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Daily Value-at-Risk Models at Financial Crisis Period: Evidence in Australia

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ATTESTATION OF AUTHORSHIP

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a sustained extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Vivienne, Bo ZHANG

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I felt a profound sense of gratitude to family for their support, patience, and love to me. I thank my parents for sharing their visions and wisdoms on all the good things that matter most in my life. And a special thank to my husband, whose encouragement, care and support motivated me to complete this dissertation.

ABSTRACT

Over the past decades portfolio and risk management techniques had adapted to increasingly complex financial instrument. Within the different forms of financial risk measurement tools, Value at Risk (VAR) which provides the most expediency measurement from the adverse market movements, is now widely accepted as a fundamental tool for risk management and it has become a standard benchmark for measuring financial risk since the 1990s. This dissertation primarily focuses on using the newly created Australian implied volatility as an input for Value-at-Risk models during the financial crisis period and then compares the testing results with other two different volatility inputs based on two back-testing methods. The results show that during the financial crisis period straight forward volatility forecasts based on Australian implied volatility do not provide meaningful volatility information in VAR models, and this was however fine in most cases when using RiskMetrics and GJR-GARCH as volatility forecasts methods. This indicates that the models' performances can be deteriorating in challenging trading environments, and in order to get protection against credit risk, operational risk and liquidity risk, the risk managers or investors should appropriate use of VAR.

Chapter One: Introduction

In recent years, the huge growth of trading activity and the well-publicized trading loss of the famous financial institutions have led the financial managements to pay great attention to the risk management skills. Among the different risk management skills, properly defining risks and its measurement is a very important topic for risk managers because they need to focus on developing reliable techniques for measuring financial instruments risk exposure. Therefore risk managers and managerial accountants have implemented many different methods so the financial risks can be correctly predicted. In contrast with traditional risk measures, VAR provides an aggregate view of a portfolio's risk that accounts for leverage, correlations, and current positions, so it has become one of the most popular techniques through the different risk management tools. As a result, most risk managers and financial institutions have implemented VAR as its financial risk predictor.

In order to provide the most accurate VAR figures for financial institutions, volatility becomes the key component for VAR models. There was a large body of research in the search for better volatility inputs to valuate VAR model adequacy, such as Kupiec (1995), Christoffersen (1998), and Berkowitz (2001). This dissertation is based on using the recently created implied volatility index as an input for VAR model in Australian stock market and to find out the accuracy of this new input. This dissertation also contrasts the testing results with using RiskMetrics and GJR-GARCH as the inputs for VAR in order to decide which method presents the outstanding performance of volatility estimates. The reasons of selecting Australia as the testing country are because: the most recent created implied volatility index (AVX) inputs is based on Australian market; there is very few literatures using AVX as an input for VAR in Australian market, and this is a relatively new market to test VAR results and it is one of the largest markets in the southern hemisphere, so it is valuable to check whether using AVX as an volatility input for VAR can be competent with the other two methods.

During a financial crisis, the risks associated with investing increase substantially. The financial crisis of 2008 had left an indelible mark on economic and financial structure worldwide. The most widely used risk model, VAR, which was developed and popularized in the early 1990s, will be affected as well. Therefore, to test whether the VAR models that based on pre-financial crisis period works become to another very important issue for the risk managers and investors.

The aim of this dissertation is to find out during the financial crisis periods, whether daily VAR model based on AVX can provide meaningful volatility information compared with RiskMetrics and GJR-GARCH. In order to answer this research question, there are a number of objectives have been set up: firstly discusses the information content of implied volatility indexes in a Value at Risk framework. Secondly it focuses on how implied volatility quantifies market risk and also whether implied volatility helps to model the VAR correctly. The implication of this study is quite obvious; correctly calculated VAR can indicate the safeness of financial institutions as well as the commercial banks. And the failure or mislead of predicting accurate VAR, can cause the banks of even the entire financial system into a serious security problem. Finally, it assesses the effectiveness of two back-testing methods to test the accuracy of risk models- that is, to determine whether the model chosen is accurate and performing consistently with assumptions on which the model is based.

The findings show that during the financial crisis period, implied volatility does not provide meaningful volatility information in VAR models as the number of VAR violations are not correctly modelled in most cases, the null hypotheses of independence and conditional coverage are usually rejected. However RiskMetrics and GJR-GARCH in most cases are working fine. This indicates that using RiskMetrics and GJR-GARCH as a volatility input for the out-of-sample VAR during financial crisis period can provide meaningful information to model Daily VAR models, wherever AVX break down during challenging trading environments.

This dissertation consists of five chapters. The first chapter introduces readers to the topic of the research study. This chapter firstly presents the research background on expatriation studies. It then identifies and discusses the research objectives for this study. The importance of the research study is also explained in the first chapter before the dissertation structure is outlined.

Chapter Two is an overview of risk management and Value at Risk. This chapter aims to provide further justification for the research, an understanding of the principal of risk management, and a basis for a literature review to be conducted. It reviews the literature covering the reorganization of the importance of risk management, different method of calculation Value at Risk, and how to input Australian Implied Volatility Index (AVX) as a variable for Value at Risk calculations.

Chapter Three discusses the data used and the procedure employed to calculate Value at Risk, and also discusses the analysis employed to test the hypotheses.

Chapter Four analyses and presents results from the research conducted for the study. It also provides further discussion of the key results presented. The recommendations which arise from the discussion are also provided in the latter part of the chapter.

The last chapter of the dissertation provides the concluding discussion. This involves identifying and discussing study limitations, future research areas, and providing an overall conclusion to the dissertation.

Chapter Two: Literature Review

Risks should be monitored carefully because of their potentials for damage, without proper controls, financial risks have the probability for creating huge losses (Jorion, 2002). The purpose of this chapter is to discuss the importance of risk management, and check what types of models have been introduced to measure financial risks based on the past literatures. Then it discusses the validity of VAR model when it has been introduced as a financial risk measurement tool based on the historical literatures. Next the past literatures that have used implied volatility index and other alternative methods as an input of the volatility for VAR have been discussed. Lastly, a conclusion is provided in this chapter.

2.1 Risk Management

2.1.1 The importance of analyse risks and measure risks

According to Jorion (2002), risk defines as the volatility of unexpected outcomes, generally the value of assets or liabilities of interest. Better understanding of risks for firms and institutions means that their financial managers can plan for the consequences of adverse outcomes on purpose and also better prepared for the inevitable uncertainty.

There are different types of risks, and generally risks are classified into the broad categories of market risks, credit risks, liquidity risks, operational risks and sometimes legal risks (Jorion, 2001).

Risk also comes from many sources. Risk can be human-created, such as business cycles, inflation, or changes in government policies. As per Duchac (1996), to protect against huge losses from unexpected market shift, risk managers and managerial accountants have focused on developing reliable techniques for measuring financial instrument risk exposure. Jorion (2002) mentions that it is very difficult to eliminate risk, but it can be transferred to another party or reduced by having good internal controls or even taking on more risk in order to anticipation of higher profits.

As Carey (2006) points out, it is very hard to manage firm wide risk although managers have tried to expect the risks from different sources. In addition, Carey (2006) mentions that some risk measurement approaches may be reasonable successful at one time, but they can be difficult to implement in a way that appropriately reflects the risks and the financial institutions at the time the measure is computed. They can be misleading if risks have changed significantly in the recent past. As a result, risk measurement is organized according to a taxonomy of risk types that has become richer as risk management has matured, but that remains incomplete.

Chirstoffersen (2003) shows that the risk management function have steadily become more and more important within commercial and investment banks during the 1990s. He also points out the key objective of the risk management function within a financial institution is to allow for a clear understanding of the risks and exposures the firm is engaged in, such that monetary loss is deemed acceptable by the firm. The acceptability of any loss should be on the level that the firm has expected as a result of business activity that the firm being engaged in. In this absence, understand of what types of financial risks are involved and how to measure them becomes to a very important issue.

2.1.2 Financial Risk Measurement

There are various types of risks, in the recent year firms have paid great attention to investigate the best-manage exposure to financial risks. According to Jorion (2002) financial risks are defined as those which relate to possible losses in financial markets, such as losses due to interest rate movements or defaults on financial obligations.

Financial risk management is a process to deal with the uncertainties resulting from financial markets (Horcher, 2005). Managing financial risk necessitates making organizational decisions about risks that are acceptable versus those that are not. Organizations manage financial risk using a variety of strategies and products. So it is very important to understand how these products and strategies work to reduce risk within the context of the organization's risk tolerance and objectives.

As Crouhy (2001) points out, the measurement of financial risk has changed over time. It has evolved from simple indicators, such as the face value or notional amount for an individual security, through more complex measures of price sensitivities such as the duration and convexity of a bond, to the latest methodologies for computing Value at Risk (VAR) numbers. Each measure has tended at first to be applied to individual securities, and then to be adapted to measure the risk of complex portfolios such as those that contain derivatives. Though all different measurements, VAR is used for managing, as well as measuring risk. VAR provides a common, consistent, and integrated measure of risk across risk factors, instruments, and asset classes, leading to greater risk transparency and a consistent treatment of risks across the firm (Crouhy, Galai, & Mark, 2001).

2.2 Value at Risk

The traditional methods of risk management normally examine the notional principal amounts, and those types of analysis only provide very limit insight into the risks associated with financial instruments because they do not consider market values, the volatility of market prices and the correlation between financial instruments (Giot, 2003). However, VAR presents a single, summary statistical measure of possible portfolio losses.

2.2.1 Definition of VAR

As Jorion (2005) states, VAR defines as follows:

VAR is a measure of market risk. It is the maximum loss which can occur with X% confidence over a holding period of t days.

Tanna (2006) points out that VAR is the expected loss of a portfolio over a specified time period for a set level of probability. VAR measures the potential loss in market value of a portfolio using estimated volatility and correlations. It is a measurement within in a given confidence interval, typically 95% or 99%. The concept of VAR seeks to measure the possible losses from a position or portfolio under ‘normal’ circumstances. The definition of normality is critical to the estimation of VAR and is a statistical concept; its importance varies according to the VAR calculation methodology that is being used.

Pearson (2000) also points out that VAR is a measure of losses resulting from “normal” market movements. Subject to the simplifying assumptions used in its calculation, VAR combines all the risks in a portfolio into a single number which is easy to understand for the regulators and other board members. According to Urbani (2003), VAR is the most widely used measurement of risk and the reasons are due to the need for a single risk measure for the setting of capital adequacy limits for banks and other financial institutions.

According to Giot (2003), the concept and use of VAR is relatively recent. VAR was first used by major financial firms in the late 1980s to measure the risks of their trading portfolios. VAR models grow remarkably since the middle of the 1990’s because of the popularity of the RiskMetrics VAR specification of JP Morgan and the risk-adjusted measures of capital adequacy enforced by the Basel committee. Since then, the use of VAR has exploded, and that is when the concept of Value-at-Risk (VAR) becomes a foundation of financial markets risk management. VAR is now widely used by other financial institutions, non-financial corporations and institutional investors. Even regulators have become interested in VAR.

VAR is one of the simplest measures of financial risk and is calculated in many different ways by each individual institution. The following part is constructed as follows: Firstly introduce the main parties who is using VAR as their risk measurement tool and secondly discusses the different methods of computing VAR.

2.2.2 Main parties of using VAR

VAR can be used by any institution exposed to financial risk (Jorion, 2005). Currently, VAR is being adopted as their financial risk management tool particularly by institutions around the world, which include:

- Regulators and Financial institutions: The financial institutions all require the prudence management of risk; they require maintaining the minimum levels of capital as reserves against financial risks. Since VAR provides a risk-sensitive measure of risk and it helps to deal with moral-hazard problems that are prevalent in financial market, the Basel Committee on banking supervision, the U.S. Federal Reserve, the U.S. Securities and Exchange Commission, and regulators in the European Union have converged on VAR as a benchmark risk measure (Jorion, 2005).

- Nonfinancial corporations: Because of the convenience to calculate VAR, it becomes to an essential tool for any corporation that has exposure to financial risks. For example, cash flow at risk (CFAR) analysis can be used to tell how likely it is that a firm will face a critical shortfall of funds (Jorion, 2005).

- Asset managers: Institutions investors are also turning to VAR to manage their financial risks. Jorion (2005) points out the director of the Chrysler pension fund stated that after they purchase the VAR system, they can view their total capital at risk on a portfolio basis, by asset class and by individual manager.

Since the principal of VAR is critically thinking about risk, institutions that go through the process of computing their VAR are forced to confront their exposure to financial risks and setup an independent risk management function supervising the front and back offices. Thus the indeed, the sensible use of VAR may have avoided many of the financial disasters experienced over the past years.

2.2.3 Different methods of computing VAR

According to Choudhry (2006), there are three basic approaches that are used to compute VAR, which include:

- Correlation Method

This method is also known as the variance-covariance method. This method assumes that the returns on risk factors are normally distributed, the correlations between risk factors are constant and the price sensitivity to changes in risk factor of each portfolio constituent is constant. This approach gives a simple way to compute VAR, but is has few weaknesses. For example, Hull & White (1998) points out if conditional returns are not normally distributed, the computed VAR will understate the true VAR. Moreover, Engle (2001) directs at bettering the estimation techniques to yield more reliable variance and covariance values to use in VAR calculations. He argues that get better estimates by using models that explicitly allow the standard deviation to change the time (heteroskedasticity). In fact, he suggests two variants – Autoregressive Conditional heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) provide better forecasts of variance and better measure of VAR.

-Historical Simulation Method

The historical simulation method represents the simplest way of estimating VAR and it avoids some of the pitfalls of the correlation method (Choudhry, 2006). According to Hull & White (1998), this approach calculates potential losses based on the actual historical returns in the risk factors so it captures the non-normal distribution of risk factor returns. This means it has considered the changes that would have occurred in each period. Although this method is easy to compute, it has its own weaknesses. Compare with the other two approaches, although all three approaches use historical data to estimate VAR, this approach is entirely based on historical price changes. There is very little room to overlay distributional assumptions or to bring in subjective information. Boudoukh, Richardson & Whitelaw (1998) presents a variant on historical simulation, where they put more weight on recent data by using a decay factor as their time weighting instrument. They use the 250 days of returns on the market crash on 1987 as an example and found that the VAR with decay factors very quickly adjusts to reflect the size of the crash. Moreover, Hull & White (1998) suggest another way for updating historical data, which is to shifts in volatility. For example, for assets, if the recent volatility is higher than historical volatility, they recommend that the historical data be adjusted to reflect the change.

-Monte Carlo simulation method

This method is more flexible than the previous two methods, as this method allows the risk manager to use actual historical distributions for risk factor returns rather than having to assume normal returns (Choudhry 2006). Compare with the other two methods, Monte Carlo simulation do not have to make unrealistic assumptions about normality in returns, and free to bring in both subjective judgements and other information to improve forecasted probability distribution, it is more likely to estimate VAR more accurately. However, its implementation requires powerful computers and there is also a trade-off in that time to perform calculations is longer. Base on the time issue, Jamshidian & Zhu (1997) suggest a method which is scenario simulations; firstly they use principal component analysis to narrow the number of factors. They choose the likely combinations of these variables to arrive at scenarios rather than allow each risk variable to take on all of the potential values. Then the values are computed across these scenarios to arrive at the simulation results.

As previous discussion concluded, there are three methods in use for calculating VAR estimates. As Cassidy (1997) points out, even where banks or other financial institutions use the same board methods to calculate VAR, there are still considerable variations in the application of those VAR methodologies- different models may be used to measure the sensitivities of particular instruments to price movements; different methods may be used to aggregate exposures across instruments; and different techniques for estimating price volatilities may be used.

2.2.4 Historical and Implied Measures of VAR

Since VAR management is a portfolio application, VAR measurement requires standard deviation and correlation estimates. Because of its importance, a great amount of research has focuses on predicting volatility. According to Frijns, Tallau,

& Tourani-Rad (2009), there are several models have been developed to forecast volatility, which can be broadly classified into GARCH-type models (see, e.g., Bollerslev et al., 1992), stochastic volatility models (see, e.g., Taylor, 1986), and, more recently, realized volatility models (see, e.g., Anderson et al., 2001). However, all of these models use historical stock price data to predict future volatility. A board survey of recent papers done by Poon and Granger (2003) indicates that forecasts based on implied volatility beat forecasts based on historical returns. Frijns, Tallau, & Tourani-Rad (2009) also show that implied volatility is a forward-looking measure of volatility for the option's lifetime. It represents the market's estimate of the future volatility of the underlying asset for the lifetime of the option.

James, Bodurtha & Qi (1999) have also used historical based forecasts and option implied forecasts to test the information content of ex-ante standard deviation and correlation estimates. They prove that the new correlation parameter estimates show dynamics and provide forecast explanatory power similar to the already created implied volatility estimates. Moreover, the implied parameter estimates provide incremental explanatory power over the historical-based estimates.
On the other hand, Neely (2002) argues that implied volatility forecasts is a biased estimator of future realized volatility and that volatility forecasts from econometric models should be taken into account. Figlewski (1997) also show that there is almost no correlation between implied volatility and future realized volatility. More importantly, Christensen & Prabhala (1998) indicates that the use of overlapping data and the inclusion of the October 1987 market crash in the Canina and Figlewski (1993) paper is one of the main explanations as to why implied volatility was found inefficient and biased and compared so poorly with volatility forecasts based on historical returns.

