchers and derivatives brokers particularly the smaller ones to evaluate and compare the accuracy of each model assessing the market risk of FCPO. This will enable researches to focus on the most effective model for the FCPO market. It is important to be cautious in selecting the right model as a study by Johansson et al. (1999) shows that using wrong VaR models can give inaccurate and misleading results by over or underestimating risk. Overestimation of risk would cause sub optimal allocation of resources while underestimating risk could expose them to loss of resources.

The study also hopes to help to understand the back testing process that is used in evaluating the accuracy of the VaR models. The research will assist in understanding the conditions and assumptions that are necessary before conducting an accurate and effective back testing. Regulators can use the findings of this research as a preliminary study in evaluating VaR as an alternative to the current minimum capital requirement imposed on derivatives brokers.

1.6 Scope and limitation of the study.

The study focuses only on FCPO traded on the Bursa Malaysian Derivatives market. Furthermore, it only examines the effectiveness of three basic models of VaR, namely, HS, DN and the AWHS. This study does not look at more advanced VaR models such as Monte Carlo Simulation and the GARCH models. The study is conducted for 255 days and 510 days of observation period and for a confidence level of 99% only. The data used comprise of approximately 3 years only.

1.7 Organization of the study

This chapter lays the introduction of the study by discussing the background of the study, the problem statements, the research objectives, the significance of the study and the scope and limitations of the study. Chapter two discusses the literature review, chapter three presents the research methodology, chapter four discusses the findings of the study and finally, chapter five provides the conclusion and recommendations of the study.

1.8 Summary of the Chapter

Insights to the relationship between market risk, and VaR models were highlighted in this chapter. This serves as an introduction into the topic of discussion. The problem statement, research questions, research objectives, significance of the study, scope and limitation of the study, and organization of study are also discussed in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This section highlights the underlying theory and empirical evidence related to this study. It begins with the importance and impact of market risk to the futures market and also focuses on VaR as a viable tool for gauging market risk. It touches on the types of models that are available. Parameters that define a VaR models are also studied. The limitations and finally the effectiveness of VaR in assessing market risk are also explored.

2.2 Market Risk

There are no specific rules on risk assessment and controls for derivatives brokers except to ensure well-documented internal controls are in place to mitigate any risk that arises. Regulators require derivatives brokers to have customized and complementary controls reflecting the risks for the particular organization and all business activities of the firm. The design and implementation of an effective risk management control system may take into consideration many factors such as the structure of the organization, client base, counterparties, trading strategies, funding, liquidity, technology, systems available, business activities and products sold. In her speech during a conference on the Securities Industry (Gadziala, 2007) has agreed that effective risk management controls are typically proactive rather than reactive. They are meant to be a defense against violations of law and potential reputational harm, financial losses, and investor harm; results that may not only be damaging to the firm and its customers but may result in firm failures or even market instability.

Futures brokers rely on Initial Margin requirement set by Bursa Malaysia Derivatives as a control mechanism against market risk. Increase in initial margin will require clients to increase their funds before buying or selling futures which acts as a deterrent for excessive speculative positions in the market which will in turn reduce the volatility of the market and reduce market risk. In another study on the effectiveness of margin requirements in controlling the volatility of the market on the Japanese stock market Sangbae and Taehun (2013) found that increasing initial margin requirement reduces long term volatility but does not affect short term volatility. On the other hand reducing initial margin reduces long term volatility but increases the short term volatility. This shows that changes in initial margin in fact increases short term volatility of the market. This also suggests that initial margin may not be enough as control tool to mitigate short term volatility in the market. This would further increase the need for brokers to assess market risk to be ready for sudden increase in market risk. There are various models to assess market risk such as geometric Brownian motion, stochastic volatility models, GARCH models and VaR Models.

2.3 VaR

In modern financial theory one of the most important principles is risk aversion. Expected return depends heavily on the amount of risk taken by investors therefore quantification of risk is a very important part of investment. There are various way of assessing risk in different markets such as using duration in the bond market, beta and correlation in the equity market and spreads in foreign exchange but risk are intricately connected with each other therefore a risk quantification method that is effective in most markets is required. The idea is to be able to answer the question of “what is the current risk”. To answer the question will not be easy as risk does not work in isolation therefore it would be logical to ask the question “what is the maximum amount of funds can we can lose over a time horizon?” The concept of VaR was born out of this question. VaR simplifies the infinite dimension of risk into a single number which allows quantifying, assessing, monitoring, mitigating, allocation of resources and reporting. Since it is relatively simple in its application, VaR comes with limitations that must be taken into account.

Study by Manganelli and Engle (2001) suggest that VaR models usually come from the characteristics of the financial data. According to Mandelbrot (1963) and Fama (1965) there are three main empirical facts of the markets:

i. Leptokurtic
ii. Negatively skewed
iii. Autocorrelated

Financial data tend to be leptokurtic which means return distribution tends to be heavier tailed and have a higher peak than a normal distribution. The second fact is financial data is usually negatively skewed which means there are more negative returns than positive returns. Finally squared returns have high autocorrelation which suggest that market factors tend to cluster. For example, observing large (small) return today is a good precursor of a large return (small) tomorrow.

The final characteristic is a very important characteristic of financial returns, since it allows the researcher to consider market volatilities as quasi-stable, changing in the long run, but stable in the short period. Most of the VaR models make use of this quasi-stability to evaluate market risk.

2.3.1 Interpretation

According to Jorion (2001, p.22**) "**VaR is a statistical method or model to measure the worst expected loss for a certain time period under a normal market condition at a given confidence level". The confidence level used can be 90%, 95% or 99% while the holding period can be a minute, a day, a week or a month. The holding period and confidence level used depends on the purpose of the VaR calculation.

Linsmeier and Pearson (1996, p.4) gave the following formal definition for VaR as: "Given a probability of x percent and a holding period of t days, VaR is the loss that is expected to be exceeded with a probability of only x percent during the next t day holding period". According to Jorion (2006), VaR can be statistically defined as:

$$P(L > Var) \leq 1 - c$$

Where,

c = confidence level.
L= the loss.
P = probability.

A simple example of VaR such as $P(L > 50{,}000) \leq 0.95$ for a holding period of 1 day would be interpreted as there is a 95% probability that we will not lose more than

RM50,000 in the next trading day or alternatively there is 5% probability that we will loss more than RM50,000 in the next trading day. This can be shown in a normal distribution graph depicted in Figure 2.1.

