School of Economics and Finance

A Tale of Two Perspectives:
Australian Risk Management in Theory and in Practice

Chow Siing Sia

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award for any other degree or diploma in any university.

Signature: ______________________

Date: 13/8/2015

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Related Thesis Publications

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Presentations

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Abstract

Value-at-Risk (VaR) is an important area connecting academic researchers with the practitioners due to its critical role in financial risk management as required by the Basel Accord. While both academic researchers and the practitioners recognize that VaR models provide a convenient method for quantifying market risk, their objectives and interests in VaR can be quite different. Academic researchers are primarily interested in the accuracy of VaR models in forecasting market risk. These results are of interest to the regulator to ensure adequate risk mitigation is undertaken by banks as a result of inadequate capital reserves. Banks, however, can choose to use standardized or the internally designed VaR models to measure market risk.

The thesis aims to demonstrate the differences in approaches and objectives to VaR modelling and forecasting by academic researchers and the practitioners. In theory, the more complex VaR models may be preferred by the academic researchers for risk forecasting as these models capture volatility structures of asset returns that are usually not directly observable. However, these models raise some difficulties in practice. For an ADI who trades large and complex portfolios of financial assets and derivatives daily, these models require continuous constructing and updating new volatility forecasts that come with high transaction costs. Therefore, combining these different objectives is crucial to developing a more practical approach that can satisfy both the literature and regulatory objectives.

The thesis begins with the background of the banking system in Australia and critically reviews the impact of the Basel Accord in Australian Authorized Deposit-taking Institutions (ADIs) over time. The thesis also investigates the precision of VaR models to measuring market risk and the regulatory role played by Australian Prudential Regulation Authority (APRA) in supervising these ADIs.

Models of time-varying volatility can be used to forecast VaR for the purpose of financial risk management. This thesis proposes developing more appropriate models that may assist Australian ADIs to calculate capital adequacy charges as a protection against market risk. This thesis also provides the first empirical comparison of the impact of model specification in estimating tail index and VaR. A consistent estimator of the tail index for the asymmetric extension of Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) error is used as an alternate method to forecast VaR. The empirical results suggest that the proposed method performs well against the more traditional approaches based on conditional and unconditional variances. Given that the regulator prefers ADIs to use VaR models that display appropriate statistical properties, the performance of these models is evaluated by various tests to assess the quality of VaR forecasts. In addition to these tests, the market risk capital charges are also calculated to capture the opportunity costs of using each model.

This thesis then analyses the importance of accommodating time-varying conditional correlations in forecasting VaR. The performance of VaR forecasts produced by Constant Conditional Correlation (CCC) model of Bollerslev (1990) is compared with the Dynamic Conditional Correlation (DCC) model of Engle (2002) and the Time-Varying Conditional

Correlation (TVC) model of Tse and Tsui (2002). The results find that VaR forecasts based on the DCC models are superior to VaR forecasts based on the CCC models. The results also suggest that the selection of an underlying distribution is more important than the choice of a model to forecast VaR.

The final section of this thesis examines the adequacy of reported VaR forecasts. This section focuses on whether the reported VaR forecasts provide any new information to investors and the bank regulators to assessing the differences in market risk exposures for each ADI. One of the main objectives for Basel III is to strengthen banks' transparency and disclosures. The thesis finds that the current financial reporting environment in Australia does not provide academic researchers and the regulator enough information to assess the quality of VaR forecasts reported by ADIs. It is worth noting that the requirements for banks to disclose information more completely can sometimes be very costly and may not necessary increase transparency.

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Chapter 1

INTRODUCTION

Charles Dickens began his *Tale of Two Cities* with the lines:

"It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way. . . ."

These famous lines hint at the novel's central tension between love and family, and on the one hand, oppression and hatred, on the other. The opening quotation characterizes the tension between academic researchers and the practitioners including investors, banks and the regulator in the use and application of Value-at-Risk (VaR) to model and forecast market risk.

An academic research is often quantitative with sophisticated methods and statistical details that are unfamiliar to the practitioners. Sometimes, the results can be inconsistent and lack a normative conclusion. Hence, the practitioners may be constrained in pursuing increased engagement with academic researchers due to lack of belief. This could lead to a less tolerant view and serious scepticism as to the ability of academic research to provide insights that are of relevance. Academic researchers, on the other hand, may not engage with the practitioners for different reasons. For a researcher, the academic system does not explicitly encourage strong research-related practitioner communication, but strongly supports the publications in peer-reviewed academic journals. Therefore, the academic researchers would rather engage their work through conferences and journals. These academic articles are exclusively read and assessed by a group of fellow academics. Hence, this restricts the ability of the academic researchers to connect with the practitioners.

In a regulatory capacity, the relationship between banks and the regulator with the academic researchers is not without tension and disagreement. They are more like separate entities pursuing their own agendas and concerns. The general society requires the regulator to regulate banks adequately, yet the nature of the regulation in practice is diverse. Banks are meant to follow the regulatory requirements of which the Basel Committee is deemed to be authorized. However, there is a tendency that banks are likely to comply with the regulatory requirement minimally. In practice, banks cannot ignore the regulator and its regulation without serious repercussion, but often do ignore academic research. Likewise, the regulator attempts to look to its resources and thinks in the name of research to regulate the banks. Typically, banks and the regulator design, develop and publish their regulatory framework first, then leave to the academic researchers to access and influence the framework proposed by publishing in academic articles. The lack of connection between the academic researchers with banks and the regulator in nature and the design of a strong regulatory framework is a good illustration of the differences in interests highlighted previously. The aim of this thesis is to examine these different objectives by carrying out an empirical investigation on the extent of, and the type of, and the importance of VaR as a market risk measure across academic literature and banking practices.

The emphasis on the definitions of ‘risk’, ‘market risk’, and ‘volatility’ is important and needs clarification before proceeding.

Risk could be roughly explained as an uncertainty of the changes of future returns, such that the greater is the uncertainty, the greater is the risk. Market risk represents the uncertainty of the future returns due to changes in market conditions. The direct impact of market risk is that adverse changes in market conditions may result in severe losses. However, volatility is not the same as risk. Financial markets often display high levels of volatility, which is reflected in the pricing of financial assets. Volatility can be characterized as the conditional variance of the underlying asset returns (see Tsay 2010, 109). This volatility evolves over time in a continuous manner and has many other financial applications. It also plays a significant role in the portfolio selection under the mean-variance analysis (Markowitz 1959, 1991). Volatility may be high for certain periods and low for other periods. However, volatility is not directly observable. Statistically, volatility is often stationary, and it does not diverge to infinity (see Poon and Granger 2003). In this thesis, the term ‘volatility’ is used loosely in a descriptive sense rather than the precise notion often implied in financial econometrics.

Since Basel I was first introduced in 1988, followed by the 1996 amendment of the Basel Capital Accord to apply minimum capital requirements for market risk, Value-at-Risk (VaR) is becoming an internationally accepted risk measure for the banking industry to manage market risk, capital adequacy and regulatory reporting. VaR is described as a procedure to measure the probability of maximum loss over a target horizon within a given confidence level (Jorion 1996, 2007). In particular, each bank has to set aside an amount of risk capital of at least three times that of VaR. The Basel Accord allows banks to design their own internal VaR models to determine their regulatory capital requirements for market risk. On one hand, banks must consider how much risk they are taking, and whether they have enough capital to cover for that risk. On the other hand, the regulator is concerned with whether banks have set aside sufficient capital to meet large unexpected losses in the event of financial market distress. The recent financial events, particularly the Global Financial Crisis (GFC), have led to a great deal of attention to providing more sophisticated and statistically justifiable VaR models. During the crisis, many international banks not only experienced a sharp increase in the level of VaR but also faced higher regulatory capital charges.

This thesis aims to demonstrate the differences in approaches and objectives to VaR modelling and forecasting by academic researchers and the practitioners. In theory, more complex VaR models may be preferred by academic researchers for risk forecasting as these models capture volatility structures of asset returns that are usually not directly observable. However, these models raise some difficulties in practice. For a bank which trades large and complex portfolios of financial assets and derivatives daily, these models require continuous constructing and updating new volatility forecasts that come with high transaction costs. Therefore, combining these different objectives is crucial to developing a more practical approach that can satisfy both the literature and regulatory objectives. This thesis proposes developing more appropriate models that may assist banks and the regulator to calculate capital charges as a protection against market risk.

This thesis is organized into six chapters.

Chapter 1 introduces the thesis, provides the necessary background and motivation of the study. It also explains in further detail the contributions of the following chapters into the literature.

Chapter 2 begins with some background on the banking system in Australia and critically reviews the impact of the Basel Accord in Australian ADIs over time. This chapter examines the extent to which Basel III had been implemented in Australian banking system and if new aspects in the treatment of market risk are adopted in Basel III. The chapter also investigates the precision of VaR models to measuring market risk and the regulatory role played by Australian Prudential Regulation Authority (APRA) in supervising these ADIs.

The Basel Committee on Banking Supervision has continued to improve the quality of worldwide banking supervision since the introduction of Basel I in 1988. Subsequently, Basel II was introduced in 2004, and Basel III in 2010 (see Basel Committee on Banking Supervision 2014a). Under Basel II and III, a new set of capital requirement is introduced to allow banks to manage their liquidity more prudently. This chapter evaluates the regulatory framework proposed by the Basel Accord and highlights any deficiencies that may exist and suggests ways in which such deficiencies may be addressed to promote higher quality and efficient banking system.

In Australia, the Australian Prudential Regulation Authority (APRA) is the prudential regulator for Australian financial services industry and is responsible for the supervision of all Australian ADIs including banks, building societies, credit unions and specialist institutions. The Banking Act 1959 has allowed APRA to implement prudential standards on Australian ADIs to enforce relevant regulation and to act in the interests of depositors. This chapter analyses the existing prudential standards in the Australian ADIs. This includes an investigation of the precision of VaR models to measuring market risk and the role played by APRA in regulating these ADIs. It also discusses some crucial facts of VaR implementation and its potential significance to Australian ADIs.

Chapter 2 provides the first empirical comparison of the impact of model specifications in estimating tail index and VaR. A consistent estimator of the tail index for the asymmetric extension of Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) error by Glosten, Jagannathan, and Runkle (1993) is proposed as an alternate method to forecast VaR. The chapter then applies the proposed estimator to forecast VaR for a portfolio of AUD with twelve other currencies. It also investigates the performance of the two conditional volatility models under two different distributional assumptions, namely normal distribution and student-t distribution. The empirical results suggest that the proposed method performs well against the more traditional approaches based on conditional and unconditional variances.

Given that the regulator prefers banks to use VaR models that display appropriate statistical properties, the performance of these models is evaluated by some statistical tests to assess the quality of VaR forecasts. The tests include Kupiec (1995) Test Until the First Failure (TUFF), followed by Christoffersen (1998) and Christoffersen, Hahn, and Inoue (2001) Serial Independence (IND) and Conditional Coverage (CC) tests. Also, the performance of VaR forecasts is evaluated by the backtesting procedures required by the Basel Committee. Backtesting procedures are where the actual returns are compared with VaR forecasts to assess the quality of banks' internal model. This has an important implication for banks and the regulator. If banks are conservative in estimating market risk by reporting a lower VaR, the amount of capital charges that a bank holds will be higher. A higher capital charge will have a direct impact on the bank's profitability. On the other hand, the regulator is concerned with minimizing the risk of default that may be due to large unexpected losses in the event of financial distress such as the GFC. If banks use VaR models that display the correct statistical properties, the chance to which they go into default is minimal.

Models of time-varying volatility can be used to forecast VaR for the purpose of financial risk management. Many researchers believe that by incorporating time-varying volatility in VaR models may provide early warnings of changing market conditions. These models provide volatility estimates of asset returns that are usually not directly observable.

Chapter 4 analyses the importance of accommodating time-varying conditional correlations in forecasting VaR. The performance of VaR forecasts produced by Constant Conditional Correlation (CCC) model of Bollerslev (1990) is compared with the Dynamic Conditional Correlation (DCC) model of Engle (2002) and the Time-Varying Conditional Correlation (TVC) model of Tse and Tsui (2002). These models are chosen as they entail a more manageable and parsimonious multivariate volatility forecasting model. The chapter then applies these models to forecast VaR for a portfolio of AUD with twelve other currencies. Some statistical tests and the backtesting procedures required by the Basel Committee are conducted to evaluate the performance of VaR forecasts.

Incorporating time-varying volatility in VaR models is not straightforward. Notice that these models raise some difficulties in practice, where banks are to trade with relatively large and complex portfolios that are unlikely to change daily. This implies that each day, the banks will have to compute a series of historical data for the new portfolios to estimate VaR. Consequently, this may create additional costs to the banks. Instead of using these models, banks appear to be taking less computationally demanding alternatives. Banks prefer to use a simple VaR measure that aggregates all of the risks of a trading portfolio into a single number, which is suitable for use in the boardroom, reporting to the regulator and disclosure in their financial reports.

Chapter 5 examines the adequacy of reported VaR forecasts for Australian ADIs. This chapter focuses on whether the reported VaR forecasts provide any new information to investors and the bank regulators to assessing the differences in market risk exposures for each ADI. The chapter uses a series of published data in electronic form, provided by APRA under the APRA Research Grant Program (the Program)[1]. This dataset contains the reported quarterly VaR forecasts from nine Australian ADIs from the year of 2008 to 2010. This study

[1] The agreement of confidentiality for undertaking the Program is committed where APRA requires the Recipient(s) to preserve and maintain the confidentiality of information and documents (see Appendix I). This dataset is subjected to the secrecy provisions of Section 56 of the Australian Prudential Regulation Authority Act 1998 (the Act). To comply with this requirement, the Recipient(s) has applied and obtained ethics approval from Curtin Human Research Ethics Committee for the Program (see Appendix II). Access to data are limited only to the Recipient(s) of the Program, Thesis Committee and APRA.

follows the approach as proposed in Jorion (2002) and examines the relationship between the reported VaR forecasts with ADIs' future operating revenues in a simple linear regression framework. One of the main objectives for Basel III is to strengthen banks' transparency and disclosures. The findings in Chapter 5 suggest the current financial reporting environment in Australia does not provide academic researchers and the regulator enough information to assess the quality of VaR forecasts reported by ADIs. It is worth noting that the requirements for banks to disclose information more completely can sometimes be very costly and may not necessary increase transparency.

Finally, Chapter 6 concludes the thesis and discusses further work for future research.

Chapter 2

RISK MANAGEMENT PRACTICES IN AUSTRALIAN AUTHORIZED DEPOSIT-TAKING INSTITUTIONS (ADIS)

2.1 INTRODUCTION

The Basel Committee on Banking Supervision aims to improve the quality of worldwide banking supervision under the Basel Framework. Following the collapse of Bretton Woods system in 1973 and the default of the German Bank Herstatt in 1974, the Basel Committee has set minimum standards for the regulation and supervision of international banks. The first Basel Accord was introduced in 1988 where a minimum capital ratio of 8 percent to total risk-weighted assets was set, followed by the 1996 Amendment to the Basel Capital Accord to include market risk. The Basel Framework is periodically revised, highlighting the constant need for establishing more prudent capital requirements to strengthen the international banking system and improve market confidence in regulation. Subsequently, Basel II was introduced in 2004, and Basel III in 2010 (see Basel Committee on Banking Supervision 2014a).

Since 1998, Australian Prudential Regulation Authority (APRA) is the prudential regulator and supervisor of all Australian authorized deposit-taking institutions (ADIs), including banks, building societies, credit unions, and specialist institutions. The *Banking Act 1959* has allowed APRA to implement prudential standards on ADIs, to enforce the relevant regulation, and to act in the interests of depositors, insurance policy holders, and other members. The purpose is to promote the stability and market confidence in the Australian financial system (Australian Prudential Regulation Authority 2011a, 2011b). APRA has played a sound supervisory role in implementing Basel II from 1 January 2008, and the Basel III from 1 January 2013 (Basel Committee on Banking Supervision 2014e).

Under Basel III, a new set of capital requirements was introduced to allow international banks to manage their risk exposure more prudently. To ensure sufficient capital reserves against large unexpected losses in banks' trading portfolios of financial assets and derivatives, the prudential regulation of minimum capital requirements is used. Minimum capital requirements are designed to mitigate the Government's role as the lender of last resort. Hence, by requiring the banks to set aside an amount of capital, there is reduced financial burden borne by the Government. In particular, the total capital ratio to risk-weighted assets is maintained at 8 percent with at least 6 percent in Tier 1 capital and 2 percent in Tier 2 capital. Tier 1 capital or 'core' capital consists of equity and disclosed reserves from after-tax retained earnings. Tier 2 capital or 'supplementary' capital consists of undisclosed reserves, revaluation reserves, general loan-loss reserves, perpetual securities, and subordinated debt with more than five years maturity. While, banks must hold at least 4.5 percent of the common equity in their total risk-weighted assets. These ratios are phasing in gradually from the beginning of 2013 and becoming fully effective by 1 January 2019 (Basel Committee on Banking Supervision 2011a). In Australia, the proportion of common equity in ADIs' total risk-weighted assets had increased from 7.5 percent to 9.1 percent, and the total capital ratio had increased from 11.5 percent to 12.5 percent, from December 2008 to December 2014[2]. These ratios show that ADIs have strengthened their capital positions considerably in the last eight years. It also highlights the fact that ADIs are holding larger proportions of common equity in their trading portfolios of financial assets and derivatives. Such exposure means that ADIs are becoming increasingly subject to market risk. APRA (2014a) claimed that ADIs particularly Australian banks have consistently held capital well above the minimum requirements since Basel I. APRA has continuously taken a more conservative approach to capital than the minimum requirements and that it becomes an important contributing factor to mitigate against the GFC of 2008.

The GFC reviewed that many international banks had built up excessive leverage and had a capital level that was inadequate to withstand unexpected losses without becoming insolvent. As part of Basel III, banks are also be required to maintain a non-risk-based leverage ratio of 3 percent on Tier 1 capital. This ratio measures the size of banks' Tier 1 capital relative to their total on- and off-balance sheet exposures. A bank's total exposure measure includes on-balance sheet exposures, derivative exposures, securities financing transaction exposures, and off-balance sheet items (Basel Committee on Banking Supervision 2014b). The leverage ratio is measured by two liquidity standards, namely Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR). LCR is the ratio of highly liquid assets to net cash flows over a 30-day period. This ratio ensures that the banks will have current assets such as cash to withstand short-term liquidity disruptions. While, NSFR is the ratio of

[2] Data obtained from Australian Prudential Regulation Authority. 2015. "Statistics: Quarterly Authorized Deposit-taking Institution Performance." http://www.apra.gov.au/adi/Publications/Pages/adi-quarterly-performance-statistics.aspx

longer-term funding such as deposits or wholesale funding to banks' asset holdings. Banks will have to meet these standards by repositioning their capital level to make them less vulnerable to unexpected shocks. If the capital levels are too low, banks may be unable to absorb high levels of losses. Excessively low levels of capital increase the risk of bank failures, which in turn, may put depositors' funds at risk. The introduction of a leverage ratio in Tier 1 capital is a step forward in Basel III. However, the effectiveness of leverage ratio in detecting the probability of financial default is yet to be empirically supported. Hlatshwayo et al. (2013) found that a higher LCR ratio is usually associated with a higher rate of bankruptcy. Also, it is not clear as to how LCR and NSFR ratios can be merged to the total capital ratio to risk-weighted assets (Moosa and Burns 2013). The implementation of leverage ratio will be reviewed in 2017 and gradually calibrated into Pillar 1 (Basel Committee on Banking Supervision 2014a).

This leads to the central issue of this chapter. Since Basel I was first introduced in 1988, followed by the 1996 amendment of the Basel Capital Accord to apply minimum capital requirements for market risk, Value-at-Risk (VaR) has become a standard market risk measure for many international banks including Australian banks. In particular, each bank has to set aside an amount of capital of at least three times that of VaR. The original amendment required ADIs to adopt a standardized approach when calculating the risk capital. The standardized approach assigns a common risk factor for each type of risk exposure, including interest rate risk, equity risk, foreign exchange risk and commodity risk. The amount of capital is calculated by the arithmetic sum of each risk factor. However, this attracted great criticism from the international community for its inability to capture highly adverse conditions in the financial market. Furthermore, the standardized approach does not allow banks to disintegrate and analyse the risk of their trading portfolios separately (Soczo 2002). A series of unpredicted financial events that caused significant financial losses suggested that the necessity of establishing robust VaR techniques to manage banks' exposure to market risk is critical. In response to the criticism, the Basel Accord was amended to allow banks to design their VaR models, provided these met some regulatory criteria. The Basel Committee also required banks to perform a series of backtesting procedures to test and improve the accuracy of their models for measuring market risk. The aim of this chapter is to provide an overview of the regulatory changes on Basel III with an emphasis on the influence of these regulations on market risk exposure.

The plan of this chapter is organized as follows. Section 2.2 describes the background of the Basel Accord in the Australian banking system. It outlines the limitations with current regulations and discusses how they may be addressed by the new proposals from the Basel Committee. Section 2.3 describes the use of VaR as a standard market risk measure to the regulatory process. It also provides the theoretical framework for VaR measures. Section 2.4 describes the backtesting procedures that are used by the Basel Accord to validate a VaR model. Banks may have a tendency to provide conservative VaR forecasts. Conservative VaR forecasts lead to a greater number of violations than reasonably expected given a confidence level. Subsequently, a penalty charge that is a function of the number of violations on the previous 250 trading days is imposed. The structure and impact of these penalty charges on banks are also discussed. Section 2.5 concludes the chapter.

2.2 BACKGROUND OF THE BASEL ACCORD IN THE AUSTRALIAN BANKING SYSTEM

Since the 1980s, Australian banks have experienced several major merger and acquisitions, which has led to the privatisation of large Australian banks including Commonwealth Bank in the early 1990s (Wright 1999). Deregulation has led to a more conservative business approach by the Australian banking sector, considering possible adversity in global financial markets. In contrast to major international banks in other countries, Australian banks performed relatively strongly during the Global Financial Crisis (GFC) (see Figure 2.1). The Australian four pillar banks, Commonwealth Bank, Westpac Banking Corporation, Australia and New Zealand Banking Group and National Australia Bank, had proven to be more resilient to the impact of the GFC. They were ranked among the world's top 20 safest banks in 2009 (see Keeler 2009) and continued to hold this position in 2014 (see Fiano 2014).

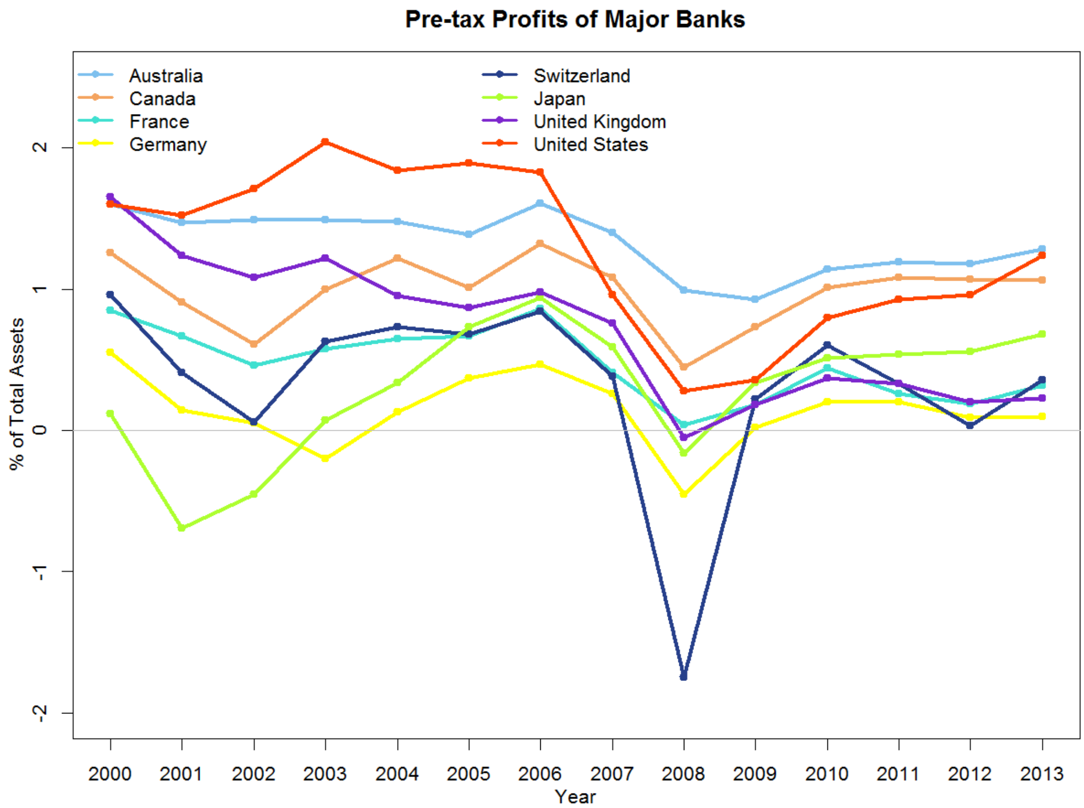
Figure 2.1[3] shows the impact of GFC on selected major banks from different countries relative to the Australian major banks. It can be seen that Australian banks have continuously generated the highest percentage of pre-tax profits to total assets relative to their peers in other countries during the GFC in 2008. In particular, the Australian major banks showed the highest pre-tax profits of 0.99 percent to total assets, followed by Canada at 0.45 percent and the US at 0.28 percent. In contrast, the major banks in Switzerland reported the pre-tax losses of 1.75 percent to total assets. Similarly, the major banks in Germany, Japan,

[3] Data obtained from the annual reports of Bank for International Settlements. "Profitability of Major Banks from Bank for International Settlements." http://www.bis.org/publ/

and the United Kingdom also reported the pre-tax losses of 0.45 percent, 0.16 percent and 0.05 percent to total assets, respectively. This could be because Australian banks benefited from a strong global demand for commodity products and an appreciating Australian dollar (International Monetary Fund 2012). Likewise, the banking system in Australia is highly concentrated and had been re-regulated before the GFC (Davis 2007). Reserve Bank of Australia (RBA) claimed that the relatively strong performance of Australian banks was a consequence of prudent regulation and tighter lending standards compared to those in the US (Reserve Bank of Australia 2009). Overall, there were 167 ADIs in Australia with total assets amounting to AUD4.15 trillion in September 2014, with the four pillar banks contributing 78.2 percent, i.e. AUD3.25 trillion, of the total assets[4].