Since the past literature provides quite different information on whether implied volatility provides meaningful information to volatility forecasts or not, especially during in challenging trading environments, it is worthwhile checking on that. Only when find out what is the best volatility input during the financial crisis period, the financial mangers and investment banks can consider the best volatility covariance parameter estimates in order to provide the most accurate VAR measurement and management.

2.2.5 Introduction to Implied Volatility Index

According to Christensen & Hansen (2002), it is widely believed that the volatility implied in a price of option is the forecast of future return volatility of option market over the remaining life. Under a rational expectations assumption, the market uses all the information available to form its expectations about future volatility, and hence the market option price reveals the true volatility estimate of the market. Furthermore, if the market is efficient, then the estimate of the market, or the implied volatility, is the best possible forecast given the currently available information. Jorion (1995) concludes from a time series perspective that implied volatility was an efficient estimator of future return volatility in the foreign exchange market. Blair, Poon, and Taylor (2001) also show that historical returns do not provide much incremental information compared to the information given by the VIX index of implied volatility.

Giot (2005) proves that forecasting volatility is one of the major success stories in quantitative finance, and volatility forecasting models have enjoyed tremendous success since Engle (1982) introduces the method in the early 1980s. A growing trend advocates the use of implied volatility as the best estimate of future volatility. Under an option pricing model such as Black and Scholes (1973), the expected volatility of an asset over the life of an option is the volatility embedded in the price of the option. If call or put option prices are available, and then based on Black and Scholes (1973) pricing formula, the expected volatility over the life of the option from the observed market option prices can be computed. When all other option parameters are known, there is a one-to-one relationship between option prices and the underlying expected asset volatility, and that is implied volatility.

Dowling and Muthuswamy (2005) firstly introduce the idea of constructing an Australian implied volatility index using index options and investigated its properties. Frijns, Tallau, & Tourani-Rad (2009) further develop the AVX based on index options and index futures options. They find that the implied volatility index based on the S&P/ASX 200 index options contained important information about future volatility for both in-sample and out-of-sample. However, Frijns, Tallau, & Tourani-Rad (2009) only constructed AVX using the daily option price data from SIRCA for the period 2003 to 2008. Since Value at Risk is a measurement tool to predict financial risk has only been introduced in the 1990s, and using AVX as its volatility measure since 2005, it is worth checking if VAR models based on this volatility input can work during the financial crisis periods, moreover, if it can work, whether VAR model based on AVX can compete with other volatility forecasting methods.

2.2.6 Other alternatives of VAR volatility Inputs

There are quite a lot other alternatives can be use as an input of VAR, such as Risk-Metrics and GJR-GARCH.

As per Pafka & Kondor (2001), RiskMetrics is a widely used methodology for measuring market risk; the results are commonly found performed satisfactorily well. However, Pafka & Kondor (2001) also show that RiskMetrics model is based on the unrealistic assumption of normally distributed returns, and completely ignored the presence of fat tails in the probability distribution, a most important feature of financial data. For this reason, the financial managements would expect the model to seriously underestimate risk. Despite this problem, RiskMetrics has played and continues to play an extremely useful role in disseminating risk management ideas and techniques, even if over-simplified.

Moreover, point out from Engle (2004), ARCH family models is attributable in large measure to the applications in finance. While the models have applicability for many statistical problems with time series data, ARCH model found particular value for financial time series. Since returns are almost unpredictable, they have surprisingly large numbers of extreme values, and both the extremes and quiet periods are clustered in time. These features are often described as unpredictability, fat tails, and volatility clustering. These are precisely the characteristics for which an ARCH model is designed. Engle (2004) also shows that the GARCH (1, 1) specification is doing very well of financial applications, it gives weights to the unconditional variance, the previous forecasts, and the news measure as the square of yesterday's return. It is remarkable that one model can be used to describe the volatility dynamics of almost any financial return series.

2.3 Back-testing of VAR model

Due to the discrepancy in the VAR methodologies and their application, it becomes essential to test the performance of VAR models. And the testing method for VAR model is often referred to as back testing. (Cassidy, 1997)

Firms that use VAR as a risk disclosure or risk management tool are facing growing pressure from internal and external parties such as senior management, regulators, auditors, investors, creditors, and credit rating agencies to provide estimates of the accuracy of the risk models being used (Jorion 2005). As Greenspan (1996) points out, disclosure of quantitative measures of market risk, such as Value-at-Risk, is helpful only when accompanied by a thorough discussion of how the risk measures were calculated and how they related to actual performance.

As per Jorion (2005), back testing is a formal statistical framework that consists of comparing the actual losses with the projected losses. This involves systematically contrast the history of VAR forecasts with their associated portfolio returns. Moreover, back testing is also central to the Basel Committee's ground-breaking decision to allow internal VAR models for capital requirements.

Christoffersen & Pelletier (2004) also points out, financial risk model evaluation or backtesting is a key part of the internal model's approach to market risk management as it laid out by the Basel Committee on Banking Supervision. They also point out that the existing backtesting methods such as those developed in Christoffersen (1998) have relatively small power in realistic small sample settings. Methods suggested in Berkowitz (2001) are fare better, but rely on information such as the shape of the left tail of the portfolio return distribution, which is often not available. However, VAR which is the most common risk measurement is defined as a conditional quantile of the return distribution, and it says nothing about the shape of the tail to the left of the quantile.

According to Jorion (2002), by checking the frequency and the size of the expected loss is a more accurate way to find out the predicting power of the back-testing analysis. And the most common statistical tests based on the frequency and time dynamics are Kupiec's (1995) test. Kupiec's test attempts to determine whether the observed frequency of exceptions is consistent with the frequency of expected exceptions according to the VAR model and chosen confidence interval. Under the null hypothesis that the model is correct, the number of exceptions follows a binomial distribution. If the estimated probability is above the desired null significance level, the model is accepted. If the estimated probability is below the significance level, the model is rejected. Jorion (2002) shows that this test is used to determine how well the model predicts the frequency of losses and gains beyond VAR numbers; however, the Kupiec's test only focuses on the frequency of exceptions, and ignores the time dynamics of those exceptions. In this absence, in the Kupiec's test, VAR models assume that exceptions should be independently distributed over time. If the exceptions exhibited some type of "clustering", then the VAR model may fail to capture P&L variability under certain condition, which could represent a potential problem.

According to Giot (2003), he shows that it is also very important that the VAR violations be uncorrelated over time, and he suggests Christoffersen's Conditional Test (1998) adds the benefit of conducting these types of tests to generate some additional useful information such as the conditional probabilities of experiencing an exception followed by an exception in the risk model, and the average number of days between exceptions. Giot (2003) also shows that Christoffersen's Conditional Test do provide valuable information to the backtesting of VAR models.

VAR models are used as the risk management tool, so they are only useful insofar as they can be demonstrated to be reasonably accurate. In order to to make sure

VAR measures are accurate, the backtesting on the predicted results becomes crucially important.

To conclude from this chapter, it discusses the importance of recognize risk management, and how does Value at Risk been introduced as a risk measurement tool based on the history literatures. Moreover, it concludes from the past literature of what has been used as volatility inputs for VAR, especially focuses on using AVX as it’s primarily inputs.

Chapter Three: Data & Methodology

3.1 Introduction

This chapter discusses the data selection as well as the methodological approach that uses to provide answers to the research question. This Chapter is organized as follows: (1) introduce the data sample and the source of the materials; (2) outline the research method and the research hypothesis; (3) conclude with a brief summary.

3.2 Data Collection

In this dissertation, Australian Stock market has mainly been focused and Australian implied volatility index (AVX) has been used as an input for VAR to quantify risk, moreover whether AVX helps to model the VAR model with the other two volatility models has been compared. As it mentions in the previous chapter, correctly identify the particular characteristics of the sample data, including the acknowledgement of its distribution, the skewness, etc is a very important element to choose the correct methods to identify volatility. This section focuses on explain the special characteristics of the sample periods.

Australian Stock Market data is used to test the stability of VAR models. Daily S&P/ASX 200 stock Index level from 02/01/2003 to 31/12/2008 are downloaded from DataStream. The constructed Australian Implied Volatility Index for the same periods is obtained from Frijns, Tallau, & Tourani-Rad (2009).

Figure 3-1 shows the S&P/ASX 200 stock prices index from the beginning of 2003 to the end of 2008. As the above figure shows, the Australian stock index price starts to increase from the beginning of 2003 from 15,613.43 points and reaches its peak at the beginning of 2008 which is over 42000 points. During these five years, the Stock Index has more than doubled. However, during 2008, the Australian Stock index prices have dropped dramatically from over 42000 points back to

24000 points. As we can see from the above figure, over the past six years, there is a huge fluctuation on the Index prices. Since Value at Risk is a measurement tool to predict financial risk has only been introduced in the 1990s, it is worth checking if VAR models can work during the financial crisis periods, moreover, if it can work, whether VAR model based on AVX can compete with other volatility forecasting methods.

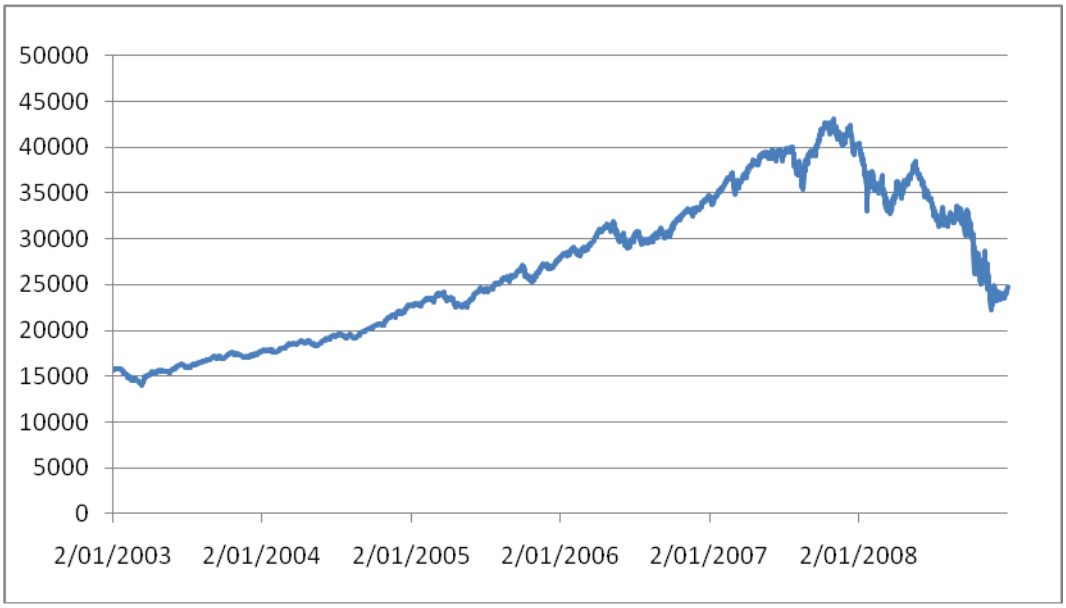

Figure 3-1: S&P.ASX 200 Stock Index Price Level
Note: This figure reports ASX 200 Index prices trends during 2003 to 2008

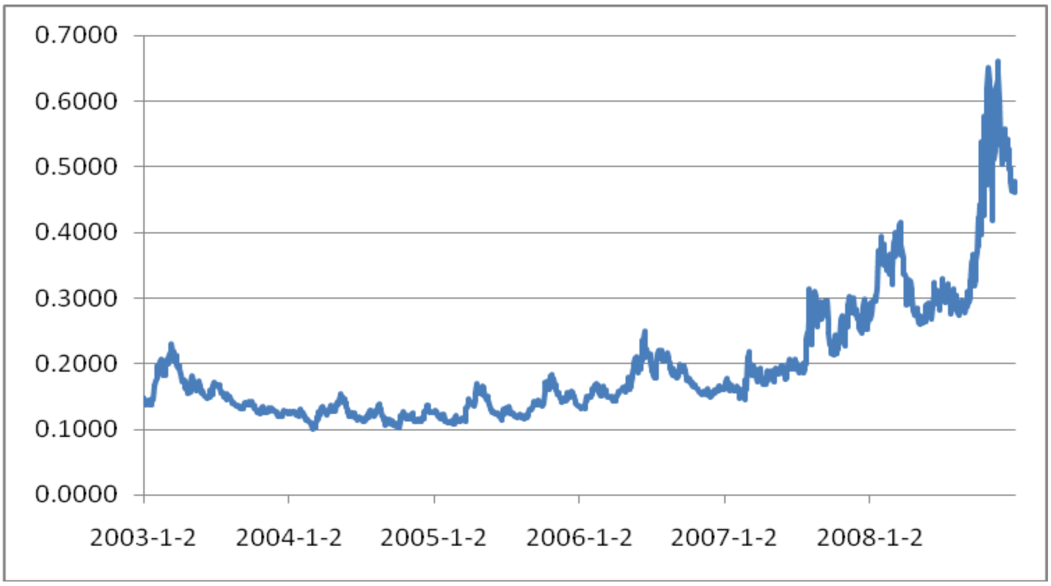

Figure 3-2: Australian Implied Volatility Index
Note: This Figure reports trends of Australian Implied Volatility Index during 2003 to 2008

Since this dissertation mainly focuses on the information content of AVX to VAR model, the above figure shows the special characteristics of AVX during the tested sample period. Figure 3-2 shows the fluctuations of Australian Implied Volatility Index during 2003 to 2008. As it shows the implied volatility index was relatively unstable at the beginning of 2003 (from 0.1485 in Jan 2003 to 0.1170 in Oct 2004). During the years 2004 to 2007, the market was quite steady. However, when the financial crisis started at end of 2007, the market became extremely volatile. The Implied Volatility Index jumped to 0.41 at March 2008 and in Dec 2008, it even leaped up to 66.15%. The Implied Volatility Index in 2008 was almost four times to the Volatility Index figure in 2003. As mentioned in the Literature Review, Implied volatility is a forward looking measure for the future volatility. Because this dissertation focuses on using Australian implied volatility index (AVX) as an input to help improving the VAR model, it is very important to check the validity of AVX as an risk management tool during the high volatility periods and low volatility periods.

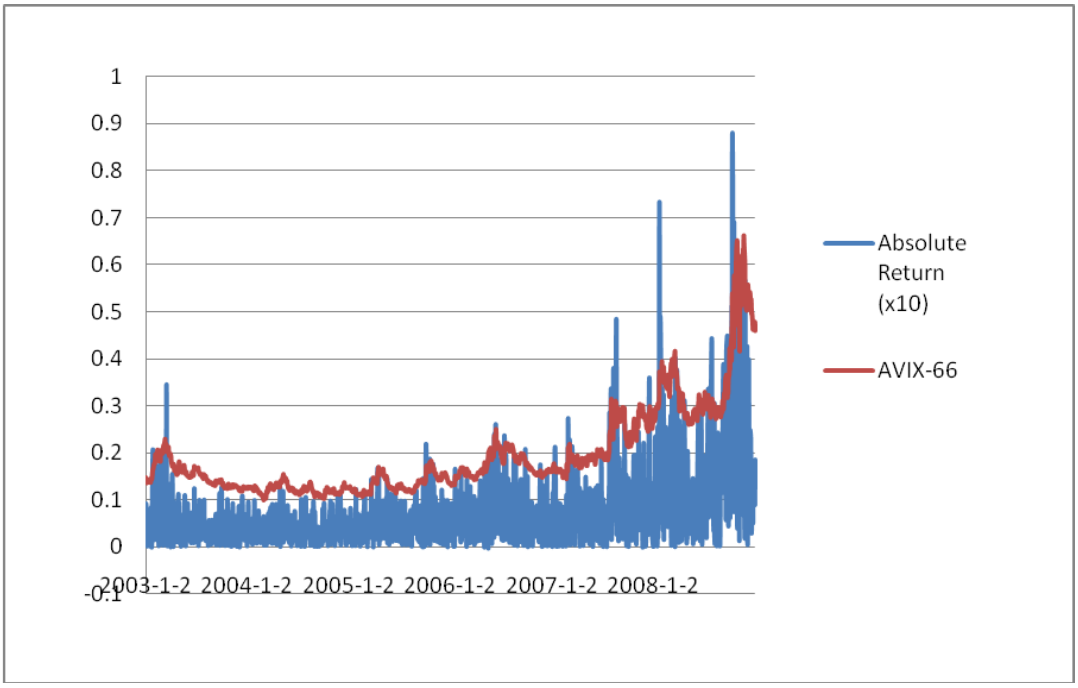

Figure 3-3: Australian VIX and Absolute Return for ASX 200

Note: This Figure shows the AVX during 2003 to 2008 and also outlines the absolute return on S&P/ASX 200. The return series have been scaled-up by ten times in order to show more clearly.

As it shows in Figure 3-3, during the first four years, the Australian implied volatility index is quite constant and the return for its stock market is quite even too. However, from the beginning of 2007, the implied volatility index becomes much more volatile than ever before, in addition, the return series for the most recent two years are much more volatile than the beginning four years.