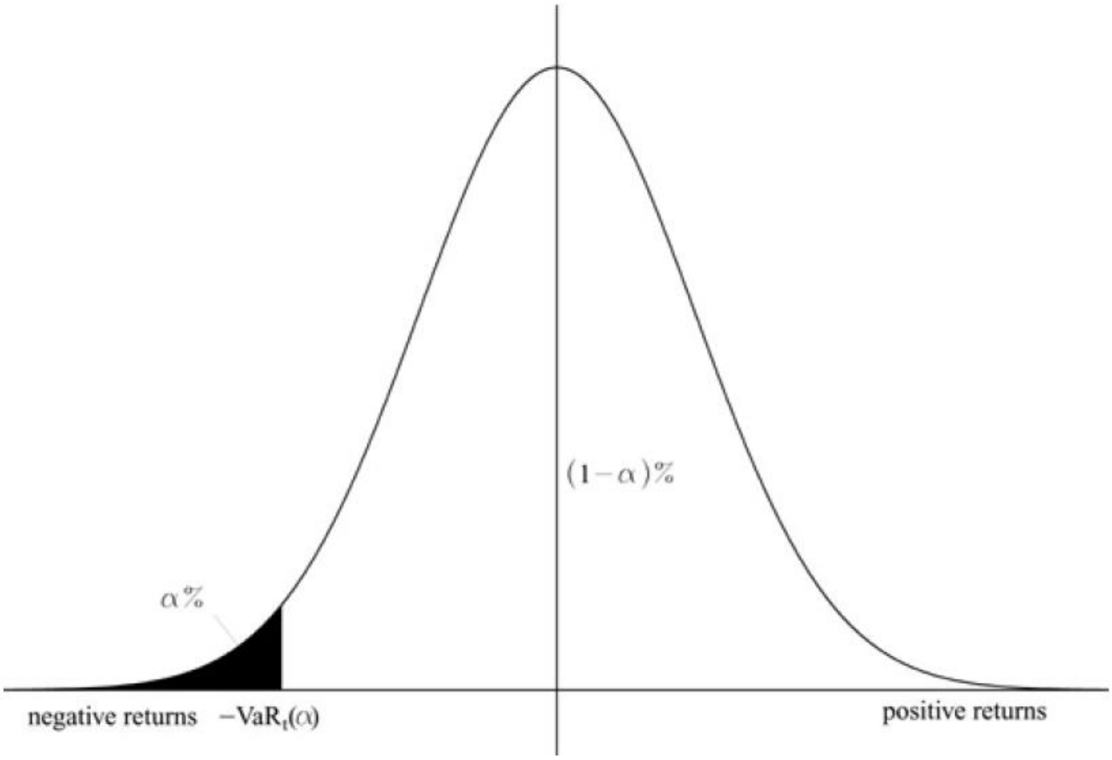

Figure 2.1
Graphical Definition of VaR at (1-α) confidence level
Source: (Lehikoinen, 2007)

The central idea of VaR is based on the mean-variance work done by Markowitz in 1952 on portfolio risk measurement (Cakir & Uyar, 2013). VaR historically was used by quantitative trading groups as risk measurement tool at most financial institutions in the US but JP Morgan CEO Dennis Weatherstone published and introduced the model outside of the financial circle (Bacon, 2012).

2.3.2 VaR Components

The three most important components of the VaR are the confidence level, holding period and the historical observation period.

2.3.2.1 Confidence level

The confidence level suggests the certainty of the test being made. The higher the confidence level means the higher the level of loss. The value is the monetary value loss suggested by the model for the time horizon for the given confidence level. In his study, Wiener (1997) suggested that the confidence level selection depends primarily on the final goal of the study which can be for internal use for management or external purpose for regulators. The choice of confidence level to satisfy regulatory purpose would normally be higher than for other purposes. For example, the Basel Committee suggested that 99% confidence level is used for official reporting while 95% can be used for internal use.

2.3.2.2 Holding period

The holding period or the horizon period is the length of time that we are looking for in the future. The holding period is the time period of the worst expected loss is forecasted for. The longer the period we take, the higher the probability of larger losses (Beder, 1997) and (Iqbal et al., 2013) suggest that the holding period used for the calculation of VaR should be based on the trading behavior of the user. For example, short term traders should use a shorter holding period since they need to be more risk conscious compared to an investor who has more risk tolerance as he or she is looking to hold the instrument or the portfolio for a longer term. In another study, Khindnova et al. (2000**)** suggested that the holding period should also be based on how liquid the market is as the less liquid market may require the use of a longer holding period due to the fact that liquidation of an instrument takes longer.

2.3.2.3 Historical Observation Period

The window length is the length of the data subsample (the observation period) used for a VaR estimation. The window length choice is related to sampling issues and availability of databases. Beder (1995) estimated VaR on HS using 100 and 250 days and observed that VaR value increased for higher period. Khindnova et al. (2000**)** have observed longer observation periods provide more accurate forecast.

2.4 VaR Models

Mangenelli and Engles (2001) studied the different types of VaR models and summarized them as of the table below:

Table 2.1

Summary of VaR Models

Parametric	Non Parametric	Semi Parametric
Delta Normal	Historical Simulation	Extreme Value Theory
GARCH		CAViar
		quasi maximum likelihood GARCH

Mangenelli and Engles (2001) suggested that VaR models can divided into Parametric, Non Parametric and Semi- Parametric models. The main difference between the three general VaR models is how they address the problem of estimating the distribution of the portfolio. The Parametric models will calculate the standard deviation and the mean of the returns before it calculates the returns VaR. This process requires the assumption that the financial data are normally distributed (Jorion, 2001).

The non-Parametric models do not require estimation of the distribution of the returns of the assets or the portfolio since it calculates VaR based on percentiles. The Semi-Parametric models are a combination of the Parametric and non-Parametric models.

Mangenelli and Engles (2001) also discussed the basic methodology of the structure of VaR which they divided into three parts. The first step will be to "mark to market" the portfolio to find the fair value of the portfolio or asset then estimate the distribution of the portfolio and finally compute the VaR. Mark to market is the process of calculating the value of the asset based on the last price of the trading day. The asset in this study is FCPO.

2.4.1 Historical Simulation (HS) Model

The HS model arranges actual historical returns in order of lowest return to the highest return and with the appropriate confidence level of 99% or 95%. The VaR suggests that there is a 95% or 99% probability that the return will not fall below the level based on the percentile. The advantage of the HS is its simplicity of use. All is needed is the historical data and arrange the data to find the percentile and we can calculate the VaR with the result obtained. The other advantage of HS is that it is not required for the data to be normally distributed. This is a clear advantage as most financial data show evidence of non-normality (Manganelli & Engle, 2001).

The critical disadvantage of HS model is that it assumes that future result will mirror that of the past. It is obvious that it is backward looking and assumes that the value of risk in the past will be the same for the future. Unlike forward looking models like Monte Carlo simulation which calculates risk based on future scenarios, it is difficult for HS to assimilate new information in the historical data and the resultant VaR may or may not be accurate (Mentel, 2013).

Another weakness of HS is that it gives equal weight to all data and does not take into account the change in volatility of the data itself. For example, the data in the year 2000 have the same effect as the data in the year 2013, however this may not hold if there are changes in volatility between the year 2000 and 2013 (Hendricks, 1996).

The HS model requires a large of amount of data to give an accurate value as shown by the study done by Vlaar (2000) on Dutch interest rate portfolio. In the study, Vlaar (2000) compared various models and concluded that HS without a long series of data will not be an effective predictor. Due to this fact; the HS model may not be useful when required to value new products in the market where there is little data to do meaningful valuation.

Beder (1995) conducted a study on HS model on 3 different portfolios with 100 and 250 prior trading days with a combination of 1 day and 2 weeks holding period. Portfolio 1 consists of US 2 years and 30 years treasury strips. Portfolio 2 consist of outrights and options positions of S&P 500 equity index contract. Portfolio 3 consists of the combination of the first two portfolios. Treasury strip in Portfolio 1 appreciated giving a negative result which Beder (1995) believes due to HS models inability to perform well with short observation period. Beder (1995) went on to suggest that HS performs well during trending market but is less accurate when there is a change in trend. For Portfolio 2, Beder (1995) observed HS model produces high probability high-return expectations and low probability large loss-return. As the models do not show the true risk a company faces, Beder (1995) suggested using stress testing and limit policies to address some of HS weaknesses. Portfolio 3 tests the model for correlation assumption and the result shows that like in Portfolio 2 return patterns change when holding period increased from 1 day to 2 weeks but a high return extreme event does not occur. This suggests results vary significantly depending highly on the correlation between assets. Beder (1995) goes on to suggest that the models can be a useful tool in predicting market losses but must be complemented with stress test, prudent checks, procedures, policies and limits.