[4] Data obtained from Australian Prudential Regulation Authority. 2015. "Monthly Banking Statistics." http://www.apra.gov.au/adi/Publications/Pages/monthly-banking-statistics.aspx

Figure 2.1 Pre-tax Profits of Major Banks (% of Total Assets)



When Basel I was introduced in 1988, one of the main problems highlighted was the requirement of a minimum 8 percent capital ratio on risk-weighted assets for credit risk only. Credit risk arises from an inability or unwillingness by borrowers to meet their obligations to an institution, such as repaying a loan (Australian Prudential Regulation Authority 2011c). While there was no capital requirement for market risk, the regulator soon realized that banks were not providing sufficient amount of capital to absorb large unexpected trading losses for excessive market risk and moved to rectify this issue. And so, Basel I was amended in 1996, requiring banks to apply minimum capital requirements for market risk. The Basel Accord defines *market risk* as the "risk of loss in on- and off-balance sheet positions arising from movements in market prices" (Basel Committee on Banking Supervision 1996, 1). The four market risks identified in the Basel Accord included interest rate risk, equity risk, foreign exchange risk and commodity risk. The prudential regulation of market risk requires banks to hold at least three times that of VaR as a risk capital to mitigate against large unexpected trading losses. The market risk capital requirements comprise of two separate charges, i.e. ‘specific risk’ and ‘general market risk’. *Specific risk* is the “risk that the value of a security will change due to issuer-specific factors” regardless of whether it is short or long position and *general market risk* is the “risk of loss due to the changes in market interest rates” (Basel Committee on Banking Supervision 1996, 9).

Market risk is measured by Value-at-Risk (VaR). VaR is described as a procedure to measure the probability of maximum loss over a target horizon within a given confidence level (Jorion 1996, 2007). For example, an Australian bank holds a trading portfolio with the daily VaR of AUD 3 million at 99 percent confidence level. It can be interpreted as there is one percent chance that a loss is exceeding AUD 3 million for the next day. So, the bank has to hold at least AUD 9 million as risk capital over the next day. J.P. Morgan introduced the RiskMetrics method to calculate VaR (see RiskMetrics Group 1996). They argued that this method reduces computational burdens in measuring market risk and can be used for any asset in a bank’s trading portfolio. Since then, the use of more sophisticated and complex VaR models in banks has escalated. The techniques of calculating VaR and their criticisms are discussed in Section 2.3.

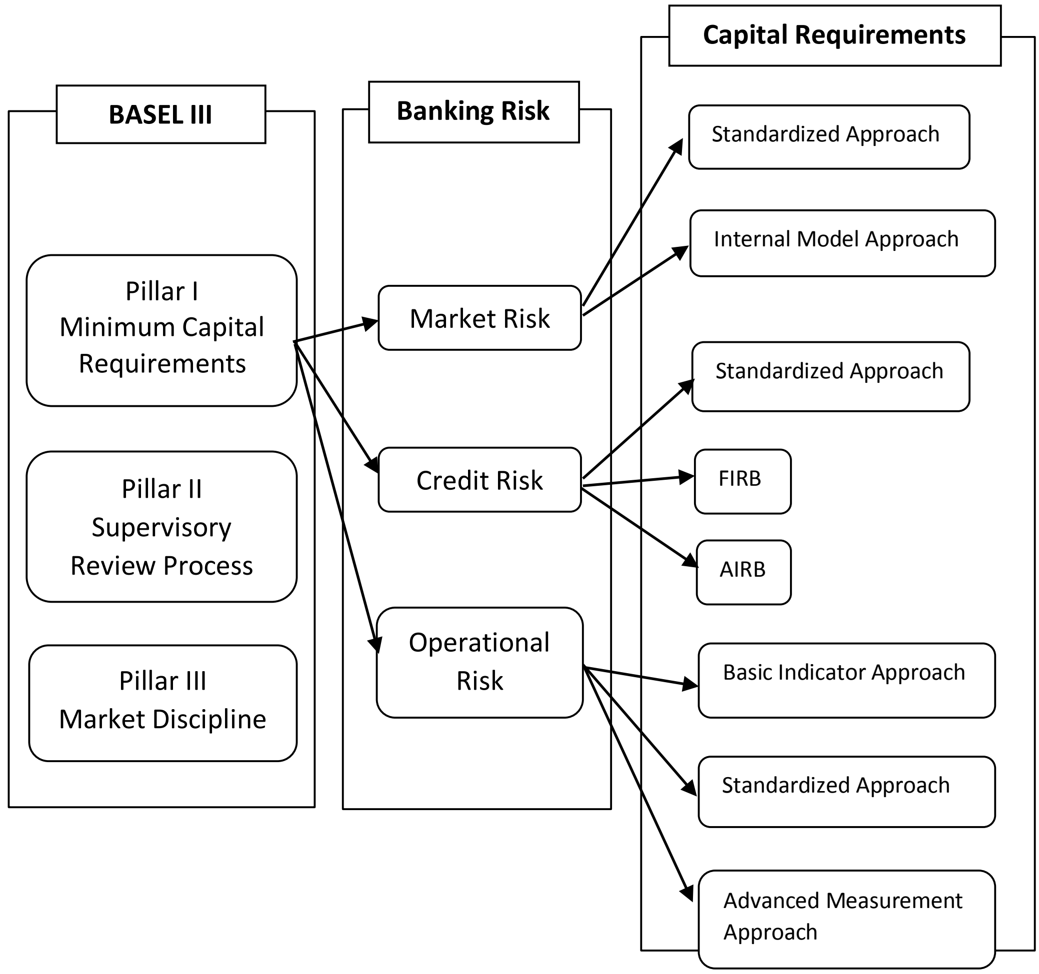
As set out in Basel III, banks are required to follow a *standardized approach* to measuring each of the four market risk identified above. The standardized approach was set by the original 1996 Basel Capital Accord. It is acknowledged that the “one-size-fits-all” approach may not be adequate to capture the risks inherent in large and complex trading and derivative portfolios (Basel Committee on Banking Supervision 2013). Hence, an *internal models approach* is introduced to the banks with large and complex trading and derivative portfolios. The use of internal models allows banks to set capital charges that closely conform to their actual market risk exposures. The internal models incorporate two criteria, namely *qualitative* and *quantitative* standards. The *qualitative* standards include the appointment of an independent risk control unit to regulate day-to-day risk management process. The board of directors and senior managers should be actively involved in the risk controlling process. The unit is also responsible for conducting a rigorous and comprehensive stress-testing programme on the bank's trading positions daily. Most importantly, the bank's internal risk measurement model must be fully integrated with other risk management systems. An independent review of the bank's risk measurement system should also be carried out regularly for audit and control purposes. *Quantitative* standards involve the specification on estimating day-to-day VaR model, and the risk assessment for large and complex portfolios. Banks are to calculate the VaR on a daily basis with 99 percent of confidence level and report the VaR over a 10-day holding period. The standards also require banks to describe the backtesting procedures that are used to validate a VaR model and the impact of backtesting results to daily capital charges. The procedures for backtesting are presented in Section 2.4. Other requirements include the need for frequently updating the bank's datasets and a minimum length of the historical observation period. A detailed description of the *qualitative* and *quantitative* standards is available from the report of Basel Committee on Banking Supervision (2011a).

To date, the Australian four pillar banks have adopted the internal models approach. Basel III has allowed these banks to design and implement their own procedures, within the approval of APRA, in measuring and managing their risk (Basel Committee on Banking Supervision 2014e). It is worth noting that the internal models approach is hard to monitor and usually expensive to administer. However, the use of internal models can provide unintended incentives to banks to underestimate minimum capital requirements.

Recent research has been attempted to assess the specification of the internal models approach and the extent to which the approach is operated in Australian ADIs. In particular, Rutkowski and Tarca (2014) explored the implementation of the internal models approach in Australian major banks to assess the adequacy of capital requirements relative to credit risk. Their findings were limited by the access of internal bank datasets that are highly confidential and not publically available. Hence, they adopted a practical modification using readily available data to evaluate the model specification of the internal models approach implemented by Australian major banks. Their results supported the notion that the Australian banking system was able to withstand severe shocks during the GFC, although some banks fell below the minimum threshold of capital requirements. They complimented APRA for its efforts in protecting the Australian banking sector against bankruptcy. They also suggested that a higher capital requirement is desirable to improve the stability of the financial system in Australia. In a recent Basel Committee on Banking Supervision (2014c) report, the internal models approach adopted by Australian ADIs had been described to be substantively in line with the Basel Accord. However, Moosa and Burns (2013) argued that the regulatory capital requirements under Basel III will not make Australian ADIs more resilient against the future financial crisis. They claimed that the probability of future financial crisis occurring and the severity of its consequences could not be reduced by merely imposing a greater amount of capital charges. Hence, they questioned as to whether the proposed regulatory changes in Basel III contribute to better risk management practice for Australian ADIs, or it is merely a compliance exercise.

Under Basel II, the emphasis on the accuracy of risk assessment relies on a three-pillar structure, namely minimum capital requirements, supervisory review process, and market discipline (Basel Committee on Banking Supervision 2006). The structure was revised in the Basel III when major international banks suffered large unexpected trading losses from the subsequent crises in the financial market. Figure 2.2 illustrates the three-pillar structure of Basel III (Basel Committee on Banking Supervision 2006, 2011a). Pillar 1 was a direct replacement of Basel I and requires banks to assess their regulatory capital requirements for the market, credit, and operational risk. This is to allow banks to determine the amount of capital requirements more adequately based on data and formal techniques to reduce regulatory arbitrary.

Figure 2.2 Structure of Basel III



Apart from market risk as explained above, credit risk has been implemented to account for the probability of default in contractual obligations such as loans on a bank's lending book. If borrowers failed to repay their loans, a bank might experience credit losses. These credit losses will reduce a bank's profitability and affect a bank's capital ratio. A comprehensive study on the Australian banks' large credit losses was conducted by Rodgers (2015) over two decades from 1980 to 2013. The large credit losses in Australia can be categorized into two episodes. One was the credit losses around the early 1990s recession, and the other was during and after the GFC. His findings showed that the Australian banks' large credit losses appear to closely related to large unexpected trading losses for excessive market risk during both episodes. Likewise, Allen and Powell (2012) showed that Australian banks' credit risk increased dramatically during the GFC.

One of the problems with the Basel I was that it focused on credit risk at the expense of the Australian banks' total risk (Hogan and Sharpe 1990). At the same time, the classification of credit risk also encouraged banks to transfer their risky assets off their balance sheets through securitization. As a result, banks were not holding sufficient amount of capital against risky assets (Santos 2001). Under Basel III, three methods are introduced in measuring the credit risk capital requirements, namely, the use of credit-ratings by external credit-rating agencies (the Standardized Approach); Foundation Internal Ratings Basis (FIRB) on the probability of loan default; and Advanced Internal Ratings Basis (AIRB) on loss given default (Basel Committee on Banking Supervision 2011a). FIRB and AIRB allow banks to assess credit risk capital requirements based on their credit exposures and internal credit-ratings on different asset classes. The Basel Committee is continually seeking to improve the design of the Standardized Approach for credit risk (Basel Committee on Banking Supervision 2014f). A several key aspects were proposed, including reduced the reliance on the use of external credit-ratings, increased credit risk sensitivity, increased comparability of capital requirements between banks using the standardized approach and the internal ratings-based approach and better clarity on the application of the standards.

Operational risk arises due to human acts of fraud and technical errors in a bank's day-to-day business activities, processes, and system (Gregoriou 2009). The initial work related to operational risk was carried out by the Basel Committee in 1998 (Basel Committee on Banking Supervision 1998). Later, operational risk was included in Basel II. A famous example of operational risk in practice is Nick Leeson, the rogue trader who brought down Barings Bank in February 1995 (Power 2005). Similarly, one of the most notorious events in Australian banking history was the large trading losses of AUD360 million incurred by the National Australia Bank (NAB) in January 2004. The losses occurred due to an increase of risk-taking in large and complex foreign currency options portfolio combined with the adverse expectation of currency movements. The traders were aware that the trading losses had been incurred and concealed losses by entering into false transactions (Hamer and Rivett 2004). As a result, APRA was called to investigate and review the circumstances associated with the trading losses. The investigation revealed that the losses were caused by the negligence of the Board and inadequacies in risk management systems. The investigation had led to the improvement in the design and implementation of NAB's risk management framework (Australian Prudential Regulation Authority 2004). Moosa and Silvapulle (2012) conducted a study of 54 operational loss events for 8 Australian banks during the period from 1990 to 2007. Their findings showed that operational losses would have a great negative impact on the banks' market values.

Operational risk has been treated as identical to market and credit risk where banks are required to set a minimum capital charge to cover for operational risk. Three methods are introduced to measure operational risk capital requirements, including Basic Indicator Approach (BIS); Standardized Approach (TSA); and Advanced Measurement Approach (AMA) (Basel Committee on Banking Supervision 2011b). A bank may use one of the above approaches to measuring their operational risk. The simplest method is the BIA by which the capital charge is calculated as a percentage of gross income, a proxy for operational risk exposure, at 15%. This method does not require the supervisory approval. Under the AMA, a bank is allowed to develop its own internal models to calculate the capital requirements for operational risk. The minimum capital ratio for a typical AMA bank is set at 10.8% of its gross income. This method involves a rigorous risk management framework and subjects to the supervisory approval. Whereas, the TSA requires banks to divide their total gross income into eight different business lines, including corporate finance, trading and sales, retail banking, commercial banking, payment and settlement, agency services, asset management and retail brokerage. The capital charges are calculated as a sum of the products of the gross income for each business line and a specific regulatory coefficient, known as beta, is assigned to each line. The use of TSA requires compliance with a set of qualitative criteria relating to operational risk management systems, and banks are required to obtain approval from the supervisory authority. A variant of the TSA, the Alternative Standardized Approach (ASA) allows banks with high interest margins to calculate their operational risk capital requirements by replacing the gross income for two business lines, retail banking, and commercial banking, with a fixed percentage of their loans and advances. In 2014, the Basel Committee proposed revisions to the TSA for measuring operational risk capital requirements (Basel Committee on Banking Supervision 2014d). The revised TSA would replace the existing approaches, BIA, and TSA, including its variant the ASA. The Business Indicator (BI) would be used to replace gross income in determining operational risk capital requirements. BI consists of three major components, interest, service, and financial components. The use of BI was proposed on the basis that it has a greater predictive power to capture a bank's business volume, hence more sensitive to operational risk. According to the International Monetary Fund (2010) report, Australian ADIs have been accredited as a low operational risk. This is due to vigilant political stability, well-regulated legal system, low security risk, steady economic growth and international trades.

Pillar 2 of Basel III focuses on the role of supervisors in evaluating each bank's overall risk exposure and assesses the regulatory capital requirements against additional risk. Supervisors are allowed to seek clarification from banks and propose immediate actions to prevent capital from falling below the minimum levels. The primary objective is to strengthen the soundness and stability of the international banking system. In Australia, APRA is responsible on ensuring the compliance with all regulatory requirements as set by the Basel Accord. Despite the increasing capital requirements resulting from the GFC, the Australian banking system continues to exhibit high performance apart from capital pressures due to global liquidity contraction (Australian Prudential Regulation Authority 2007a, 2007b). Arguably, APRA has played a sound supervisory role in enforcing Basel III requirements and has built robust regulatory and supervisory guidelines by promoting a well-capitalized banking system in the current financial environment. However, it is important to recognize that the APRA's effectiveness as a prudential regulator for dealing with financial distressed ADIs depends on having a clear mandatory and operational independence, a strong prudential framework, an active risk management programme, and adequate staffing and financial resources to meet its statutory objectives (Australian Prudential Regulation Authority 2014b).

As a response to the extreme events over the past decades, the Basel Committee has undertaken desperate measures in requiring banks to disclose comprehensive capital guidelines in their trading books. Under Basel II, Pillar 3 - Market Discipline, was introduced as a supervisory and regulatory tool for monitoring and controlling banking risk. Subsequently, new disclosure requirements were greatly increased in Basel III. Pillar 3 seeks to promote market discipline through the public disclosure of every detail of each bank's regulatory capital requirements. In particular, Pillar 3 requires banks to report the nature, frequency and types of risk exposure including market, credit, operational risk. It also outlines general and specific disclosure requirements on the banks' trading books. The disclosure as suggested in Pillar 3 can be extensive such that the implementation of internal models by banks to accurately capturing the regulatory capital requirements can be onerous and sometimes costly to administer.

Given that banks are allowed by the Basel Accord to design their own VaR models, the extent to which VaR models are reported, and the accuracy of reported VaR measures raise some concerns to the regulator. Hirtle (2003) found that the market risk capital charges provide useful information about banks' future trading risk. An earlier study by Jorion (2002) analysed the informativeness of quarterly VaR forecasts disclosed in the financial reports of 8 major banks in the US. He showed that VaR measures appear to be useful in forecasting the variability of banks' next quarter trading revenues. Liu, Ryan, and Tan (2004) examined the technical complication on VaR models across 17 banks in the US. Consistent with Jorion (2002), they stated that banks with better information and complex VaR models are informative in predicting banks' future trading risk. A study by Pérignon and Smith (2010a), using a sample of 60 large US and international banks, argued that banks provide very little useful information about banks' future trading risk. Consequently, they commented that the level and quality to which VaR measures is disclosed is indifferent to the regulator.

In Australia, APRA is responsible for collecting data for its own purposes and acts as a national statistical agency for the financial sector, collecting data on behalf of the Reserve Bank of Australia (RBA) and the Australian Bureau of Statistics. ADIs are required to follow the prudential standard as set by APRA, particular on capital adequacy on public disclosure and market risk (Australian Prudential Regulation Authority 2013a, 2013b, 2013c). Most of the ADIs in Australia do report their VaR forecasts in their financial reports; however only a small number of ADIs provide detail information about their risk models and measurement results. Instead of presenting their risk positions on each of the components of market risk, ADIs frequently present only a general discussion of their overall trading risk in their reports. Perhaps, due to the confidentiality and loss of competitive advantage, ADIs may be unwilling to disclose complete information that potentially unveil their weaknesses and improprieties to other competitors in the same industry. In spite these criticisms, APRA completed the implementation of Basel III disclosure requirements in 2013, and the level of public disclosures by Australian ADIs was regarded as satisfactory by the Basel Committee (Basel Committee on Banking Supervision 2014e).

It is worth noting that the requirements for banks to disclose information more completely can sometimes be very costly and may not necessary increase transparency. The content and format of disclosure and the need to manipulate numerical data to make it more meaningful may hinder the purpose of VaR disclosure. In some instances, banks may report only quarterly instead of daily VaR numbers. Some banks are more forthcoming and include daily time-series plots for their trading risk and revenues. Establishing the requirements for VaR disclosure alone cannot ensure an efficient and robust banking system. However, combined with other forms of efforts including the role of supervising authorities in assessing and validating VaR models may reinforce regulatory exertions to improve the current banking system.

2.3 WHAT IS VALUE-AT-RISK (VAR), AND WHY IS IT IMPORTANT?

According to Frey and McNeil (2002), VaR is defined as follows:

Let F_L denote the distribution of loss L such that $F_L(l) = P(L \le l)$. Given some confidence level $\alpha \in (0,1)$, the VaR of a portfolio is given by the smallest number l such that the probability that the loss L exceeds l is no larger than α. Formally,

$$VaR_\alpha = \sup\left\{l \in \mathbb{R}, P(L < l) \le \alpha\right\}$$

Alternatively, VaR_α can be defined as the lower α-quantile of the loss distribution F_L. Then, VaR_α can be computed using the quantile function F_L^{-1}.

$$VaR_\alpha = F_L^{-1}(\alpha) = q_\alpha^L$$

where q_α^L is the lower α-quantile of the loss distribution of asset returns of a portfolio. Typically, α is set at 0.01.

Under current regulations, banks are required to calculate VaR on a daily basis at 99 percent confidence level, i.e. $\alpha = 0.01$, and report VaR over a 10-day holding period. Based on the square-root-of-time rule, the 10-day VaR can be represented through 1-day VaR at

$$10\text{-}day\ VaR_\alpha = \sqrt{10} \times 1\text{-}day\ VaR_\alpha$$

This rule assumes that the daily returns are normal and iid. Banks are allowed to scale 1-day VaR to longer horizons depending on the liquidity of a bank's trading portfolios. For example, a time horizon of 10 days will be used for a foreign currency portfolio while a time horizon of 120 days will be used for the credit spreads of an options portfolio. Typically, a bank rebalances its portfolios very frequently, and the assumption that the risk of a portfolio remains unchanged over a longer horizon is questionable. Hence, to extrapolate 1-day VaR to 250-day VaR using a square-root-of-time rule is meaningless. Similarly, the rule does not hold when the asset returns are modelled with a GARCH(1,1) process. Drost and Nijman (1993) derived the temporal aggregation for GARCH(1,1) processes and showed that GARCH(1,1) is not closed under temporal aggregation. The best approximation to *h*-day volatility is unlikely to produce similar parameters by aggregating the approximation to 1-day volatility. Hence, the square-root-of-time rule is inappropriate, and the scaling of time-varying volatility into longer horizon does not work. See also Christoffersen, Diebold, and Shuermann (1998) and Wang, Yeh, and Cheng (2011). The square-root-of-time rule is simple and easy to calculate, but it has some serious drawbacks. Nonetheless, the square-root-of-time rule has been widely used and accepted by banks and the regulator.

One of the biggest criticisms regarding the use of VaR is that it is not subadditive. Artzner et al. (1999) demonstrated that VaR fails subadditivity, i.e. a property that is desirable for a risk measure. Following the principle of diversification in modern portfolio theory, a subadditivity measure should reduce the risk for a diversified portfolio. Subadditivity can be illustrated by using a simple example. Consider two assets which returns are independent and identically distributed (iid). If VaR is homogeneity,

$$VaR_{\alpha}(L_1) + VaR_{\alpha}(L_2) \geq VaR_{\alpha}(L_1 + L_2)$$

However, Artzner et al. (1999) proved that VaR does not satisfy the subadditivity property since

$$VaR_{\alpha}(L_1) + VaR_{\alpha}(L_2) < VaR_{\alpha}(L_1 + L_2)$$

The property of subadditivity is of particular importance for the regulator in unexpected events such as the GFC. The purpose of VaR is to calculate the amount of capital required to protect against unexpectedly large trading losses. Intuitively, if the regulator uses a non-subadditive risk measure in determining the regulatory capital needed, then banks have an incentive to use VaR to reduce their capital charges. Therefore, banks may not, in fact, have an adequate amount of capital to mitigate against unexpectedly large trading losses. The study by Basak and Shapiro (2001) supports this intuition, and they found that VaR risk managers who optimized their portfolios to minimize VaR may intentionally or unintentionally choose an allocation that is of larger exposure to risky assets than non-VaR risk managers. As a result, VaR risk managers consequently incur greater losses when unexpected adverse market events occur. By definition, VaR only represents one quantile of the profit and loss distribution and disregards the tail loss beyond the quantile (see Daníelsson 2002). An alternative method to calculate the conditional expectation of loss beyond VaR at a confidence level is the Expected Shortfall (ES) proposed by Artzner et al. (1999) and introduced by Rockafellar and Uryasev (2002) as Conditional Value-at-Risk (CVaR). A more general definition of ES is given by Acerbi and Tasche (2002a, 2002b). ES not only accounts for the severity of losses beyond VaR, but it is also a coherent risk measure that displays the property of subadditivity. These desirable properties have been shown by Artzner et al. (1999), Acerbi and Tasche (2002a, 2002b), and Rockafellar and Uryasev (2002).

Despite the main criticism of VaR not having subadditivity, Garcia, Renault, and Tsafack (2007), Ibragimov (2009) and Daníelsson et al. (2013) found that VaR can be subadditive in circumstances when asset returns have a fatter tail distribution than the normal distribution. These studies showed that VaR violates subadditivity when assets are subjected to occasional very large returns and when the tails of distributions are super fat. In reality, asset returns are found to be non-normal and have been shown to produce fat tails in the return distributions (see, for example, Mandelbrot 1963, Fama 1965, Bollerslev 1987). Therefore, VaR is still relevant given that asset returns are moderately fat-tailed at the lower tail of the distribution and VaR displays subadditive property in these regions.