To conclude from the above three Figures, total test sample periods is divided into two sub-periods: 02/01/2003 – 29/12/2006 which are low volatility, low returns; 02/01/2007 – 31/12/2008 which are high volatility, high fluctuation on returns. The characteristics of the first sample period (02/01/2003 – 29/12/2006) and second sample period (02/01/2007 – 31/12/2008) are quite different, where the first period shows the market is bull market with low volatility and the second period shows it is a bear market with high volatility. The total sample periods is divided into the above two sub-periods because of the following three reasons: (1) the first period can be seen as the pre-financial crisis period and the second period is the post-financial crisis period, and by doing dividing the sample period into these two periods, I can find out whether the estimated VAR model based on the pre-crisis period can work during the financial crisis period; (2) during the second sample periods, ASX 200 stock index have got a much higher return compared with the first sample period, it is worth checking if VAR works during the high return period; (3) this dissertation focuses on using AVX as an important input of VAR to measure its risk predication ability compared with other methods, it's very important to check the accuracy of using AVX at both high volatility periods and low volatility periods.

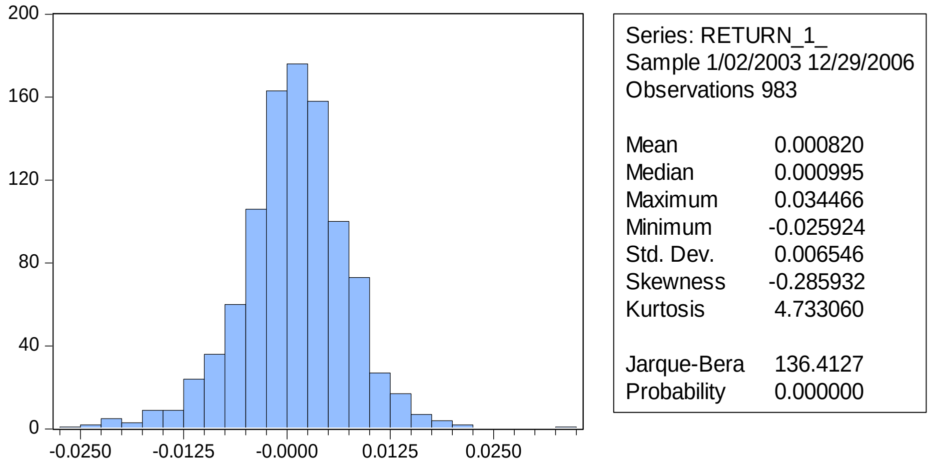

Figure 3-4: Distribution Plot of S&P/ASX 200 Returns for Sub-Period One: 02/01/2003- 29/12/2006 at One-day Interval

Figure 3-4 shows the distribution plot of S&P/ASX 200 returns for the pre-financial crisis period at one-day interval. The graph is quite similar to a bell shape, but it has slightly skewed to the left and is relatively taller than the standard bell shape since its kurtosis is exist to three.

The same outputs of the return distribution plot for the pre-and post financial crisis period at three different observation intervals is summarized and presented in the Table 3-1. This table shows the summarize statistics of the pre- and post financial crisis periods under 1-, 5-, 10 days return interval. Under the pre-financial crisis period (2003- 2006), the return series have a long left tail as Skewness is always negative, and it shows more clearly under 10 days return interval compared with 1 day interval. Kurtosis shows the return distribution is peaked than normal distribution, as under normal distribution, Kurtosis should be equals to 3. Moreover, under Jarque-Bera Test, the p-value is all equals to zero, which is less than 5%, and this indicates the returns series are not under normal distribution. The post-financial crisis period shows the similar results to the pre-financial crisis period. The Skewness figures show the return series for the post crisis period also have a long left tail. Compare with the post-financial crisis period, the returns series for pre-financial crisis period is flatter than the next two years return distribution.

To conclude from the above figures, the first four years return distribution is more normally distributed than the next three years, and this also proved by Jarque-Bera figures. Normally distributed means frequency analysis of the data reveals bell curve and most of the values near the middle datum or average of the sample, very few values near the upper and lower extremes. In this case, the Figures of the two sub-periods show that in sub-period one, there is more return series near the middle or average of the sample, and in sub-period two, there is more series near the upper and lower extremes. This also proves that during the sub-period two, where the market is more volatile, and the return is becoming more unstable. And although sub-period one is more normally distributed compare with sub-period two, they are still not normal distributed, as all of the Jarque-Bera test have been rejected.

Table 3-1: Summary Descriptive Statistics of Return Series for S&P/ASX 200 for two sub-periods

	Pre-Crisis Period (983 Observations) (02/01/2003 - 29/12/2006)			**Post-Crisis Period (496 Observations) (02/01/2007 - 31/12/2008)**		
	1Day Interval	5Days Interval	10Days Interval	1Day Interval	5Days Interval	10Days Interval
Mean	0.000820	0.004044	0.008096	-0.000619	-0.003616	-0.007323
Median	0.000995	0.005192	0.011268	-0.000052	0.001256	0.002460
Maximum	0.034466	0.061856	0.072392	0.056273	0.122101	0.103255
Minimum	-0.025924	-0.056154	-0.073392	-0.087062	-0.170134	-0.213293
Std. Dev	0.006546	0.014008	0.019895	0.017452	0.034600	0.046262
Skewness	-0.285932	-0.608248	-0.649208	-0.320043	-0.700723	-1.362366
Kurtosis	4.733060	4.491820	3.646752	5.821989	5.530057	6.148838
Jarque-Bera	136.412700	151.766660	86.183400	173.048800	172.881600	357.623900
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Since this dissertation focuses on using AVX as VAR model's input, implied volatility index have also divided into two sub-periods in order to differentiate the special characteristics of those two periods, the following two figures show the descriptive statistics:

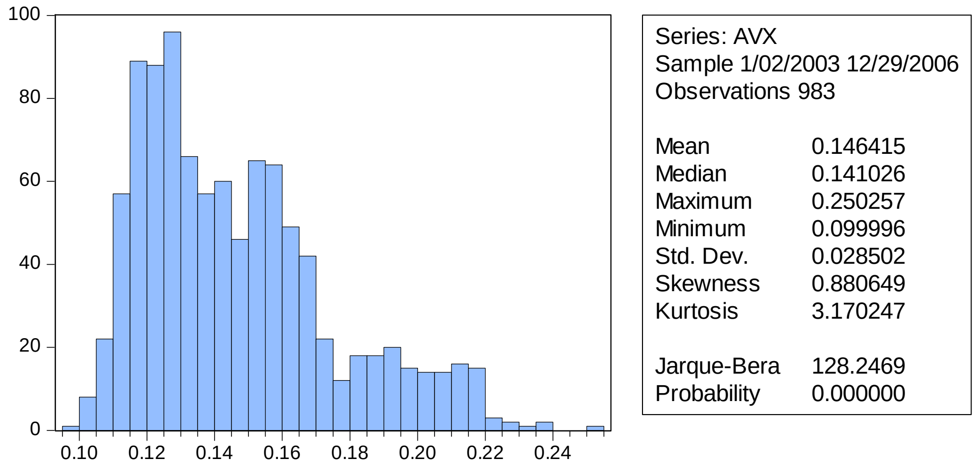

Figure 3-5: Distribution Plot for AVX for Period One: 02/01/2003 – 29/12/2006

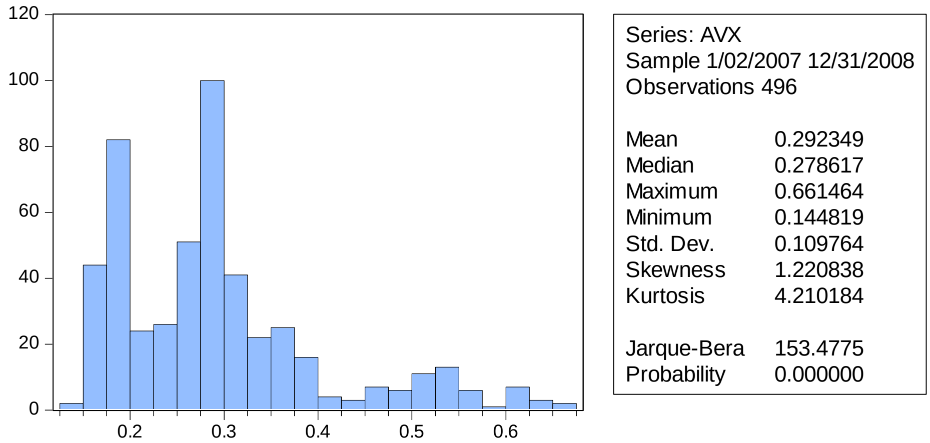

Figure 3-6: Distribution Plot for AVX for Period two: 02/01/2007 – 31/12/2008

To conclude from figure 3-5 and figure 3-6, the spread of volatility during financial crisis period has become much bigger than pre-financial crisis period, it has increased from 0.24 to 0.6. Also during the financial crisis period, there are lots of extreme events since the plot is hardly maintain to a bell shape, there are quite a few gaps in between the return columns.

Moreover, in order to find out whether these two periods are similar or not, Test of equality is also been completed. The following table shows the results:

Table 3-2: Test of Equality for AVX1 and AVX2

<u>Test for Equality of Means Between Series</u>

Sample: 1983

Included observations: 983

Method	df	Value	Probability
t-test	1477	-39.1614	0
Satterthwaite-Welch t-test*	528.9456	-29.1189	0
Anova F-test	(1, 1477)	1533.618	0
Welch F-test*	(1, 528.946)	847.9082	0

*Test allows for unequal cell variances

As Table 3-2 shows, the probability of this test is equal to zero, it means the test of quality of means between AVX1 and AVX2 have been rejected. So there are some major differences between sub-period one and sub-period two. In this absence, it will be worth while checking the VAR performance during those two significant different periods.

To conclude from collected data, the total sample period has been divided into two special periods: Sub-period one summarizes as the pre-financial crisis period; sub-period two is the post-financial crisis period. There is quite a distinctive difference between these two periods as all the figures and tables show above. So it is necessary to find out whether VAR models based on pre-financial crisis period will work during the post-financial crisis period.

3.3 Research Methodology

VAR modelling is a natural application of volatility models as VAR measures are directly related to the expected volatility over the relevant time horizon.

The following formula shows the parametric one-day VAR at time t is:

$$VAR_t = Z_\alpha \sqrt{g_t}$$

Where Z_α is the quantile at 100*α percent of the standardized density distribution.

To estimate the best VAR forecasting results, there are two important components for VAR analysis: Distribution and Volatility. This dissertation focuses on using three different inputs for measuring volatility for VAR and compares the measuring performance based on two different periods of times. The rest of this section will explain how to use probability distribution functions to find the probability of loss, and back testing the VAR measurements.

3.3.1 Distribution

Every VAR measure makes assumptions about the return distribution. The normal distribution is the most common type of distribution, and is often found in stock market analysis. With delta-normal estimates of VAR, it is assumed that the multivariate return distribution is the normal distribution. So this dissertation assumes the S&P/ASX 200 returns are all under normal distribution.

3.3.2 Volatility Analysis

As previous discussed, volatility input is a very important input of VAR analysis and in this dissertation, the implied volatility indexes are the key inputs in the g_t specification, i.e. the volatility part of the VAR model is directly specified by the AVX. There are lots of different types of models to define g_t, the following three models will be used in this dissertation:

- Lagged implied volatility

$$g_t = \omega + \pi \sigma^2_{imp,1,t-1}$$

In this method, the volatility input is directly proportional to the 1-day scaled implied volatility, e.g. for the 5-day interval, $\sigma_{\mathrm{imp},5,t} = \sqrt{\frac{5}{360}}\,\mathrm{VIX}_t$

- RiskMetrics

$$g_t = 0.04 r_{t-1}^2 + 0.94 g_{t-1}$$

- GJR-GARCH

$$g_t = \omega + \alpha_1 r_{t-1}^2 + \alpha_n r_{t-1}^2 d_{t-1} + \delta_1 g_{t-1}$$

3.3.3 Efficiency and unbiasedness of implied volatility

This dissertation focuses on using AVX as an input of Value at Risk and then compares the prediction results with Risk-Metrics model and GJR-GARCH model. In order to find out whether volatility forecast based on historical returns deliver unbiased and efficient forecasts of future realized volatility, the encompassing regression analysis has been chosen. In particular, the forecast performance of the Australian implied volatility index based on historical returns have been calculated in three different time horizons in order to check if the implied volatility series add information beyond that included in models based on past prices. Moreover, the Risk-Metrics approach as well as the GJR-GARCH (1, 1) for forecasts with 5-, 10-day horizon have both been included in order to compare prediction of AVX. The performance of the various forecasters can be determined by running a performance regression of the realized volatility against each specific forecaster, i.e.

$$RV_{5,t} = \beta_0 + \beta_1 IV_{5,t} + e_t$$

Where $IV_{5,t}$ is derived previously. In order for $IV_{5,t}$ to be an unbiased forecast of $RV_{5,t}$, $\beta_0 = 0$ and $\beta_1 = 1$ is required. In addition, to assess the predictive power of $IV_{5,t}$, the adjusted R^2 have been compared.

In order to run the comparison test, three different methods will be used to calculate implied volatility:

- Lagged implied volatility

The measurement of implied volatility is given by the level of the Australian Implied volatility index for the S&P/ASX 200. By definition, the implied volatility indexes are expresses in annualized terms, so in this dissertation, firstly the implied volatility indexes have been switched to the required 5- or 10-day interval. Hence and for the 5-day forward looking horizon, the implied volatility forecast on the day t for the S&P/ASX 200 index is equal to:

$$\sigma_{imp,5,t} = \sqrt{\frac{5}{360}}\, VIX_t \quad (1)$$

The $\sigma_{imp,5,t}$ is the expected volatility over the [t+1, t+5] period. For the 10 day time horizon, the volatility forecasts are the $\sigma_{imp,10,t} = \sqrt{\frac{10}{360}}\, VIX_t$.

Given the daily returns $r_t = Ln(P_t) - Ln(P_{t-1})$ for the S&P/ASX200 index, the forward-looking realized volatility over a time horizon of 5 days is computed by taking the square root for the sum of the (future) squared returns over this 5 days period. At time t, the forward-looking realized volatility $RV_{5,t}$, for the time period [t+1, t+5] is thus computed as:

$$RV_{5,t} = \sqrt{\sum_{j=1}^{5} r_{i+j}^2} \quad (2)$$

This volatility measure is computed ex-post, i.e. at time t+5 when all returns have been observed. Similar expressions can be computed for the 10-day time horizon. For the encompassing regressions, the realized volatility is defined from non-overlapping data. Indeed, the measure of realized volatility computed using Equation (2) and using all $\{RV_{5,t}\}$ for the t=1…T yields strongly correlated volatility measures. As pointed out in Christensen & Prabhala (1998), the use of realized volatility computed from overlapping data in regression analysis yields potentially big estimation problems as the regression's residuals will be strongly auto-correlated. Hence in this dissertation, the realized volatility measures computed from non-overlapping squared return data have been defined. While Equation (2) is still valid, so this dissertation no longer compute it for all t=1…T, but for a subset of those times such that the newly defined $\{RV_{5,t}\}$ use unique data. In this case, it is straightforward to see that the sampling times k are {1,5,10…} for the 5-day horizon and {1,10,20…} for the 10-day horizon.

- Risk-Metrics

$$rm = 0.04r_{t-1}^2 + 0.94rm_{t-1}$$

$$\mathrm{RM}_{n,t} = \sqrt{n\ rm_t}$$

$\mathrm{RM}_{n,t}$ is the n^{th} day volatility forecast according to the Risk-Metrics approach. In this dissertation, I have used 1-, 5- and 10-day observation interval for Risk-Metrics method as well, and this is in order to compare the prediction results with AVX approach.

- GJR-GARCH (1,1)

To construct forecasts based on the GJR-GARCH (1, 1) model, the one-step-ahead forecasts can be easily derived from the GARCH specification:

$$h_{t+1} = \omega + \alpha h_t + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \mathrm{I}_{t-1} \varepsilon_{t-1}^2$$

For longer horizon, this equation will be equal to:

$$h_{t+k} = \omega + (\alpha + \beta_1 + 0.05\beta_2)\mathrm{h}_{t+k-1}$$

And the total volatility n days ahead can be computed as:

$$\mathrm{GJR-GARCH}_{n,t} = \sqrt{\sum_{k=1}^{n} h_{t+k}}$$

In this section, the information content of the AVX based volatility forecasts in a market risk evaluation framework is focused. More precisely, this dissertation spotlight the added value of the AVX based on volatility forecasts when these forecasts are used to quantify short-term market risk.

3.3.4 Back-testing the VaR models

VAR models are only useful when they are accurate. In order to check the volatility of VAR models, the validity of the underlying valuation and risk models through comparison of predicted and actual loss levels have checked systematically. When the model is perfectly calibrated, the number of observations falling outside VAR should be in line with the confidence level. For example, if the confidence level of VAR model is set as 5%, the percentage of its violation should be around to 5%. If the violation (failure rate) is far too above the rate, it means the model haven't correctly identify the risk and it's far too small than it, it means the range of VAR model has been setup too wide. In this dissertation, in order to test whether VAR models based on pre-financial crisis period works for the post financial crisis period, back-testing have becoming crucial important. There are two models used to check how do Value at Risk under each methods perform to a certain benchmark: (1) Kupiec (1995) LR test; (2) Independence and Conditional coverage test.

Firstly Kupiec (1995) LR test is used to back-test the VAR results. As per its definition, Kupiec (1995) LR test gives the ex-post observed returns and ex-ante forecastes, the empirical failure rate f is given by the number of returns smaller than the VAR. So if the VAR model provides valid forecasts, this proportion must be equal to α. In this dissertation, when the confidence level is at 5 percent, if VAR model presents the accurate forecast, the LR value should be less or equal to 5 percent. If LR test value is large than 5 percent, it shows the VAR is not perform well.