Karamah (2013) performed a study on the HS model on the Malaysian stock exchange. The stocks selected are from the Main Board and the data used are from the year 2008 to 2012. The confidence levels of 95% and 99% are used while the holding periods selected are 1 day, 10 days and 1 month. The results of the value of VaR for 1 day and 1 month holding period show consistency with earlier studies of Beder (1995) and Hendricks (1996) that VaR results tend to increase with time horizon and length of the observation period. However the result for 10 days holding period shows result that are inconsistent with earlier studies. Karamah (2013) suggest that for 10 days holding period the selected stocks were unable to capture the turnover rapidly. The study also confirms that value of VaR differs slightly when confidence level was increased. The study reiterates the importance of selecting the right confidence level and observation period when using HS (Dowd, 1998).

2.4.2 Delta Normal Model

The Delta Normal (DN) model or also called as Variance Covariance model is similar to the historical model as it uses the historical data but instead of directly calculating the VaR from the data it calculates the standard deviation and the mean of the data. The standard deviation and the mean then will be used to calculate the VaR by deriving probability distribution of the potential returns (Cheung & Powell, 2013).

The most important assumption when deriving the DN or Variance Covariance model is the assumption that data is normally distributed. Financial time series data is generally known to be non- normal and this can cause distortion of the final result obtained from the DN models (Haas & Pigorsh, 2007).

The formula for DN VaR is given by:

$$Var = -\mu_p + \sigma_p \alpha$$

Where,

µp = Mean

σ_p = standard deviation

α = confidence interval

For example, in the case of a single asset, when the potential values are normally distributed with a mean of $ 120 million and an annual standard deviation of $ 10 million, with 95% confidence, one can assess that the of value of the asset will not drop below $ 80 million (two standard deviations below from the mean) or rise about $120 million (two standard deviations above the mean) over the next year.

The advantage of using DN model is it is relatively an easy and fast model to compute. It also does not require data distribution to be stationary as it is incorporated in the model with the calculation of standard deviation (Bohdalova, 2007).

The weakness of the DN approach is that it assumes that the data is normally distributed which may not be accurate as most financial data show elements of fat tail and skewness (Manganelli & Engle, 2001). Fat tails and extreme events occurring more frequently than predicted by normal distribution will cause the DN model to underestimate VaR since VaR is concerned with the tails of the distribution (Bohdalova, 2007).

DN approach also has difficulty in accounting for non-linear financial instruments such as options and embedded options as the valuation can be more complex (Jones & Schaefer, 1999). According to Amman and Reich (2001) non linearity is a problem for assets with nonlinear payoff such as options; VaR cannot be directly calculated from its risk distribution but rather need to be converted to profit and loss before VaR can be calculated.

2.4.3 Age Weighted Historical Simulation Model

The Age Weighted Historical Simulation (AWHS) model combines the HS method with the exponential smoothing and estimates the percentile of the return directly using the declining weights on past data. Unlike the HS method which gives equal weights to all the values in the data, the AWHS method gives heavier weighting to recent data; this is based on the findings by Butler (1999) who suggested that future volatility is affected more by recent events. Therefore it would require that recent data are given more weight and this is solved by using the decay factor (λ). Billinger and Eriksson (2009, p.14) in their master's thesis explained how decay factor is used in AWHS, "If w(1) is the weight of the most recent observation then λw(1) = w(2) is the weight given to the second most recent observation, w(3) should consequently be w(1) and so forth. λ is the decay factor and is given a value between 0 and 1 and is interpreted as the decaying importance of the observations. A λ value close to 1 indicates a slow decay of the importance of the observations while a λ value close to zero indicates a rapid decay" .

The weight of return observation *i* is given by:

$$w(i) = \frac{\lambda^{i-1}(1-\lambda)}{1-\lambda^{n}}$$

As with HS, AWHS also needs large volume of data to produce a valid VaR estimate and it is also backward looking. A study by Boudoukh, Richardson and Whitelaw (1997) showed that AWHS produced better result than both DN and HS. They also suggested that the

AWHS approach shows less autocorrelation than the HS. Autocorrelation is the cross correlation of time series to itself and can cause the result obtained from a VaR model to be inaccurate. Autocorrelation is caused by the non- normality of the financial time series data. As AWHS is not affected by autocorrelation, it would be well suited for fat tailed and skewed series.

2.5 Limitations of VaR

Dowd and Rowe (2004) emphasized that one of the limitations of VaR is that it is an estimate and not a uniquely defined value. The very fact that the calculation of VaR is based on historical data and on the premise that future behavior of a market can be predicted by past behavior should render VaR at best an estimate. All VaR models ultimately rely on historical data to assess risk, even forward looking models such as Monte Carlo simulation has to rely on historical data to simulate future scenarios. Damodaran (2005) suggested that accuracy of VaR will depend on the time series, if it is calculated during a stable period the VaR will be low; this can understate the risk but during period of high volatility the VaR will be high which can overstate risk. The trading positions under review are fixed for the period in question. Trading can be a static or a dynamic process where traders and investors can take an active or more passive role. Traders who are active could buy or sell position within a short period of time. VaR cannot take into account trades that are dynamic which needs more advanced models. VaR does not address the distribution of potential losses on those rare occasions when the VaR estimate is exceeded. Empirical evidence by Mandlebrot (1963) suggested that financial data do not show normality and the study was further supported by the work done by

Peters (1991) who found that the distribution of the S&P500 stock returns exhibit negative skewness, fat tails, and a high peak. This is a major disadvantage for certain models such as the DN model that relies on a normally distributed data for accurate assessment of risk.

Artzner, Delbaen, Eber and Heath (1999) further addressed the limitation of VaR by describing risk measures that can be viewed as a function of the distribution of portfolio's value which is summarized into the following properties:

- Monotonicity which means if a portfolio has systematically lower returns than another for all states of the world then it should have lower risk.
- Translation invariance which means adding k amount cash to a portfolio should reduce the risk by k amount.
- Homogeneity which means increasing the size of the portfolio by k scale should simply scale its risk by the same factor of k.
- Sub additive which states that merging portfolios cannot increase risk.

The last rule of sub-additivity is the most important property among the four as it states that the risk of the overall portfolio can never be more than the addition of the risk of the smaller portfolios that is part of the overall portfolio, or simply,

$$\mathrm{VaR}(X + Y) \leq \mathrm{VaR}(X) + \mathrm{VaR}(Y)$$

Dowd (2004) claims that sub-additivity is the fundamental requirement of any effective risk measure, because it means that risk aggregation does not increase overall risk and this invalids the use of VaR as a coherent risk measure.

The other most criticised aspect of VaR is its weakness of becoming ineffective during abnormal market conditions. According to Mitra and Mitra (2011) VaR becomes inflexible and unresponsive with regard to abnormal market condition and becomes unstable during high impact economic events or a sudden economic crisis. Kourouma, Dupre, Sanfilippo and Taramsco (2011) in their study performed a comparison study of VaR models particularly the HS model against Extreme Value Theory models to study their impact in extreme market conditions. Back testing process was conducted to compare the performance of both models and the study showed that at 5 and 10 days holding periods EVT model performed better than the HS model while at the 1 day holding period both models did not perform well. On the contrary, the study conducted by Lee and Saltoglu (2001) on the predictive ability of various VaR models during the Asian Financial crisis of 1998 show that ARCH and traditional VaR models have shown better coverage probabilities compared to other Extreme Value Theory models. This study clearly contradicts with the argument that VaR models do not perform well during abnormal market conditions. This suggests that there is no concrete consensus of VaR ability to predict risk during abnormal conditions.