Currently, a debate is going on whether the use of ES should be recommended in the future proposition of the Basel Framework. So far, VaR is still prescribed by the regulator because of its superior statistical performance and its simplicity in mathematical application. Yamai and Yoshiba (2005) found that VaR estimates are more accurate than ES estimates when the loss distributions have fat tails. A larger number of observations is required to reduce the estimation error of ES. Hence, ES is computationally more complex under fat-failed distribution. Intuitively, VaR models are statistically more stable than ES thus lead to a superior out-of-sample forecasting performance. Consequently, the quality of VaR models is easier to verify than ES.

Theoretically, ES has some advantages over VaR models. In practice, banks and the regulator use VaR extensively, and its importance as a risk measure is, therefore, unlikely to diminish. From the perspective of industry practice, they are looking for a simple and robust risk measure. A notable survey conducted by EDHEC Risk-Institute for 229 financial institutions based in Europe in 2008 showed that VaR continued to be one of the most commonly used risk measures by the industry. However, the survey found that most of the risk managers failed to measure risk optimally due to lack of sufficient knowledge in VaR techniques. They ignored the fact that VaR primarily focuses on the tail of return distribution under the assumption that asset returns are normally distributed. Whereas, it is widely documented that the probability distribution of asset returns is fat-tailed. This means that the extreme price movements occur more often than normally predicted. After all, the choice of the best performing risk measure depends on the complexity of mathematical procedures and the stability of statistical assumptions. Hence, more advanced and sophisticated risk measurement methods are less likely to be used by the financial industry due to lack of practical applications and difficulties in assessing the quality of these models by the regulator.

2.4 BACKTESTING

The current regulatory framework requires banks that use their own internal risk models to calculate the VaR on a daily basis at 99 percent confidence level and report the VaR over a 10-day holding period. Backtesting procedures have been used to evaluate the performance of VaR models, where the actual returns are compared with the VaR forecasts to assess the quality of banks' internal models. Specifically, the market risk capital charge is determined as the lower of either the bank's current assessment of 99 percent VaR over the next 10 trading days or a multiple of the bank's average reported 99 percent VaR over the previous 60 trading days plus an additional amount that reflects the underlying market risk of the bank's trading portfolios (Basel Committee on Banking Supervision 2011a).

According to the Basel Accord, banks are allowed to backtest their VaR models using actual or hypothetical profit and loss from their trading portfolios (Basel Committee on Banking Supervision 2006). Hypothetical profit and loss for banks' trading portfolios are calculated by applying the current day's price movements to the previous day's end-of-day portfolios. If banks are using the actual profit and loss of their trading portfolios, they must exclude fees, commissions, and net interest incomes, which are not directly related to market risk. Hypothetical backtesting may be more realistic, but it imposes substantial computational burdens given that the banks' trading positions and the composition of their portfolios change daily.

A violation is recorded when an actual loss on a portfolio exceeds the forecasted VaR. Banks using VaR models that lead to a significant number of violations are required to hold a higher level of capital charges. Subsequently, if they violate more than 1 percent in a financial year, they may be required to adopt the standardized approach (Basel Committee on Banking Supervision 2011a). The imposition of such penalty can be inappropriate as it affects banks' profitability and exposes banks to high default risk. Particularly, in situations of severe market conditions. A large number of violations may signal that the bank is undergoing serious financial difficulties. Imposing a high penalty charge will add additional financial burdens to the bank (Lucas 2001).

A procedure is used to calculate the number of times that the actual losses exceed VaR forecasts on the previous 250 trading days. Hence,

$$V_t = \begin{cases} 1 & \text{if } L_t > VaR_{\alpha,t} \\ 0 & \text{if } L_t \leq VaR_{\alpha,t} \end{cases} \tag{2.1}$$

The total number of violations on the previous 250 trading days is calculated as:

$$V_t^{250} = \sum_{t=1}^{250} V_t \tag{2.2}$$

The percentage of violations on the previous 250 trading days is given by:

$$V_T = \frac{1}{T}\sum_{t=1}^{250} V_t = \frac{V_t^{250}}{T} \quad \text{where T = 250 in the Basel Accord} \tag{2.3}$$

Ideally, a good model will have a percentage of violation that is very close to one percent.

$$V_T = 0.01: \text{ VaR model correctly forecasts market risk}$$
$$V_T < 0.01: \text{ VaR model overesimates market risk}$$
$$V_T > 0.01: \text{ VaR model underesimates market risk}$$

The market risk capital charges (MRCC) on each bank must be set either at the lower VaR of the previous day, or the average reported 99 percent VaR over the previous 60 days trading days, multiplied by a scaling factor of (3+k) for a violation penalty. The scaling factor calculates the probability that a violation occurs for a given day over the previous 250 trading days. Formally, it can be written as:

$$MRCC_t = \min\left(VaR_{\alpha,t}, (3+k_t)\times \frac{1}{60}\sum_{i=1}^{60} VaR_{\alpha,t} \right) \quad (2.4)$$

where,

$$k_t = \begin{cases} 0 & V_t^{250} \leq 4(Green) \\ 0.40 & V_t^{250} = 5(Yellow) \\ 0.50 & V_t^{250} = 6(Yellow) \\ 0.65 & V_t^{250} = 7(Yellow) \\ 0.75 & V_t^{250} = 8(Yellow) \\ 0.85 & V_t^{250} = 9(Yellow) \\ 1 & V_t^{250} \geq 10(Red) \end{cases} \quad (2.5)$$

A bank is categorized in the green zone if its VaR model is adequately accurate with no additional capital charge required. While, if a bank falls into the yellow zone, an additional capital charge will be imposed to justify the excessive number of violations. Finally, a bank is categorized in the red zone if its VaR model is not appropriate, and will be required to include a greater amount of capital charge. This penalty factor will only be reduced when the bank can demonstrate that there is an improvement made to its model.

Pérignon, Deng, and Wang (2008) showed that banks are likely to be cautious when reporting their VaR forecasts. This could be due to the difficulties for banks to aggregate VaR forecasts across different business lines, or banks do not want to put their reputation at risk. Similarly, in the earlier study by Berkowitz and O'Brien (2002) indicated that banks prefer to report high VaR forecasts to avoid the structural complication and the possibility of regulatory intervention in their risk models. If too many numbers of VaR violations are reported, a greater amount of penalty charges is imposed. The banks may be required to adopt the standardized approach for VaR estimation (Basel Committee on Banking Supervision 2011a). Lucas (2001) found that the current penalty structure is unlikely to provide a strong incentive for banks to design VaR models that provide good estimates to reflect their actual market risk exposure. It is profitable for banks to underreport their actual VaR forecasts. Consequently, da Veiga, Chan, and McAleer (2011) showed that a more severe penalty structure is probably desirable to discourage banks from choosing forecasting models that underestimate VaR. In particular, they proposed a new penalty structure that is based on the magnitude of violations instead of the current penalty structure that is based on the number of violations. An appropriate penalty structure may encourage banks to improve their risk models in forecasting VaR more precisely. Santos et al. (2012) proposed an alternative approach to determining the minimum capital requirements based on an optimal portfolio strategy. They applied Sharpe ratio to find the optimal weights of portfolios. By comparing the level of VaR forecasts and the number of VaR violations based on the optimal portfolio approach, a lower level of capital requirements can be achieved.

Even though the Basel Accord does not require banks to test their VaR models statistically, some formal statistical procedures are desirable, and many tests are proposed in the academic literature. These tests reflect mostly the concerns of the regulator who prefers banks to use VaR models that display correct statistical properties. While, most statistical tests focus on the number of violations, they give a low power of testing (see, for example, Kupiec 1995). Other tests looking at the timing and magnitude of violations have demonstrated to be more useful (see, for example, Christoffersen, Hahn, and Inoue 2001). A detailed description of the techniques of the statistical tests is presented in Chapter 3.

Ideally, banks should be able to report their VaR forecasts based on different models to minimize daily capital charges and to manage the number of violations strategically. In which case, banks can adopt different strategies depending on the current and future expectation of market conditions. In the study by McAleer, Jimenez-Martin, and Pérez-Amaral (2010), they proposed an alternative decision rule that allows adjustment of the penalty structure based on the past period violations in calculating daily capital charges. They showed that during periods of adverse market conditions when the number of violations is expected to be high, a higher capital charge can be imposed to cover the worst possible loss. While, in periods of low market volatility, when the number of violations is expected to be small, banks are allowed to pay a lower capital charge. Hence, more funds can be invested in assets at a lower marginal cost to increase banks' profitability.

2.5 CONCLUSION

The level of capital a bank holds indicates the future ability of the bank to grow, as well as its ability to withstand unexpected losses without becoming insolvent. The Basel Accord framework has undergone several revisions to address the inadequacy of minimum capital requirements to accommodate risk. The 1988 Basel Accord considered only the credit risk of bank assets and was not explicitly accounted for market and operational risk. Basel I was amended in 1996 to include market risk capital requirements given that banks were increasing exposed to market risk from their trading activities of financial assets and derivatives. This amendment is also allowed banks to use either the standardized approach or their own internal models to determine their regulatory capital requirement for market risk. This is to accommodate the original Basel Accord of "one-size-fits-all" approach which may not be adequate to capture the risks inherent in banks' large and complex trading and derivative portfolios. Basel II was reformed in 2004 to improve the modelling approaches to risk management, particularly the regulatory capital requirement for operation risk. Basel II also established the supervisory review process (Pillar 2) and the role of disclosure and market discipline (Pillar 3). However, the GFC showed that many international banks had built up excessive leverage and had a capital level that was inadequate and of insufficient quality. Hence, the Basel II regulatory framework was revised as it was clear that there was an insufficient amount of capital held to withstand large unexpected trading losses. As a result, Basel III has extended the scope of its regulatory framework to accommodate more sophisticated risk factors in the current financial environment. Basel III considers new aspects of risk management, in particular, the responsibility of supervisory authority in monitoring and controlling the current risk management system in Pillar 2 and the stringent disclosure requirements in Pillar 3 (Basel Committee on Banking Supervision 2011a). The framework also introduced a non-risk-based leverage ratio with two liquidity standards, namely LCR and NSFR. These ratios are intended to strengthen banks' short-term liquidity position and to ensure banks to maintain a stable funding level.

While it is too soon to determine the success of Basel III, some insights could be drawn from the implementation of the previous Basel Accord. Australia may have avoided the GFC; however, this does not rule out a future crisis. APRA needs to be prepared for future bank failures and to consider options for minimizing the risk of failure. Perhaps, a contingency plan is critical in the case of a major event, for example, the decision to bailout banks in the period of crisis. Nonetheless, APRA has the responsibility to improve supervision and prudential standards, by ensuring that banks meet regulatory capital requirements, provision for bad loans, and publish informative financial information timely. Under the direction of APRA, Australian banks have extended these efforts by evaluating their capital positions to cover for market risk exposure. Stress-testing techniques have been used to identify the probability at which a large unexpected trading loss may occur beyond the minimum level of capital requirements. It requires banks to keep enough amount of capital even under highly adverse market conditions. Even though the stress-testing was useful as part of a risk management process, the difficulties of the application of these tests were often too restrictive. Banks may decide not to publish the full specification of their models that frustrate the efforts of the supervising authority in validating the accuracy of the models. At the same time, banks are worried that, with the increased level of disclosure, they may potentially unveil their weaknesses to other competitors in the same industry. Practically, the implementation of a fully integrated VaR model can be very costly, and the ability to model VaR accurately may be constrained by limited data availability and computational burdens. Note that banks may wish to select models that not only satisfy the regulatory requirements by the Basel Committee but also minimize capital costs. These arguments will be highlighted in the next chapters.

Chapter 3

TAIL INDEX OF MAJOR CURRENCIES TRADED IN AUSTRALIA

3.1 INTRODUCTION

In recent years, extreme events, such as the Global Financial Crisis (GFC), have caused large unexpected losses in financial institutions. The necessity of central banks to continuously bail out financially distressed firms has cast doubt on the adequacy of current risk management strategies. Hence, establishing robust risk evaluation techniques to manage losses during extreme events become increasingly critical. In particular, Value-at-Risk (VaR) has become an important risk measurement tool in finance. Despite its popularity, the major challenge of VaR concerns with its robust construction to provide an accurate forecast of extreme events without knowing the exact dynamics in portfolio's returns. A detailed discussion of VaR is presented in Chapter 2.

This study proposes an alternative method to forecast VaR. From a probabilistic viewpoint, asset returns can be modelled as the outcomes of a sequence of continuous random variables. In that case, extreme observations belong to the tail of associated probability distribution. Therefore, an understanding of the tail behaviour is crucial where the measurement of risk are mostly referred to the observations located at the lower tail (Hols and De Vries 1991). The tail index can be characterized as the rate at which probability mass decays in the tail of a distribution (Kearns and Pagan 1997). Let $X_{1,} X_2, \ldots, X_n$ be iid random variables that represent returns from a distribution, f ,

$$f(x) = P(X_i > x) = 1 - Ax^{-k} \tag{3.1}$$

where $A > 0$ is a constant and $k = \frac{1}{\lambda} > 0$ is the tail index.

The seminal work of Hill (1975) proposed an estimator of tail index based on a sample of independently and identically distributed (iid) random variables. Hill (2010) extended the Hill (1975) estimator further to accommodate a much wider class of data generating processes. Mikosch and Starica (2000) and Berkes, Horváth, and Kokoszka (2003) applied those estimators for tail index under the assumption that the conditional variances of asset returns follow a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process. This study generalised Hill (1975) estimator to the case of asymmetric extension of GARCH model (GJR-GARCH) by Glosten, Jagannathan, and Runkle (1993).

Empirical studies using the tail index in foreign exchange returns are numerous. A notable study by Wagner and Marsh (2005) performed a simulation analysis of tail index on foreign exchange returns in a small sample setting to estimate the tail of a distribution. While, Payaslioğlu (2009) investigated potential regime switching behaviours of the exchange rate in Turkey. More importantly, the relationship between the tail index and VaR of the unconditional distribution was explored in the studies of Iglesias and Linton (2009), Iglesias (2012), and Iglesias and Lagoa Varela (2012). Their results suggested that tail index provides an important avenue to estimate VaR.

The contribution of this study is threefold. Firstly, the study extends the results found in Mikosch and Starica (2000) and Berkes, Horváth, and Kokoszka (2003) to accommodate the presence of asymmetric GARCH error in the estimation of a tail index. Secondly, it forecasts VaR of foreign exchange returns by the proposed estimator with daily exchange rate data for an equally-weighted portfolio of AUD with twelve other currencies. This approach is based on Iglesias (2012), and Iglesias and Lagoa Varela (2012), which apply the tail index estimator proposed in Mikosch and Starica (2000), and Berkes, Horváth, and Kokoszka (2003). This study provides the first empirical comparison on the impact of model specifications in estimating tail index and VaR for the case of GJR-GARCH. It is worth noting that the VaR obtained by tail index is unconditional to past information. This study will then compare the empirical performance of this unconditional VaR forecasts by tail index with the unconditional VaR forecasts as suggested by Jorion (1996, 2007) in addition to conditional VaR forecasts that incorporate time-varying volatility information. An unconditional VaR model provides an overview of market risk over long periods, hence, it is appropriate for calculating large loss forecasts. Even when the time horizon is shorter, banks often prefer unconditional models to avoid frequent undesirable changes in market risk limits (Danielsson and de Vries 2000). For a bank which rebalances its large and complex portfolios very frequently, the conditional models may not be feasible since this requires continuous constructing and updating new volatility forecasts that associate with high transaction costs. Nevertheless, conditional volatility forecasts are important in many situations. When the investment horizon is short, e.g. intra-day, conditional models may be preferred for risk forecasting to accommodate for very large extreme returns in a high volatility period. Hence, conditional models imply more volatile risk forecasts than unconditional models given that they can quickly adapt to recent volatility in the market. Notice that the use of conditional models may lead to capital requirements that fluctuate extremely over time. Hence, it is impossible for a bank to rapidly adjust its capital base to accommodate changing market conditions. A bank may very well use unconditional models for market risk capital charges. While, conditional and unconditional models give banks different but beneficial information about market risk, the choice of the models mainly depends on a bank's trading strategy and its trading environment. Since foreign exchange returns are known to be fat-tailed, this study also suggests the use of student-t distribution as an alternative to the normal distribution to make the comparison between VaR forecasts (see Bollerslev 1987, and Angelidis, Benos, and Degiannakis 2004).

Finally, the robustness of VaR forecasts is also investigated. Some statistical tests are conducted to evaluate the quality of VaR forecasts. These tests include Kupiec (1995) Test Until the First Failure (TUFF), followed by Christoffersen (1998) and Christoffersen, Hahn, and Inoue (2001) Unconditional Coverage (UC), Serial Independence (IND) and Conditional Coverage (CC) tests. In addition, the performance of VaR forecasts is also evaluated by the backtesting procedure required by the Basel Committee. A violation is recorded when an actual loss exceeds the VaR forecast. This metric is important because a good VaR model should lead to a correct estimation of market risk at every point in time. At the same time, the regulator can obtain an idea about how well a bank's VaR model predicts its actual market risk exposure. Furthermore, the amount of capital charges that a bank holds depends on its reported VaR. If banks are conservative in estimating risk, higher capital charges are subsequently required. Banks are therefore allocated too much capital to their trading activities. Nevertheless, the accuracy of VaR forecasts and the discipline of risk-sensitive capital charges have crucial repercussions for banks and the regulator to improve current risk management practices.

This chapter is organized as follows: Section 3.2 presents the new estimator for a tail index. A selection of adaptive methods to test the models is described in Section 3.3. Section 3.4 provides a review of market risk capital requirements by the Basel Committee. Data and main results are presented in Section 3.5. Finally, a conclusion is drawn in Section 3.6.

3.2 New Estimator for Tail Index

This section provides a concise overview of the estimation of tail index under the assumption that the data generating process follows the GARCH model of Bollerslev (1986) and its asymmetric extension by Glosten, Jagannathan, and Runkle (1993).

Let r_t denotes the exchange rate return at time *t* such that:

$$r_t = \log\left(\frac{s_t}{s_{t-1}}\right) \tag{3.2}$$

where, s_t denotes the exchange rate of an Australian dollar to foreign currency at time *t* for *t* = 2, …, T.

Consider the GARCH(1,1) model of Bollerslev (1986),

$$r_t = \sigma_t \eta_t \qquad \eta_t \sim iid(0,1) \tag{3.3}$$

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3.4}$$

with $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$. The parameters of the model can be estimated by Maximum Likelihood Estimator (MLE) under normality, which becomes Quasi-MLE (QMLE) if η_t does not follow a normal distribution. Bougerol and Picard (1992) showed that if the log-moment condition,

$$E \log\left(\alpha \eta_t^2 + \beta\right) < 0, \tag{3.5}$$

is satisfied, then GARCH(1,1) is stationary and ergodic. Moreover, under the same condition, Jeantheau (1998) and Boussama (2000) showed that QMLE is consistent and asymptotically normal, respectively. Ling and McAleer (2003) provided necessary and sufficient conditions for stationarity and ergodicity as well as sufficient conditions for consistency and asymptotic normality of QMLE for GARCH(p,q) but their results require slightly stronger assumptions than the log-moment condition in the case of GARCH(1,1).

Glosten, Jagannathan, and Runkle (1993) proposed an alternative specification for the conditional variance equation aiming to capture the asymmetric effects of shocks on the conditional variance. The GJR-GARCH(1,1) model can be written as:

$$\sigma_t^2 = \omega + \left(\alpha + \gamma I_{t-1}\right) r_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3.6}$$

with $\omega > 0, \alpha \geq 0, \alpha + \gamma \geq 0$ and $\beta \geq 0$, where

$$I_t = \begin{cases} 0 & r_t > 0 \\ 1 & r_t \le 0 \end{cases}$$

McAleer, Chan, and Marinova (2007) showed that the log-moment condition for GJR-GARCH(1,1) model, namely

$$E\log\left[\left(\alpha + \frac{1}{2}\gamma\right)\eta_t^2 + \beta\right] < 0 \qquad (3.7)$$

is sufficient for consistency and asymptotic normality of QMLE.

Note that by Jensen's inequality,

$$\log E\left(\alpha\eta_t^2 + \beta\right) < E\log\left(\alpha\eta_t^2 + \beta\right) < 0 \Rightarrow E\left(\alpha\eta_t^2 + \beta\right) - 1 < 0$$

and similar argument holds for the GJR-GARCH case. That is $\log E\left[\left(\alpha + 0.5\gamma\right)\ \eta_t^2 + \beta\right] < E\log\left[\left(\alpha + 0.5\gamma\right)\ \eta_t^2 + \beta\right] \Rightarrow E\left[\left(\alpha + 0.5\gamma\right)\eta_t^2 + \beta\right] - 1 < 0$. Let $\hat{\alpha}, \hat{\beta}, \hat{\eta}_t$ be consistent estimates of α, β, η_t , respectively. Define $A_t = \alpha\eta_t^2 + \beta$and $\hat{A}_t = \hat{\alpha}\hat{\eta}_t^2 + \hat{\beta}$, then Mikosch and Starica (2000) and Berkes, Horváth, and Kokoszka (2003) proposed to estimate the tail index, κ, by solving:

$$\hat{\phi}_T(\kappa) = 0 \qquad (3.8)$$

where

$$\hat{\phi}_T(\kappa) = T^{-1}\sum_{t=1}^{T}\hat{A}_t^{\frac{\kappa}{2}} - 1 \qquad (3.9)$$

When $\kappa = 2$, equation (3.6) can be viewed as the sample estimate of the log-moment condition. Moreover, if equation (3.5) is true when $\kappa = 2$, it implies that the log-moment condition does not hold. Thus, equation (3.8) provides an alternative way to test the validity of the log-moment condition given the fact that $\hat{\kappa}$ is consistent and asymptotically normal as shown in Berkes, Horváth, and Kokoszka (2003). Similar results can be obtained for GJR-GARCH(1,1) model as demonstrated in the following proposition.

Proposition 1. Let r_t follows the dynamics as defined in equations (3.3) and (3.6) with $0<\kappa_0<\infty$ such that $E\left(\sigma_t^{\kappa}\right)<\infty$ for all $\kappa<\kappa_0$. Let $\theta=\left(\omega,\alpha,\beta,\gamma\right)'$ denotes the true parameter vector governing the dynamic of r_t with $\omega>0,\alpha>0,\beta\geq 0$ and $\hat{\theta}_T=\left(\hat{\omega}_T,\hat{\alpha}_T,\hat{\beta}_T,\hat{\gamma}_T\right)'$ be an estimator of θ based on T observations. Define $A_t(\gamma)=\left(\alpha+0.5\gamma\right)\eta_t^2+\beta$ and $Z(\kappa,\gamma)=E\left[A_t(\gamma)\right]^{\frac{\kappa}{2}}$ with their empirical counterparts $\hat{A}_t(\hat{\gamma}_T)=\left(\hat{\alpha}_T+0.5\hat{\gamma}_T\right)\eta_t^2+\hat{\beta}_T$ and $Z_T\left(\kappa,\hat{\gamma}_T\right)=T^{-1}\sum_{t=1}^{T}\hat{A}_t^{\frac{\kappa}{2}}\left(\hat{\gamma}_T\right)$, respectively. If

(i) $E\left[\log A_t(\gamma)\right]<0$

(ii) $\|\hat{\theta}_T-\theta\|=o_p(1)$

(iii) $E\left|\eta_t^2\right|^{\delta}<\infty$ for some $\delta>\kappa_0$

then

$$\left|\hat{\kappa}_T-\kappa_0\right|=o_p(1) \quad \text{and} \quad \left|Z_T(\hat{\kappa}_T,\hat{\gamma}_T)-Z(\kappa_0,\gamma)\right|=o_p(1),$$

where $\hat{\kappa}_T$ is the smallest positive number satisfying $Z_T\left(\hat{\kappa}_T,\hat{\gamma}_T\right)=1$.