More precisely and in the binomial framework, Kupiec (1995) shows that the hypothesis $H_0: f = \alpha$ against$H_1: f \neq \alpha$, can be tested with the LR statistic:

$$LR = -2\ln(\alpha^{T-N}(1-\alpha)^{N}) + 2\ln\left((1-\left(\frac{N}{T}\right))^{T-N}\left(\frac{N}{T}\right)^{N}\right)$$

where N is the number of VAR violations, T is the total number of observations and f is the theoretical failure rate. Under the null hypothesis that f is the true failure rate, the LR test statistic is asymptotically distributed as $x^2(1)$.

Kupiec (1995) LR test assesses only the equality between the proportion of VAR violations and the expected alpha level. According to Giot (2005), in risk management framework, it is also of paramount importance that the VAR violations are uncorrelated over time which leads to the independence and conditional coverage tests based on the evaluation of interval forecasts. So secondly I have used independence and conditional coverage tests suggested by Christoffersen (1998) to test the VAR results. Using the same notation as Christoffersen (1998), the indicator sequence of VAR violations as $\{I_t\}$ can be defined, where I_t is a dummy variable that is equal to 1 if there is a VAR violation at time t (i.e. r_t is smaller than VAR_t) and is equal to 0 if there is no VAR violation at time t. If $\pi_{i,j}$ is the transition probability for two successive I_t dummy variables, i.e. $\pi_{i,j} = P(I_t = j/I_{t-1}$ =i), then the approximate likelihood function for the sequence of I_t is equal to:

$$L_1 = \pi_{0,0}^{n_{0,0}}\pi_{0,1}^{n_{0,1}}\pi_{1,0}^{n_{1,0}}\pi_{1,1}^{n_{1,1}}$$

Where $n_{i,j}$ is the number of observations with value i followed by value j. The approximate maximized likelihood function is then equal to:

$$\hat{L}_1 = \left[\frac{n_{0,0}}{n_{0,0}+n_{0,1}}\right]^{n_{0,0}} \left[\frac{n_{0,1}}{n_{0,0}+n_{0,1}}\right]^{n_{0,1}} \left[\frac{n_{1,0}}{n_{1,0}+n_{1,1}}\right]^{n_{1,0}} \left[\frac{n_{1,1}}{n_{1,0}+n_{1,1}}\right]^{n_{1,1}}$$

If the $\{I_t\}$ sequence, i.e. the sequence of VAR violations, is (first-order) independent, then $\pi_{0,0} = 1 - \pi, \pi_{0,1} = \pi, \pi_{1,0} = 1 - \pi$ and $\pi_{1,1} = \pi$. this gives the likelihood under the null of first-order independence:

$$L_2 = (1-\pi)^{n_{0,0}+n_{1,0}} \pi^{n_{0,1}+n_{1,1}}$$

This is then estimated as:

$$\hat{L}_2 = \left[1 - \frac{n_{0,1}+n_{1,1}}{n_{0,0}+n_{1,0}+n_{0,1}+n_{1,1}}\right]^{n_{0,0}+n_{1,0}} \left[\frac{n_{0,1}+n_{1,1}}{n_{0,0}+n_{1,0}+n_{0,1}+n_{1,1}}\right]^{n_{0,1}+n_{1,1}}$$

The LR test statistic for (first-order) independence in the VAR violations is equal to:

$$LR_{ind} = -2(\ln(\hat{L}_2) - \ln(\hat{L}_1)) \sim x^2(1)$$

Provided that we condition on the first observation in the test for unconditional coverage, the LR statistic for conditional coverage (i.e. the joint hypothesis of unconditional coverage and independence) is equal to:

$$LR_{cc} = LR_{uc} + LR_{ind} \sim x^2(2)$$

Where $\mathrm{LR}_{\mathrm{uc}}$ is the LR statistic for unconditional coverage (computed above for the Kupiec 1995 test).

So this dissertation bases on Kupiec(1995) LR test to find out the failure rate of VAR results, then Christoffersen (1998) method has been used to carry the independence and conditional coverage tests results in order to test if VAR violations are un-correlated over time. For both of the backtesting tests, the VAR results under different methods for volatility inputs at different observation levels are presented. Based on the available data and method, results of VAR models are disclosed in the Chapter Four.

Chapter Four: Empirical Analysis

This chapter firstly presents the results for implied volatility and realized volatility regression, this will point out whether implied volatility based the three chosen methods can forecast realized volatility and which is best forecasting method. Next the results for the methodology previous chapter has mentioned to assess the VAR forecasts for the S&P/ASX 200 stock index are presented. Finally, Kupiec LR test and Independence and Conditional coverage test results are presented for back testing on VAR.

4.1 Implied volatility and Realized Volatility Regression Analysis

The following table shows the comparison results of using these three different methods for the two different sub-periods. This table includes the coefficients and the adjusted R^2. The prediction results with the highest adjusted R^2 means it produces better forecasts. The table above includes three different panels, which presents the results under three different forecasting methods at three different observation intervals. Moreover, under each panel, the testing results are divided into two sub-periods as previous chapter mentioned. To conclude from the above table, there are four significant results that can be summarized from the above table: firstly the best method of calculating implied volatility in order to predict realized volatility is based RiskMetrics, for both of those two sub-periods; Secondly the GJR-GARCH does not produce better forecasts than AVX at any of the horizons; Thirdly, the prediction of realized volatility based on three different methods do not seem to depend on the sub-period and whether it is a bull or bear market, or a market exhibiting high or low volatility; Finally, during the last period: 2/1/2007-31/12/2008, the best method of predict implied volatility is Risk-Metrics, then Australian Implied volatility index. This means during the financial crisis period, AVX cannot provide the best prediction results compare with Risk-Metrics method. But since we have run the regression of implied volatility with realized volatility, it has given the coefficient between them, with the control of the biasness; we can still input them as the volatility measurement instrument for VAR models.

Table 4-1: Implied Volatility and Realized Volatility Regression under AVX, RM, and GARCH

	Forecasting Regression For VIX			**Forecasting Regression For Risk-Metrics**			**Forecasting Regression For GARCH**		
02/01/2003-30/12/2005	β_0	β_1	R^2	β_0	β_1	R^2	β_0	β_1	R^2
RV1	0.9407	0.4490	0.4098	0.0016	0.9199	0.9971	1.0413	-0.0319	0.1300
RV5	0.2986	0.7699	0.7942	0.0519	0.9644	0.9964	0.3088	0.7507	0.7538
RV10	0.2263	0.8806	0.9263	0.0674	0.9684	0.9983	0.2230	0.8432	0.8816
03/01/2006- 31/12/2008									
RV1	0.9329	0.0710	0.4098	0.0027	0.9448	0.9849	0.8585	0.0993	0.2223
RV5	0.1374	0.8738	0.8859	0.0519	0.9609	0.9966	0.1796	0.8246	0.8840
RV10	0.0862	0.9463	0.9618	0.0723	0.9627	0.9980	0.1516	0.9113	0.9614

4.2 Volatility forecasts and back testing on VAR

As the previous Chapter introduced, VAR measure promises that the actual return will only be worse than the VAR forecast p*100% of the time. Which indicate for the ideal VAR model, the total number of violation should be equal or less than p*100%.

Figure 4-1 shows VAR results under standard deviation of the return series at 99 percent confidence level versus the returns series of S&P/ASX 200. As we can conclude from the above figure, the returns series is quite fluctuate during the test-sample period as the stock Index prices always go up and down. However, when calculating VAR based on the standard deviation of the return series, it will only provide a flat line as the figure shows above and this will never correctly indicate the number of violations based on each methods and, it will be difficult to pinpoint the likelihood of extreme events, doing so enables the risk manager to construct a pseudo data set that combines the actual data with the financial crisis scenarios. So in order to examine whether VAR under each model can provide a reasonable results, the two different methods on back testing will be used in this dissertation. As it is widely known, significant in-sample evidence of predictability does not guarantee significant out-of-sample predictability. So in order to find out which method is supreme to the others, both In-sample test and Out-of-sample test results under each method are presented, and back-testing results have also shown under each method.

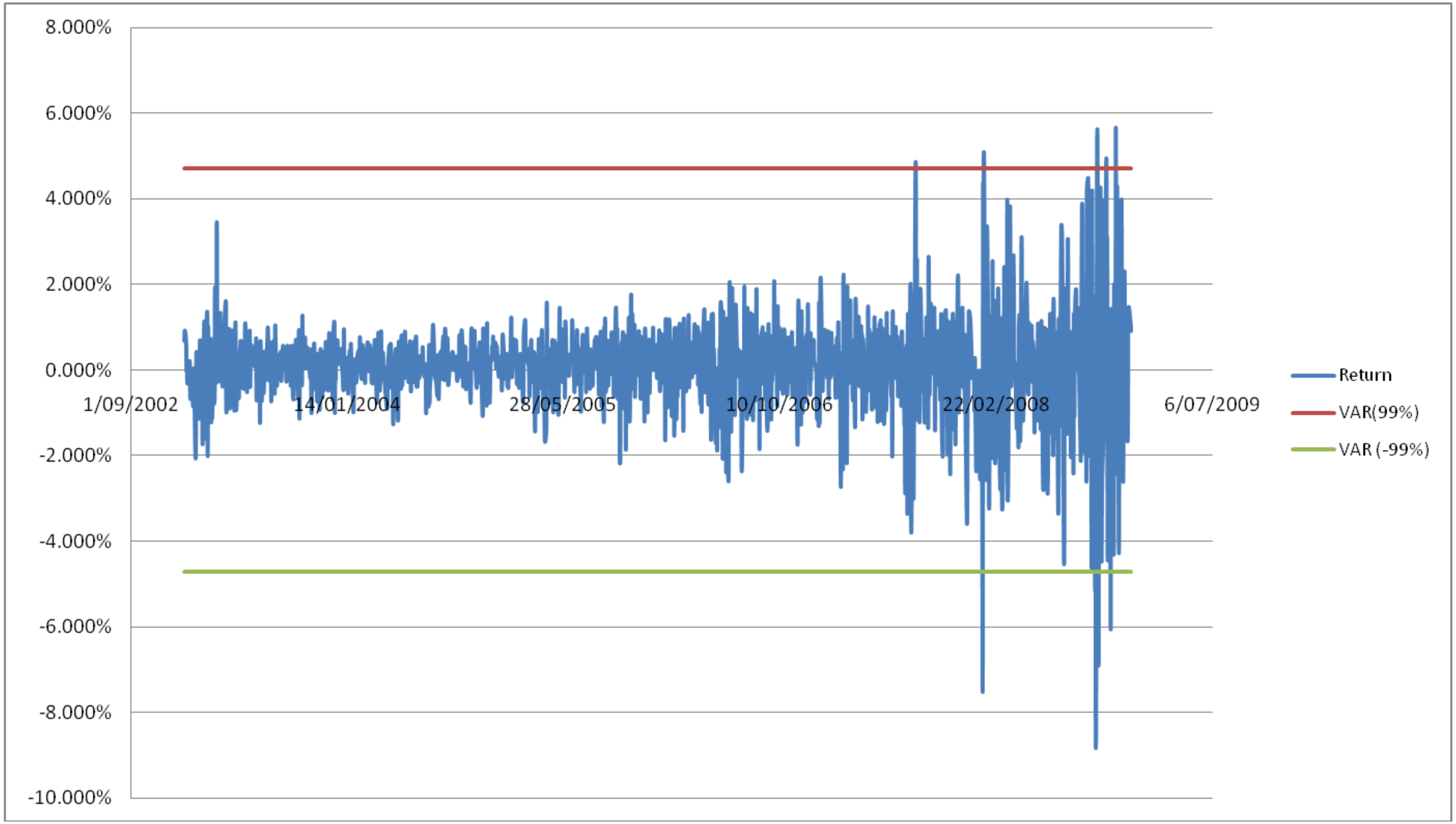

Figure 4-1: VAR results under standard Deviation at 99 percent confidence level

As the previous chapter introduced, the sample period of In-sample test has only been chosen for the pre-crisis period, which is from 02/01/03 to 29/12/06. In-sample test will indicate which VAR methods can provide best predicting results within the tested sample period. Out-of-sample results will examine the estimation model based on the pre-crisis period, and use that model to compare the testing results with the post-crisis real data. To decide on the sample-split parameter, there are two points have been considered: the first reason of chosen this period to do the in-sample test is due to the significant different characteristics of the two sub-periods as previous chapter mentioned, it is worth checking whether the estimated models based the pre-crisis period will be working for the post-crisis period; secondly, if the out-of-sample forecasts have been limited to very recent periods, there will be very few out-of-sample observations to use in calculating the out-of-sample test statistics, and this will make the inferences regarding out-of-sample predictability less reliable. And if the out-of-sample periods have been decided very early in the sample, there will not be enough in-sample observations available to estimate the predictive regression models used to generate out-of-sample periods. As a reasonable compromise, this dissertation have used the first years to predict the volatility to be as an input for VAR model, so that our out-of –sample forecasts are from beginning of 2007. Then two back-testing methods have been introduced to test which methods will show the least number of violations.

4.2.1 In Sample Test

The sample period for the in-sample test is from 02/01/03 to 29/12/06, which is the first four years from the whole sample period. There are 983 observations for the in-sample period. There are three methods have been used in order to find the testing results: AVX, Risk-Metrics and GJR-GARCH. In this section, the testing results at 99 percent confidence level at one day interval for using those three methods as an input for VAR model are presented, the plots for using these methods at different observation intervals are shown in the appendix.

4.2.1.1 Volatility Forecast Results

A: AVX

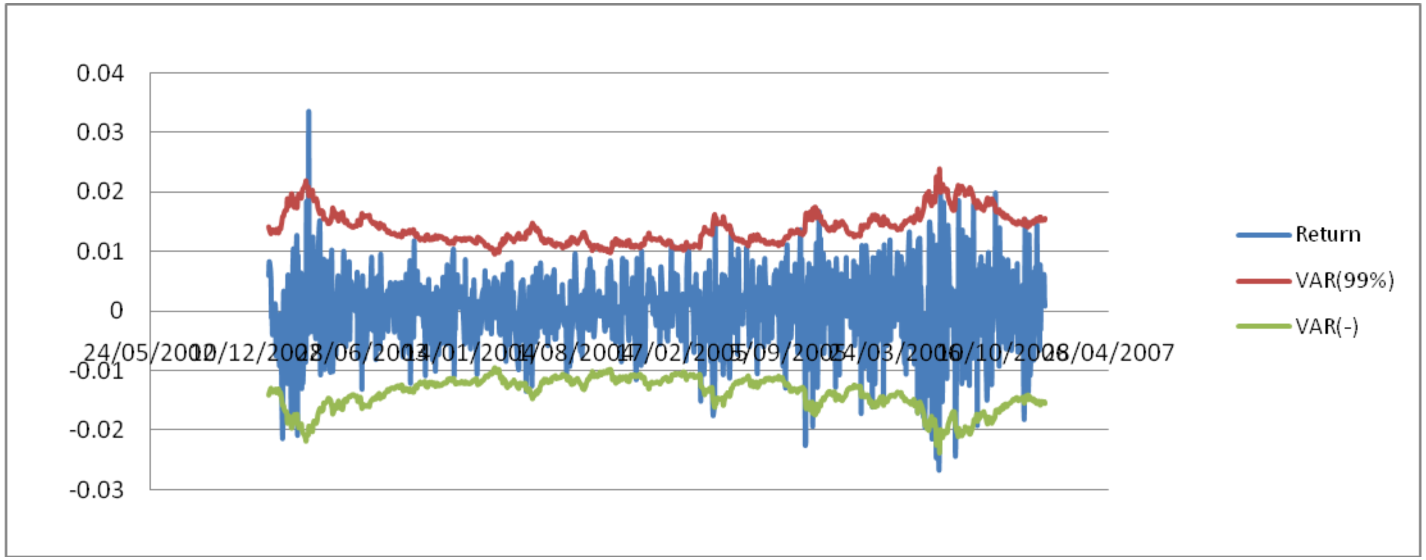

Figure 4-2: In Sample Result of VAR under AVX at one day interval at 99 percent confidence level

Figure 4-2 shows the in-sample-results of VAR when using AVX as its input a one day interval. As it shows in the figure, the red line indicates the calculated VAR number at the maximum gain and green line indicates the calculated VAR at its maximum loss. If the returns fit inside of those two lines, it means there is no violation of the VAR model, and also shows the model is with high accuracy. To conclude from the figure, there are only a few violations at the beginning of the tested sample and few at the end of the sample periods. From the observation of the graph, it shows pretty good prediction of results; however, it does not provide a precise result of the total violations, so back-testing have been used to indicate the total number of violations as well as whether those violations are uncorrelated over time.