Although VaR does have its weak points, it seems to be still relevant and widely used in gauging market risk and has even been expanded to evaluate operational risk. VaR model is recommended by the Basel Committee for assessing market risk (Basel Committee on Banking Supervision, 2004) which shows that regulators have confidence in the model. According to Culp, Mensink and Neves (1998) one of the most important and advantageous features of VaR is its consistency as a measure of financial risk. It provides a common consistent measure of risk for different positions and instrument types. VaR expresses all measures of risk in terms of currencies which allows comparison to be made across different portfolios such as bonds against stocks or foreign currencies against interest rates. They also stated that VaR enables managers or investors to examine potential losses for a particular time horizon. This gives users of VaR, flexibility of choosing the time horizon that fits the purpose of their requirement.

Culp et al. (1998) also suggested that VaR allows the user to choose the level of confidence according to their requirement be it for internal or external purpose and also takes into account the correlation between different risk factors. Dowd (1998) suggested this property is absolutely essential whenever computing risk figures for a portfolio of more than one instrument.

Finally VaR is essentially a very simple method to calculate; unlike other market risk management tools which can be complex and tedious to calculate. VaR is also easy to understand and to be interpreted to ordinary people (Krause, 2003).

2.6 Comparison of VaR models.

The early comparison study of VaR is mainly focused on the developed markets such as the American and European markets while little study has been done on the emerging markets. Hendricks (1996) applied Equally Weighted Moving Average method, Exponentially Weighted Moving Average method and the HS method on daily Foreign

Exchange data. He back tested the data based on holding periods of 50, 125, 250, 500 and 1250 days using 95% and 99% confidence interval. He concluded that all three models showed accurate 95% percentile risk measure but somewhat unreliable on the 99% percentile.

Boudoukh et al. (1998) study compared the AWHS, DN and HS on the dollar exchange rate, Brent crude oil, S&P 500 index and Brady bond index. A trading window period of 250 days with confidence level of 97% and 99% were used. The study shows that the AWHS is more effective than the HS and DN model particularly for markets with high fat tailed data series such as the oil price and the Brady bond index.

A back testing was conducted on HS, DN (equally and exponentially weighted) and Monte Carlo simulation by de Raaji and Raunig (1998). Confidence level of 95% and 99% with holding period of 1 day and 250 days and 1250 days of date were used. The result suggests that the Equally Weighted Historical Simulation was the slowest to react to changes and was the weakest among the four models especially for 250 days of data but performed better when 1,250 days of data were used. Exponential Weighted Delta Normal model fared better than Historical Simulation model. Monte Carlo simulation was the most accurate among the four models tested. This confirms earlier study done by Hendricks (1996) that showed HS model performed very accurately for 1,250 days of data for both 95% and 99% confidence level.

Billinger and Ericksson (2009) compared non-parametric and parametric models in order to find the best risk model for banks' trading portfolios. The non-parametric models consist of three different approaches: Age Weighted Historical Simulation, Volatility Weighted Historical Simulation and Simple Historical Simulation by means of the EWMA and GARCH models for forecasting volatility. The parametric models comprise six different approaches: VaR based on the normal distribution (Delta Normal), VaR with Student's t-distribution, RiskMetrics, VaR with implied volatility and VaR with GARCH volatility dynamics (both assuming normality and t-distribution). The models are estimated and tested on the S&P500 and a hypothetical bank trading portfolio. The finding is that models that assume normality with or without volatility dynamics performed badly while those with leptokurtic features and time-varying volatility perform the best.

A study on the effectiveness of different types of VaR models was also done by Gustafason and Lundberg (2009) in their master's thesis on three different asset classes, namely; Brent crude oil, OMXs30 and Swedish three months treasury bills. The study used different VaR models such as the non-HS models, the GARCH approach and the Moving Average approach. The models were tested and compared to each other on the accuracy of each models. The study showed that there is no significant advantage in using the more complex models in terms of accuracy of the results. It also shows that the characteristics of the assets along with the chosen confidence level determine how well the model holds.

Fuss, Adam and Kaiser (2010) conducted a study on the predictive power of various VaR models on commodity futures. They selected S&P GSCI long-only passive excess return indices for five sectors: agricultural, energy, industrial metals, livestock, and precious metals. They compared eight types of VaR models for the period from January 1991 to December 2006 in three phases. The models tested consist of Normal, Cornish Fisher, GARCH, RiskMetrics, Adaptive CaViaR, Asymmetric slope CAViaR, Indirect GARCH CAViaR and Symmetric Absolute Value CAViaR. This performance measure reveals that the GARCH-type VaR and three of the CAViaR models are the best performers, because they can react sufficiently to changes in volatility and limit the risk of large negative shocks, and find the best trade-off between risk and the efficient allocation of reserves.

In the Asian context, Iqbal, Azher and Ijaz (2013) performed a study on the accuracy of VaR on the Karachi 100 Index for the period of 1992 to 2008. The researcher compared the four VaR models which include both DN and non-DN models. The DN models include Equally Weighted Moving Average, Exponentially Weighted Moving Average, and Equally Weighted Moving Average with t-Distribution Method and Autoregressive Conditional Heteroskedasticity (ARCH) Model. The Non DN models include HS Method and the Bootstrap method. The confidence levels of 95% and 99% were used. The Likelihood Ratio Kupiec test was conducted. The study concluded that the GARCH model showed the highest accuracy as it only exceeds the actual VaR in three years out of the 17 years of study.

Azizan, Kuang and Ahmed (2012) in their study compared VaR models against GARCH models. The GARCH model is a risk assessment model that estimates a best-fitting autoregressive model and then computes autocorrelations of the error term and lastly, test for significance. In this study the VaR models comprising the HS and DN model with 99% confidence level was compared with a GARCH model on the Japan, Malaysian, Indian and Singapore stock indices. They concluded from their study that VaR models are the better predictor of volatility compared to the GARCH model. They further suggested that the HS model was the better predictor compared to DN model at 99% confidence level. The findings of this study contradict other findings that suggest that GARCH models perform better than basic VaR models.

The literature review shows that studies are not consistent in concluding which is the more accurate model although most studies are in agreement that the advanced VaR such as GARCH and Monte Carlo simulation fare better then the basic VaR models, although studies by the likes of Azizan et al. (2012) and Gustafason and Lundberg (2009) suggest otherwise. From the literature review, it can be concluded that VaR models can be an effective tool but its limitation must be taken into account. Among the three VaR models, the DN model has fared the worst and is also considered the weakest because of the need for normality assumption. HS has not fared better but the model seems to work well if longer data is used. No concrete conclusion can be made of the AHWS model but based on the few studies conducted; AWHS has shown to be a reliable model particularly for fat tailed data series.

Hendricks (1996) and Lechner and Ovaert (2010) suggest that no one model of VaR is considered superior but it would depend on many factors. Factors such as the type of market, assumption used, data series, confidence interval and holding period all plays an important part in determining the best model to be used. The ease of use and speed of calculation will also need to be considered by the risk managers as trading can be a dynamic process and quick decision need to be made by the users. This further strengthens the importance of back testing the models to ensure it works efficiently in the chosen market before using the models.