Proof of Proposition 1. Under conditions (i)-(iii), it is straightforward to show there exists decompositions analogue to equations (3.8) and (3.9) in Berkes, Horváth, and Kokoszka (2003) GJR-GARCH model as defined in equations (3.3) and (3.6) This means there is an integer $N = N(\xi_1, \xi_2)$ where $\xi_1 > 0$ and $\xi_2 > 0$ such that

$$\liminf_{T\to\infty} P\left\{\beta+(\alpha+0.5\gamma)\eta_t - \xi_1 \le \hat{\beta}_T + (\hat{\alpha}_T + 0.5\hat{\gamma}_T)\hat{\eta}_t \le \beta+(\alpha+0.5\gamma)\eta_t + \xi_1, \forall N \le t \le T\right\}$$
$$\ge 1-\xi_2$$

Using the fact that convergence of monotone functions to a limit is uniform over finite intervals, the strong law of large number implies:

$$\sup_{0\le\kappa\le\delta}\left|\begin{matrix}(T-N)^{-1}\sum_{N\le t\le T}\left[\beta+(\alpha+0.5\gamma)\eta_t^2+\xi_1\right]^{\frac{\kappa}{2}} I\left\{\beta+(\alpha+0.5\gamma)\eta_t^2+\xi_1\le 1\right\}- \\ E\left\{\left[\beta+(\alpha+0.5\gamma)\eta_0^2+\xi_i\right]^{\frac{\kappa}{2}} I\left\{\beta+(\alpha+0.5\gamma)\eta_t^2+\xi_1\le 1\right\}\right\}\end{matrix}\right| \overset{a.s.}{=} o(1)$$

and

$$\sup_{0\le\kappa\le\delta}\left|\begin{matrix}(T-N)^{-1}\sum_{N\le t\le T}\left[\beta+(\alpha+0.5\gamma)\eta_t^2+\xi_1\right]^{\frac{\kappa}{2}} I\left\{\beta+(\alpha+0.5\gamma)\eta_t^2+\xi_1 > 1\right\}- \\ E\left\{\left[\beta+(\alpha+0.5\gamma)\eta_0^2+\xi_i\right]^{\frac{\kappa}{2}} I\left\{\beta+(\alpha+0.5\gamma)\eta_t^2+\xi_1 > 1\right\}\right\}\end{matrix}\right| \overset{a.s.}{=} o(1)\cdot$$

Combining these equations give

$$\sup_{0\le\kappa\le\delta}\left|(T-N)^{-1}\sum_{N\le t\le T}\left[\beta-(\alpha+0.5\gamma)\eta_t^2+\xi_1\right]^{\frac{\kappa}{2}} - E\left[\beta+(\alpha+0.5\gamma)\eta_t^2+\xi_1\right]^{\frac{\kappa}{2}}\right| \overset{a.s.}{=} o(1)$$

and this implies

$$\lim_{\xi_1\to 0}\sup_{0\le\kappa\le\delta} E\left|\left[\beta+(\alpha+0.5\gamma)\eta_0^2+\xi_1\right]^{\frac{\kappa}{2}} - Z(\kappa,\gamma)\right| = 0$$

and

$$\sup_{0\le\kappa\le\delta} T^{-1}\sum_{1\le t\le T}\left[\hat{\beta}_T + (\hat{\alpha}_T + 0.5\hat{\gamma}_T)\hat{\eta}_t^2\right]^{\frac{\kappa}{2}} = o_p(1).$$

Following the same arguments as in the proof of Theorem 2.1 in Berkes, Horváth, and Kokoszka (2003) using the results above gives $|\hat{\kappa}_T - \kappa_0| = o_p(1)$ and $|Z_T(\hat{\kappa}_T, \hat{\gamma}_T) - Z(\kappa_0, \gamma)| = o_p(1)$. This completes the proof.

Remark 1. The proposition above extends the consistency result in Berkes, Horváth, and Kokoszka (2003) to GJR-GARCH(1,1) model. When $\gamma = 0$, the result above reduces to Theorem 2.1 in Berkes, Horváth, and Kokoszka (2003).

In practice, $\hat{\kappa}$ can be obtained by solving

$$\phi(\hat{\kappa}) = 0$$

where

$$\phi(\hat{\kappa}) = T^{-1} \sum_{t=1}^{T} \hat{A}_t^{\frac{\hat{\kappa}}{2}}(\hat{\gamma}_T) - 1$$

Iglesias and Linton (2009) also demonstrated the relationship between κ and VaR for a given significant level, ν. Formally,

$$\nu = P[r_t > VaR_\nu] \equiv c_0 VaR_\nu^{-\kappa_0} \tag{3.10}$$

which implies

$$VaR_\nu = \left(\frac{c_0}{\nu}\right)^{\frac{1}{\kappa_0}}. \tag{3.11}$$

Furthermore, Iglesias and Linton (2009) showed that

$$\hat{c} = \frac{1}{2T} \sum_{t=1}^{T} |\hat{\eta}_t|^{\hat{\kappa}_T} \frac{\sum_{t=1}^{T} \left[\left(\hat{\omega} + \hat{A}_t(\hat{\gamma}_T)\hat{\sigma}_t^2\right)^{\frac{\hat{\kappa}_T}{2}} - \left(\hat{A}_t(\hat{\gamma}_T)\hat{\sigma}_t^2\right)^{\frac{\hat{\kappa}_T}{2}} \right]}{\frac{\hat{\kappa}_T}{2} \sum_{t=1}^{T} \hat{A}_t^{\frac{\hat{\kappa}_T}{2}}(\hat{\gamma}_T) \ln \hat{A}_t(\hat{\gamma}_T)} \tag{3.12}$$

is a consistent estimator for c_0.

Therefore, VaR can be estimated as

$$\widehat{VaR}_{v} = \left(\frac{\hat{c}}{v} \right)^{\frac{1}{\hat{\kappa}_T}} \tag{3.13}$$

If the portfolio returns follow a normal distribution, VaR_{α} can be estimated by:

$$\widehat{VaR}_{\alpha,d}^{m} = \hat{r}_t - q_{\alpha,d}\hat{\sigma}_t^{m} \tag{3.14}$$

where $\widehat{r_t}$ is the forecast of the portfolio return at time t, $q_{\alpha,d}$ is the quantile at $\alpha = 0.01$ of the density of MLE, d, and $\widehat{\sigma_t}$ is the estimated standard deviation of $\widehat{r_t}$ with m denotes the model used. Alternatively, if the portfolio returns follow a student-t distribution, $q_{\alpha,d}$ is the quantile at $\alpha = 0.01$ of t-density with δ degrees of freedom. Noted that the superscripts "std" and "norm" denotes estimates assuming a normal-distributed return and a t-distributed return.

If r_t follows the dynamics as defined in equations (3.3), (3.4) and (3.6), VaR can be estimated from the conditional mean and variance from the GARCH(1,1) and GJR-GARCH(1,1) models. Similarly, if the returns have a conditional student-t distribution, the estimates for the degree of freedom, δ, and $\widehat{\sigma_t}$ can be obtained from the fitted GARCH(1,1) and GJR-GARCH(1,1) models.

3.3 Backtesting VaR Models

As proposed by Berkowitz and O'Brien (2002) and Pérignon and Smith (2008), a backtesting procedure is included to verify if the number of actual violations is in line with the forecasted violations over a period of time. A violation is recorded when an actual loss on a portfolio exceeds the estimated VaR.

Accordingly, a violation is defined as follows:

$$I_t = \begin{cases} r_t < VaR_t \\ r_t \geq VaR_t \end{cases} \tag{3.15}$$

Hence, the probability of observing x violations in a sample size, T, under the null hypothesis, is given by:

$$P(r_t < VaR_t \,|\, I_{t-1}) = (1-\pi)^{T-x} = p \tag{3.16}$$

where π is the desired proportion of observations that should be lower than the estimated VaR, which is typically set at 1%. Given that $\hat{\pi} = \frac{x}{T}$, the unconditional coverage test statistic is defined to be

$$LR_{uc} = 2\log\left[\frac{\hat{\pi}^x (1-\hat{\pi})^{T-x}}{\pi^x (1-\pi)^{T-x}}\right] \tag{3.17}$$

Asymptotically, LR_{uc} is distributed at χ^2 with one degree freedom. In which case, Kupiec (1995) showed that if the proportion of $\hat{\pi}$ increases then the VaR model underestimates the portfolio’s risk. While, if the proportion of $\hat{\pi}$ decreases then the VaR model understates the probability of large losses in a portfolio, thus, the VaR model becomes overly conservative.

Kupiec (1995) also introduced TUFF test that is based on the number of observations until the first violation. Under the null hypothesis, LR_{TUFF} is asymptotically distributed at χ^2 with one degree freedom.

$$LR_{TUFF} = -2\log\left[\hat{\pi}(1-\hat{\pi})^{\tau-1}\right] + 2\log\left[\frac{1}{\hat{\pi}}\left(1-\frac{1}{\hat{\pi}}\right)^{\tau-1}\right] \tag{3.18}$$

where τ denotes the number of observations before the first violation.

Christoffersen (1998) highlighted that the accuracy of a VaR model can be further identified by finding if violations are serially dependent. If violations are independent, the probability of a violation should be equal to the probability of violation conditional on the previous state. More formally, define a sequence of binary random variables $\{x_t\}_{t=1}^{T}$ such that

$$x_t = \begin{cases} r_t \geq VaR_t \\ r_t < VaR_t \end{cases} \tag{3.19}$$

with $\pi_i = P(x_t = i)$ and $\pi_{ij} = P(x_t = j \mid x_{t-1} = i)$ for $i, j = 0,1$. If the violation is independent then $\pi_1 = \pi_{10} = \pi_{11}$. In order to test this, Christoffersen (1998) proposed the LR_{ind} test statistic as follows:

$$LR_{ind} = 2\log\left[\frac{\left(1-\hat{\pi}_{01}\right)^{n_{00}} \hat{\pi}_{01}^{n_{01}} \left(1-\hat{\pi}_{11}\right)^{n_{10}} \hat{\pi}_{11}^{n_{11}}}{\left(1-\hat{\pi}_{01}\right)^{n_{00}+n_{01}} \hat{\pi}_{01}^{n_{01}+n_{11}}}\right] \tag{3.20}$$

where n_{ij} is the number of times that the event "$x_t = j$ and $x_{t-1} = i$" occurred with $\hat{\pi}_{01} = \frac{n_{01}}{n_{00}+n_{01}}$ and $\hat{\pi}_{11} = \frac{n_{11}}{n_{10}+n_{11}}$.

It is possible to test the hypotheses of serial independent and unconditional coverage jointly by combining the two test statistics. The test for conditional coverage as proposed in Christoffersen (1998) and Christoffersen, Hahn, and Inoue (2001) defined the test statistic, LR_{cc}, as

$$LR_{cc} = LR_{uc} + LR_{ind} \tag{3.21}$$

which is distributed asymptotically as χ^2 with two degrees of freedom.

3.4 THE MARKET RISK CAPITAL REQUIREMENTS

The use of VaR models was officially sanctioned by the Basel Committee on Banking Supervision, which amended the 1996 Basel Capital Accord to include a capital charge for market risk (Basel Committee on Banking Supervision 1996). Banks have a choice between using a standardized approach, or their own internal VaR models as the basis for their capital charges for market risk (Basel Committee on Banking Supervision 2011a). In practice, the internal models approach leads to lower capital charges than the standardized approach, hence, banks prefer to set up their own internal VaR models to hold less amount of capital. Consequently, the regulator faces an important task of determining the quality of internal VaR models that banks use to measure market risk. The performance of banks' internal VaR models and the market risk capital requirements can be evaluated as follows (Basel Committee on Banking Supervision 2011a):

1. A backtest VaR model at time t with $\alpha = 0.01$ is used.
2. A bank must backtest its internal VaR models over the previous 250 trading days and update its dataset at least once a quarter.
3. To monitor the frequency of violations, the number of times that the actual losses exceed VaR forecasts are calculated. Subsequently, the

percentage of violations can also be calculated. A good model will have a percentage of violation that is very close to one percent and should lead to a correct estimation of risk at every point in time. A VaR model that overestimates risk in a period of low volatility will lead to insufficient violations and requires a large amount of capital. On the other hand, a VaR model that underestimates risk in a period of high volatility will be penalized by the regulator due to excessive violations.

4. The magnitude of a violation is assessed given that large violations are of greater concerns than small violations; the actual losses are compared with the VaR forecasts.
5. The market risk capital charge (MRCC) is set either at the lower VaR of the previous day or the average VaR of the previous 60 days trading days, multiplied by a scaling factor of (3+k). The scaling factor calculates the probability that a violation occurs for a given day over the previous 250 trading days. It can be written as:

$$MRCC_t = \min\left(VaR_{\alpha,t}, (3+k_t) \times \frac{1}{60} \sum_{i=1}^{60} VaR_{\alpha,t} \right) \tag{3.22}$$

where,

$$k_t = \begin{cases} 0 & V_t^{250} \leq 4(Green) \\ 0.40 & V_t^{250} = 5(Yellow) \\ 0.50 & V_t^{250} = 6(Yellow) \\ 0.65 & V_t^{250} = 7(Yellow) \\ 0.75 & V_t^{250} = 8(Yellow) \\ 0.85 & V_t^{250} = 9(Yellow) \\ 1 & V_t^{250} \geq 10(Red) \end{cases} \tag{3.23}$$

6. The proportion of each color zone based on equation (3.23) is also indicated. A bank is categorized in the green zone if its VaR model is

adequately accurate with no additional capital charge required. While, if a bank falls into the yellow zone, an additional capital charge will be imposed to justify the excessive number of violations. Finally, a bank is categorized in the red zone if its VaR model is not appropriate, and will be required to include a greater amount of capital charges.

3.5 RESULTS

Daily exchange rates on Australian dollar (AUD) with twelve other currencies, namely US Dollar (USD), Japanese Yen (JPY), Pound Sterling (GBP), New Zealand Dollar (NZD), Korean Won (KRW), Singapore Dollar (SGD), Swiss Franc (CHF), Chinese Renminbi (CNY), Hong Kong Dollar (HKD), Indian Rupee (IDR), Malaysian Ringgit (MYR), and New Taiwan Dollar (TWD) are collected from Thomson Reuters DataStream Professional, from the period of 2 January 1984 to 31 December 2013. This time is chosen to capture as many major financial events as possible. This includes US stock market crash in 1987, European Monetary System (EMS) crisis in 1992, Asian currency crisis in 1997, 9/11 events in 2001, and the GFC in 2008.

Using the data above, an equally-weighted portfolio of twelve currencies is constructed. This portfolio composition has been widely used in the empirical literature, see, for example, DeMiguel, Garlappi, and Uppal (2009). The conditional variance of portfolio returns is modelled through GARCH(1,1) and GJR-GARCH(1,1) under normal distribution which lead to two sets of conditional VaR forecasts and two sets of unconditional VaR forecasts by the tail index estimator as proposed in the study. The study also investigates the performance of the two conditional volatility models under student-t distribution. The degrees of freedom set by t-density are estimated from the standardized residuals that follow a normal distribution or a student-t distribution with four critical values that leads to four sets of conditional VaR forecasts. In addition, two sets of unconditional VaR forecasts derived directly from the mean and standard deviation of portfolio returns will also be calculated (see Jorion 1996, 2007). All VaR forecasts are constructed at 1% level. A total ten sets of VaR forecasts is presented for comparison purposes. The sample size used for estimation is from 2 January 1984 to 31 December 2002 with 4,950 observations and the forecasting period is from 2 January 2003 to 31 December 2013 with 2,871.

Table 3.1 Summary Statistics

	Estimation Period (4,950 observations)	Forecast Period (2,871 observations)
Mean	-0.003917	0.010600
Median	0.001514	0.009578
Standard Deviation	0.596796	0.659199
Minimum	-4.105	-6.331
Maximum	4.760	5.998
Skewness	-0.34603***	-0.56366***
Kurtosis	8.18774***	13.35082***
Jacque-Bera	5649.52***	12968.60***
Asterisks indicate ***1% significant, **5% significant, *10% significant		

The daily returns of the portfolio for both estimation and forecast periods are summarized in Table 3.1. The means of the portfolio returns for both estimation and forecast periods are close to zero. The standard deviation of portfolio returns during estimation period is slightly larger than that of the forecast period, indicating the portfolio returns during forecast period was more volatile than the portfolio returns during the estimation period. The skewness of the portfolio returns for both estimation and forecast periods are negative. While, the portfolio returns display high kurtosis and fat-tailed.

Figure 3.1 Histograms of Portfolio Returns

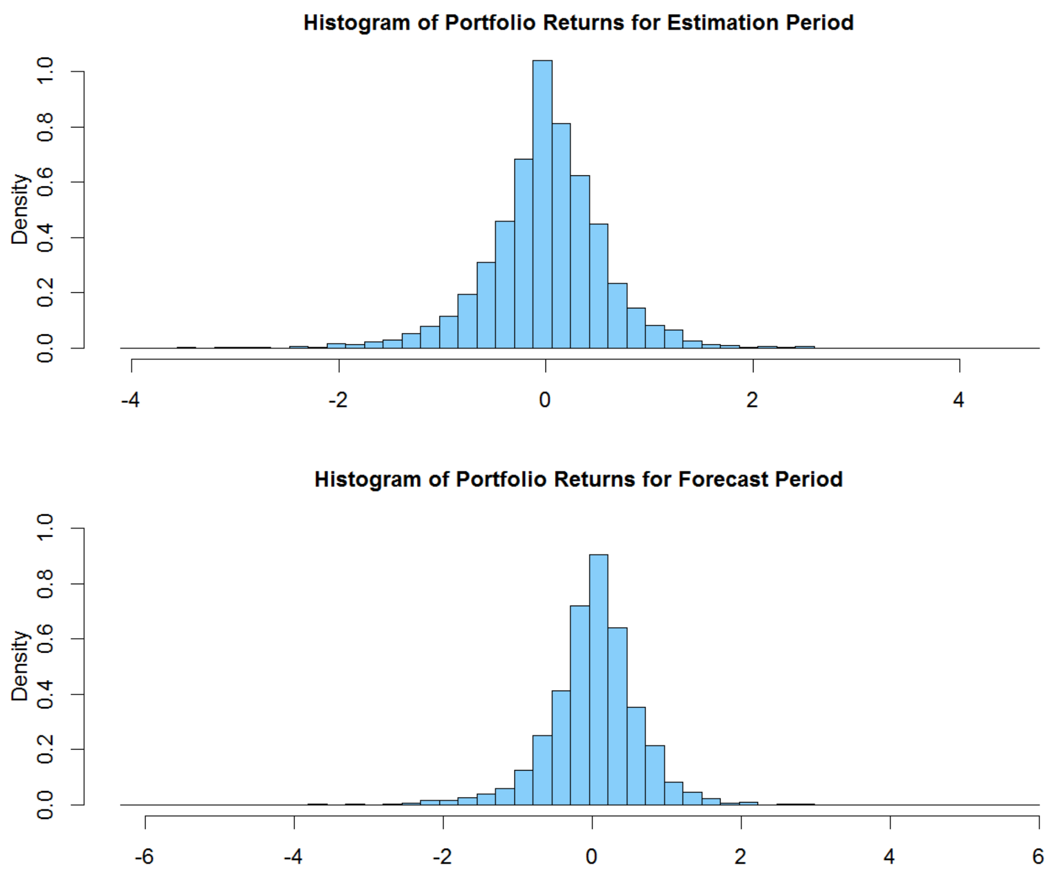


Figure 3.1 presents the histograms of the normal density for portfolio returns for both estimation and forecast periods.

Table 3.2 Parameter Estimates

Density in MLE	Model	Parameter Estimates						
		$\hat{\omega}$	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\gamma}$	$\hat{\lambda}$	Second moment	Log-moment
Normal	GARCH(1,1)	0.0057*** (0.0012)	0.0560*** (0.0062)	0.9299*** (0.0080)			0.9859	-0.0207
	GJR-GARCH(1,1)	0.0064*** (0.0013)	0.0310*** (0.0066)	0.9314*** (0.0079)	-0.0386*** (0.0087)		0.9817	-0.0256
Student-t	GARCH(1,1)	0.0069*** (0.0017)	0.0834*** (0.0112)	0.9050*** (0.0118)		4.2317*** (0.2676)	0.9884	-0.0239
	GJR-GARCH(1,1)	0.0076*** (0.0018)	0.0519*** (0.0118)	0.9057*** (0.0119)	-0.0516*** (0.0154)	4.2465*** (0.2698)	0.9834	-0.0293
Asterisks indicate ***1% significant, **5% significant, *10% significant Standard errors are in parentheses								

Table 3.2 reports the parameter estimates in the GARCH(1,1) and GJR-GARCH(1,1) models. For GARCH(1,1) model, the estimates for $\widehat{\omega}$, $\widehat{\alpha}$, and $\hat{\beta}$ are positive. This satisfies the sufficient condition to ensure $\sigma_t^2 > 0$ in both cases. Notice that $\widehat{\alpha} + \hat{\beta} < 1$, indicating that the second moment condition is satisfied as well as the log-moment condition, so the QMLE is consistent and asymptotically normal. For GJR-GARCH(1,1) model, the estimates for $\widehat{\omega}$, $\widehat{\alpha}$, and $\hat{\beta}$ are also positive. Moreover, $0 < \widehat{\alpha} + \hat{\beta} + \frac{\widehat{\gamma}}{2} < 1$, thus the sufficient conditions to ensure $\sigma_t^2 > 0$ are satisfied in both cases. Interestingly, the asymmetric coefficient, $\hat{\gamma}$, is smaller under student-t distribution than the normal distribution. The asymmetric

effect presented in the student-t distribution has a greater impact on conditional variance than the one in the normal distribution. As the second moment condition is satisfied, the log-moment condition is necessarily satisfied, so the QMLE is consistent and asymptotically normal.

Table 3.3 Estimated Values of $\hat{\boldsymbol{\kappa}}$, and $\hat{\mathbf{c}}$ with $\alpha = 0.01$

Density in MLE	**Model**	$\hat{k}$	$\hat{c}$
Normal	GARCH(1,1)	4.2119	0.2654
	GJR-GARCH(1,1)	4.8762	0.5906

Table 3.3 shows the estimated values for $\hat{\kappa}$ and $\hat{c}$ obtained from equations (3.8), (3.9) and (3.12). It can be observed that $\hat{\kappa}$ present estimated values of greater than 4 in both GARCH(1,1) and GJR-GARCH(1,1) models. In particular, $\hat{\kappa}$ obtained under the GJR-GARCH(1,1) model shows a greater value of 4.8762 compared to 4.2119 from the GARCH(1,1) model. Whereas, the estimated values of $\hat{c}$ from GJR-GARCH(1,1) and GARCH(1,1) models are positive. These results are consistent with the literature when describing the tail behaviour of foreign exchange returns, see, for example, Iglesias and Linton (2009).

Table 3.4 Critical Values

Model	$\widehat{VaR}_{std}^{GARCH-N}$	$\widehat{VaR}_{std}^{GJR-N}$	$\widehat{VaR}_{std}^{GARCH-t}$	$\widehat{VaR}_{std}^{GJR-t}$	$\widehat{VaR}_{std}^{\text{Standard-}t}$
Degrees of Freedom	11.3969	11.3969	11.8123	11.9033	3.4566

Table 3.4 presents the critical values for conditional VaR forecasts by GARCH(1,1) and GJR-GARCH(1,1) models estimated from the standardized residuals under normal and t-densities. While, the critical value for unconditional VaR forecasts by the Standardized Approach is estimated from the t-distribution of portfolio returns.

Table 3.5 VaR Forecasts at 1% level

Model	**Conditional**					**Unconditional**
	Mean	Median	Minimum	Maximum	Standard deviation	
$\widehat{VaR}_{norm}^{GARCH-N}$	-1.3999 (2)	-1.2480	-5.8300	-0.7841	0.5987	-2.1780 (1)
$\widehat{VaR}_{norm}^{GJR-N}$	-1.3906 (2)	-1.2250	-5.8070	-0.8195	0.5947	-2.3081 (1)
$\widehat{VaR}_{std}^{GARCH-N}$	-1.6262 (3)	-1.4490	-6.7720	-0.9108	0.6955	
$\widehat{VaR}_{std}^{GJR-N}$	-1.6154 (3)	-1.4230	-6.7460	-0.9520	0.6908	
$\widehat{VaR}_{std}^{GARCH-t}$	-1.6495 (4)	-1.4670	-7.6580	-0.8670	0.7531	
$\widehat{VaR}_{std}^{GJR-t}$	-1.6396 (4)	-1.4380	-7.6460	-0.8850	0.7587	
$\widehat{VaR}_{norm}^{\text{Standard}-N}$						-1.3884 (2)
$\widehat{VaR}_{std}^{\text{Standard-}t}$						-1.6567 (4)

(1) VaR forecasts are estimated from equation (3.13)

(2) VaR forecasts are estimated from equation (3.14) based on normal distribution

(3) VaR forecasts are estimated from equation (3.14) based on normal distribution at δ degrees of freedom set by t-density

(4) VaR forecasts are estimated from equation (3.14) based on student-t distribution at δ degrees of freedom set by t-density

Table 3.5 summarizes the results for the ten sets of conditional and unconditional VaR forecasts. The importance of unconditional VaR forecasts by Tail Index Estimator is evident by comparing unconditional VaR forecasts by the Standard Approach and conditional VaR forecasts. The unconditional VaR forecasts by Tail Index Estimator are lower compared to all other VaR forecasts, given that greater estimated values of $\hat{\kappa}$ and $\hat{c}$ are shown in Table 3.3. Likewise, the means of conditional VaR forecasts constructed under the Student-t distribution appear to be lower than the means of conditional VaR forecasts under the normal distribution. This should not be surprising as the critical values under the student-t distribution are greater than the normal distribution in absolute value (see Table 3.4). These results suggest that the distributional assumptions are far more important than the choice of models in forecasting VaR since foreign exchange returns are non-normal with fat-tailed.