B: Risk-Metrics

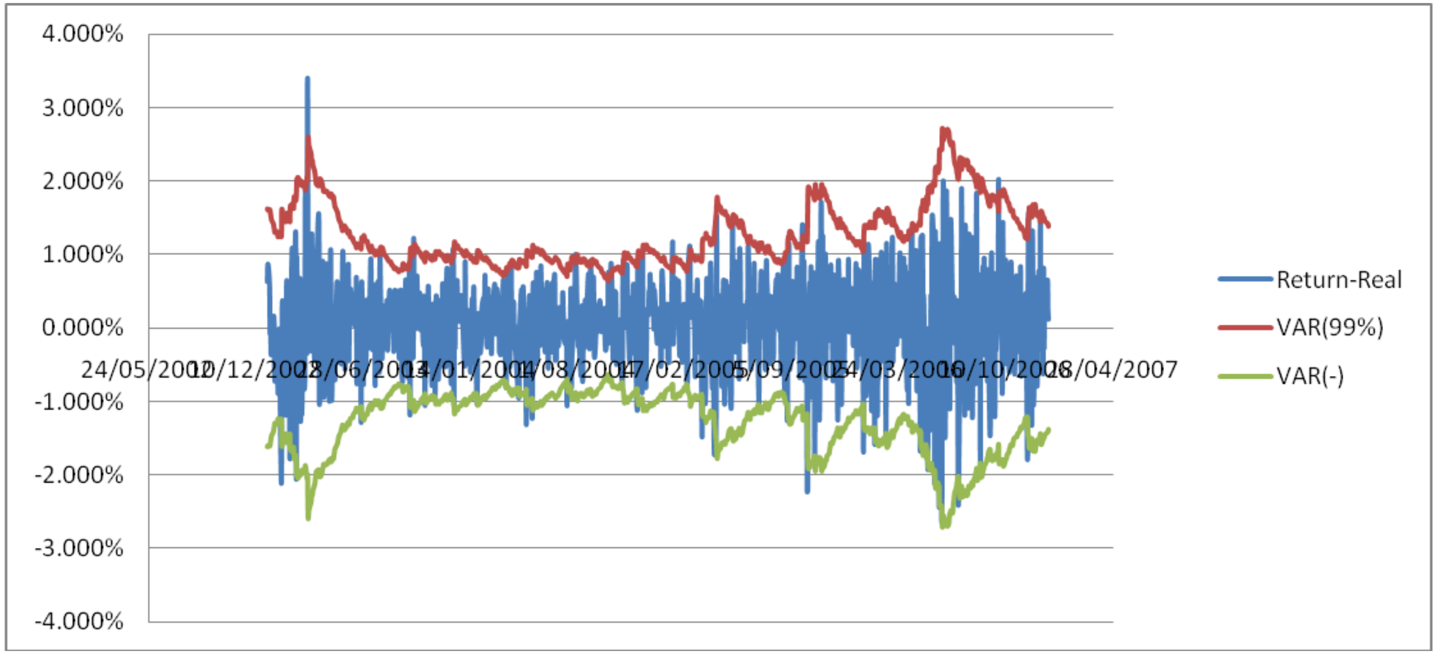

Figure 4-3: In Sample Result of VAR under RiskMetrics at One day interval at 99 percent confidence level

Figure 4-3 shows the in-sample results of VAR model when using RiskMetrics as its input at 1 day interval at 99% confidence level. As the figure above shows, for the one-day interval, the VAR pattern follows the return series more firmly compare with the using AVX as the input for VAR.

C: GJR-GARCH

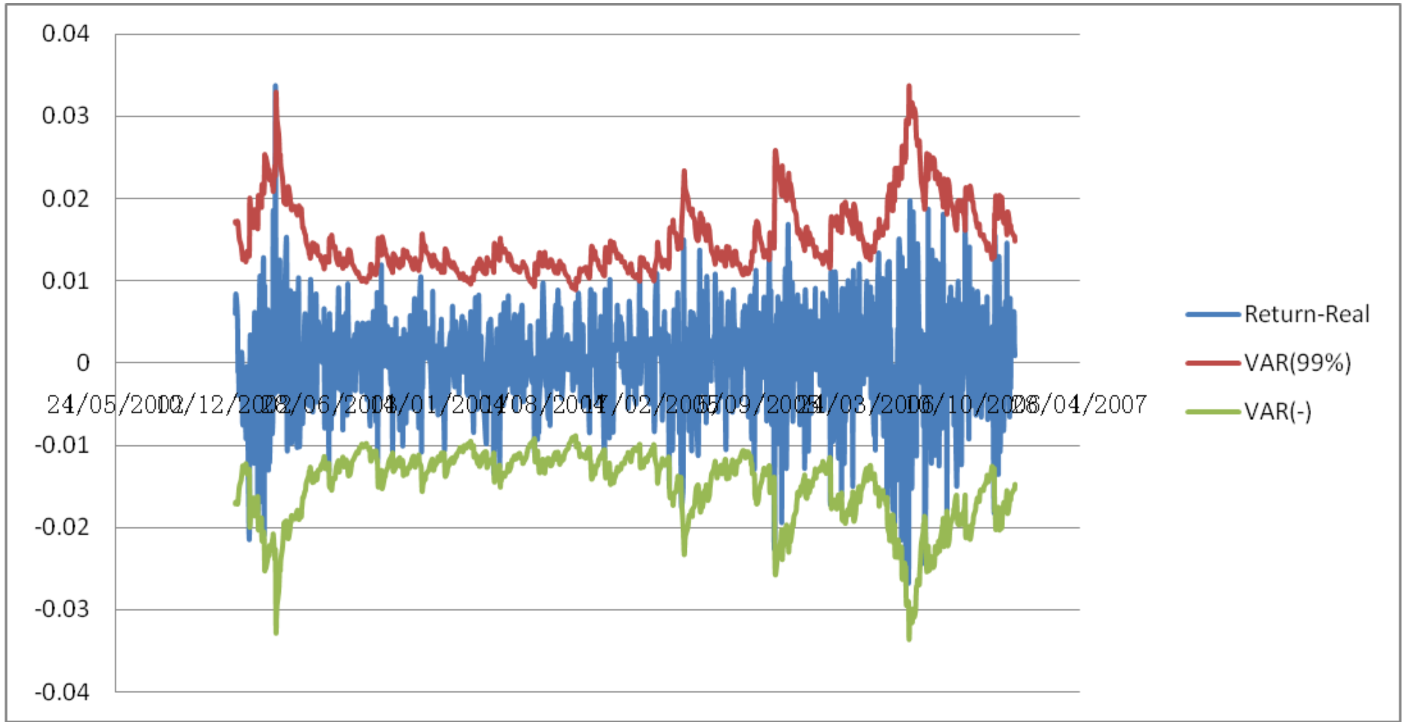

Figure 4-4: In sample Result of VAR model under GARCH method at one day interval at 99 percent confidence level

Figure 4-4 shows the in-sample results of VAR model when using GJR-GARCH as its input at 1 day interval at 99% confidence level. Similar to the previous Figures, using GARCH model as an input of VAR for volatility forecasting, it have also provide a accurate measure at most of the times.

To conclude from the three figures above, they all indicate that during the pre-financial crisis period, AVX, RiskMetrics and GJR-GARCH have provided meaningful volatility information in VAR models as the number of VAR violations is correctly modelled in most cases, and in order to check which methods have provided the most accurate results, back-testing have been used for all of the three methods.

4.2.1.2 Back-testing on In-Sample Results

In the following table, the empirical failure rates and Kupiec LR tests for the right and left quantiles at 5% and 1% are firstly computed. Second, the independence and conditional coverage tests results are presented. This table shows the summary results for the back-testing of the in-sample VAR models on the S&P/ASX 200 index, 02/01/2003- 29/12/2006 at three different observation intervals: 1-, 5- and 10-days. The first volatility specification (top panel) is based the input of AVX, the second specification (middle panel) is based on the input of Risk-Metrics while the third volatility specification (bottom panel) is based on the input of GJR-GARCH, all three with a skewed Student density distribution for the error term. I firstly give the empirical failure rates for the Left (LQ) and right (RQ) quantiles at 5 and 1%. A bold figure indicates that the empirical failure rate is significantly different (LR test or unconditional coverage) from the theoretical value. Secondly, I and CC give the P-value for the independence and conditional coverage tests respectively.

Table 4-2: In Sample Back-testing Results for VAR based on AVX, RM and GARCH

In-Sample VAR results for ASX/S&P 200 Index
(In-Sample Test: 02/01/2003 - 29/12/2006)
Implied Volatility Index (AVX)

	LQ=5%	RQ=5%	LQ=1%	RQ=1%
1-Day Interval				
f (Failure Rate)	3.8657%	4.6796%	0.7121%	**1.9329%**
Kupiec	2.8785	0.2169	0.9148	**6.7887**
I	0.1811	1.4239	N/A	0.7817
CC	3.0596	1.6408	N/A	7.5705

5-Days Interval				
f (Failure Rate)	2.4420%	2.5430%	0.3052%	0.8138%
Kupiec	16.5638	15.1192	6.5869	0.3674
I	25.8294	69.3604	N/A	19.6240
CC	42.3932	84.4796	N/A	19.9916
10-Days Interval				
f (Failure Rate)	2.340%	4.270%	0.410%	1.220%
Kupiec	18.0939	1.1492	4.5017	0.4521
I	41.2284	129.1001	N/A	62.3936
CC	59.3223	130.2497	N/A	62.8457

Risk-Metrics

	LQ=5%	RQ=5%	LQ=1%	RQ=1%
1-Day Interval				
f (Failure Rate)	5.3900%	6.2100%	1.6300%	**3.6600%**
Kupiec	0.3099	2.8026	3.2879	**41.8319**
I	0.3179	0.4073	N/A	0.3311
CC	0.6277	3.2099	N/A	42.1631
5-Days Interval				
f (Failure Rate)	**8.0400%**	4.0700%	2.0300%	1.5300%
Kupiec	**16.2467**	1.9096	8.1784	2.3659
I	63.9491	93.1460	12.5177	32.9362
CC	80.1958	95.0556	20.6961	35.3020
10-Days Interval				
f (Failure Rate)	5.4900%	5.4900%	1.3200%	1.4200%
Kupiec	0.4888	0.4888	0.9376	1.5792
I	66.8952	121.2962	28.2717	26.4550
CC	67.3839	121.7849	29.2093	28.0343

GJR-GARCH

	LQ=5%	RQ=5%	LQ=1%	RQ=1%
1-Day Interval				
f (Failure Rate)	3.764%	3.662%	0.407%	1.333%
Kupiec	3.4444	4.0665	4.5017	0.9376
I	N/A	0.3312	N/A	1.9753
CC	N/A	4.3977	N/A	2.9128
5-Days Interval				
f (Failure Rate)	4.680%	2.543%	0.712%	0.814%
Kupiec	0.2169	15.1192	58.8889	55.0402
I	41.1257	52.5324	12.0855	19.6241
CC	41.3427	67.6515	70.9744	74.6643
10-Days Interval				
f (Failure Rate)	0.610%	3.360%	0.000%	1.120%
Kupiec	63.0264	6.2853	N/A	0.1354
I	N/A	107.2381	N/A	54.3675
CC	N/A	113.5235	N/A	54.5029

4.2.2 Out-of-Sample Test

For the out-of-sample test, there are three different methods that previous chapter mentioned are used to generate implied volatility based on the in-sample data for year 2007 and 2008, and I used those figures as an input for VAR model. There are total of 496 observations for the out-of-sample period. In order to check the volatility of out-of-sample forecasting results, both Kupiec (1995) LR test and Independence and Conditional Tests have been used.

4.2.2.1 Volatility Forecast Results

A: AVX

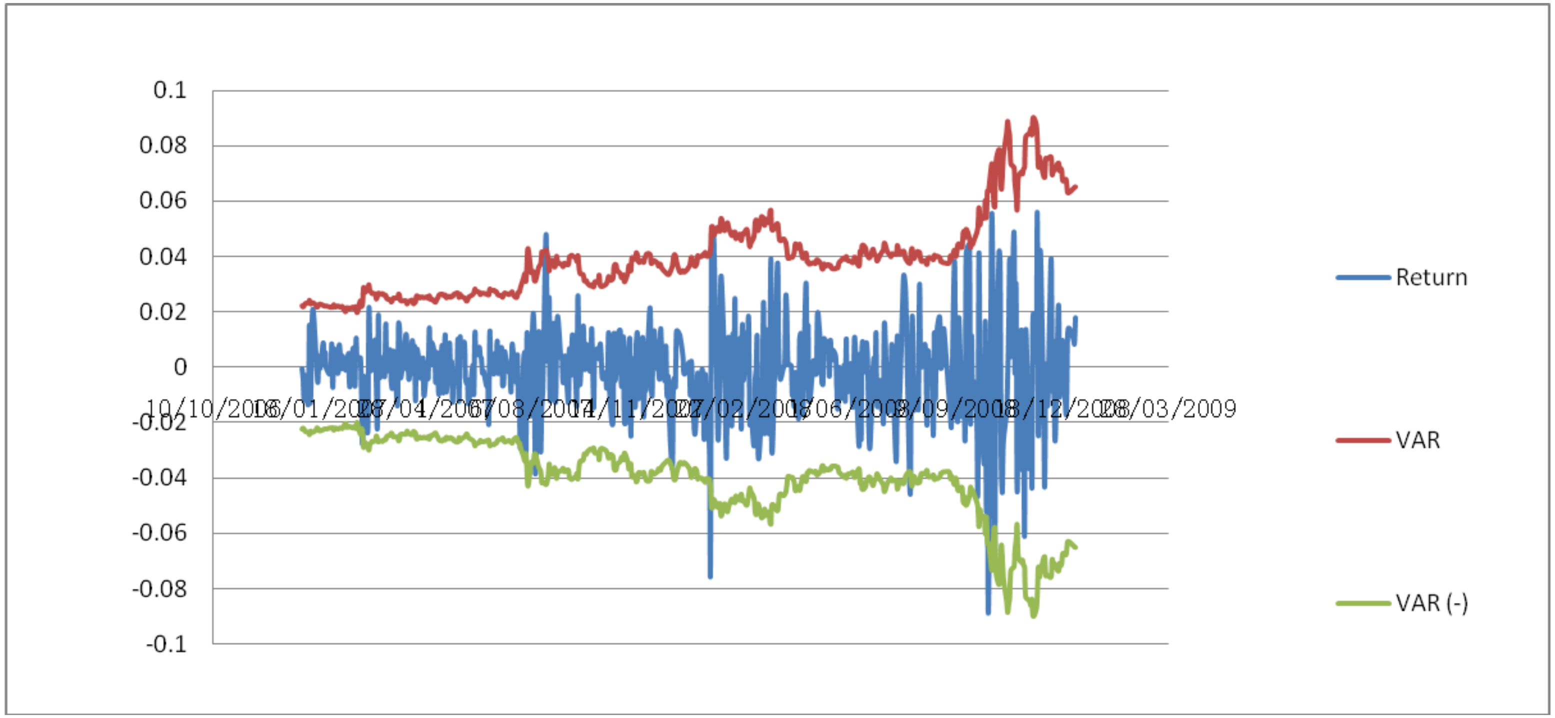

Figure 4-5: Out of Sample Result: AVX at One day interval at 99 percent confidence level

The above Figure shows the out-of-sample predictive ability using AVX as an input of VAR at 99% confidence level at 1-day interval. This out-of-sample prediction is based on the estimated AVX of the pre-financial crisis periods.

B: Risk-Metrics

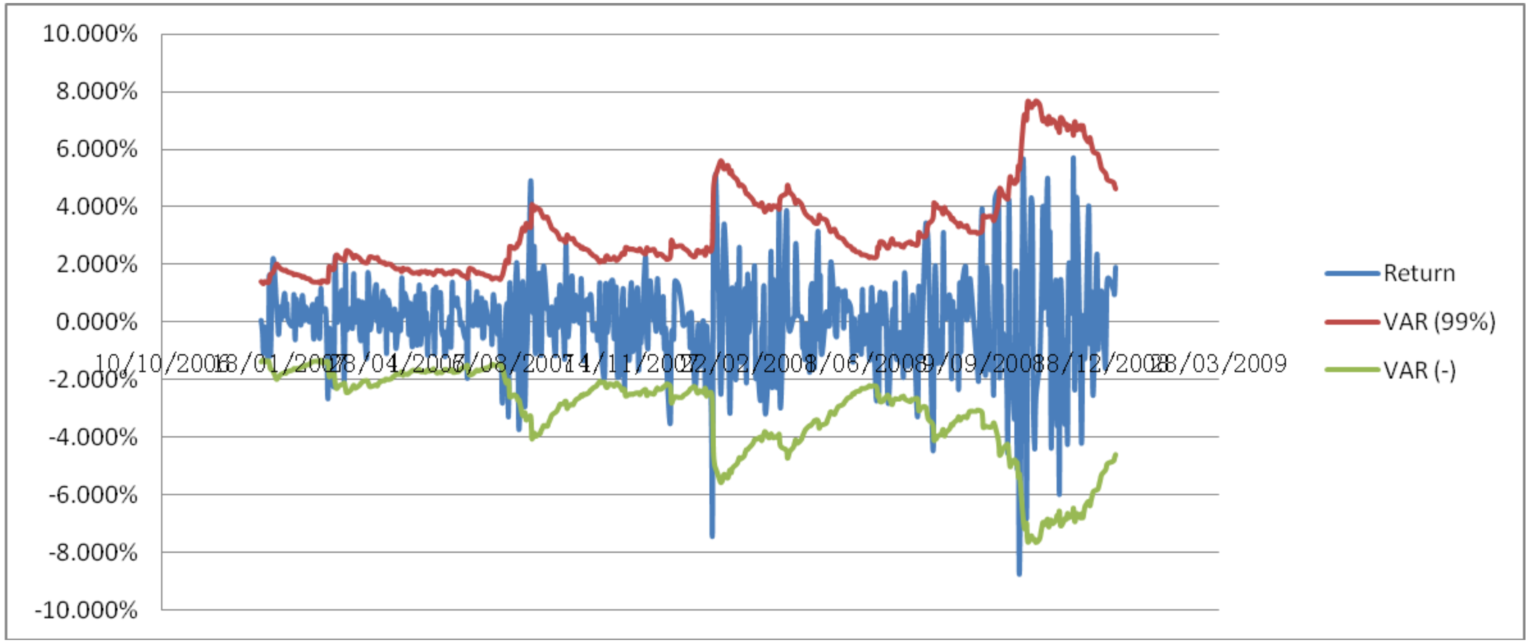

Figure 4-6: Out of Sample Result under RM at one day interval at 99 percent confidence level

The above Figure shows the out-of-sample predictive ability using RiskMetrics as an input of VAR at 99% confidence level at 1 day interval. This out-of-sample prediction is based on the estimated RiskMetrics of the pre-financial crisis periods. The figures for 95% confidence level and other observation intervals will be show in the Appendix. Compare the prediction results with using AVX as an input for VAR, VAR results of using RiskMetrics as its input at 1 day interval is not following the return series as well as using AVX as its input.