2.7 Summary of the Chapter

This chapter focused on the various literatures that are available on VaR. It focused on the components of VaR, the advantage and limitation of each model and finally touched on the effectiveness of the models.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The purpose of this study is to determine which model out of the Historical Simulation, Age Weighted Historical Simulation and Delta Normal model that best predicts the losses in the Malaysian palm oil futures market. This information can be helpful in trading participants to gauge market risk in the Futures market. This chapter focuses on the research method carried out in order to test the hypotheses of this study. The study is based on deductive reasoning on which according to Sekaran and Bougie (2010, p.28) is the “process of making a specific conclusion based on a general statement”. The research methodology starts with the concept of the back testing. It discusses the important parameters and the process of back testing. This chapter also consists of data collection, technique of data analysis and the method used in determining the effectiveness of the models.

3.2 Theoretical Framework

The theoretical framework of this research paper is depicted in Figure 3.1.

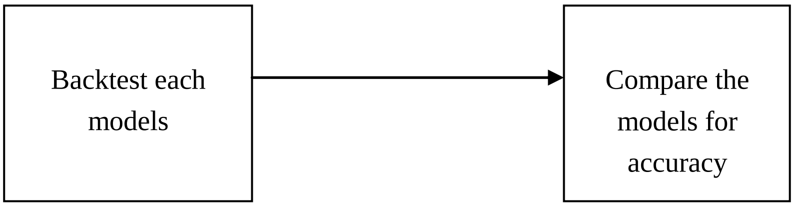

Figure 3.1
Theoretical Framework

The study tries to find the most accurate VaR model out of three models in the FCPO market. The models are Historical Simulation, Delta Normal and Age Weighted Historical Simulation. The models are gauged for their accuracy by using the back testing method.

3.3 The Hypotheses

This study focuses on finding the most effective VaR models to assess market risk of the FCPO futures market thus the following hypotheses are developed for this study:

Objective 1

H1a: HS model predicts FCPO market losses accurately at 99% confidence level for 255 days observation period.

H1b: DN Model predicts FCPO market losses accurately at 99% confidence level for 255 days observation period.

H1c: AWHS Model predicts FCPO market losses accurately at 99% confidence level for 255 days observation period.

Objective 2

H2a: HS Model predicts FCPO market losses accurately at 99% confidence level for 510 days observation period.

H2b: DN Model predicts FCPO market losses accurately at 99% confidence level for 510 days observation period.

H2c: AWHS Model predicts FCPO market losses accurately at 99% confidence level for 510 days observation period.

3.4 Data Collection:

The data is obtained from LT International Futures (M) Sdn Bhd a derivatives broker licensed by the Securities Commission and active participant of the Bursa Deivatives Exchange. The FCPO futures contract consists of spot month, the next succeeding months and thereafter alternate months up to 24 months forward. The 3rd month, the most liquid and with the highest volume has been selected for the research. The data used for the back testing is for the duration of 20th December 2010 to 30th January 2014.

3.5 Techniques of Data Analysis

The analysis process is primarily focused on back testing. The back testing process was done using the Excel sheet. The VaR of all three models were calculated using Excel formulas. SPSS was used to study the normality and to produce descriptive statistics of the data.

3.6 The Concept of Back Testing

According to Jorion (2001, p.129) *back testing* is a "formal statistical framework that consists of verifying actual losses are vis-a-vis with projected losses". Users of VaR must ensure that the model they are using is adequate and reliable. This is the step Jorion calls model validation. Meanwhile, Finger (2005, p.2) defined "back testing as the process of comparing ex-ante risk forecast to ex-post realizations of the portfolio profit and loss with the aim of identifying if the risk model is performing up to expectation". Back testing will allow users of VaR to constantly monitor the validity of the model and take measures if they find that the model is not performing as efficiently as it should. If the back test reveals that the model is faulty then the user should take steps in reviewing their parameters and assumptions and make the appropriate changes. Another very important motivation of performing back testing is liberating capital to be used for operations rather than holding to the cash as required by the regulators as minimum capital requirement. Regulatory requirement is also another reason for the need for back testing. The Basel Committee has recommended the use of back testing to validate the VaR measurement by banks. Basel Committee however has left the type of back testing and the method of back testing up to the bank.

In his working paper, Campbell (2006) suggested that a truly effective back testing method should be able to test for two properties, namely unconditional coverage property and independence property. Hurlin and Tokpavi (2006) suggested that unconditional coverage property means the confidence level p matches the empirical probability of violation. It tests on how often the exception occurs. Kupiec's Proportion of Failure (POF) test, Kupiec's Time Until First Failure (TUFF) tests are examples of unconditional coverage tests. In unconditional coverage 1% VaR back tested should show a violation or exception of not more than 1%. If it shows a violation of more than 1% then the model is underestimating the risk but on the other hand if it shows less than 1% the model could be overestimating the risk. Underestimating the risk is dangerous as it would mean taking more risk than the trading participants are capable of while overestimating risk could mean that they are losing opportunity due to not taking more risk than they are capable of.

Independence property tests on the exception sequence to be independent of each other.

Intuitively the fact that an exception has been observed today should not convey any information of the observed exception tomorrow (Campbell, 2006). This is a restriction on how an exception can occur. Examples of Independent tests include Mixed Kupiec-Test and Christoffersen's Test (Christofferesen & Pelletie, 2004). Campbell (2006) also suggested that both properties are separate and must both satisfy in order for the VaR model to be considered reliable. This is implied as the identically and independently distributed or I.I.D or also known as the Conditional Coverage test. He recommended that the back testing of the effectiveness of a VaR models should be tested for both properties. Example of Conditional Coverage test includes Mixed Kupiec-Test.

However in this study, due to time restriction; only Unconditional Coverage property test was conducted. For this study the Kupiec’s POF (proportion of failure) test was used to measure whether the number of exceptions is consistent with the confidence level. The back testing process must consider a number of factors that will decide a good back testing result. This includes the type of profit and loss used and the number of times VaR fail to predict the loss accurately which are called Exceptions.

3.6.1 Profit and Loss

Finger (2005) suggested that there are two general types of Profit and Loss (P&L), the actual and the hypothetical. The actual P&L records all gains and losses from market movement including trading fees and revenue income. Hypothetical P&L is when the portfolio remains constant for the given period which means the trading fees and the income revenue will not be included. The hypothetical P&L can be further divided into

Model and Market types. The Model type is based on valuation changes using the same function that exists in the risk model. The Market type is the actual market valuation changes for each instrument in the portfolio. In this study the Hypothetical Market Model is used for Profit and Loss calculation.

3.6.2 Exception

Gustafason and Lundberg (2009, p.2) defined "exceptions as the cases where the loss in a given time period exceeds that is suggested by the VaR model". An accurate VaR model will have the number of exception consistent with the confidence level suggested by the model (Campbell, 2006). For example, if the confidence level is 99%; the exceptions should be not more than 1%. If there were 100 observations the model should only produce 1 exception (100 x 1%). This is the crux of the unconditional property that was highlighted earlier. Any exception more than 1 suggests that the model is not reliable. It is also important to note that VaR is not a model that is used to keep exception as low as possible. The simplest method of back testing would be to record the failure rate which gives the proportion of times VaR is exceeded in a given sample.

Where,

x	=	Exception
T	=	Number of days
x/T	=	Failure rate

The idea is to find out whether, at a given confidence level say 99%, the x (Exception) is too small or too large under the null hypothesis that p=0.01 in a sample of size T. it must be noted that this test makes no assumption about the return distribution. The return distribution can be skewed, normal or with heavy tail. Under null hypothesis of the model the number of exception follow the binomial distribution discussed in the previous section. Hence, the only information required to implement a POF-test is the number of observations (T), number of exceptions (x) and the confidence level (c) (Dowd, 2006).