Figure 3.2 Portfolio Returns and VaR Forecasts at 1% level

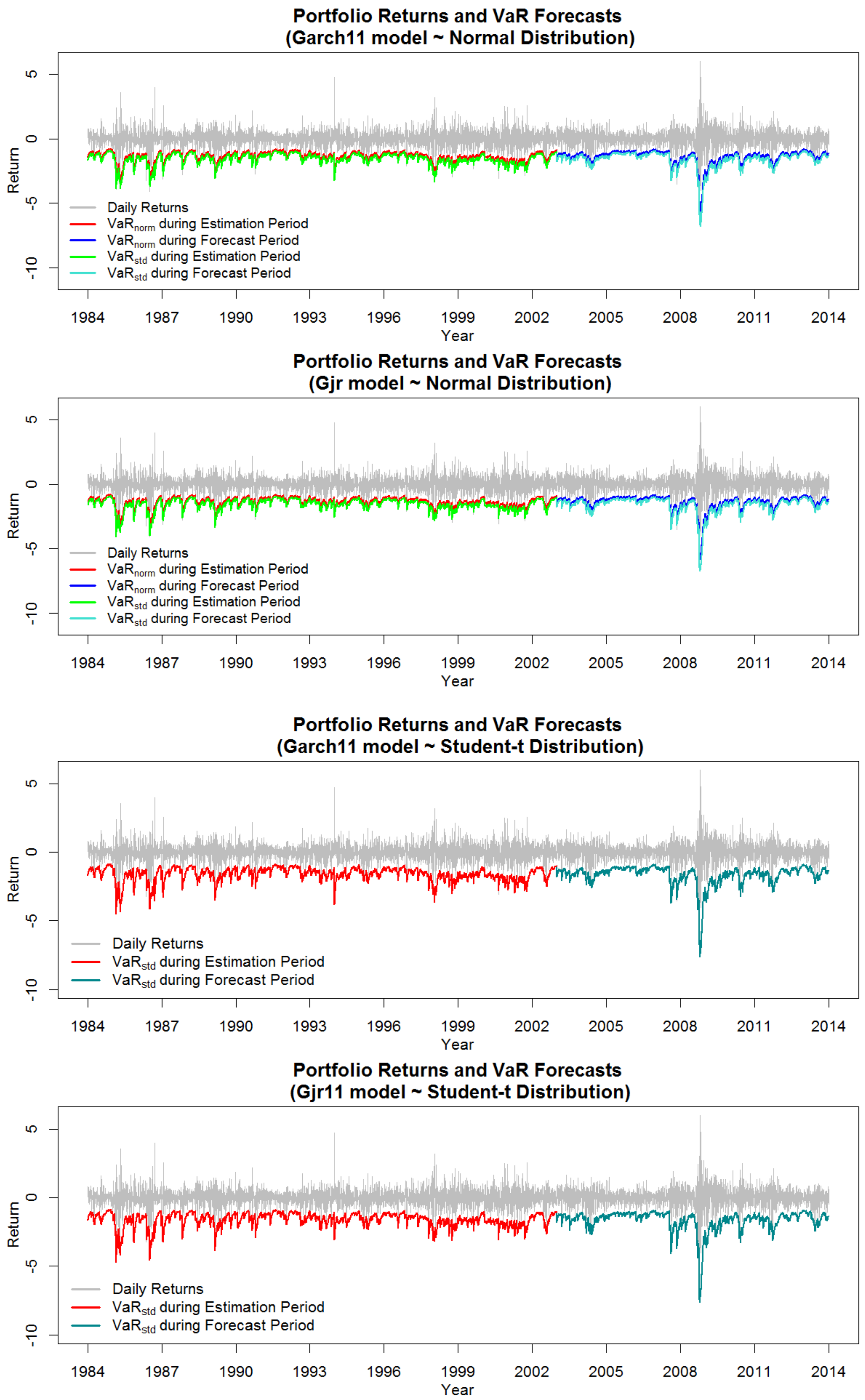
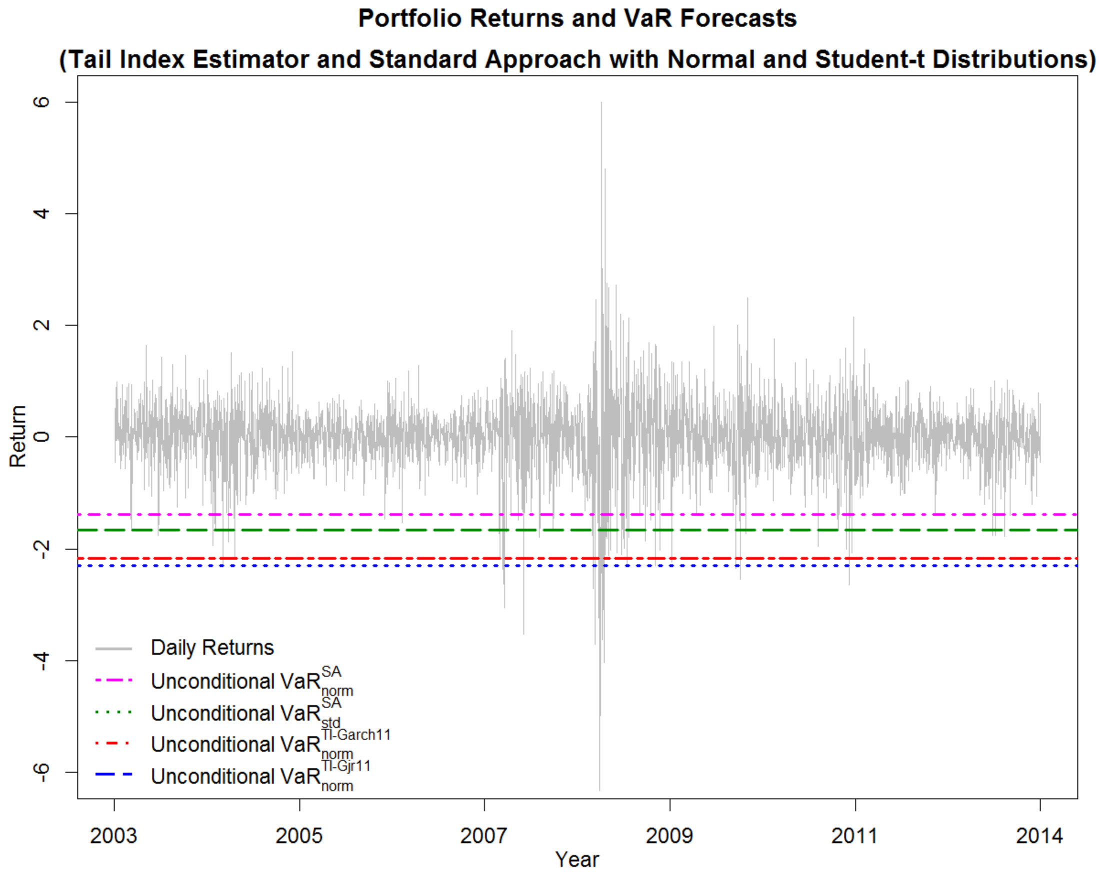


Figure 3.3 Portfolio Returns and Unconditional VaR Forecasts at 1% level



The time series of the daily portfolio returns together with conditional VaR forecasts using GARCH(1,1) and GJR-GARCH(1,1) models are illustrated in Figure 3.2. As can be seen, the portfolio returns were found to be non-normal and appeared to be volatility clustering. The significant spikes indicated the events at which high volatility occurred. The conditional VaR forecasts from student-t distribution are lower than the conditional VaR forecasts from the normal distribution.

Figure 3.3 presents unconditional VaR forecasts by the Standard Approach and Tail Index Estimator. Unconditional VaR forecasts remain stable over long periods. While, unconditional VaR forecasts by Tail Index Estimator are lower than unconditional VaR forecasts by the Standard Approach.

Table 3.6 Number and Percentage of Violations for VaR Forecasts at 1% Level

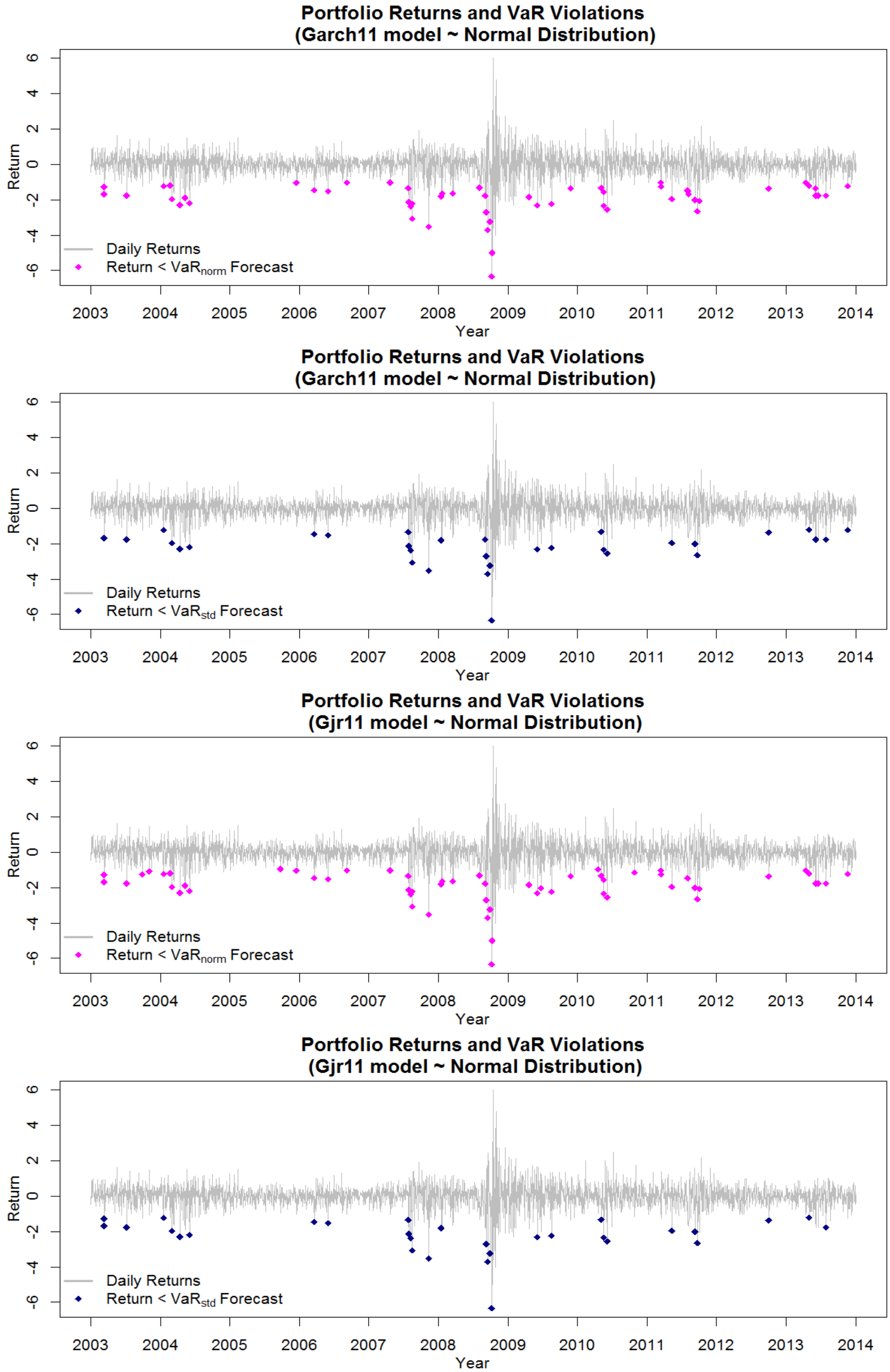
Model	**Conditional**		**Unconditional**	
	No. of violation	% of violation	No. of violation	% of violation
$\widehat{VaR}^{GARCH-N}_{norm}$	56	1.95%	20	0.70%
$\widehat{VaR}^{GJR-N}_{norm}$	59	2.06%	15	0.52%
$\widehat{VaR}^{GARCH-N}_{std}$	32	1.11%		
$\widehat{VaR}^{GJR-N}_{std}$	30	1.04%		
$\widehat{VaR}^{GARCH-t}_{std}$	28	0.98%		
$\widehat{VaR}^{GJR-t}_{std}$	26	0.91%		
$\widehat{VaR}^{Standard-N}_{norm}$			71	2.47%
$\widehat{VaR}^{Standard-t}_{std}$			50	1.74%

Table 3.6 reports the number and percentage of violations for VaR forecasts. Ideally, a good model would have a percentage of violation that is very close to one percent. A model that underestimates market risk gives a percentage of violation that is more than one percent. A model that overestimates market risk gives a percentage of violation that is less than one percent. For the conditional VaR forecasts from GARCH(1,1) and GJR-GARCH(1,1) models under normal distribution, namely $\widehat{VaR}^{GARCH-N}_{norm}$ and $\widehat{VaR}^{GJR-N}_{norm}$, high percentages of violation are presented at 1.95% and 2.06%, respectively. In contrast, the conditional VaR forecasts from GARCH(1,1) and GJR-GARCH(1,1) models that utilized student-t distribution, namely $\widehat{VaR}^{GARCH-N}_{std}$, $\widehat{VaR}^{GARCH-t}_{std}$, $\widehat{VaR}^{GARCH-t}_{std}$, and $\widehat{VaR}^{GJR-t}_{std}$ appear to perform well with each of the percentage of violation very close to one percent. Likewise, the unconditional VaR forecasts modelled through the Standard Approach provide more conservative estimation in student-t distribution than the normal distribution. These results suggest that the VaR forecasts under normality assumption are

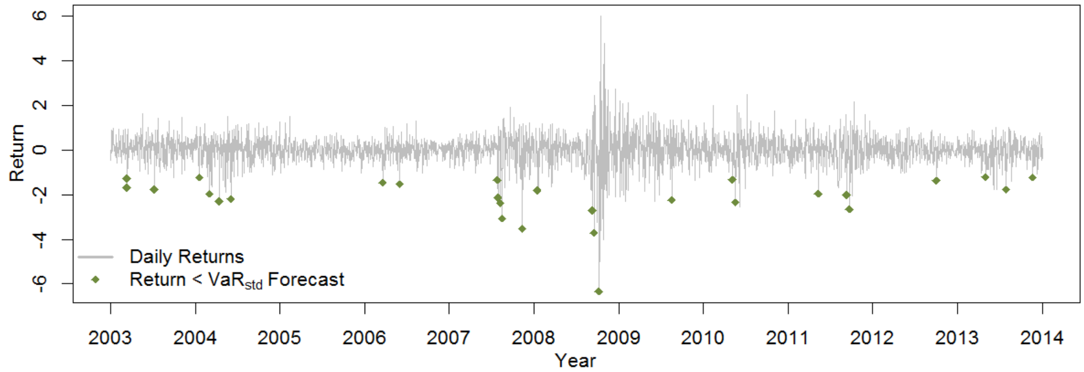
inappropriate for measuring portfolio risk. It also implies that the probability for large losses is expected under the normality assumption. Note that the unconditional VaR forecasts by Tail Index Estimator, $\widehat{VaR}_{norm}^{GARCH-N}$ and $\widehat{VaR}_{norm}^{GJR-N}$, have the lowest and second-lowest number and percentage of violations among all models. These results imply that no excessive violation occurred during periods of low volatility in the foreign exchange market, with an exception of the extreme financial event in 2008 due to GFC. Another interesting comparison is the unconditional VaR forecasts by the Standard Approach, $\widehat{VaR}_{norm}^{\mathrm{Standard}-N}$ and $\widehat{VaR}_{std}^{\mathrm{Standard}-t}$ that consistently underestimate market risk with high percentages of violation.

Figures 3.4 to 3.6 illustrate the time series of the daily portfolio returns during the forecast period and the time at which VaR violations occurred. A violation is recorded when an actual loss exceeds the VaR forecast. The episodes of VaR violations are often centralized during the periods of high volatility. The events of VaR violations under student-t distribution give fewer violations than VaR violations under the normal distribution. Note that the unconditional VaR forecasts by Tail Index Estimator provide the lowest number of VaR violations (see Table 3.6) and can capture the events of violations during periods of high volatility. This model is computationally more attractive given that it incorporates time-varying conditional information into unconditional VaR forecasts.

Figure 3.4 Portfolio Returns and VaR Violations for GARCH(1,1) and GJR-GARCH(1,1) models



Portfolio Returns and VaR Violations
(Garch11 model ~ Student-t Distribution)



Portfolio Returns and VaR Violations
(Gjr11 model ~ Student-t Distribution)

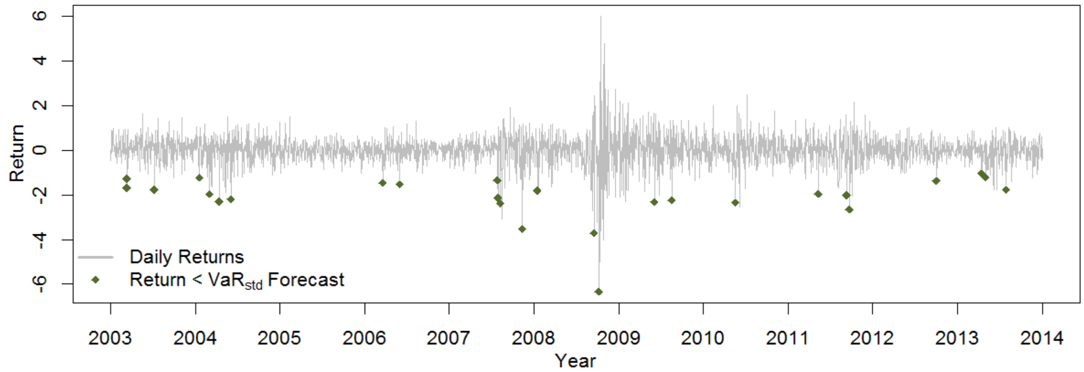


Figure 3.5 Portfolio Returns and VaR Violations for Tail Index Estimator

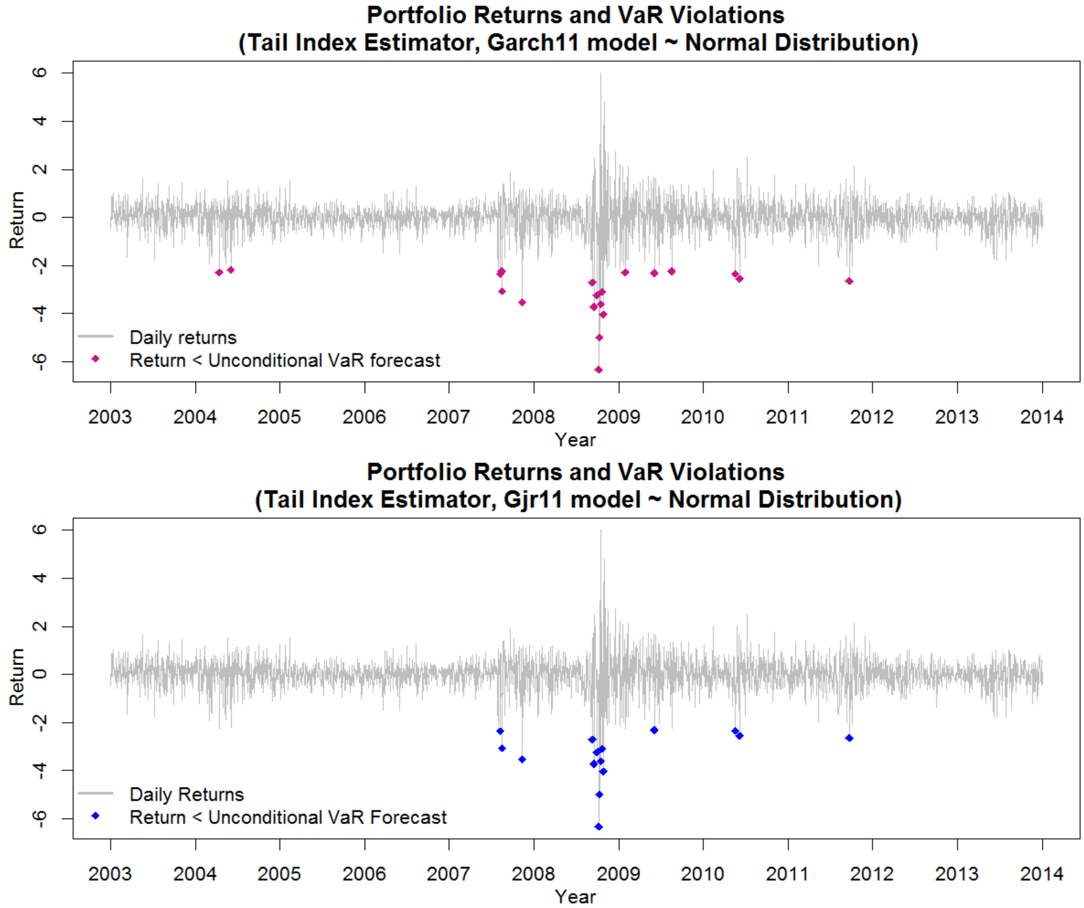
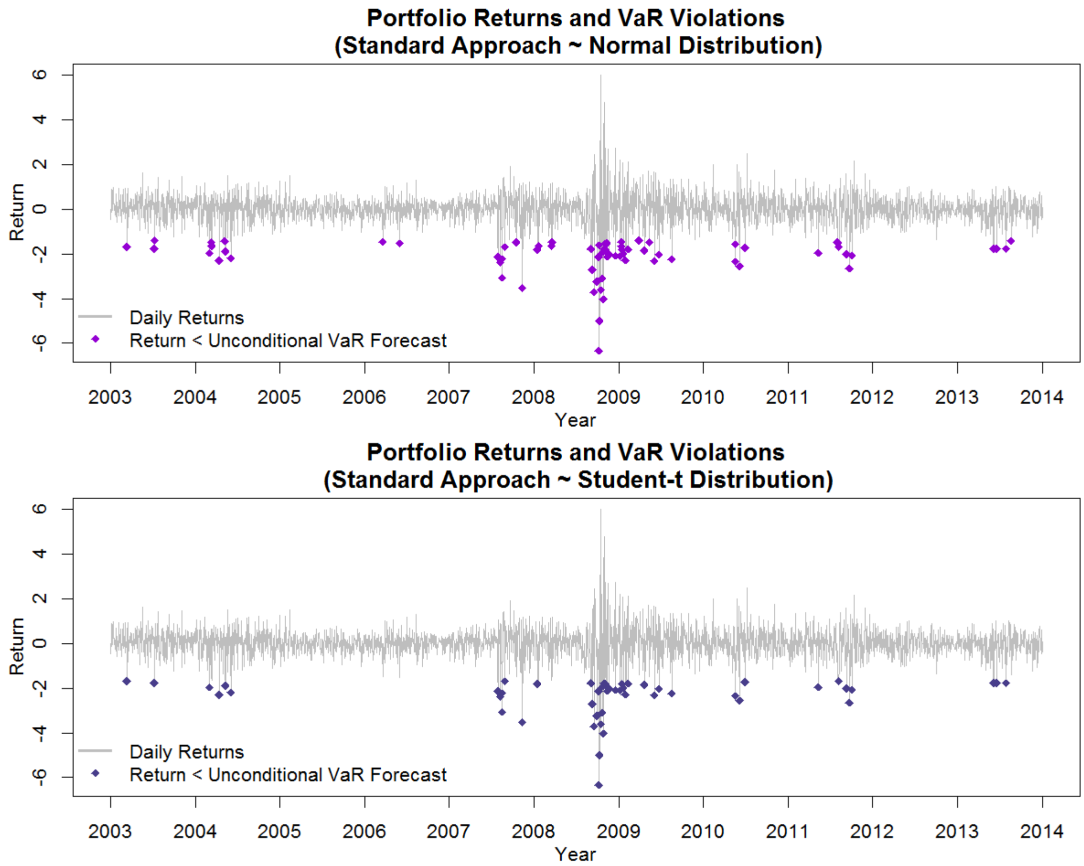


Figure 3.6 Portfolio Returns and VaR Violations for Standard Approach



The magnitude of violations can be assessed by the ratios of absolute deviation between the actual returns and VaR forecasts. The regulator is concerned with whether the VaR forecasts are large enough to cover banks' unexpected trading losses. Hence, the size of large losses can be determined by the magnitude of violations. Table 3.7 summarizes the ratios of actual losses to the length of VaR forecasts for all models. The conditional VaR forecasts under student-t distribution, $\widehat{VaR}_{std}^{GARCH-N}$, $\widehat{VaR}_{std}^{GJR-N}$, $\widehat{VaR}_{std}^{GARCH-t}$, and $\widehat{VaR}_{std}^{GJR-t}$, consistently provide a mean ratio of 1.012. Whereas, a mean ratio of 1.019 is shown by conditional VaR forecasts from the normal distribution, $\widehat{VaR}_{norm}^{GARCH-N}$ and $\widehat{VaR}_{norm}^{GJR-N}$. The unconditional VaR forecasts by Tail Index Estimator appear to provide the lowest mean ratio. While, the unconditional VaR forecasts by the Standard approach provide the highest mean ratio.

Table 3.7 Ratios for Absolute Deviation between Portfolio Returns and VaR Forecasts at 1% level

Model	**Conditional**				**Unconditional**			
	Mean	Median	Minimum	Maximum	Mean	Median	Minimum	Maximum
$\widehat{VaR}_{norm}^{GARCH-N}$	1.019	1.008	0.0015	2.651	1.011	1.006	0.0050	3.754
$\widehat{VaR}_{norm}^{GJR-N}$	1.019	1.008	0.0005	2.570	1.009	1.006	0.0011	3.599
$\widehat{VaR}_{std}^{GARCH-N}$	1.012	1.007	0.0024	2.421				
$\widehat{VaR}_{std}^{GJR-N}$	1.012	1.007	0.0041	2.352				
$\widehat{VaR}_{std}^{GARCH-t}$	1.012	1.007	0.0049	2.415				
$\widehat{VaR}_{std}^{GJR-t}$	1.012	1.007	0.0012	2.334				
$\widehat{VaR}_{norm}^{\text{Standard}-N}$					1.034	1.012	0.0011	5.320
$\widehat{VaR}_{std}^{\text{Standard-}t}$					1.021	1.010	0.0050	4.620

(1) The ratio is calculated by (VaR Forecast minus Actual Return) divided by Actual Return

Figures 3.7 and 3.8 plot the ratios of actual returns to the length of VaR forecasts during the forecast period. A smaller magnitude of violations can be seen during periods of low volatility. Whereas, the highest magnitude of violations, i.e. the largest size of losses, was observed in the year of 2008.