C: GJR-GARCH

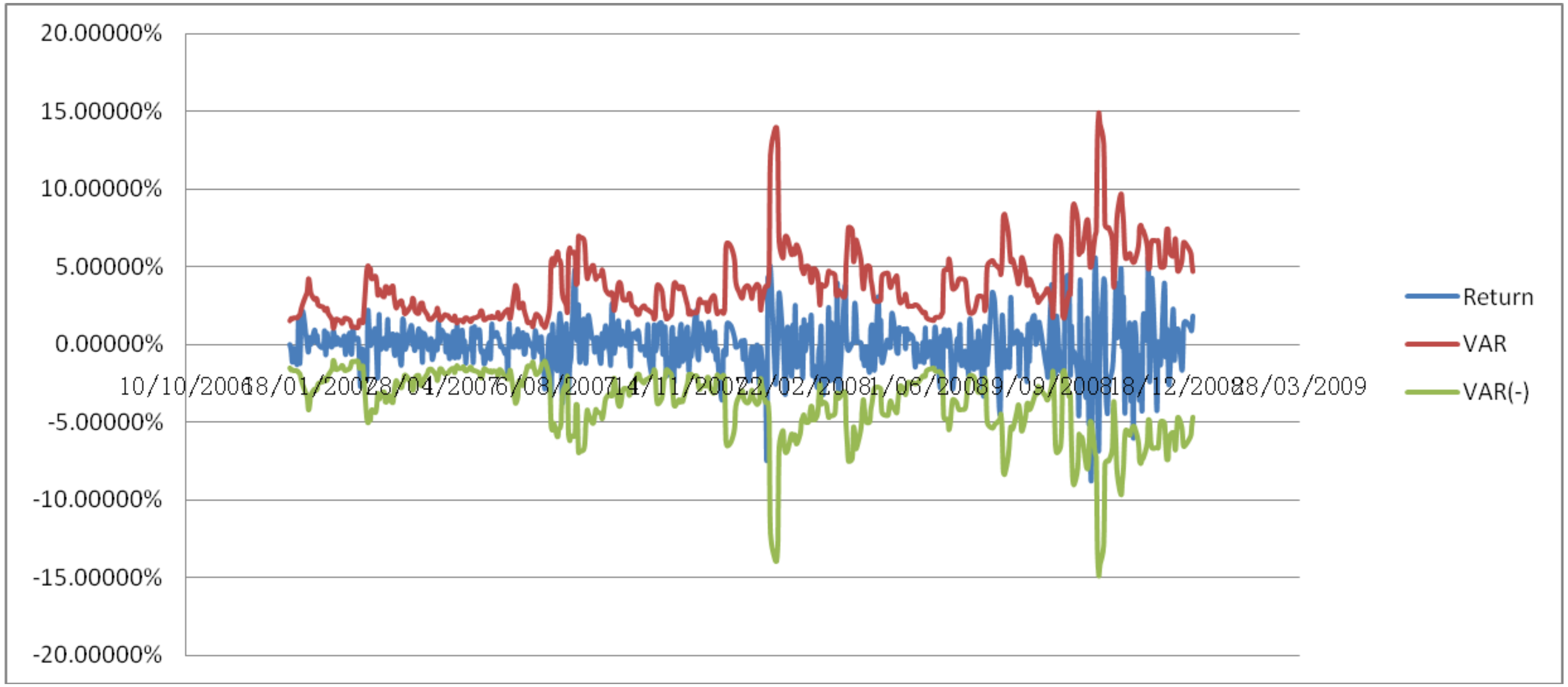

Figure 4-7: Out of sample Result under GARCH at one day interval at 99 percent confidence level

4.2.2.2 Back-testing on Out-of-Sample Results

Table 4-3: Out-of-Sample Back-testing Results for VAR based on AVX, RM and GARCH

Out-of-Sample VAR results for ASX/S&P 200 Index
(Out-of-Sample Test)
Implied Volatility Index (AVX)

	LQ=5%	RQ=5%	LQ=1%	RQ=1%
1-Day Interval				
f (Failure Rate)	**1.815%**	3.226%	0.403%	1.411%
Kupiec	13.8788	3.7392	2.3048	0.7515
I	2.1160	N/A	1.3592	N/A
CC	15.9949	N/A	3.6639	N/A
5-Days Interval				
f (Failure Rate)	**11.490%**	**11.690%**	**5.850%**	**6.850%**
Kupiec	32.724	34.5497	55.5384	74.5692
I	2.9363	0.6466	21.2335	0.0564
CC	35.6603	35.1963	76.7717	74.6257
10-Days Interval				
f (Failure Rate)	3.831%	3.427%	**0.403%**	1.410%
Kupiec	1.5477	2.8898	2.3048	0.7515
I	1.6839	0.2674	1.3592	N/A
CC	3.2317	3.1564	3.6640	N/A

Risk-Metrics

	LQ=5%	RQ=5%	LQ=1%	RQ=1%
1-Day Interval				
f (Failure Rate)	5.2400%	6.4500%	1.4100%	**3.8300%**
Kupiec	0.0602	2.0236	0.7515	23.3606
I	0.2941	0.4324	5.2814	0.0994
CC	0.3543	2.4562	6.0327	23.4599
5-Days Interval				
f (Failure Rate)	6.4516%	6.2500%	1.8145%	**2.8226%**
Kupiec	2.0237	1.1517	2.6781	11.1417
I	12.8893	31.8189	6.3147	13.4418
CC	14.9130	33.3358	8.9928	24.5835
10-Days Interval				
f (Failure Rate)	5.4435%	5.8468%	1.4113%	**3.6290%**
Kupiec	0.1999	0.7117	0.7515	20.6721
I	0.1945	0.9452	5.2814	0.0723
CC	0.3944	1.657	6.0329	20.8445

GJR-GARCH

	LQ=5%	RQ=5%	LQ=1%	RQ=1%
1-Day Interval				
f (Failure Rate)	4.0300%	5.8500%	1.8100%	**2.8200%**
Kupiec	1.0442	0.7118	2.6781	11.1417
I	0.0471	5.0643	6.6278	3.6767
CC	1.0914	5.7761	9.0358	14.8184
5-Days Interval				
f (Failure Rate)	3.8300%	5.6500%	1.2100%	**2.4200%**
Kupiec	1.5477	0.4179	0.2064	7.2254
I	0.0994	3.0595	4.0776	N/A
CC	1.6471	3.4774	4.2840	N/A
10-Days Interval				
f (Failure Rate)	**1.4100%**	**2.8200%**	0.4000%	**1.4100%**
Kupiec	18.555	5.8357	2.3048	0.7515
I	N/A	N/A	1.3592	N/A
CC	N/A	N/A	3.6640	N/A

Table 4-3 presents the summary results for the back-testing of the out-of-sample VAR models from 2007 to 2008. The first volatility specification (top panel) presents the results under AVX, the second volatility specification is for the risk-metrics where the third panel are the results for GJR-GARCH, all three with a skewed student density distribution for the error term. Firstly the empirical failure rate for the Left and right quintiles at 5, 1% is provided. The bold figure indicates that the empirical failure rate is significantly different from the theoretical value. Secondly, Kupiec, I and CC give the p-value for the independence and conditional coverage tests respectively.

Chapter Five: Conclusions and Recommendations for future research

This dissertation is dealing with information content of AVX when these are taken as volatility inputs in a daily Value-at-Risk model. The empirical analysis focuses on Australian Stock market from 02/01/2003- 31/12/2008, and I have divided the total sample period into two distinct sub-periods: pre-financial crisis period and post-financial crisis period. This allows us to test whether the performance of Daily VAR models based on AVX as its volatility inputs in challenging trading environments and look at the stability of model over time. Moreover, in order to compare the testing results, RiskMetrics and GJR-GARCH model have also been introduced to be used as the volatility inputs for VAR. Prior to the VAR application, the efficiency and unbiased of the implied volatility indexes with respect to the realized volatility during these two sub-periods are assessed. Furthermore to assess the VAR performance, a wide range of back-testing methods such as LR tests, independence and conditional coverage tests are used.

Regarding the VAR application, the statistical tests show that implied volatility indexes does not provide meaningful volatility information in VAR models as the number of VAR violations is not correctly modelled in most cases, the null hypotheses of independence and conditional coverage are usually rejected. This is however fine in most cases for the RiskMetrics and GJR-GARCH specifications. This indicates that the use of RiskMetrics and GJR-GARCH as a volatility input for the out-of-sample VAR during financial crisis period can provide significant information to model Daily VAR models, wherever AVX breaks down during challenging trading environments. This indicates that VAR makes no attempt to measure the losses beyond the specific limit. Even with a 99 percent confidence interval, unusual events happen, and they sometimes do so with a vengeance. This is why VAR must be augmented by backtesting, which aims at assessing the effect of unusual market conditions.

The purpose of this dissertation is to assess the information content of volatility inputs for VAR models during financial crisis period for Australian stock market, which has been successfully been completed. However, limitations exist in the current research and theses must be taken into account for future research.

Firstly, all the volatility inputs for VAR models in this dissertation are assumed under normal distribution. This is however not accurate in some cases.

Secondly, the skewness of the sample data is not considered. This dissertation assumes the data sample is under standard deviation, without considering the skewness of the data set sometimes can bring significant biases of the final results.

Finally, the out-of-sample test only contains 496 observations. The insufficient of numbers of observation might pass the biased backtesting results for VAR models, especially at 5- or 10-days interval.

My recommendation for the similar research in the future is that more observations of out-of-sample should be involved as well as the skewness of the data and different distribution level.

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Appendices

Appendix A: Distribution plot of two sub-sample periods at three different observation intervals

Figure 1: Distribution Plot of S&P/ASX 200 Returns for Sub-Period One: 02/01/2003 – 29/12/2006 at one-day Interval

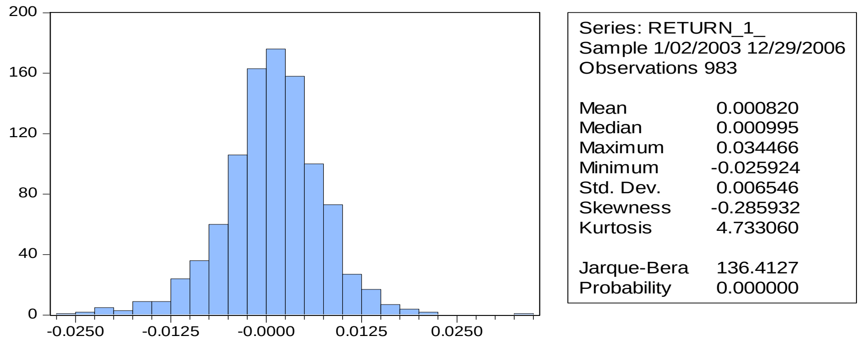


Figure 2: Distribution Plot of S&P/ASX 200 Returns for Sub-Period One: 02/01/2003 – 29/12/2006 at five-days Interval

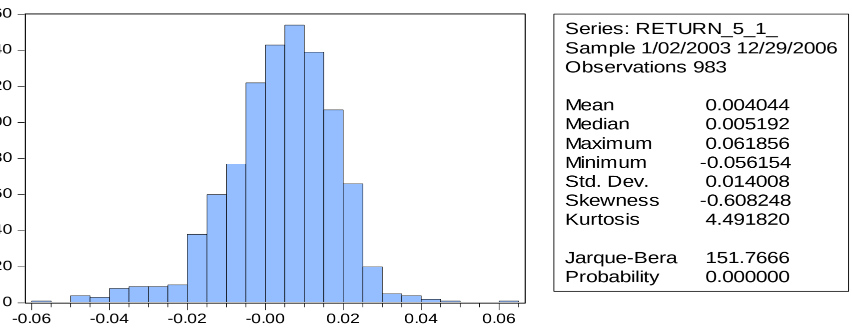


Figure 3: Distribution Plot of S&P/ASX 200 Returns for Sub-Period One: 02/01/2003 – 29/12/2006 at ten-days Interval

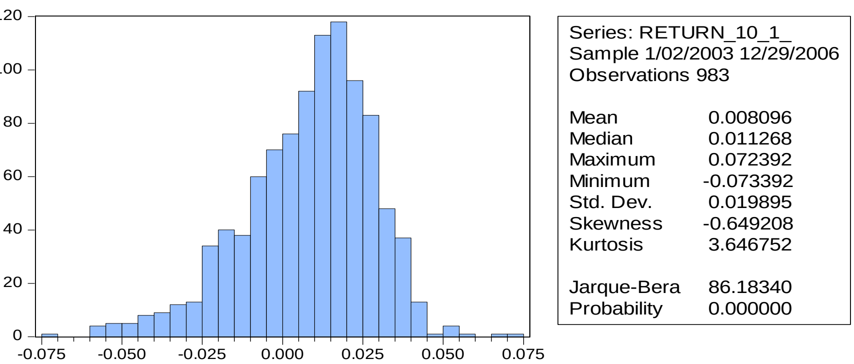


Figure 4: Distribution Plot of S&P/ASX 200 Returns for Sub-Period two: 02/01/2007 – 31/12/2008 at one-day Interval

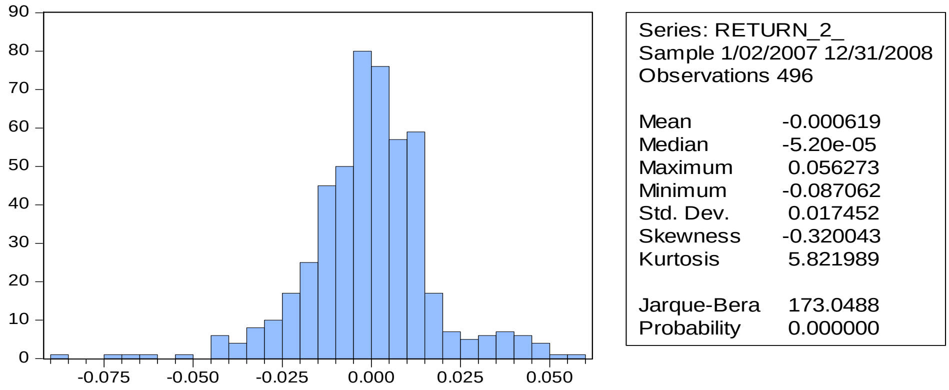


Figure 5: Distribution Plot of S&P/ASX 200 Returns for Sub-Period two: 02/01/2007 – 31/12/2008 at five-days Interval

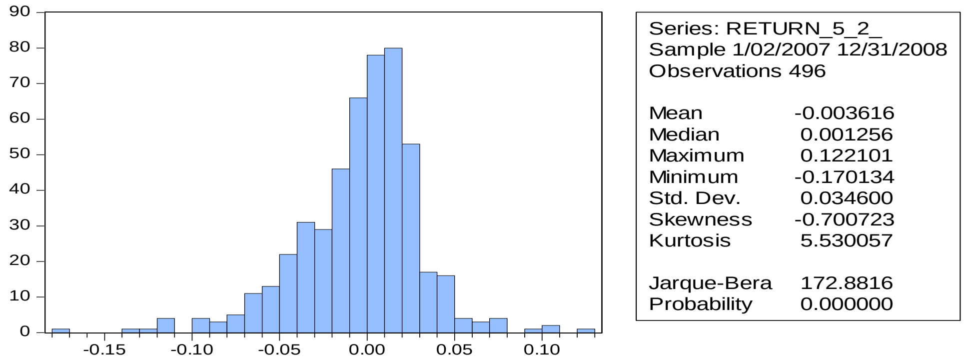
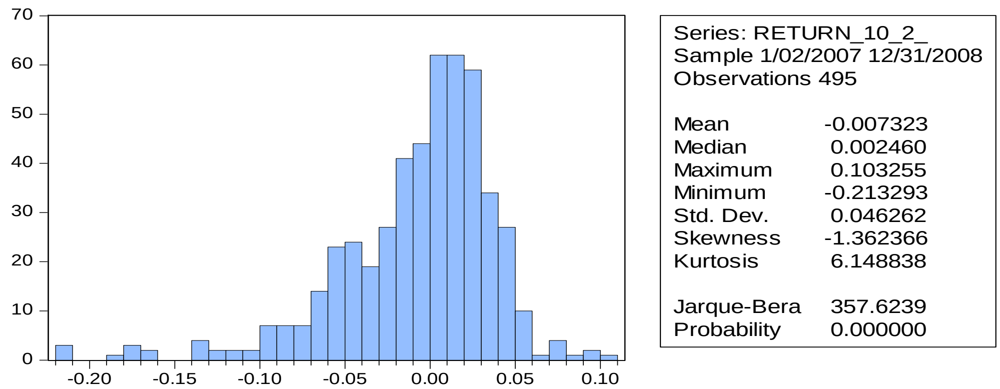