Since the exception can only take the form of either success or failure, for example 1 (exception) or 0 (no exception) therefore this type of test is called Bernoulli trials and the number of exception (x) follows a Binomial probability distribution:

$$f(x) = \binom{T}{x} p^x (1-p)^{T-x}$$

Where,

T	=	the total number of days,
x	=	number of exceptions
p	=	probability of success

The analysis of the data will begin with the back testing of historical return of the FCPO market to obtain the daily VaR, which will then be compared with the next day's loss. If the loss is bigger than the calculated VaR we conclude that exception has occurred. We will repeat the process for 255 days and 510 days to obtain the number of exception each model produces. The exception will then be tested for validity and then compared with the other models. Finally with the result obtained we will conclude which of the three models is the most effective as a tool for risk management for the FCPO market.

3.7 Backtesting Process

The idea of back testing is simply to compare the number of exception or violation against the expected expectation. The Exception occurs when the Estimated VaR loss calculated in the estimation window is more than the actual Loss.

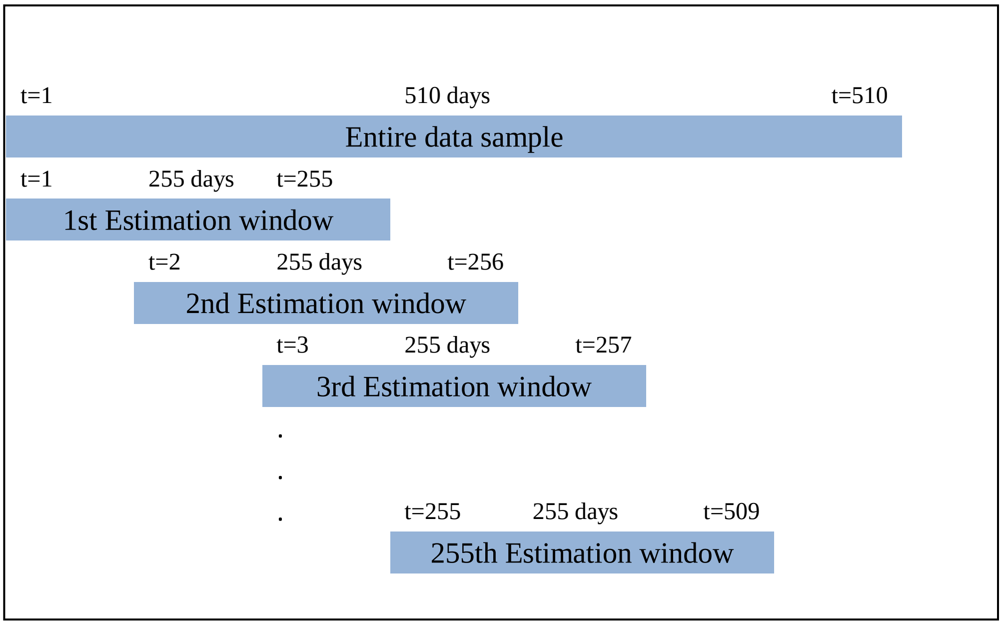

Figure 3.2
Back testing Process
Source: (Danielsson, 2011)

Based on Figure 3.2, for the first Estimation window, the VaR is calculated with 255 historical observation periods and 99% confidence interval. This VaR value is then compared with the Profit and Loss of the 256th day, if the loss on the 256th day is bigger than the historical VaR, this suggests that an exception has occurred and will be denoted as 1, otherwise it will be denoted as 0. This process is repeated for the next 255 days to find the total number of exceptions. This total number of exceptions will then be tested to find the accuracy of the VaR model. The process remains the same for finding the number of exception for 510 observation period.

3.8 Parameters for the Backtesting.

The confidence level for this research paper will be 99%. The holding period will be 1 day and the historical observation period will be 255 days corresponding to number of FCPO trading days in a year. The observation period used will be 255 days and 510 days. The P&L will be based on the hypothetical P&L where the amount on the portfolio will be fixed and because transaction fees or levies are not included.

3.9 VaR calculation methodology

The method to calculate VaR in excel for each model is outlined as follows:

3.9.1 HS Model:

Step 1: Obtain FCPO price time series.
Step 2: Convert price to Geometric return.
Step 3: Calculate the 1% percentile loss.
Step 4: Calculate the loss by multiplying capital of RM100,000 to obtain VaR.

3.9.2 AWHS Model:

Step 1: Obtain FCPO price time series.
Step 2: Convert price to Geometric return.
Step 3: Assign weight age using decay factor to give more weight to newer return.
Step 4: Calculate the 1% percentile loss using interpolation.
Step 5: Calculate the loss by multiplying capital of RM100,000 to obtain VaR.

3.9.3 DN Model:

Step 1: Obtain FCPO price time series.
Step 2: Convert price to Geometric return.
Step 3: Calculate the standard deviation and the mean.
Step 4: Calculate the confidence level.
Step 5: Use the formula -Mean + standard deviation x Confidence level.
Step 6: Calculate the loss by multiplying capital of RM100,000 to obtain VaR.

3.10 The Kupiec test

According to Jorion (2006) there are two types of decision errors and he suggested that we use a powerful statistical test to minimize this errors:

Table 3.1
Decision Errors
Source: Jorion (2001).

	Model	
Decision	Correct	Incorrect
Accept	Ok	Type 2 error
Reject	Type 1 error	Ok

Type 1 error: Represents the possibility of rejecting a correct model
Type 2 error: Represents the possibility of accepting an incorrect model

As shown in Table 3.1, Type 1 error is an error of being too conservative in restricting the VaR models available for risk management; this error is less severe than the Type II error which causes major misjudgment of allowing the use of the wrong VaR model as a risk management tool.

The Kupiec Proportion of Failure (POF) will be used to compare the three Values at Risk models. The Kupiec POF test will test the unconditional property of the three models. The POF test examines the number of times the VaR model is violated over a given time frame. The violations are called the Exceptions. If statistically too many or too few Exceptions are observed, the model is rejected. The research will focus to see which of the three models is showing the number of Exceptions that is considerably different from the given confidence level.

The Null Hypothesis will be

$$H_0 : p = \hat{p} = x/T$$

Where,

p = Failure rate suggested by confidence level.
$\hat{p}$= Observed failure rate.
x = Number of Exceptions observed.

T = Number of Observation.

The idea is to find out whether the observed failure rate is significantly different from the failure rate suggested by the confidence level. According to Kupiec (1995), the POF-test is best conducted as a likelihood-ratio (LR) test.

The test Statistic takes the form:

$$LR_{POF} = -2ln\left(\frac{(1-p)^{T-x}p^{x}}{\left[1-\left(\frac{x}{T}\right)\right]^{T-x}\left(\frac{x}{T}\right)^{x}}\right)$$

Under the null hypothesis the model is correct if LR_{POF} is asymptotically χ^2 (chi squared) distributed with one degree of freedom. If the value of the LR_{POF} statistic exceeds the critical value of the χ^2 distribution of 3.84 for 99%, the null hypothesis will be rejected and the model is deemed as inaccurate. The Kupiec Non Rejection table (Table 3.2) is used to decide whether to accept or reject the Hypothesis.

According to Dowd (2006), the confidence level (i.e. the critical value) for any test should be selected to balance between type 1 and type 2 errors. It is common to choose some arbitrary confidence level, such as 99%, and apply this level in all tests. A level of this magnitude implies that the model will be rejected only if the evidence against it is fairly strong.