Figure 3.7 Absolute Deviations between Portfolio Returns and VaR Forecasts at 1% level

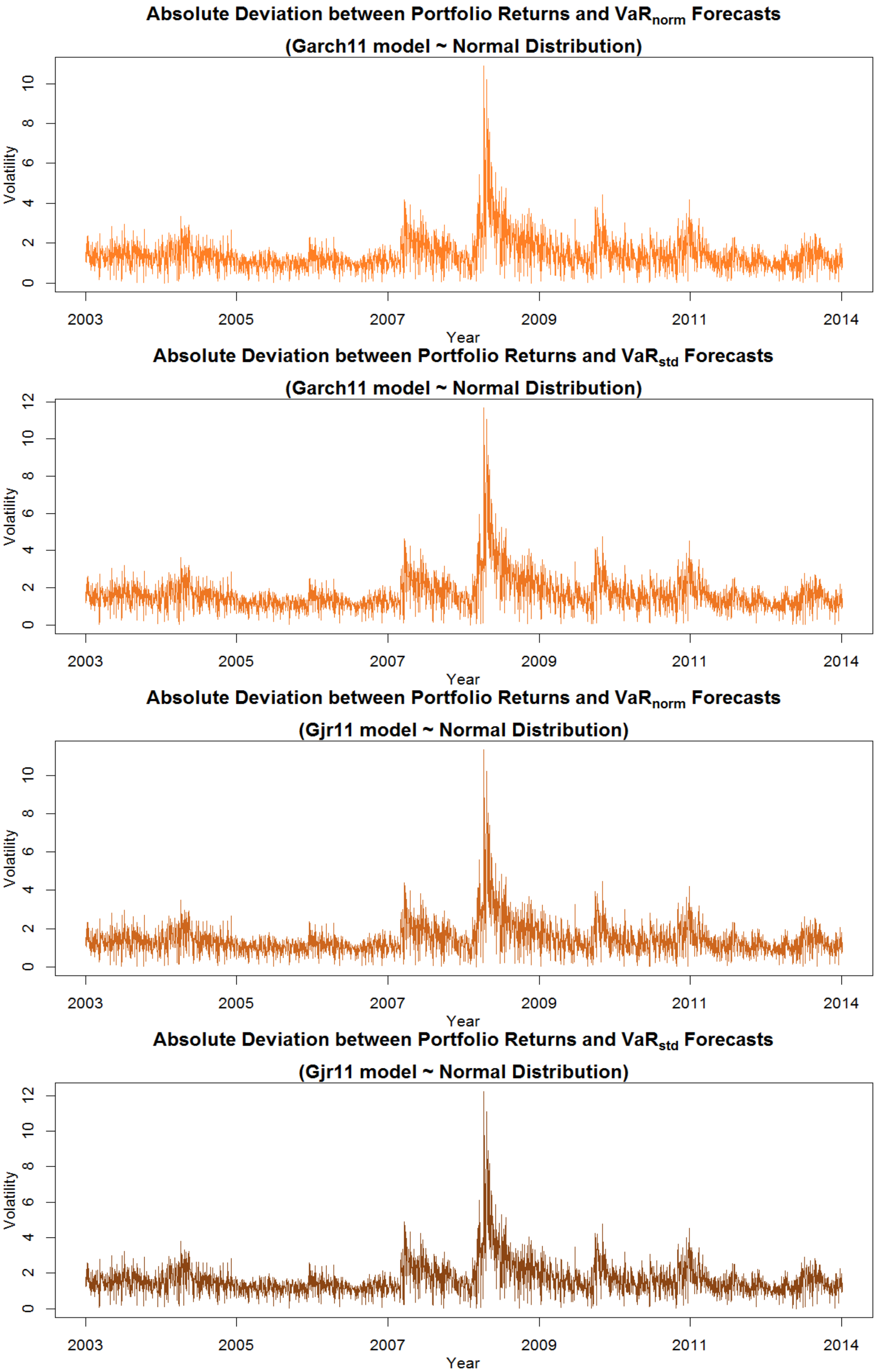


Figure 3.8 Absolute Deviations between Portfolio Returns and Unconditional VaR Forecasts at 1% level

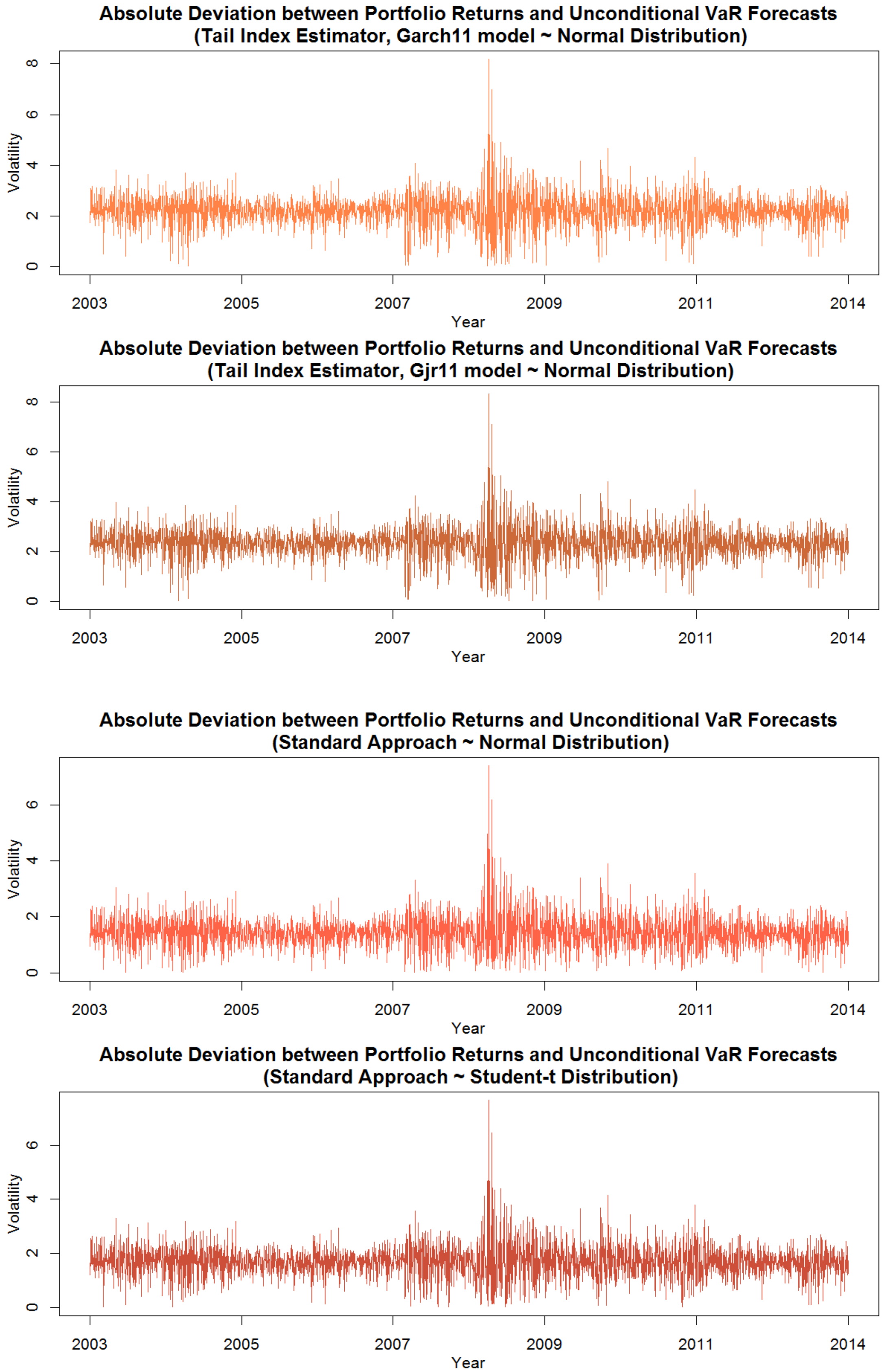


Table 3.8 Backtesting Results for VaR Forecasts at 1% level

Model	**Conditional**				**Unconditional**			
	TUFF (1)	UC (1)	Ind (2)	CC (2)	TUFF (1)	UC (1)	Ind (2)	CC (2)
$\widehat{VaR}_{norm}^{GARCH-N}$	0.3715	**20.5108**	**11.5361**	**32.0469**	2.3128	2.9861	2.2959	5.2820
$\widehat{VaR}_{norm}^{GJR-N}$	0.3715	**24.7384**	4.2482	**28.9866**	**17.1870**	**8.0102**	0.1576	**8.1678**
$\widehat{VaR}_{std}^{GARCH-N}$	0.3523	0.3672	0.8013	1.1685				
$\widehat{VaR}_{std}^{GJR-N}$	0.3715	0.0577	4.2348	4.2925				
$\widehat{VaR}_{std}^{GARCH-t}$	0.3715	0.0179	4.7303	4.7482				
$\widehat{VaR}_{std}^{GJR-t}$	0.3715	0.2668	5.2757	5.5425				
$\widehat{VaR}_{norm}^{\text{Standard}-N}$					0.3523	**44.6241**	**24.4911**	**69.1152**
$\widehat{VaR}_{std}^{\text{Standard-}t}$					0.3523	**13.0576**	3.3508	**16.4085**

(1) The Unconditional Coverage (UC) and Time Until First Failure (TUFF) tests are asymptotically distributed as χ^2 (1).

(2) The Serial Independence (Ind) and Conditional Coverage (CC) tests are asymptotically distributed as χ^2 (2).

(3) Entries in bold denote rejection of the tests.

The results from the TUFF, UC, Ind and CC tests are given in Table 3.8. For the conditional VaR forecasts, $\widehat{VaR}_{norm}^{GARCH-N}$ and $\widehat{VaR}_{norm}^{GJR-N}$, the models fail the UC, Ind and CC tests due to excessive violations with an exception for Ind test in the GJR-GARCH(1,1) model. This suggests that the conditional VaR forecasts from those models under normality have serial dependent violations. Similarly, the unconditional VaR forecasts modelled by the Standard Approach also fail the UC, Ind and CC tests with an exception for Ind test in the $\widehat{VaR}_{std}^{\text{Standard-}t}$ model. Ironically, the unconditional VaR forecasts by Tail Index Estimator under GARCH(1,1) pass TUFF, UC, IND and CC tests. While, the unconditional VaR forecasts from GJR-GARCH(1,1) model did not pass TUFF, UC and CC tests. This result suggests that the unconditional VaR forecasts by the Tail Index Estimator using the GARCH(1,1) model provide a more precise estimation of market risk.

For the conditional VaR forecasts modelled through the GARCH(1,1) and GJR-GARCH(1,1) that follow a student-t distribution, namely $\widehat{VaR}_{std}^{GARCH-N}$, $\widehat{VaR}_{std}^{GARCH-t}$, $\widehat{VaR}_{std}^{GARCH-t}$, and $\widehat{VaR}_{std}^{GJR-t}$, pass TUFF, UC, IND and CC tests. This implies that the violations are likely to be independent and the models are accurate in estimating the conditional VaR forecasts. Finally, the TUFF test results of conditional and unconditional VaR forecasts using normal and student-t distributions suggest that all models perform well with an exception for the unconditional $\widehat{VaR}_{norm}^{GJR-N}$ by Tail Index Estimator fails the TUFF test.

Table 3.9 VaR^{min} at 1% level

Model	**Conditional**				
	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}_{norm}^{GARCH-N}$	-1.506	-1.314	-5.830	-0.854	0.662
$\widehat{VaR}_{norm}^{GJR-N}$	-1.500	-1.292	-5.807	-0.877	0.656
$\widehat{VaR}_{std}^{GARCH-N}$	-1.749	-1.534	-6.772	-0.992	0.769
$\widehat{VaR}_{std}^{GJR-N}$	-1.742	-1.510	-6.746	-1.019	0.762
$\widehat{VaR}_{std}^{GARCH-t}$	-1.792	-1.564	-7.658	-0.959	0.827
$\widehat{VaR}_{std}^{GJR-t}$	-1.789	-1.548	-7.646	-0.975	0.829

(1) VaR^{min} is calculated as the lower VaR of the previous day or the average VaR on the previous 60 days

Table 3.9 summarizes the results for VaR^{min} at 1% level. It represents the lower VaR of the previous day or the average VaR on the previous 60 days. These VaR values are used to verify the VaR forecasts from Table 3.5. The market risk capital charges can then be calculated as the product of VaR^{min} multiplied by a scaling factor from equation (3.22).

Table 3.10 Number and Percentage of Violations for VaR^{min} at 1% level

Model	No. of Violation	% of Violation
$\widehat{VaR}_{norm}^{GARCH-N}$	50	1.74%
$\widehat{VaR}_{norm}^{GJR-N}$	48	1.67%
$\widehat{VaR}_{std}^{GARCH-N}$	28	0.97%
$\widehat{VaR}_{std}^{GJR-N}$	27	0.94%
$\widehat{VaR}_{std}^{GARCH-t}$	23	0.80%
$\widehat{VaR}_{std}^{GJR-t}$	21	0.73%

Table 3.10 reports the number and percentage of VaR^{min} violations on the previous 250 days. The regulator is concerned with whether the internal VaR models adopted by banks provide correct coverage for losses. The best model presented is $\widehat{VaR}_{std}^{GARCH-N}$ at 0.97%, given that it is the closest to one percent, followed by $\widehat{VaR}_{std}^{GJR-N}$ at 0.94%. While, $\widehat{VaR}_{norm}^{GARCH-N}$ and $\widehat{VaR}_{norm}^{GJR-N}$ show percentages of greater than one percent of 1.74% and 1.67%, respectively. An excessive number of VaR violations is undesirable as it indicates that the models underestimate market risk over time. At the same time, the capital charges implied by these models may not be sufficient to cover the losses. According to the Basel Accord, if too many violations are reported, a greater amount of penalty charges is imposed.

$\widehat{VaR}_{std}^{GJR-t}$ model leads to the lowest number and percentage of VaR violations at 0.73%.

Table 3.11 Scaling Factors

Model	**Conditional**				
	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}_{norm}^{GARCH-N}$	3.27	3	3	4	0.3149
$\widehat{VaR}_{norm}^{GJR-N}$	3.23	3	3	4	0.2994
$\widehat{VaR}_{std}^{GARCH-N}$	3.06	3	3	3.65	0.1477
$\widehat{VaR}_{std}^{GJR-N}$	3.04	3	3	3.50	0.1138
$\widehat{VaR}_{std}^{GARCH-t}$	3	3	3	3	0
$\widehat{VaR}_{std}^{GJR-t}$					
	Unconditional				
	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}_{norm}^{GARCH-N}$	3.08	3	3	4	0.2417
$\widehat{VaR}_{norm}^{GJR-N}$	3.07	3	3	3.85	0.2143
$\widehat{VaR}_{norm}^{\text{Standard}-N}$	3.32	3	3	4	0.3909
$\widehat{VaR}_{std}^{\text{Standard-}t}$	3.19	3	3	4	0.3380

(1) The scaling factor is calculated as 3+*k*, where *k* is the violation penalty

Table 3.11 shows the scaling factors as required by the Basel Committee. Of particular interest, $\widehat{VaR}_{norm}^{\text{Standard}-N}$ gives the highest mean of scaling factor at a level of 3.32, while $\widehat{VaR}_{std}^{GARCH-t}$ always give a consistent scaling factor of 3. While, the maximum scaling factor of 4 is observed for $\widehat{VaR}_{norm}^{GARCH-N}$, $\widehat{VaR}_{norm}^{GJR-N}$, $\widehat{VaR}_{norm}^{GARCH-N}$, $\widehat{VaR}_{norm}^{\text{Standard}-N}$, and $\widehat{VaR}_{std}^{\text{Standard-}t}$.

Table 3.12 Capital Charges for VaR^{min} at 1% level

Model	**Conditional**				
	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}^{GARCH-N}_{norm}$	-5.043	-4.235	-23.070	-2.562	2.7555
$\widehat{VaR}^{GJR-N}_{norm}$	-4.978	-4.112	-23.230	-2.632	2.7290
$\widehat{VaR}^{GARCH-N}_{std}$	-5.420	-4.614	-23.450	-2.976	2.7124
$\widehat{VaR}^{GJR-N}_{std}$	-5.307	-4.552	-22.940	-3.057	2.4032
$\widehat{VaR}^{GARCH-t}_{std}$	-5.424	-4.706	-22.970	-2.876	2.5049
$\widehat{VaR}^{GJR-t}_{std}$	-5.367	-4.645	-22.940	-2.926	2.4881
	Unconditional				
	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}^{GARCH-N}_{norm}$	-6.698	-6.534	-8.712	-6.534	0.5264
$\widehat{VaR}^{GJR-N}_{norm}$	-7.077	-6.924	-8.886	-6.924	0.4947
$\widehat{VaR}^{\text{Standard}-N}_{norm}$	-4.604	-4.165	-5.553	-4.165	0.5426
$\widehat{VaR}^{\text{Standard}-t}_{std}$	-5.279	-4.970	-6.627	-4.970	0.5599

(1) The capital charge is calculated as the lower VaR of the previous day or the average VaR on the previous 60 days (VaR^{min}), multiplied by a scaling factor of (3+*k*), where *k* is the violation penalty

A major reason for the implementation of VaR models by the Basel Committee is the determination of market risk capital requirements. If the banks underestimate the VaR forecasts, they are penalized by an increase in the scaling factor. If, however, the banks overestimates the VaR forecasts, a constant scaling factor of 3 is imposed. Table 3.12 shows the market risk capital charges that are a product of VaR^{min} (Table 3.9) multiplied by a scaling factor (Table 3.11). For the case of conditional VaR models, it can be seen that $\widehat{VaR}_{std}^{GARCH-t}$ gives the lowest mean of capital charge at -5.424 and $\widehat{VaR}_{norm}^{GJR-N}$ gives the highest mean of capital charge at -4.978. While, the lowest capital charge is given by $\widehat{VaR}_{std}^{GARCH-N}$ at -23.45, followed by $\widehat{VaR}_{norm}^{GJR-N}$ at -23.23, and $\widehat{VaR}_{norm}^{GARCH-N}$ at -23.07. These capital costs are mostly charged during the GFC, where sharp negative spikes of capital charges are shown in Figure 3.9. On the other hand, the highest capital charge is given by $\widehat{VaR}_{norm}^{GARCH-N}$ at -2.562, followed by $\widehat{VaR}_{norm}^{GJR-N}$ at -2.632. These charges occur during periods of low volatility in the foreign exchange market. For the case of unconditional VaR models, the lowest mean of capital charge is presented by unconditional $\widehat{VaR}_{norm}^{GJR-N}$ by Tail Index Estimator at -7.077 and the highest mean of capital charge is presented by unconditional $\widehat{VaR}_{norm}^{\text{Standard}-N}$ by the Standard Approach at -4.604. Likewise, unconditional $\widehat{VaR}_{norm}^{GJR-N}$ by Tail Index Estimator has the lowest capital charge at -8.886, followed by unconditional $\widehat{VaR}_{norm}^{GARCH-N}$ by Tail Index Estimator at -8.712, unconditional $\widehat{VaR}_{std}^{\text{Standard-}t}$ at -6.627 and unconditional $\widehat{VaR}_{norm}^{\text{Standard}-N}$ at -5.553.

A higher amount of capital charge is undesirable by banks as it increases the capital costs in their trading activities. Banks prefer to maintain capital charges as low as possible with a scaling factor of 3. More importantly, banks can now design their own internal models and make decisions by focusing on the current volatility levels by applying past information. These volatility levels can assist banks to select the most appropriate VaR model for periods of high or low volatility. For a bank which rebalances its large and complex portfolios very frequently, the conditional models may not be feasible since this requires continuous constructing and updating new volatility forecasts that associates with high transaction costs. Notice that the use of conditional models may lead to capital charges that fluctuate extremely over time. It is impossible for a bank to adjust its capital base rapidly to accommodate changing market conditions. A bank may very well use unconditional models for market risk capital charges during periods of high volatility. On the other hand, a bank may apply conditional models during periods of low volatility to avoid high market risk capital charges. The use of unconditional VaR forecasts by Tail Index Estimator is evident in this case as it has the lowest potential for large extreme losses given that it has the lowest number and percentage of violations. This situation is desirable by banks since the capital charges can be maintained at a consistent level without suffering from additional capital costs (see Figure 3.10).

Figure 3.9 demonstrates the episodes at which capital charges are most likely to occur. It can be seen that due to extreme negative returns during the GFC of 2008, the capital charges are imposed at the highest costs. Figures 3.10 and 3.11 show that capital charges can be maintained at a constant level during periods of low volatility with an exception of additional capital charges during periods of high volatility.