Figure 6: Distribution Plot of S&P/ASX 200 Returns for Sub-Period two: 02/01/2007 – 31/12/2008 at ten-days Interval



Appendix B1: VAR in sample results under three different volatility forecasting methods at three different observation intervals at 99% confidence level

Figure 1: In Sample Result: AVX at One Day Interval (99%)

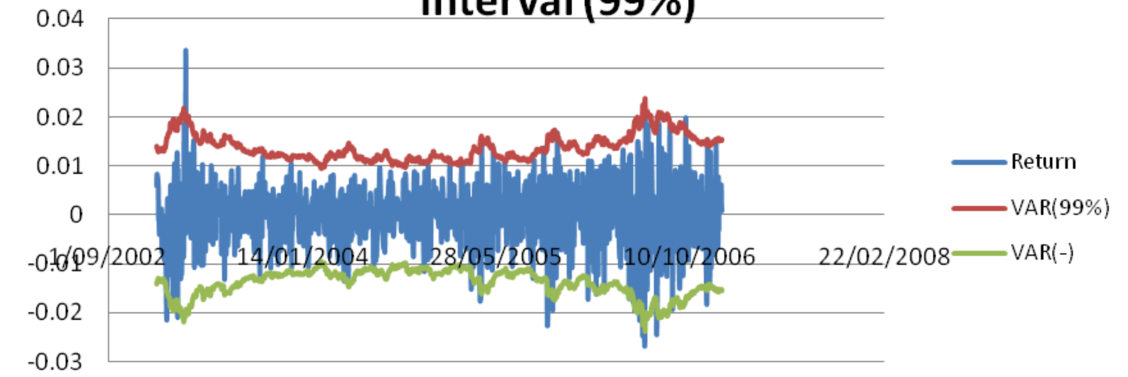


Figure 2: In Sample Result: AVX at Five Days Interval (99%)

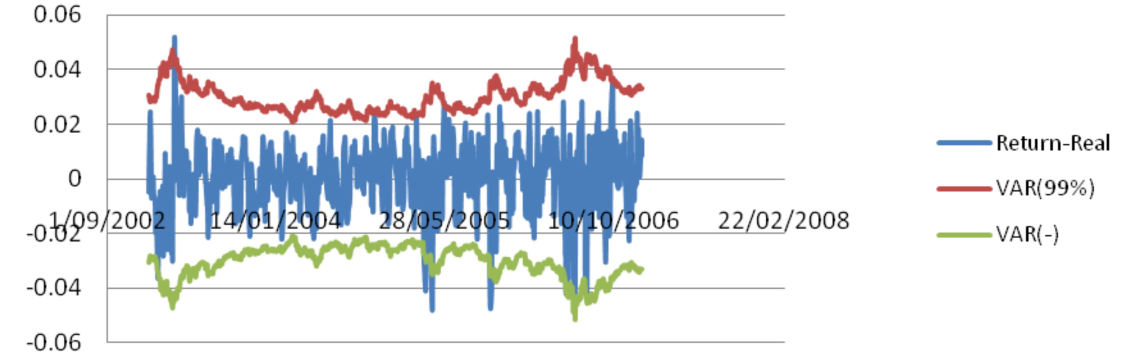


Figure 3: In Sample Result: AVX at Ten Days Interval (99%)

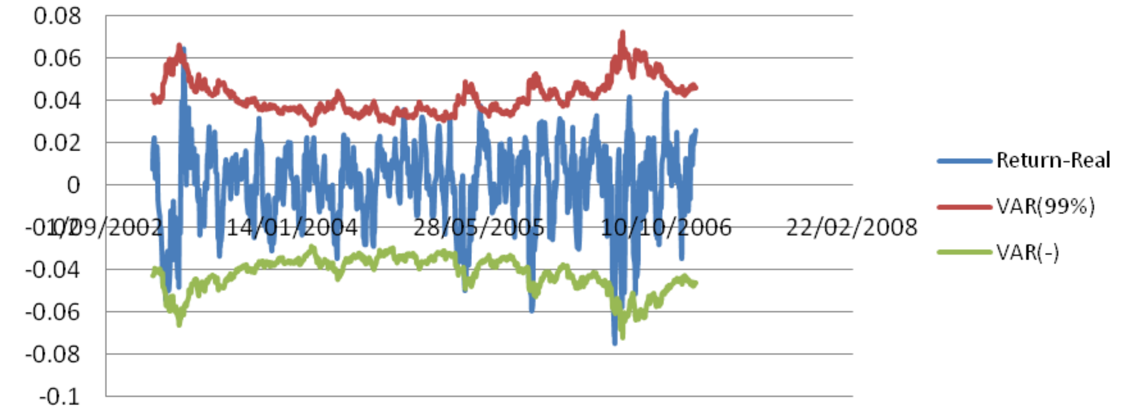


Figure 4: In Sample Result: Risk Metrics at One Day Interval (99%)

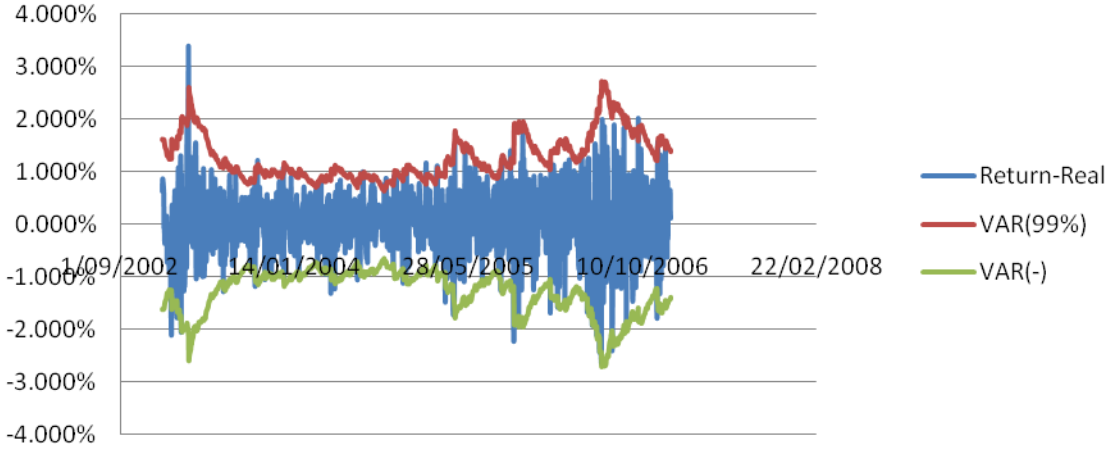


Figure 5: In Sample Result: Risk Metrics at Five Days Interval (99%)

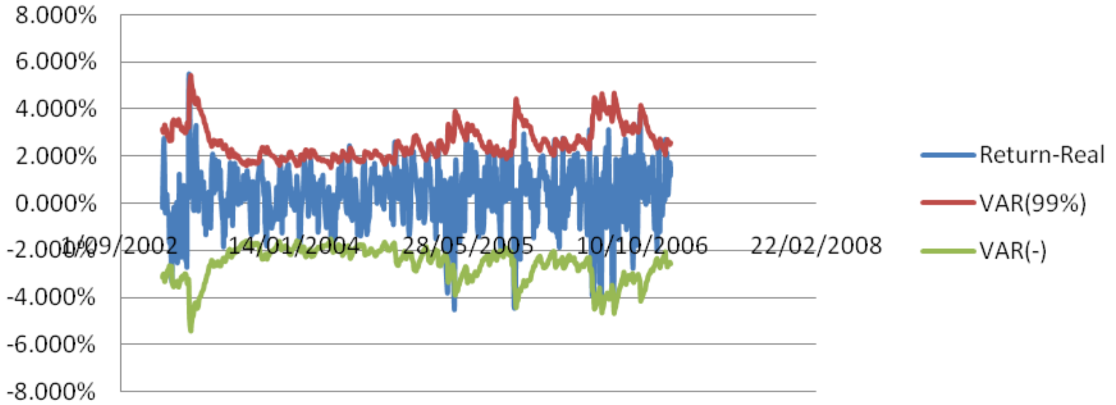
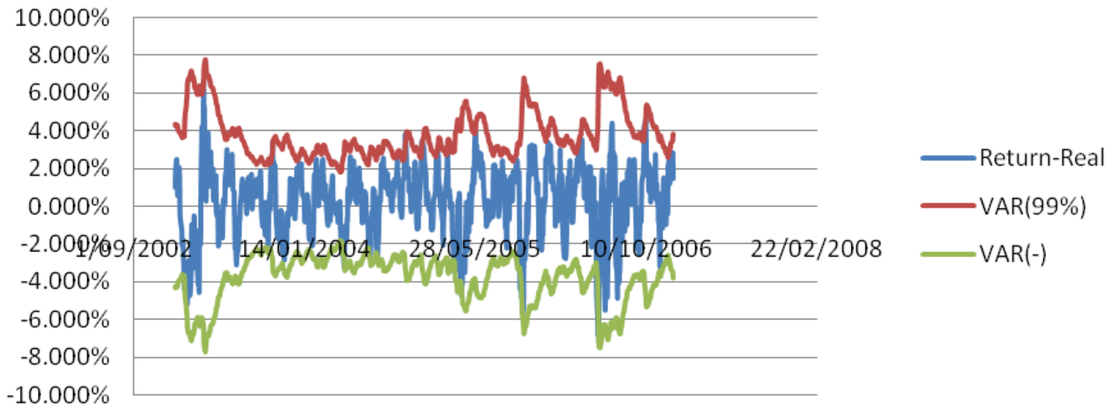


Figure 6: In Sample Result:Risk Metrics at Ten Days Interval (99%)



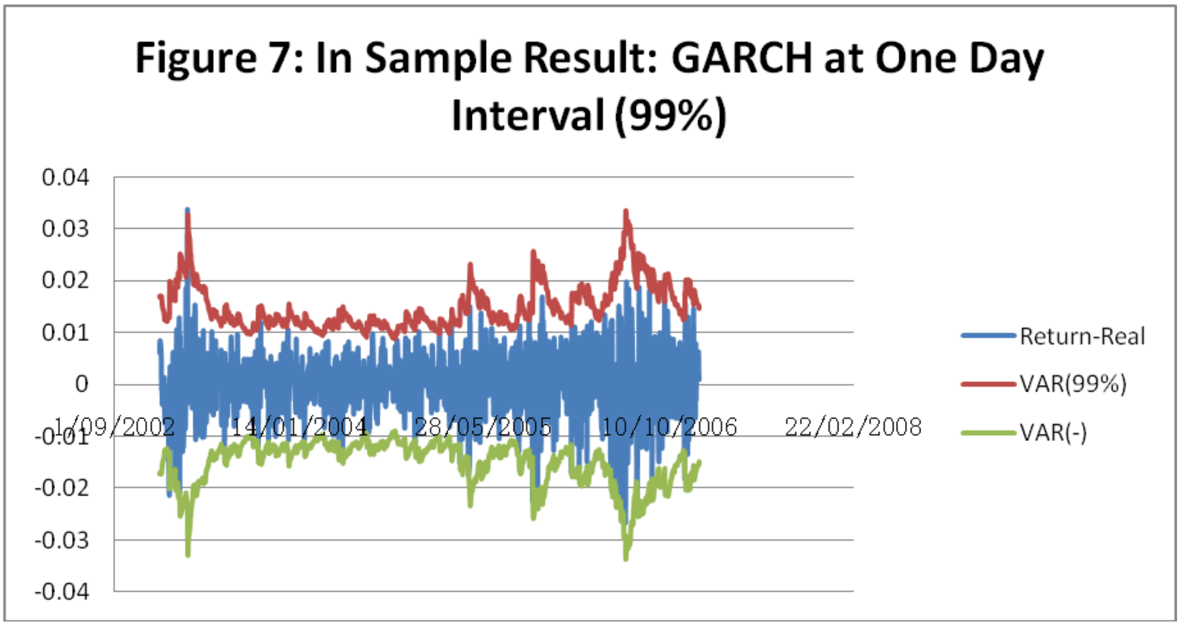


Figure 7: In Sample Result: GARCH at One Day Interval (99%)
0.04
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
-0.04
1/09/2002
14/01/2004
28/05/2005
10/10/2006
22/02/2008
Return-Real
VAR(99%)
VAR(-)

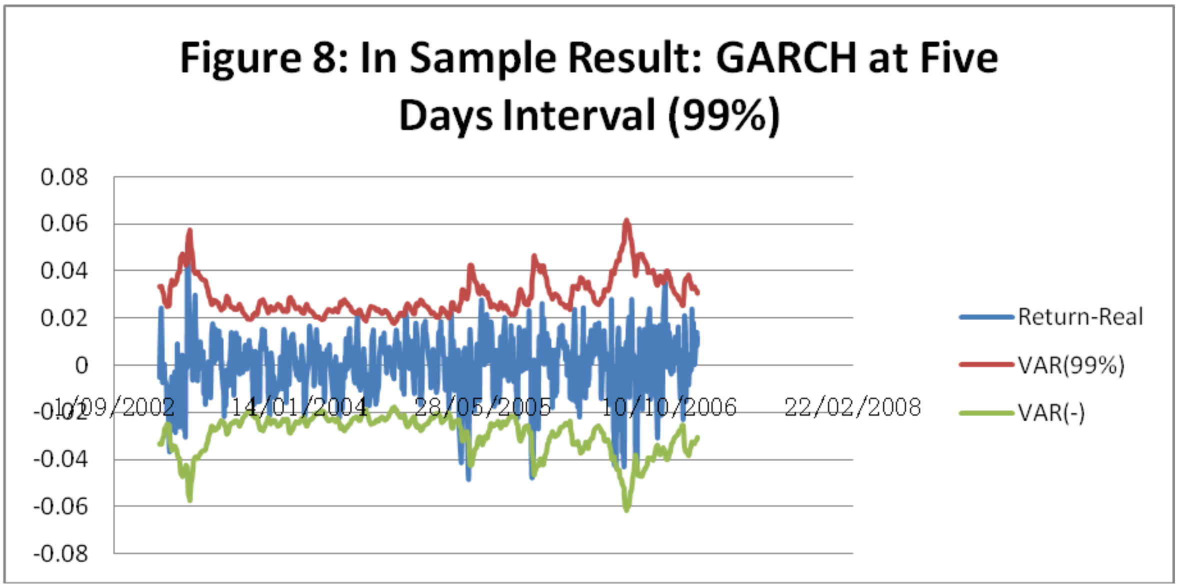


Figure 8: In Sample Result: GARCH at Five Days Interval (99%)
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
1/09/2002
14/01/2004
28/05/2005
10/10/2006
22/02/2008
Return-Real
VAR(99%)
VAR(-)