Table 3.2
Non Rejection Region table

Source: Kupiec (1995)

Probability Level *(p)*	Confidence Level	Non Rejection Region for Number of Failures (N)	
		T=255 day	T=510 days
0.01	99	N <7	1 <N <11

3.11 Summary of Chapter

This chapter has outlined the methodology that is used in testing the effectiveness of the VaR models. The backtesting process and the methodology in calculating the VaR for each model was studied and finally the Kupiec Proportion of Failure test was also explained.

CHAPTER 4

ANALYSIS OF FINDINGS

4.1 Introduction

This chapter will elucidate the descriptive statistics, the results of the back testing and the Kupiec test conducted. Finally the summary of the results will be discussed.

4.2 Descriptive Data

The descriptive data consist of the FCPO price trend, price volatility and SPSS results. The SPSS result focuses on the skewness, kurtosis and the normality of the data used in the research.

4.2.1 FCPO Price Trend

Figure 4.1 shows the price movement of FCPO for the period from 20th December 2010 to 30th January 2014. The price generally shows a trend of decline from 2010 to 2012 but in a non-trending movement from late 2012 to early 2014.

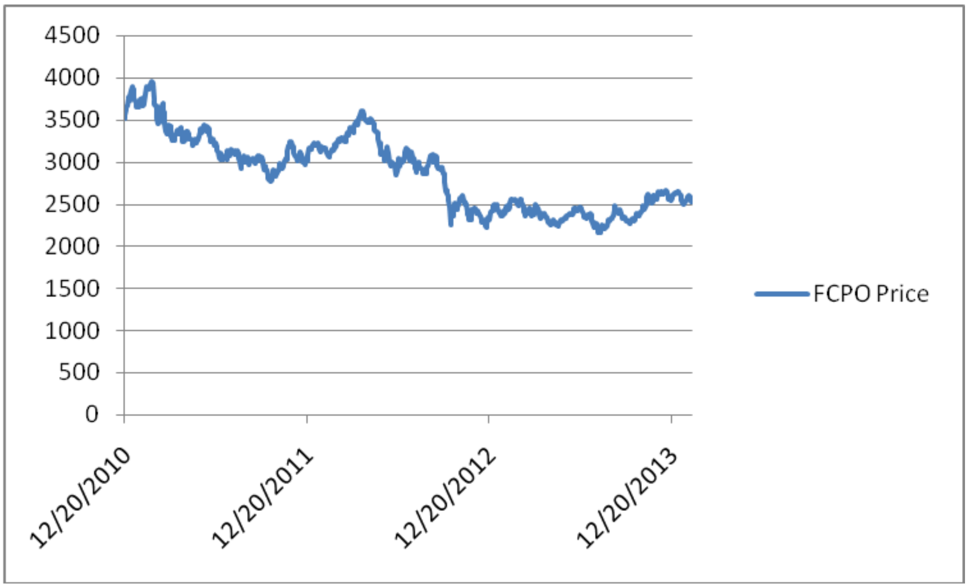

Figure 4.1: FCPO Price trend during the period: 20th Dec 2010 to 30th Jan 2014.

4.2.2 FCPO Return Volatility

As shown in Figure 4.2, the FCPO volatility for the period is generally between 3% to -3% with some extreme gain of more than 4% and a loss of 9%. The movement in return is not overly excessive in one direction and would be a good sample for the calculation of VaR.

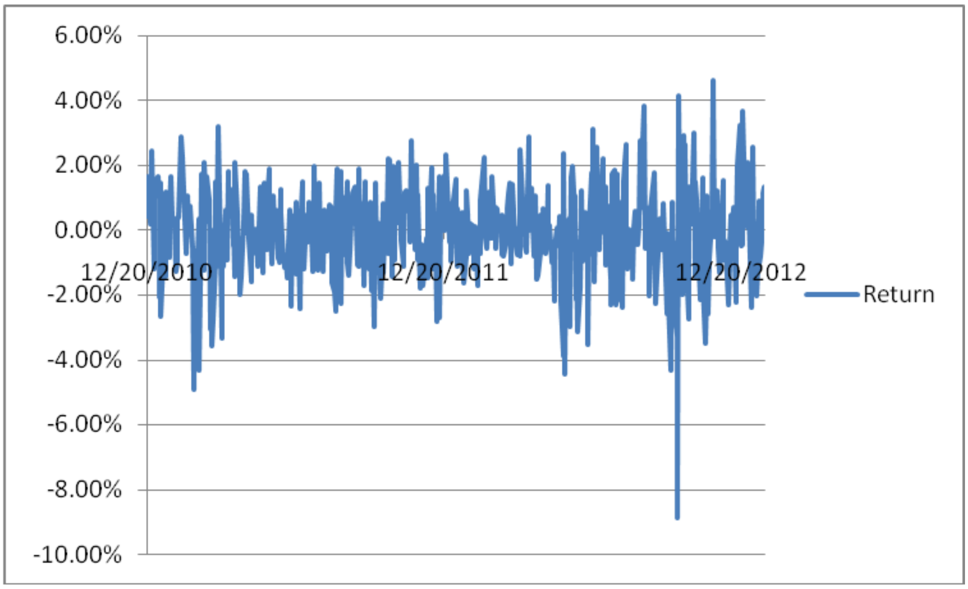

Figure 4.2: The FCPO Return volatility during the period: 20th Dec 2010 to 30th Jan 2014.

Table 4.1: **Descriptive Statistics of Data of FCPO Return**

No	Minimum	Maximum	Mean	Median	Std. Deviation	Skewness	Kurtosis
765	-0.0886	0.0462	-0.00041	-0.00042	0.0133759	-0.43	2.461

Based on SPSS descriptive data on Table 4.1; the skewness level show -0.43 which indicates negative skewness and most of the values are on the left of the mean which means there are more losses than gains for the period. This is important as we would prefer a situation to test the models on occasion where there are more losses than gains.

Most financial data show high level of skewness as financial data are known to be non-normally distributed. The Kurtosis based on the SPSS result as shown in Table 4.1 shows positive value of 2.461 which means it is leptokurtic and indicates a higher peak with fat tails. These are the normal characteristics of financial data.

4.2.3 Normality

Based on table 4.2, the Shapiro-Wilk test shows the significant value stands at 0.00 suggesting non-normality of data. This is consistent with previous findings that financial data are non-normal. Non-parametric model like the HS and the AWHS are generally not affected by the non-normality but the Delta Normal model is affected by normality as mentioned in the literature review.

Table 4.2: **Normality Test**

Shapiro-Wilk		
Statistics	degree of freedom	Significance
0.982	765	0.000

4.3 BACK TESTING RESULTS

The back testing results for each model for the 255 and 510 days holding period are given below.

Table 4.3: **HS Model Results for 255 days.**

Confidence level	Number of Observations	Expected Number of Exceptions	Observed Number of Exceptions
99%	255	2.5	7

Table 4.3 shows the back testing of the HS model produced 7 exceptions compared to the expected number of expectation of 2.5. Based on Kupiec's POF test for 255 days observation period with 99% confidence level suggest a model with 7 Exceptions is rejected as an accurate model.

Table 4.4: **DN Model Results for 255 days.**

Confidence level	Number of Observations	Expected Number of Exceptions	Observed Number of Exceptions
99%	255	2.5	8

Table 4.4 shows the back testing of the DN model for 255 days observation period produced 8 exceptions compared to the expected number of expectation of 2.5. Based on Kupiec's POF test for 255 days observation period with 99% confidence level suggest a model with 8 Exceptions is rejected as an accurate model.