Figure 3.9 Capital Charges and VaR^{min} at 1% level

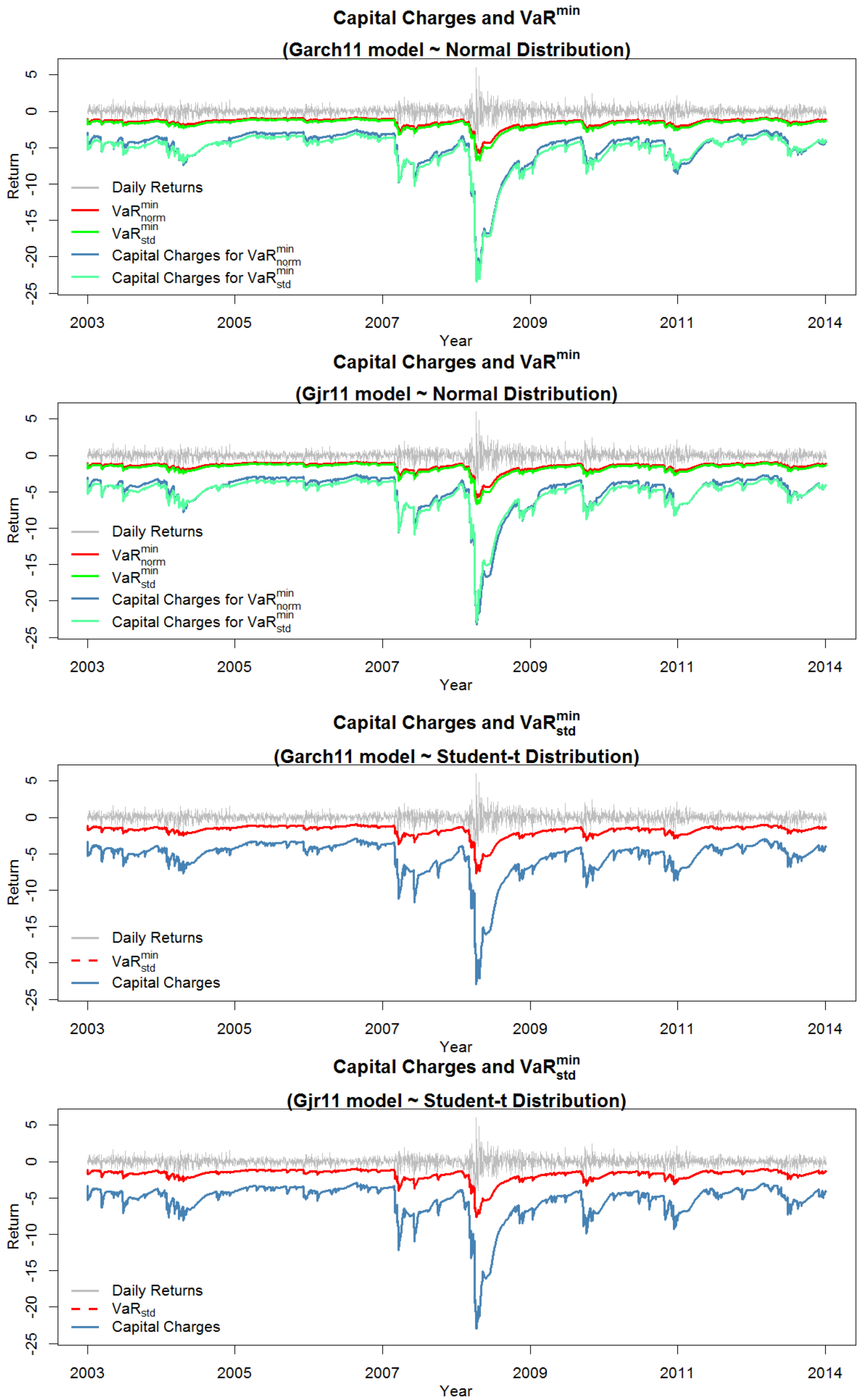


Figure 3.10 Capital Charges and Unconditional VaR^{min} for Tail Index Estimator

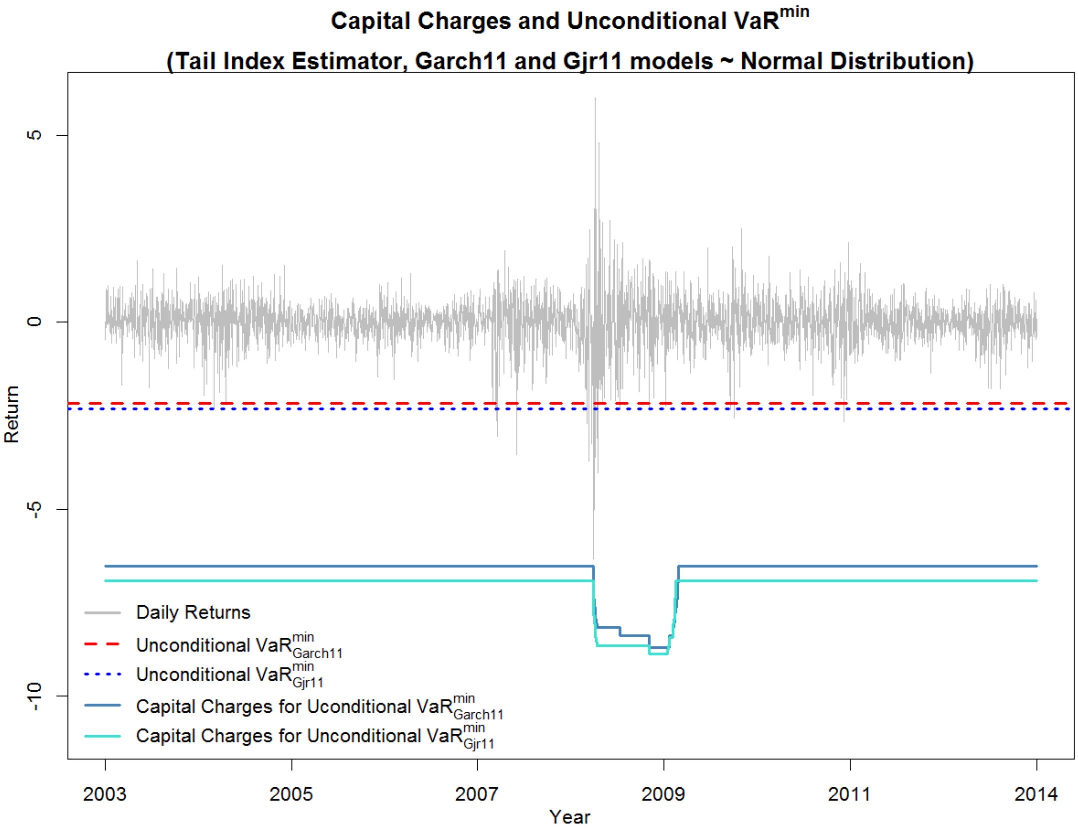


Figure 3.11 Capital Charges and Unconditional VaR^{min} for Standard Approach

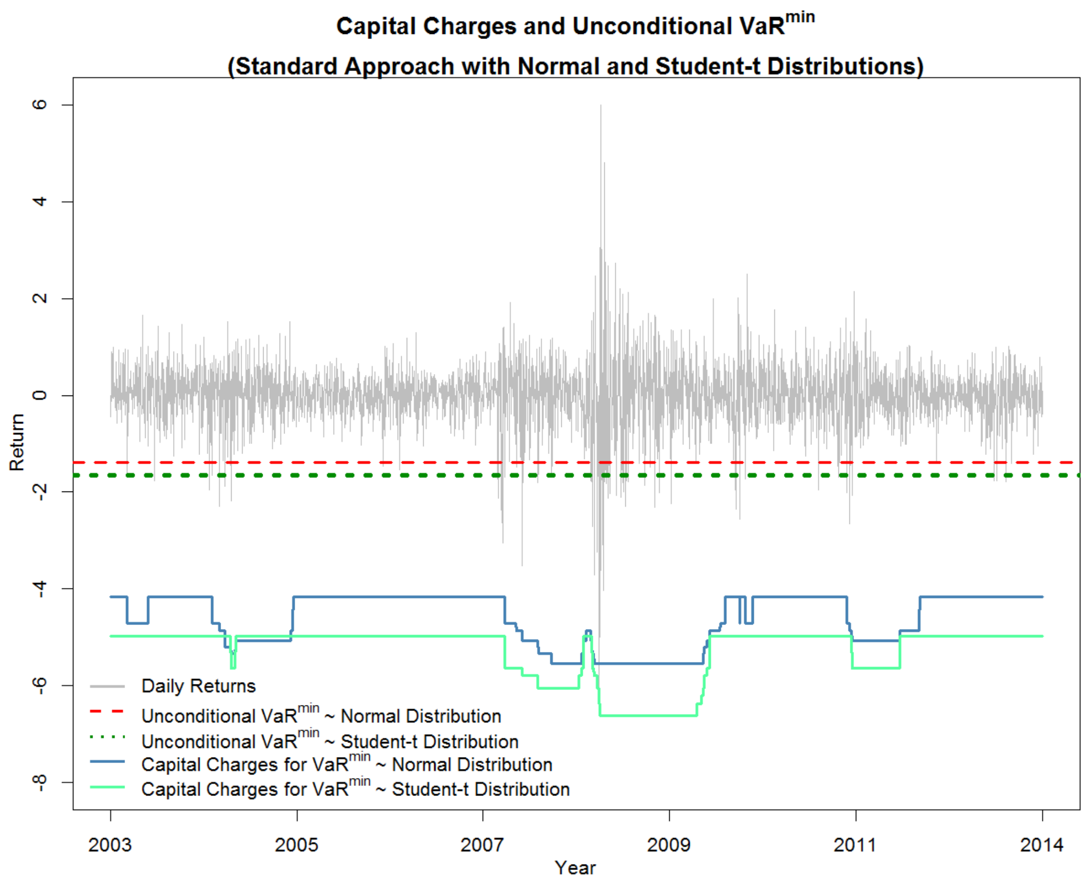


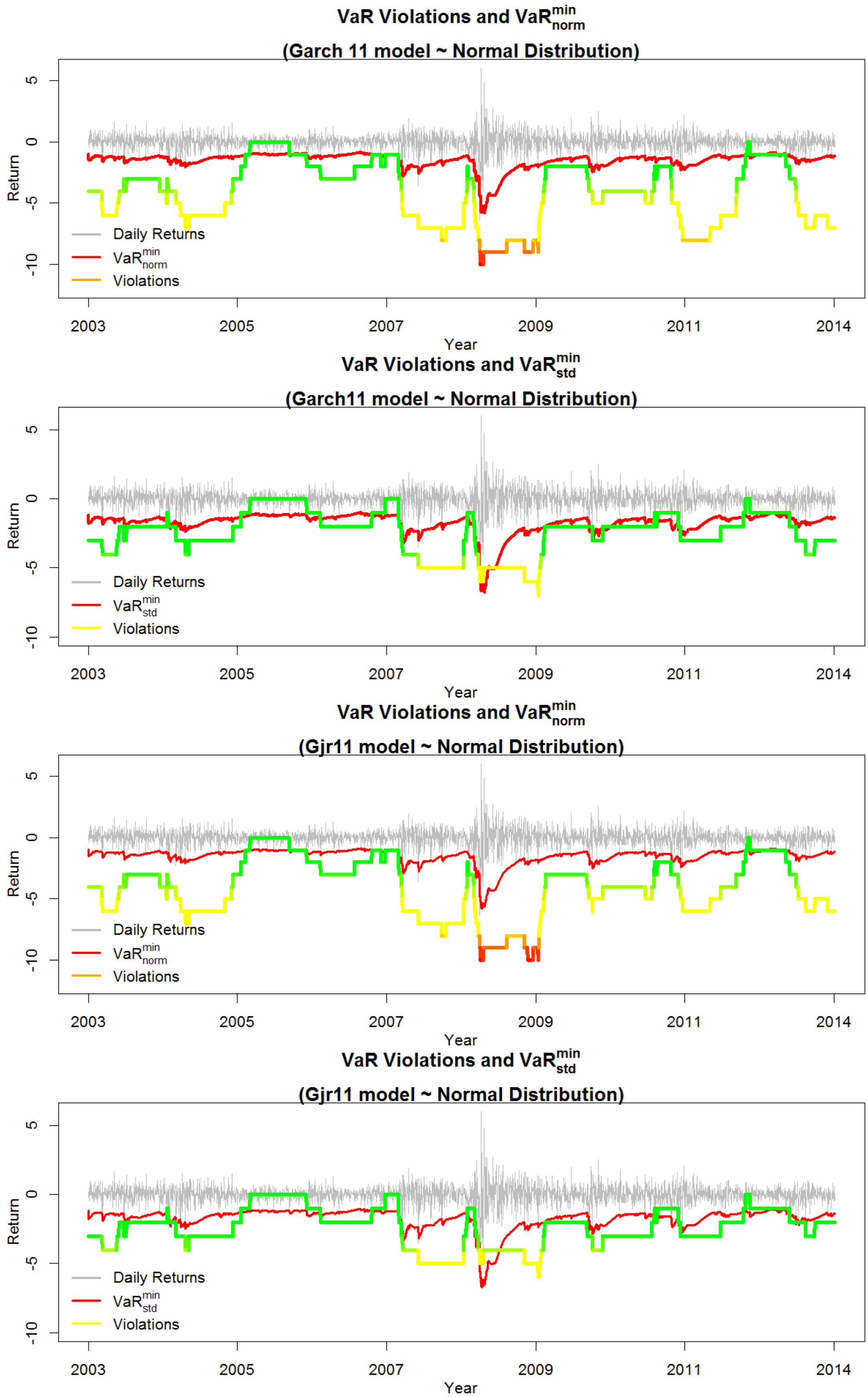
Table 3.13 Proportion of Time Staying in a Color Zone

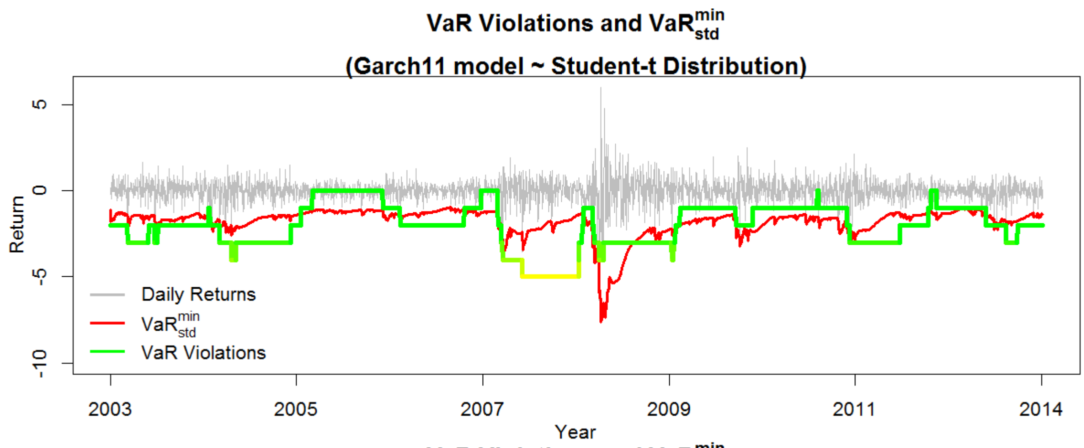
Model	Conditional			Unconditional		
	Green	Yellow	Red	Green	Yellow	Red
$\widehat{VaR}_{norm}^{GARCH-N}$	56.16%	43.45%	0.38%	90.91%	6.90%	2.19%
$\widehat{VaR}_{norm}^{GJR-N}$	59.19%	39.66%	1.15%	91.19%	8.81%	0%
$\widehat{VaR}_{std}^{GARCH-N}$	85.61%	14.42%	0%			
$\widehat{VaR}_{std}^{GJR-N}$	91.29%	8.74%	0%			
$\widehat{VaR}_{std}^{GARCH-t}$	93.97%	6.06%	0%			
$\widehat{VaR}_{std}^{GJR-t}$	100.00%	0.00%	0%			
$\widehat{VaR}_{norm}^{\text{Standard}-N}$				56.77%	28.21%	15.01%
$\widehat{VaR}_{std}^{\text{Standard-}t}$				73.42%	16.13%	10.45%

Table 3.13 provides the proportion of time staying in green, yellow and red zones as indicated by the Basel Accord. The green zone is desirable by all banks, as this shows the number of violations is within the limit set by the Basel Accord. A bank is categorized in the red zone if its VaR model is not appropriate, and will be required to pay a greater amount of capital charges. Figures 3.12, 3.13 and 3.14 exhibit the periods of when green, yellow and red zones are likely to occur for all VaR models. Conditional $\widehat{VaR}_{std}^{GJR-t}$ model spends most of the time in the green zone. Conditional $\widehat{VaR}_{std}^{GARCH-t}$, $\widehat{VaR}_{std}^{GJR-N}$, and $\widehat{VaR}_{std}^{GARCH-N}$ models under student-t distribution represent a proportion of time above 80% in the green zone, and substantially spending less time in the yellow zone. Similarly, unconditional $\widehat{VaR}_{norm}^{GJR-N}$ by Tail Index Estimator appears to stay in the green zone more often than yellow zone. However, conditional $\widehat{VaR}_{norm}^{GARCH-N}$ and $\widehat{VaR}_{norm}^{GJR-N}$, and unconditional $\widehat{VaR}_{norm}^{GARCH-N}$ by Tail Index Estimator models

under normal distribution tend to stay in the red zone due to excessive losses during the GFC (see Figures 3.12 and 3.13). Unconditional $\widehat{VaR}_{norm}^{\text{Standard}-N}$ and $\widehat{VaR}_{std}^{\text{Standard-}t}$ models by the Standard Approach have performed poorly with 15.01% and 10.45% stay in the red zone, respectively (see Figure 3.14). It can be concluded that during periods of low volatility, VaR violations are expected to be less, all models tend to stay in the green zone. During periods of high volatility, more VaR violations are expected hence, there is a tendency to stay in the red zone.

Figure 3.12 VaR Violations and VaR^{min} at 1% level




VaR Violations and VaR$^{min}_{std}$
(Garch11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
VaR$^{min}_{std}$
VaR Violations
2003
2005
2007
2009
2011
2014
Year

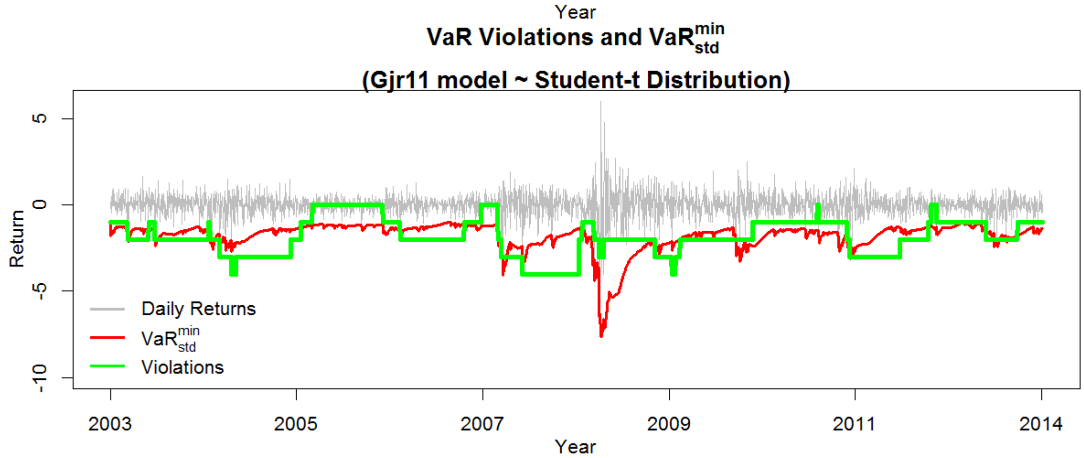

VaR Violations and VaR$^{min}_{std}$
(Gjr11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
VaR$^{min}_{std}$
Violations
2003
2005
2007
2009
2011
2014
Year

Figure 3.13 VaR Violations and Unconditional VaR^{min} for Tail Index Estimator

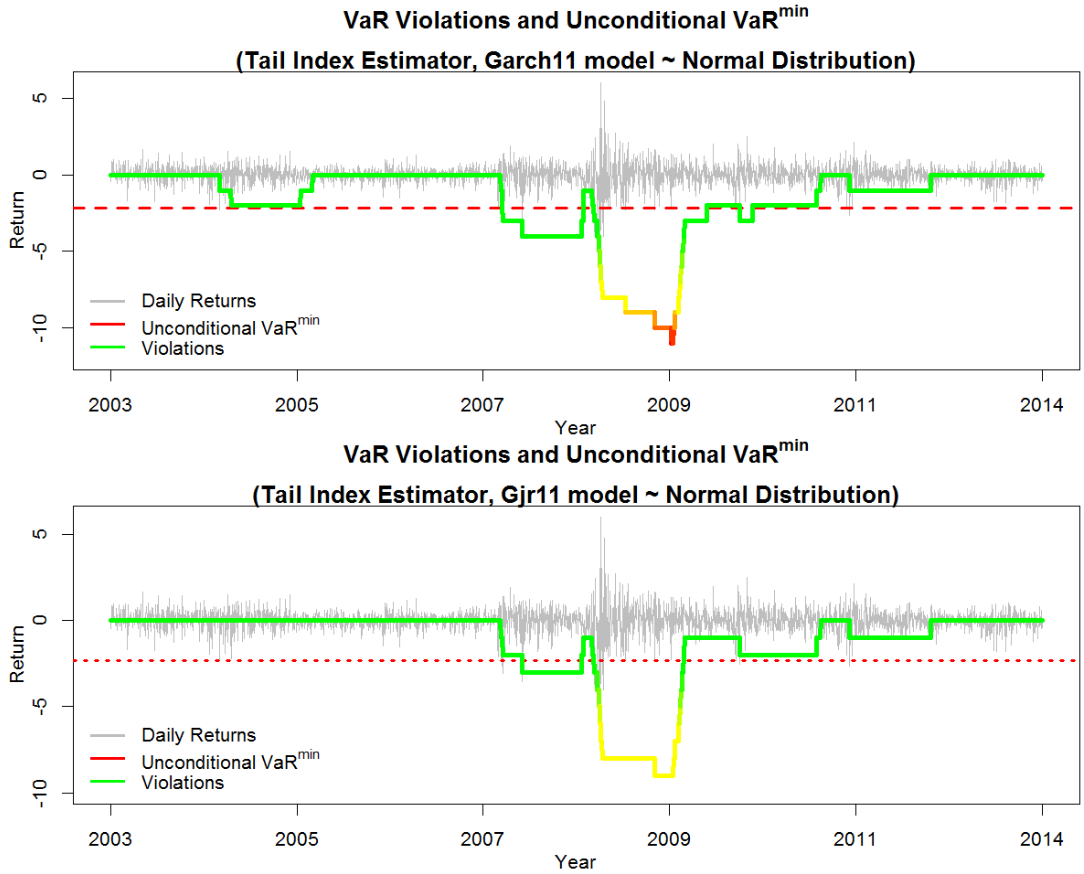
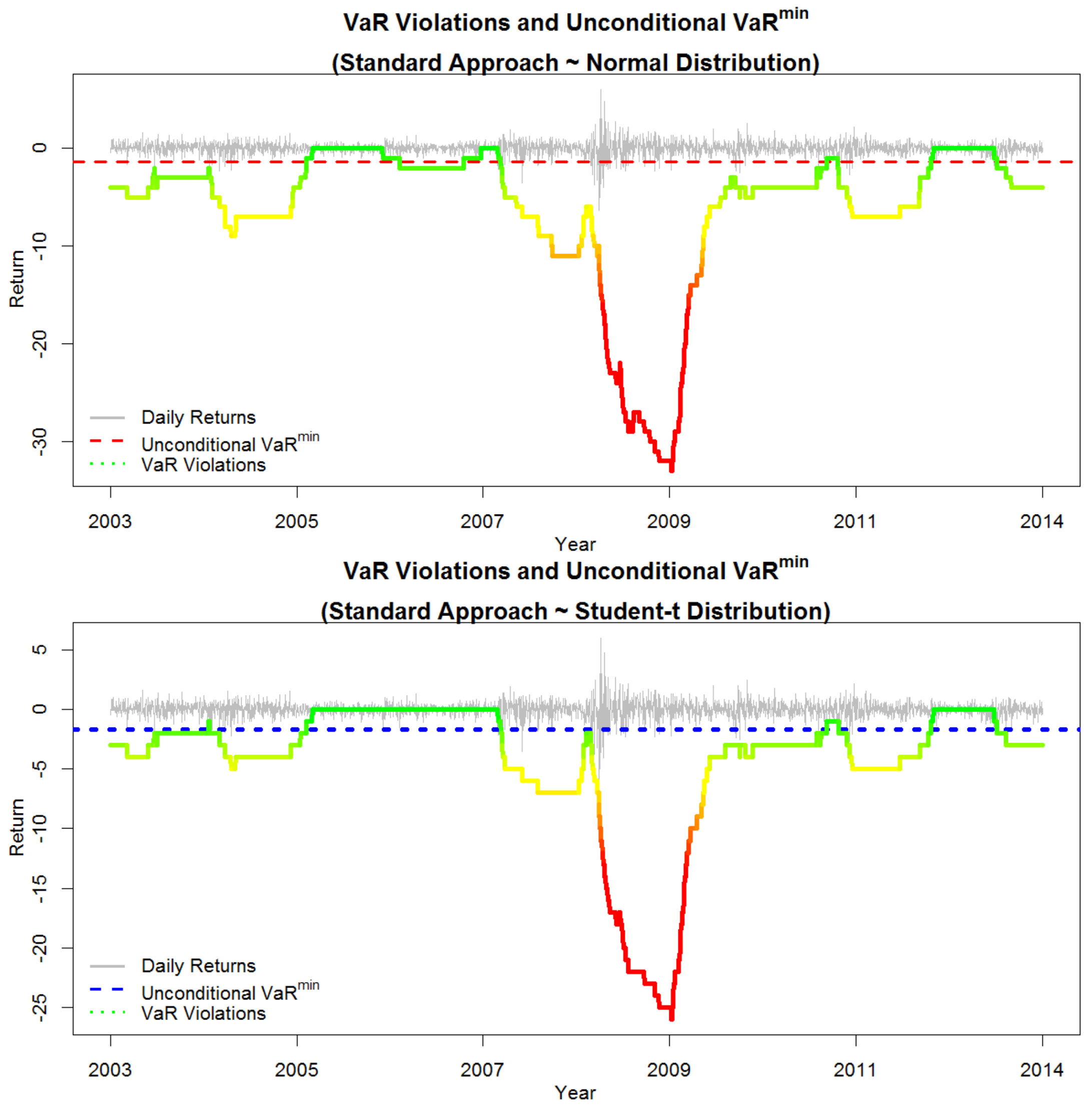


Figure 3.14 VaR Violations and Unconditional VaR^{min} for Standard Approach



3.6 CONCLUSION

By extending the results in Berkes, Horváth, and Kokoszka (2003), this study proposes a consistent estimator of the tail index for GJR-GARCH error. The performance of VaR forecasts under the GARCH(1,1) and GJR-GARCH(1,1) models following different distributional assumptions are also investigated. Also, this study provides the first empirical comparison of the impact of model specifications in estimating tail index and VaR. This study adds to the literature in several important directions. Firstly, when the student-t distribution is used, VaR forecasts lead to more accurate number and percentage of violations compared to the normal distribution. The result suggests that VaR forecasts under normal distribution are more conservative in estimating portfolio risk. Secondly, even though modelling unconditional VaR forecasts using the Standard Approach is widely accepted and used by the financial industry, the results are overly conservative as compared to the unconditional VaR forecasts by Tail Index Estimator as proposed in the study. This study also provides a significant input where banks can assess the likelihood of trading losses parsimoniously and efficiently and able to develop trading strategies according to their trading environments. Finally, the conditional VaR forecasts from GJR-GARCH(1,1) model represents the most appropriate model given that it ranks the best among all models with a percentage of violation that is very close to one percent. Besides, the model has correctly accepted all statistical tests including TUFF, UC, Ind and CC tests.

Theoretically, conditional models that incorporate time-varying volatility information are more desirable than unconditional models that consider the conditional distribution of asset returns. In practice, unconditional models are more desirable by banks given that it is less complicated and easy to calculate. In addition, capital charges can be maintained at a constant level during periods of low volatility without additional transaction costs. Nevertheless, an accurate VaR measure relying on appropriate modelling is necessary to correctly estimate the market risk as such that the risk management process is aided considerably by the backtesting procedures described in this study. As capital charges represent a significant cost to the banks, this study shows that banks should exercise great care in selecting an optimal VaR model. In risk forecasting, VaR is often concerned with multivariate return series. The empirical applications of conditional correlations across different assets in a portfolio are presented in Chapter 4.

Chapter 4

A TALE BETWEEN UNIVARIATE AND MULTIVARIATE VOLATILITY MODELS

4.1 INTRODUCTION

Modelling volatility in financial time series has been an important research area in the past decades. The family of Autoregressive Conditional Heteroskedasticity (ARCH) model was first introduced by Engle (1982) who laid the foundation for a new approach to describe and forecast conditional variance for financial time series. Subsequently, numerous variants and extensions of ARCH models have been proposed. See for examples, the Generalized ARCH (GARCH) model of Bollerslev (1986) and its asymmetric extension by Glosten, Jagannathan, and Runkle (1993). Some of the details of these models can be found in preceding chapter that has a specific focus on Value-at-Risk (VaR) forecasting.