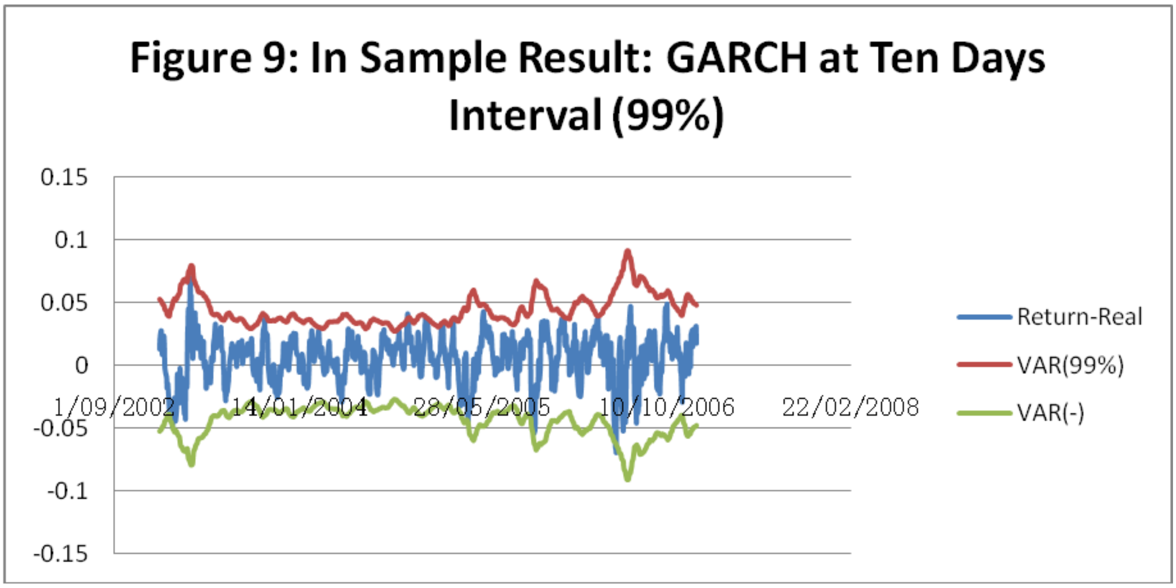
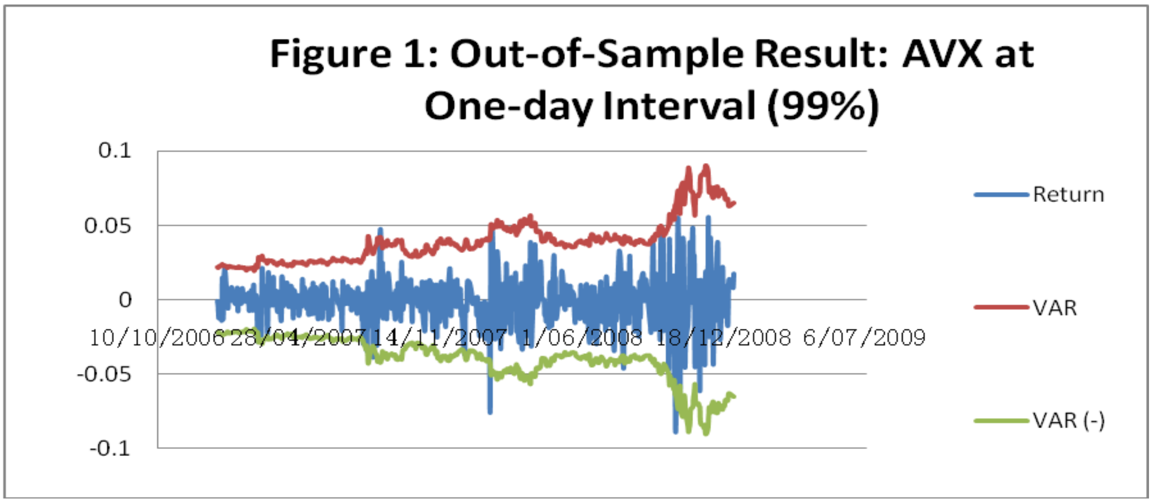
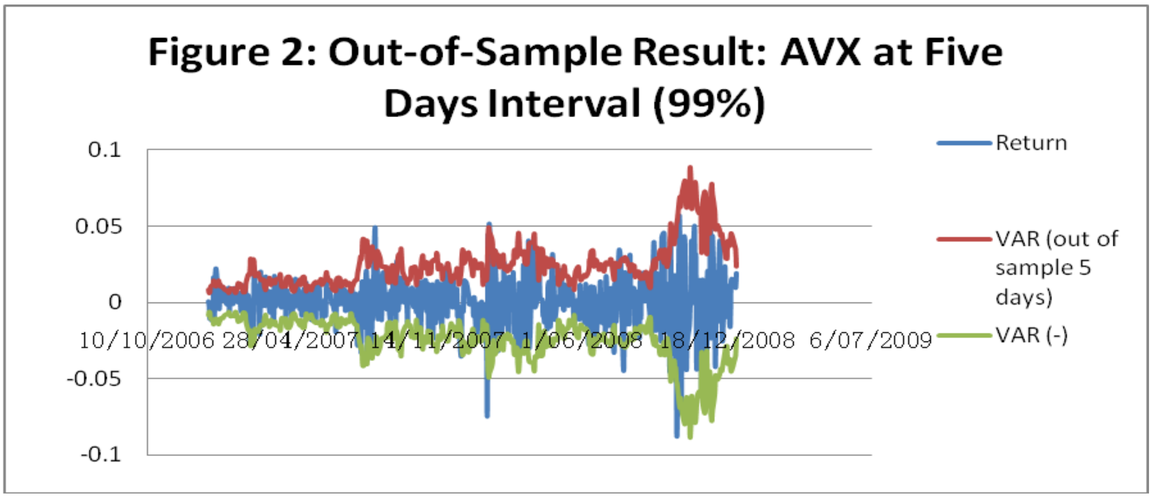
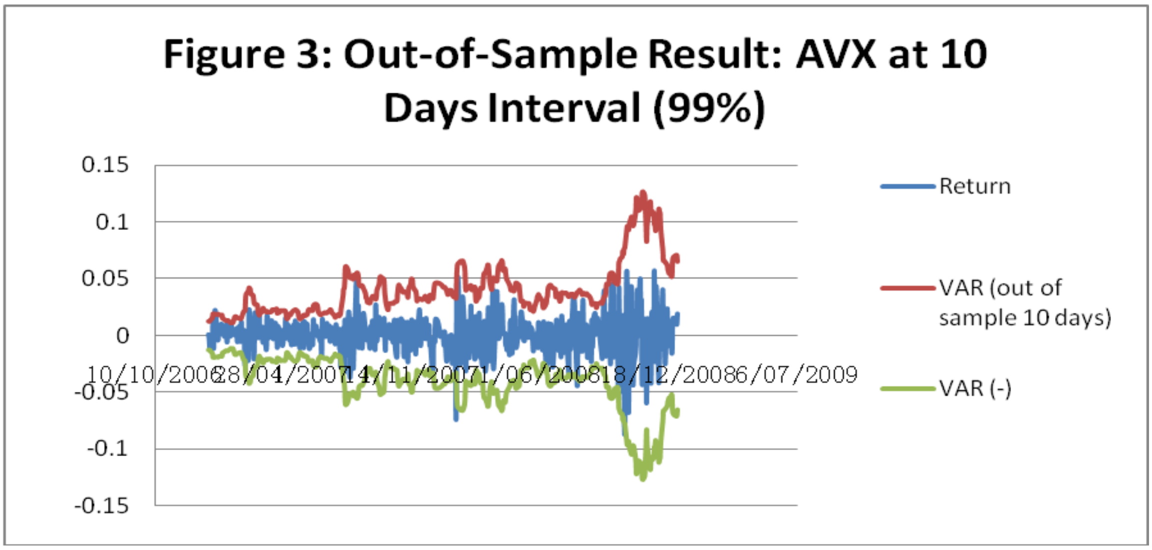


Figure 9: In Sample Result: GARCH at Ten Days Interval (99%)
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1/09/2002
14/01/2004
28/05/2005
10/10/2006
22/02/2008
Return-Real
VAR(99%)
VAR(-)

Appendix B2: VAR out of sample results under three different volatility forecasting methods at three different observation intervals at 99% confidence level







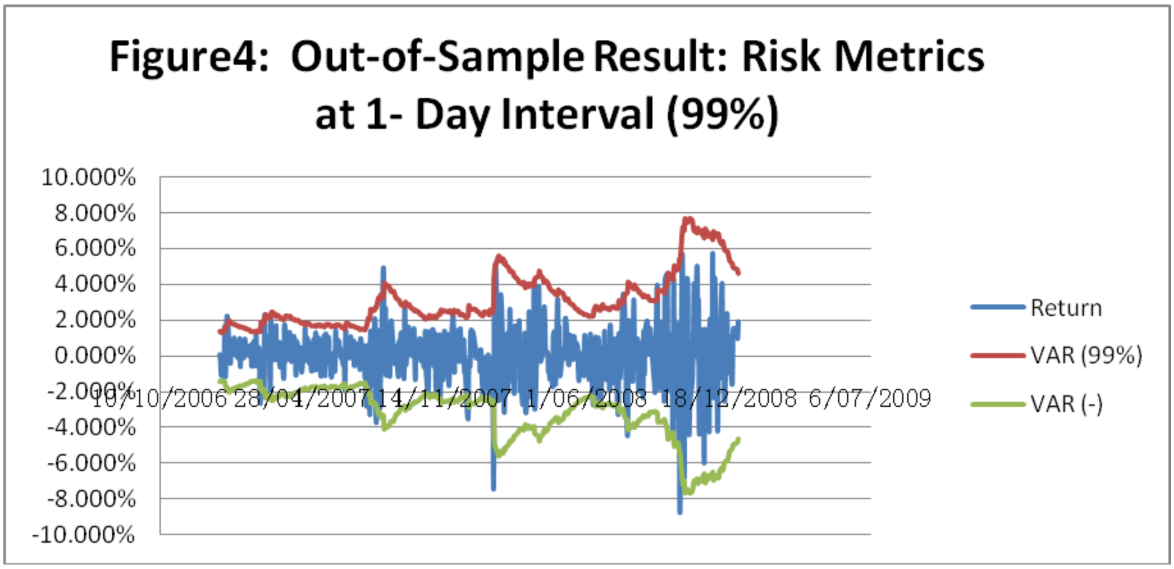


Figure4: Out-of-Sample Result: Risk Metrics at 1- Day Interval (99%)
10.000%
8.000%
6.000%
4.000%
2.000%
0.000%
-2.000%
-4.000%
-6.000%
-8.000%
-10.000%
10/10/2006 28/04/2007 14/11/2007 1/06/2008 18/12/2008 6/07/2009
Return
VAR (99%)
VAR (-)

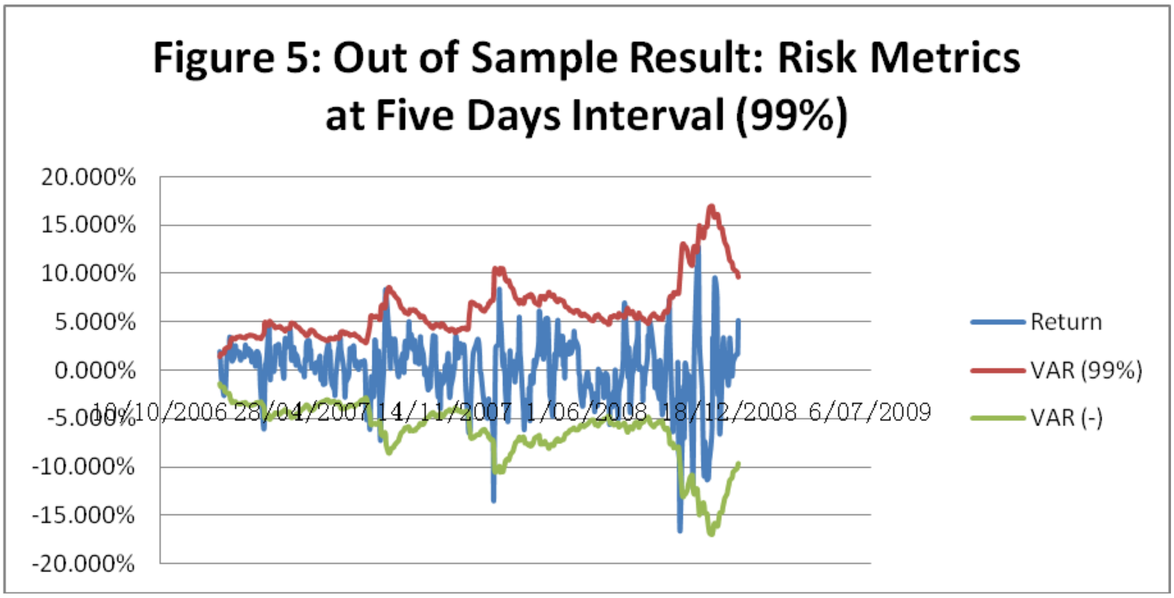


Figure 5: Out of Sample Result: Risk Metrics at Five Days Interval (99%)
20.000%
15.000%
10.000%
5.000%
0.000%
-5.000%
-10.000%
-15.000%
-20.000%
10/10/2006 28/04/2007 14/11/2007 1/06/2008 18/12/2008 6/07/2009
Return
VAR (99%)
VAR (-)

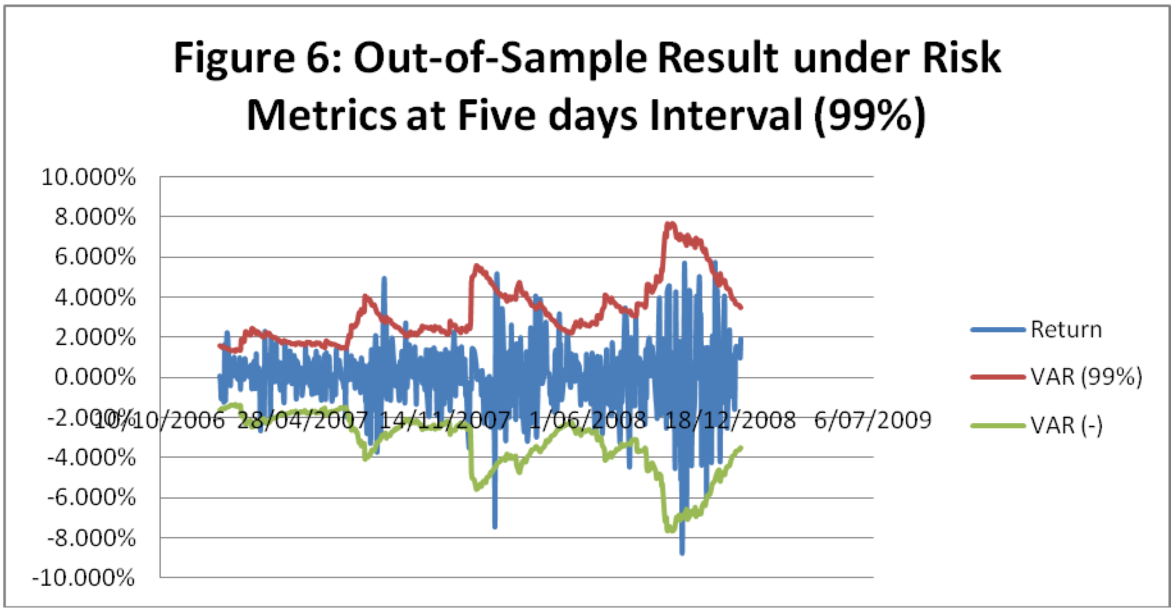


Figure 6: Out-of-Sample Result under Risk Metrics at Five days Interval (99%)
10.000%
8.000%
6.000%
4.000%
2.000%
0.000%
-2.000%
-4.000%
-6.000%
-8.000%
-10.000%
10/10/2006 28/04/2007 14/11/2007 1/06/2008 18/12/2008 6/07/2009
Return
VAR (99%)
VAR (-)

Figure 7: Out-of-Sample Result: GARCH at 1-Day Interval (99%)

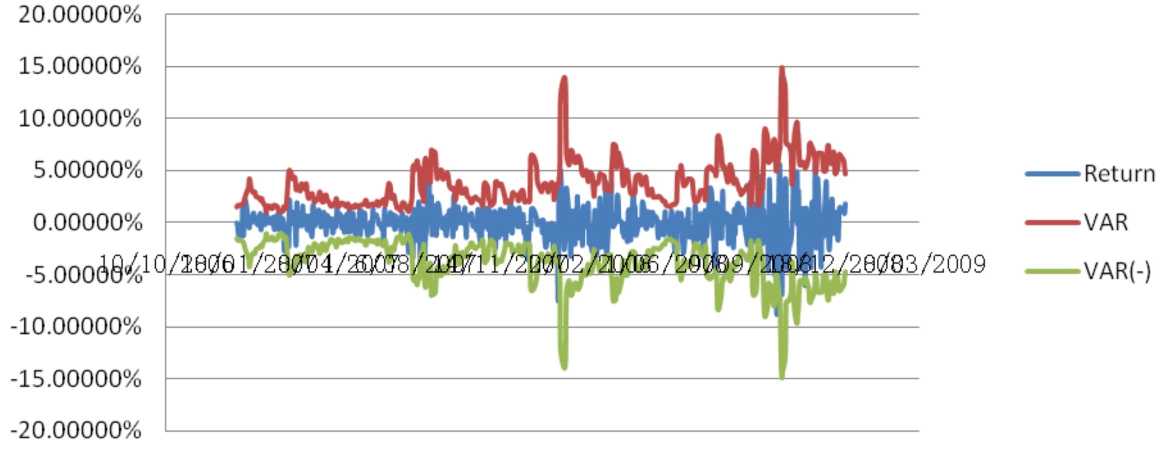


Figure 8: Out-of-Sample Result under GARCH at Five days Interval (99%)

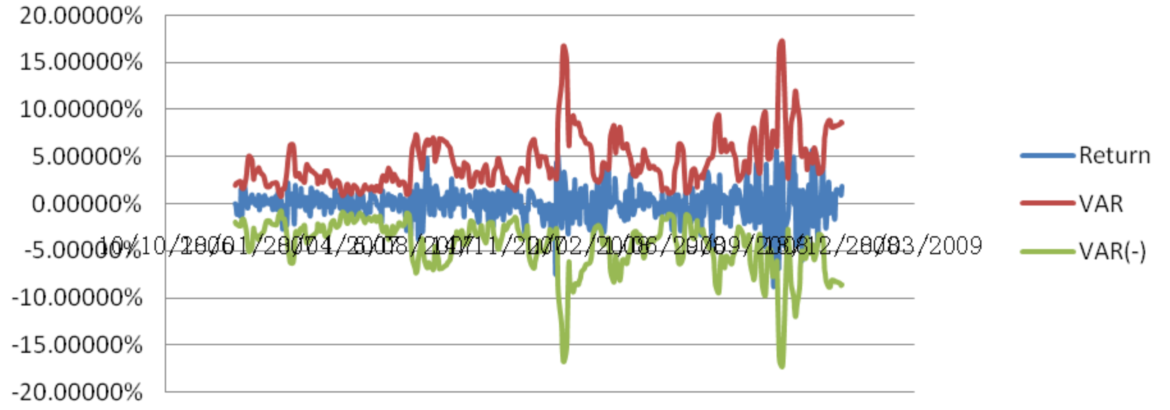


Figure 9: Out-of-Sample Result under GARCH at Ten days Interval (99%)