Table 4.5: **AWHS Model Results for 255 days.**

Confidence level	Number of Observations	Expected Number of Exceptions	Observed Number of Exceptions
99%	255	2.5	6

Table 4.5 shows the back testing of the AWHS model produced 6 exceptions compared to the expected number of expectation of 2.5. Based on Kupiec's POF test for 255 days observation period with 99% confidence level suggests a model with 6 Exceptions is accepted as an accurate model.

Table 4.6: **HS Model Results for 510 days.**

Confidence level	Number of Observations	Expected Number of Exceptions	Observed Number of Exceptions
99%	510	5.1	7

Table 4.6 shows the back testing of the HS model produced 7 exceptions compared to the expected number of expectation of 2.5. Based on Kupiec's POF test for 510 days observation period with 99% confidence level suggests a model with 7 Exceptions is accepted as an accurate model.

Table 4.7: **DN Model Results for 510 days.**

Confidence level	Number of Observations	Expected Number of Exceptions	Observed Number of Exceptions
99%	510	5.1	8

Table 4.7 shows the back testing of the DN model for 255 days observation period produced 8 exceptions compared to the expected number of expectation of 2.5. Based on Kupiec's POF test for 510 days observation period with 99% confidence level it is suggested a model with 8 Exceptions is accepted as an accurate model.

Table 4.8: **AWHS Model Results for 510 days.**

Confidence level	Number of Observations	Expected Number of Exceptions	Observed Number of Exceptions
99%	510	5.1	7

Table 4.8 show the back testing of the AWHS model produced 6 exceptions compared to

the expected number of expectation of 2.5. Based on Kupiec's POF test for 510 days observation period with 99% confidence level suggests a model with 7 Exceptions is accepted as an accurate model.

4.4 Summary of Backtest Results.

The result shows that only the AWHS model was accepted at the 99% confidence level for 255 days observation period but all three models were accepted for 510 days. Table 4.9 summarizes the result of the Kupiec Test:

Table 4.9
Summary of Kupiec Test result

Number of Observations Period	**255 days**	**510 days**
	Confidence Level	
	99%	**99%**
Model	Result	
AWHS	**Accept**	**Accept**
Historical Simulation	**Reject**	**Accept**
Delta Normal	**Reject**	**Accept**

4.5 ACCEPTANCE/REJECTION OF HYPOTHESES

Objective 1

H1a: *HS model predicts FCPO market losses accurately at 99% confidence level for 255 days observation period.*

Based on the Observed Exceptions the HS model does not predict the FCPO market losses accurately at 99% confidence level for 255 days observation period as the number of

Observed Exceptions was out of the non rejection region.

H1b*: DN Model predicts losses accurately at 99% confidence level for 255 days observation period.*

Based on the observed Exceptions the DN model does not predict the FCPO market losses accurately at 99% confidence level for 255 days observation period as the Number of Observed Exceptions was out of the non rejection region.

H1c*: AWHS Model predicts losses accurately at 99% confidence level for 255 days observation period.*

Based on the observed Exceptions the AWHS model predicts the FCPO market losses accurately at 99% confidence level for 255 days observation period as the Number of Observed Exceptions was within the non rejection region.

Objective 2

H2a*: HS Model predicts losses accurately at 99% confidence level for 510 days observation period.*

Based on the observed Exceptions the HS model predicts the FCPO market losses accurately at 99% confidence level for 510 days observation period as the Number of Observed Exceptions was within the non rejection region.

H2b*: DN Model predicts losses accurately at 99% confidence level for 510 days observation period.*

Based on the observed Exceptions the DN model predicts the FCPO market losses accurately at 99% confidence level for 510 days observation period as the Number of Observed Exceptions was within the non rejection region.

H2c*: AWHS Model predicts losses accurately at 99% confidence level for 510 days observation period.*

Based on the observed Exceptions the AWHS model predicts the FCPO market losses accurately at 99% confidence level for 510 days observation period as the Number of Observed Exceptions was within the non rejection region.

4.6 SUMMARY OF CHAPTER

This chapter consists of the descriptive statistics of the FCPO data. This chapter also consists of the back testing results of the three models. Lastly, this chapter discusses the acceptance and rejection of the hypotheses.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1 Introduction

The chapter summaries the overall study and is separated into five sections. Firstly, section 5.1 provides the conclusion of the study while 5.2 presents implication of the findings and section 5.3 provides recommendations for future study. Lastly, section 5.4 summaries the chapter.

5.2 Summary

For the 255 days of observation period the AWHS was the only model that was accepted in the test conducted while the HS and DN models were rejected. This clearly shows that the AWHS model is the more reliable model out of the three models in predicting the FCPO market losses for 255 days of observation period. The study also shows that the HS and DN models are not reliable at 255 observation period. However all the three models show accuracy in predicting losses when the observation period was increased to 510 days which corresponds to earlier studies done by the likes of Hendricks (1996) and Beder (1995) that suggests the models tend to perform better for larger observation periods.

The study suggest that AWHS model is more robust then the HS and DN models when assessing FCPO market loss as it shows to be accurate for both 255 days and 510 days and has the potential to be used as a viable tool in assessing FCPO market risk. The study also shows that the models tend to perform better in assessing FCPO market losses when the observation period is increased.

5.3 Implication

These findings potentially will allow smaller brokers who are participating in the Malaysian FCPO market to consider using AWHS model as a viable market risk management tool to monitor their probability of losses in the market. This will give them an opportunity to use a quantitative tool to gauge the market and make informed judgment on their trades rather than relying only on instinct and experience. A more reliable and informed trade decision by futures brokers will ensure that the futures market will be less volatile especially during market uncertainty. This in turn can help in ensuring a fair and orderly derivatives market.

An effective VaR model can be a useful tool in enhancing small derivatives overall risk management framework. Regulators are encouraging brokers to establish Enterprise Risk management framework which focuses on integrating all risk issues in an organization rather than viewing them in silo. VaR models such as AWHS can be included in the brokers overall risk management process and can greatly enhance the broker's management of risk which will allow the broker to be more resilient during difficult times. VaR models allow aggregation of risk which will enable the brokers to set appropriate risk appetite and tolerance to ensure the brokers take risk within their capacity. A well managed organization can ensure their clients interest are safeguarded and will also help establish a more stable and mature FCPO market.

Malaysian Derivatives regulatory bodies such as SC and BMDB can use the findings to study the potential of using VaR models such as AWHS as an alternative to the fixed minimum capital requirement imposed on brokers. The capital requirement is imposed to ensure Futures brokers have enough funds during market uncertainty. The rigidity of imposing fixed amount can at times, especially during low volatility market condition, stop brokers to utilize their funds to take up more position in the market and losing the opportunity to earn commission. If a VaR model is used instead, its ability to predict market risk can allow regulators to impose higher capital requirement during high volatility but reduce the amount during low volatility. This will allow the brokers to increase position in the market and could potentially increase their income from the commission earned and reduce their position in the market when the market is volatile to ensure sufficient liquidity.

5.4 Recommendations for Future studies

Further study on AWHS model robustness at different confidence level and holding period should be done to test its predictive ability before it is introduced as a viable risk management tool. Study on the accuracy of using VaR to predict market risk of the FCPO market can be expanded to include situations where independence of the back testing is tested as well. Conditional coverage test such as Christoffersen test can be used to test the accuracy of the three models on the FCPO market. Comparison study on the effectiveness of the VaR models on the Malaysian Equity derivatives as well as other derivatives market in the ASEAN region can also be conducted.

5.5 Summary of Chapter

This chapter entails the conclusion of the study, the implication of the study and suggestion on future research on this study.

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