In many financial applications, conditional covariance and correlations play a direct and important role in volatility forecasting. A bank is very likely to trade with large and complex portfolios daily. It is unlikely that the asset returns in a portfolio would move independently of each other. Therefore, understanding their correlation structures is essential in deriving sensible investment strategies to maximize returns while minimizing risk. Most of the existing univariate volatility models focus on the dynamics of a single time series, and they do not provide any information on the potential dependency between asset returns within a portfolio. It is worth noting that the correlation between asset returns may be driven by individual heterogeneity as well as any potential common factors. This implies that the correlation structures may be time-varying. For example, the correlation between Standard & Poor's 500 (S&P 500) and Nikkei 225 is likely to be different before and after the Global Financial Crisis (GFC). The correlation before the crisis may be driven by normal market condition whereas the GFC forms a single factor that caused significant changes in the correlation between the two indices.

To capture the conditional covariance and correlations for the different type of assets in a portfolio, many researchers expanded the univariate to multivariate volatility models. McAleer (2005) pointed out that one important aspect of modelling financial volatility is to study multivariate extensions of the conditional volatility models. Bollerslev, Engle, and Wooldridge (1988) proposed the diagonal vector ARCH (DVEC) model that is a direct extension of the univariate Generalized ARCH (GARCH) model to multivariate model. Other alternative approaches for achieving more parsimonious and empirically tractable multivariate volatility models are the Constant Conditional Correlation (CCC) model of Bollerslev (1990); Baba, Engle, Kraft and Kroner (BEKK) model described by Engle and Kroner (1995); the Dynamic Conditional Correlation (DCC) model of Engle (2002); the Time-Varying Correlation (TVC) model of Tse and Tsui (2002); the Vector ARMA-GARCH (VARMA-GARCH) model of Ling and McAleer (2003); and the VARMA-asymmetric GARCH (VARMA-AGARCH) model of McAleer, Hoti, and Chan (2009). However, the practical usefulness of these models can be affected by 'the curse of dimensionality' (see Caporin and McAleer 2014). That is, the number of parameters increases dramatically in these models as the number of asset increases.

The CCC model of Bollerslev (1990) assumed that the conditional covariance is driven solely by the corresponding conditional variances so that the conditional correlations are constant. This assumption greatly reduces the number of parameters and thus simplifies the multivariate estimation problem. The model follows a 2-step estimation procedure: in the first step, univariate models are estimated for each of the asset returns and then, in the second step, the conditional correlations are estimated from the standardized residuals for each of the univariate series provided by the first step. An advantage of CCC model is that when the conditional variances are positive, and the conditional correlation matrix is positive definite, the conditional covariance matrix is guaranteed to be positive definite. The specification for CCC model is explained the subsequent section.

Even though CCC model has been widely used in the empirical literature because of its computational simplicity, several empirical studies have shown that the assumption of constant conditional correlation may not hold in practice. In particular, Longin and Solnik (1995) performed Likelihood Ratio (LR) tests with a CCC-GARCH(1,1) model to assess the conditional covariance and conditional correlations for a set of cross-country stock market returns from the year of 1960 to 1990. They found evidence in support of strong correlations between cross-country stock market returns during periods of extreme market conditions but weak or no correlations outside of these events. Similarly, Tse (2000) applied Lagrange Multiplier (LM) tests for three datasets with daily frequency on spot-future returns, foreign exchange returns, and stock market returns. While, Nakatani and Teräsvirta (2009) extended LM tests with a CCC-GARCH(1,1) model and the Extended Constant Conditional Correlation (ECCC) GARCH model of Jeantheau (1998) to daily foreign exchange returns and stock market returns. On the other hand, Bera and Kim (2002) conducted Information Matrix (IM) tests for the constancy of the conditional correlation on selected stock market returns in a bivariate GARCH model. These researchers showed that the structure of conditional correlations between asset returns is time-varying, hence, CCC model is inappropriate for some empirical applications.

To accommodate possible time-varying conditional correlations, Engle (2002) and Tse and Tsui (2002) proposed alternative approaches to model time-varying conditional correlations by extending the CCC model. Similar to the CCC model, the DCC model of Engle (2002) and the TVC model of Tse and Tsui (2002) follow a 2-step estimation procedure. First, univariate models for each of the asset returns are estimated. In contrast to the CCC model, the second step estimation in the DCC and TVC models require the use of numerical optimization techniques to estimate the parameters of the time-dependent conditional correlations matrix. The DCC and TVC models are useful in high dimensional financial time series and are likely to provide additional information regarding the correlation structures between the time series.

Some alternatives to the DCC and TVC models have been proposed to allow for greater flexibility to capture different dependencies in the correlations across different types of assets and different responses to the past negative and positive returns. One such alternative is the Generalized Autoregressive Conditional Correlation (GARCC) model of

McAleer et al. (2008). It provides a more general representation in which the standardized residuals follow Vector Autoregressive (VAR) process with random coefficients. Other multivariate models that allow for greater reduction of the dependencies in the correlation across different types of assets by selecting a reasonability small numbers of factors are Factor ARCH models proposed by Diebold and Nerlove (1989) and Engle, Ng, and Rothschild (1990); Orthogonal GARCH model of Alexander (2001); and Generalized Orthogonal GARCH (GO-GARCH) model of van der Weide (2002). Another approach in modelling conditional covariance and correlations is the use of copulas proposed by Patton (2002) and Jondeau and Rockinger (2006).

There are a huge number of studies that estimate VaR forecasts using multivariate GARCH models. Hsu Ku and Wang (2008) examined the performance of multivariate GARCH models, namely the CCC, DCC and BEKK models, regarding VaR violations on a portfolio of foreign exchange rates. They found that time-varying conditional correlation is an important consideration for portfolio risk management. The DCC model is considered to be the best model that offers a better forecasting performance among the other two models in estimating VaR.

da Veiga, Chan, and McAleer (2011) also examined the importance of accommodating time-varying conditional correlation when forecasting VaR. They used both CCC and DCC models on the portfolios of Chinese A and Chinese B stock returns. On one hand, DCC model provides a lower number of violations than the CCC model. On the other hand, CCC model tends to generate a lower amount of daily capital charges than the DCC model. Consequently, they showed that a more severe penalty structure is probably desirable to discourage banks from choosing forecasting models that underestimate VaR. In particular, they proposed a new penalty structure that is based on the magnitude of violations instead of the current penalty structure that is based on the number of violations. An appropriate penalty structure may encourage banks to improve their risk models in forecasting VaR more precisely.

Santos, Nogales, and Ruiz (2013) compared the performance of VaR forecasts using univariate and multivariate GARCH models, namely the GARCH model of Bollerslev (1986), the asymmetric extension of GARCH (GJR) model by Glosten, Jagannathan, and Runkle (1993), the Exponential GARCH (EGARCH) model of Nelson (1991), the Asymmetric Power ARCH (APARCH) model of Ding, Granger, and Engle (1993), CCC and DCC models on a portfolio of the US stock returns. Their results showed that the multivariate GARCH models particularly DCC-GJR model under student-t distribution improves VaR estimation. Nevertheless, these studies showed that accommodating time-varying conditional correlations improve the forecasting performance of VaR.

There are some studies in the literature that considered the use of different distributional assumptions in multivariate GARCH models to forecast VaR. In particular, Bauwens and Laurent (2005) proposed a multivariate skewed-t distribution for multivariate GARCH models on the portfolios of the US stock returns and foreign exchange rates. They found that the multivariate GARCH models under multivariate skewed-t distribution improve the performance of VaR forecasts. Similarly, Rombouts and Verbeek (2009) evaluated the performance of VaR forecasts at the 1-percent, 2.5-percent and 5-percent significance levels using multivariate GARCH models, namely the DVEC, TVC and DCC models, on a portfolio of stock market returns. These models consider three different distribution assumptions including normal, student-t and non-parametric distributions. Their results showed that the multivariate GARCH models under a non-parametric distribution obtained using a kernel density technique improves VaR estimation. Pesaran and Pesaran (2010) examined the DCC model, assuming a student-t distribution instead of a normal distribution of the portfolios of foreign exchange rates, bonds and stock index futures. They found that the DCC model with a student-t distribution gives a more robust estimation of VaR forecasts than the DCC model with a normal distribution, given that the financial time series exhibit heavy tails (see also, Lee, Chiou, and Lin 2006). Hence, these studies suggested that the choice of density assumptions is critical to improving the performance of VaR forecasts.

This chapter is outlined as follows. The structural properties of VARMA-GARCH, VARMA-AGARCH, CCC and DCC models are given in Section 4.2. Section 4.3 describes the data and presents some summary statistics. Subsequently, the empirical results and the performance of VaR forecasts based on CCC and DCC models are discussed. Section 4.4 concludes the chapter.

4.2 CONDITIONAL VOLATILITY MODELS AND VAR FORECASTS

This section provides a brief discussion of conditional volatility models for purposes of their estimation and the relationship between conditional volatility and VaR forecasts.

Consider the following model:

$$\begin{aligned}\Phi(L)r_t &= \Theta(L)\,\varepsilon_t \\ \varepsilon_t &= D_t^{\frac{1}{2}}\eta_t \qquad \eta_t \sim MV(0,I) \\ D_t^{\frac{1}{2}} &= diag(h_{1t},...,h_{kt})\end{aligned} \tag{4.1}$$

where $r_t = \left(r_{1t},...,r_{kt}\right)'$ is a $k \times 1$ vector of asset returns and $t = 1,...,T$, with L denotes the lag operator such that for any time series y_t, $Ly_t = y_{t-1}$. $\Phi(L) = I - \sum_{i=1}^{p}\phi_i L^i$ and $\Theta(L) = I + \sum_{i=1}^{q}\theta_i L^i$ are the lag polynomials of order p and q, respectively. η_t is a $k \times 1$ independently and identically distributed multivariate random vector with zero mean and identity variance-covariance matrix.

Following the model as defined in equation (4.1), McAleer, Hoti, and Chan (2009) proposed the VARMA-AGARCH model, namely,

$$H_t = W + \sum_{i=1}^{r} A_i\vec{\varepsilon}_{t-i} + \sum_{i=1}^{r} C_i I_{t-i}\vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \tag{4.2}$$

where $H_t = \left(h_{1t},...,h_{kt}\right)'$ and $\vec{\varepsilon}_t = \left(\varepsilon_{1t}^2,...,\varepsilon_{kt}^2\right)'$. W is a $k \times 1$ vector; A_i , B_i and C_i are $k \times k$ matrices with $i = 1,...,r$ and ; $I_t = diag\left(I_{1t},...,I_{kt}\right)$ with $I_{it} = \begin{cases} 0, & \varepsilon_{it} \geq 0 \\ 1, & \varepsilon_{it} < 0 \end{cases}$. This model assumes that the positive and negative shocks have differential impacts on the conditional variance, h_{it}, $i = 1,...,k$.

If $C_i = 0$, equation (4.2) reduces to the VARMA-GARCH model of Ling and McAleer (2003). In that case,

$$H_t = W + \sum_{i=1}^{r} A_i\vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \tag{4.3}$$

This model assumes that a positive shock has the same impact on the conditional variance as a negative shock.

By setting $k=1$ and $\Phi(L)=\Theta(L)=1$ or by specifying A_i and B_j are diagonal matrices for all i and j, equation (4.3) reduces to the CCC model of Bollerslev (1990). The CCC model assumes that the conditional variance follows a univariate GARCH process. If C_i , A_i and B_j are diagonal matrices for all i and j, equation (4.2) reduces to the asymmetric GARCH (GJR) model of Glosten, Jagannathan, and Runkle (1993).

Following equation (4.1), the conditional variance and covariance matrix of r_t is $\Omega_t = D_t^{\frac{1}{2}} \Gamma_t D_t^{\frac{1}{2}}$, where $\Gamma_t = \mathbb{E}_t(\eta_t \eta_t')$ denotes $k \times k$ matrix of the conditional correlations between the conditional shocks. $\mathbb{E}$ and $\mathbb{E}_t$ denotes the unconditional and conditional expectation with respect to the information set at time t, respectively. The CCC model assumes that the conditional correlations are constant over time. In that case, $\Gamma = \{\rho_{ij}\}$ is a constant conditional correlation matrix with $\rho_{ij} = \rho_{ji}$. Engle (2002) and Tse and Tsui (2002) proposed the DCC model and the TVC model, respectively, to allow the conditional correlations to be time-varying, so that the conditional variance and covariance matrix of r_t is time-varying. Hence, the dynamic of volatility depends on the specification of Ω_i .

An alternative model is represented by Engle and Kroner (1995) who introduced the Baba, Engle, Kraft and Kroner (BEKK) model. Following the specification of conditional mean in equation (4.1),

$$\Omega_t = \Pi'\Pi + \sum_{i=1}^{r} \mathrm{M}'_i \varepsilon_{t-i} \varepsilon'_{t-i} \mathrm{M}_i + \sum_{j=1}^{s} \mathrm{N}'_j \Omega_{t-j} \mathrm{N}_j \qquad (4.4)$$

where Π, M_i and N_j are $k \times k$ matrices, $i = 1,...,r$ and $j = 1,...,s$. In the case of BEKK, the number of parameters is $\left(\frac{k(k+1)}{2}\right) + (r+s)k^2$. An advantage of this specification is that the conditional covariance matrix is positive definite as long as Π also is. Caporin and McAleer (2012) provides a comprehensive discussion of the empirical applications between BEKK and DCC models.

The parameters in these models are typically estimated by Quasi-Maximum Likelihood Estimator (QMLE), which is defined to be:

$$\hat{\theta} = \arg\max_{\theta \in \Lambda} \left(-\frac{T}{2} \sum_{t=1}^{T} \log|H_t| + \varepsilon'_t H_t^{-1} \varepsilon_t \right) \tag{4.5}$$

where

$\theta = \left(vec(\Phi)', vec(\Theta)', \overrightarrow{(W)}', vec(A_1), vec(A_2)' ..., vec(A_r)', vec(B_1), ..., vec(B_s)' \right)'$, with vec denotes the vec operator such $vec\,A$ converts a $m \times n$ matrix A into a $mn \times 1$ vector by stacking the columns of A. $|H_t|$ denotes the determinant of H_t. See McAleer (2005) and McAleer et al. (2008) for more technical discussions on this class of models, including the sufficient conditions for the existence of moments and the sufficient conditions for consistency and asymptotic normality of QMLE.

Under the assumption of equation (4.1), the VaR forecast at $\alpha = 0.01$ for asset i at time $t+1$ can be obtained as:

$$\widehat{VaR}_{i,t+1}^{m} = \mathbb{E}_t(r_{i,t+1}) + q_{\alpha,d}\sqrt{h_{i,t+1}^{m}} \tag{4.6}$$

where $\mathbb{E}_t(r_{i,t+1})$ is the forecast of the asset i's return based on the information at time t, $q_{\alpha,d}$ is the critical value based on the significant level of VaR and the distribution of η_t. Although η_t is typically assumed to be normally distributed, a student-t distribution with δ degrees of freedom can be used an alternative. $\sqrt{h_{i,t+1}^{m}}$ is the estimated standard deviation of $\mathbb{E}_t(r_{i,t+1})$ with m denotes the model used. Noted that the superscripts "std" and "norm" denotes estimates assuming a normal distributed return and a t-distributed return.

4.3 RESULTS

This section describes the data used and presents some summary statistics. The empirical results for VaR forecasts based on the CCC and DCC models are also discussed. The analysis of some statistical tests and the backtesting procedures set by the Basel Accord to evaluate the performance of VaR forecasts are also presented. The details of backtesting procedures can be found in the preceding chapters.

A dataset of daily exchange rates on Australian dollar (AUD) with twelve other currencies is used. The exchange rates are US Dollar (USD), Japanese Yen (JPY), Pound Sterling (GBP), New Zealand Dollar (NZD), Korean Won (KRW), Singapore Dollar (SGD), Swiss Franc (CHF), Chinese Renminbi (CNY), Hong Kong Dollar (HKD), Indian Rupee (IDR), Malaysian Ringgit (MYR), and New Taiwan Dollar (TWD). These exchange rates are collected from Thomson Reuters DataStream Professional, for the period of 2 January 1984 to 31 December 2013. Using the data above, an equally-weighted portfolio of twelve currencies is constructed.

A rolling window approach is used to estimate the parameter estimates for the CCC models. In that case, the patterns for changing conditional correlations and the possibility of structural breaks between each pair of currencies can also be observed. The entire period ranges from 2 January 1984 to 31 December 2013, with a total of 7,821 observations. Rolling conditional correlations are estimated with a window size set to 4,950 observations. The estimation sample is then rolled over the entire period. By keeping the estimation period constant, the estimation sample starts at the beginning of the data period until the sample ends on the last day of the data period. In this case, the estimation period starts from 2 January 1984 to 31 December 2002, with observations from the 1st to the 4,950th observation. Then, the window is rolled 1-day forward from 3 January 1984 to 1 January 2003, with observations from the 2nd to the 4,951th observation, until the last rolling window with observations from the 2,871th to the 7,821th. Each rolling window size is constantly kept at 4,950 observations. The result of this procedure will cover all the consecutive rolling sample periods, with a total of 2,871 observations.

There are four sets of VaR forecasts estimated from the CCC-GARCH(1,1), CCC-GJR(1,1), DCC-GARCH(1,1) and DCC-GJR(1,1) models for normal distribution. The study also investigates the performance of these models under a student-t distribution with δ degrees of freedom. The degrees of freedom set by t-density are estimated from the standardized residuals that follow GARCH(1,1) and GJR(1,1) processes utilized under normal and student-t distributions. This gives eight critical values that lead to eight sets of VaR forecasts (see Table 4.1). Another approach is used where the degrees of freedom set by t-density are estimated from the standardized residuals that follow GARCH(1,1) and GJR(1,1) processes utilized under normal and student-t distributions for every rolling window (see Figure 4.1). This leads to additional eight sets of VaR forecasts. A total 20 sets of VaR forecasts are presented for comparison purposes. All VaR forecasts are constructed at 1% level.

Table 4.1 Critical Values for CCC and DCC models

Degrees of Freedom	CCC-GARCH(1,1)	CCC-GJR(1,1)	DCC-GARCH(1,1)	DCC-GJR(1,1)
δ^{N}_{std}	11.2305	11.2961	13.2883	13.2979
δ^{t}_{std}	11.9481	11.9791	13.2691	13.2724

Figure 4.1 Rolling Critical Values for CCC and DCC models

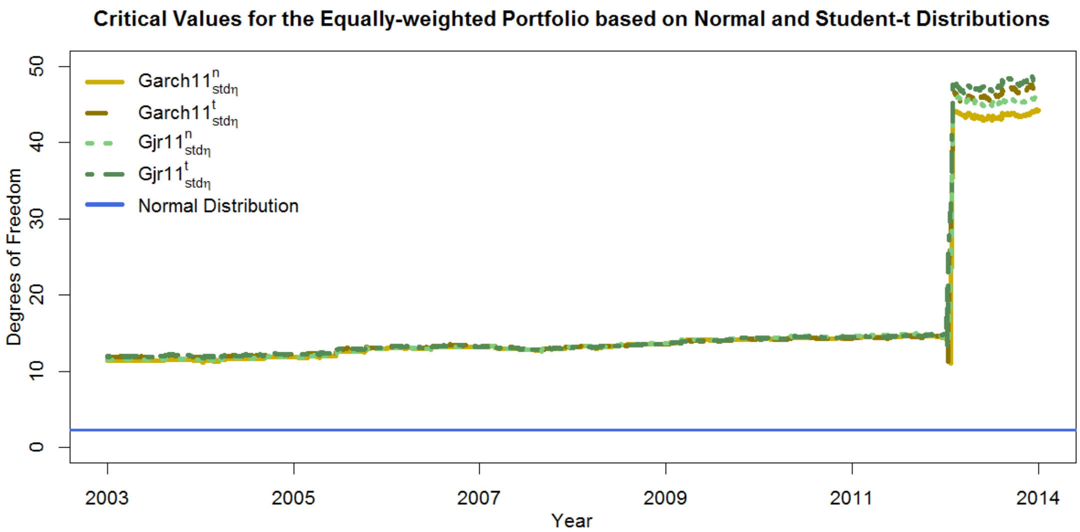


Figure 4.1 plots the critical values estimated from the standardized residuals that follow GARCH(1,1) and GJR(1,1) processes utilized under a normal distribution or a student-t distribution for every rolling window. It can be seen that the critical values based on student-t distribution are lower than the critical values from the normal distribution. There is a very sharp increase in critical values after the year 2012. This implies that as the estimation sample is rolled over towards the end of the sample period, the degrees of freedom increase to the normal distribution.

Tables 4.2 and 4.3 show the daily returns of each currency during the estimation and forecast periods. All currencies display means and medians that are very close to zero. CNY has the highest return at 42.04 and KRW has the lowest return at -23.13 during the estimation period. Whereas, CHF has the highest return at 9.527 and JPY has the lowest return at -10.06 during the forecast period.

All currencies, except NZD, CNY, IDR, and MYR, are negatively skewed during the estimation period. While during the forecast period, all currencies, except NZD and CHF, are negatively skewed. All currencies exhibit excess kurtosis during estimation and forecast periods. Of particular interest, CNY, NZD, KRW, and IDR have extreme excess kurtosis at 760.7898, 269.3207, 121.0553 and 109.4368, respectively, during the estimation period. Finally, all currencies are found to be non-normal according to Jarque-Bera test statistic with CNY, NZD, KRW, and IDR display extreme non-normalities during estimation period. While during the forecast period, CHF, KRW, JPY, MYR, and SGD display extreme non-normalities.

Figure 4.2 and 4.3 illustrate the histograms of normal density for each currency during estimation and forecast periods. NZD, KRW, CNY, and IDR show greater dispersions at a mean of zero during the estimation period. While, the distributions of all foreign exchange returns during the forecast period are asymmetric. This is established by the minimum and maximum returns in Table 4.3.

Table 4.2 Summary Statistics for Each Currency Returns during the Estimation Period

	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
Mean	-0.0092	-0.0229	-0.0114	-0.0049	-0.0011	-0.0133	-0.0184	0.0197	-0.0092	0.0352	0.0006	-0.0122
Median	0.0000	0.0000	0.0000	0.0000	0.0035	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000	0.0000
Standard Deviation	0.6331	0.8307	0.7815	0.6545	0.9755	0.6343	0.8868	0.9819	0.6318	1.6488	0.7639	0.6661
Minimum	-4.5610	-5.1920	-4.4780	-7.7680	-23.1300	-4.4940	-5.1370	-5.9050	-4.5290	-16.2500	-6.4320	-4.8940
Maximum	3.3870	4.9690	5.7070	6.5440	9.5550	3.6230	5.3520	42.0400	3.3770	38.2900	11.4900	4.3430
Skewness	**-0.5007**	**-0.4224**	**-0.0148**	**7.6332**	**-2.8596**	**-0.4230**	**-0.2362**	**19.3925**	**-0.5090**	**4.2672**	**0.5852**	**-0.4147**
Kurtosis	**7.4198**	**5.7410**	**5.9273**	**269.3207**	**121.0553**	**6.6482**	**5.4427**	**760.7898**	**7.4370**	**109.4368**	**21.6650**	**7.8994**
Jacque-Bera	**4235.73**	**1696.71**	**1767.56**	**14676698.99**	**2881261.63**	**2892.69**	**1276.65**	**118748380.60**	**4274.13**	**2351586.44**	**72135.97**	**5092.66**

(1) Entries in bold denote 1% significant

Table 4.3 Summary Statistics for Each Currency Returns during the Forecast Period

	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
Mean	0.0158	0.0117	0.0146	0.0003	0.0115	0.0047	0.0005	0.0049	0.0156	0.0265	0.0107	0.0105
Median	0.0000	0.0338	0.0150	0.0000	0.0041	0.0000	0.0000	0.0000	0.0043	0.0132	0.0110	0.0000
Standard Deviation	0.8586	1.0831	0.6813	0.4686	0.7390	0.6642	0.8349	0.8448	0.8545	0.8022	0.7326	0.7725
Minimum	-7.7370	-10.0600	-6.6950	-3.1750	-7.9620	-6.7860	-6.3480	-7.8180	-7.7750	-6.6590	-7.4810	-7.0960
Maximum	7.1560	9.3060	4.0670	3.0930	5.2250	6.0390	9.5270	7.3090	7.1460	5.6660	6.4780	6.9060
Skewness	**-0.3687**	**-0.5873**	**-0.5313**	**0.0233**	**-1.0796**	**-0.6229**	**0.1513**	**-0.3758**	**-0.3838**	**-0.4495**	**-0.4984**	**-0.4244**
Kurtosis	**11.2852**	**14.5525**	**9.3842**	**6.7236**	**15.7178**	**14.3853**	**16.4509**	**11.9349**	**11.5793**	**9.4866**	**14.5438**	**12.0706**
Jacque-Bera	**8276.71**	**16130.25**	**5010.73**	**1658.89**	**19906.05**	**15692.03**	**21654.26**	**9617.45**	**8875.33**	**5130.10**	**16060.08**	**9928.35**
(1) Entries in bold denote 1% significant												

Figure 4.2 Histograms for Each Currency Returns during the Estimation Period

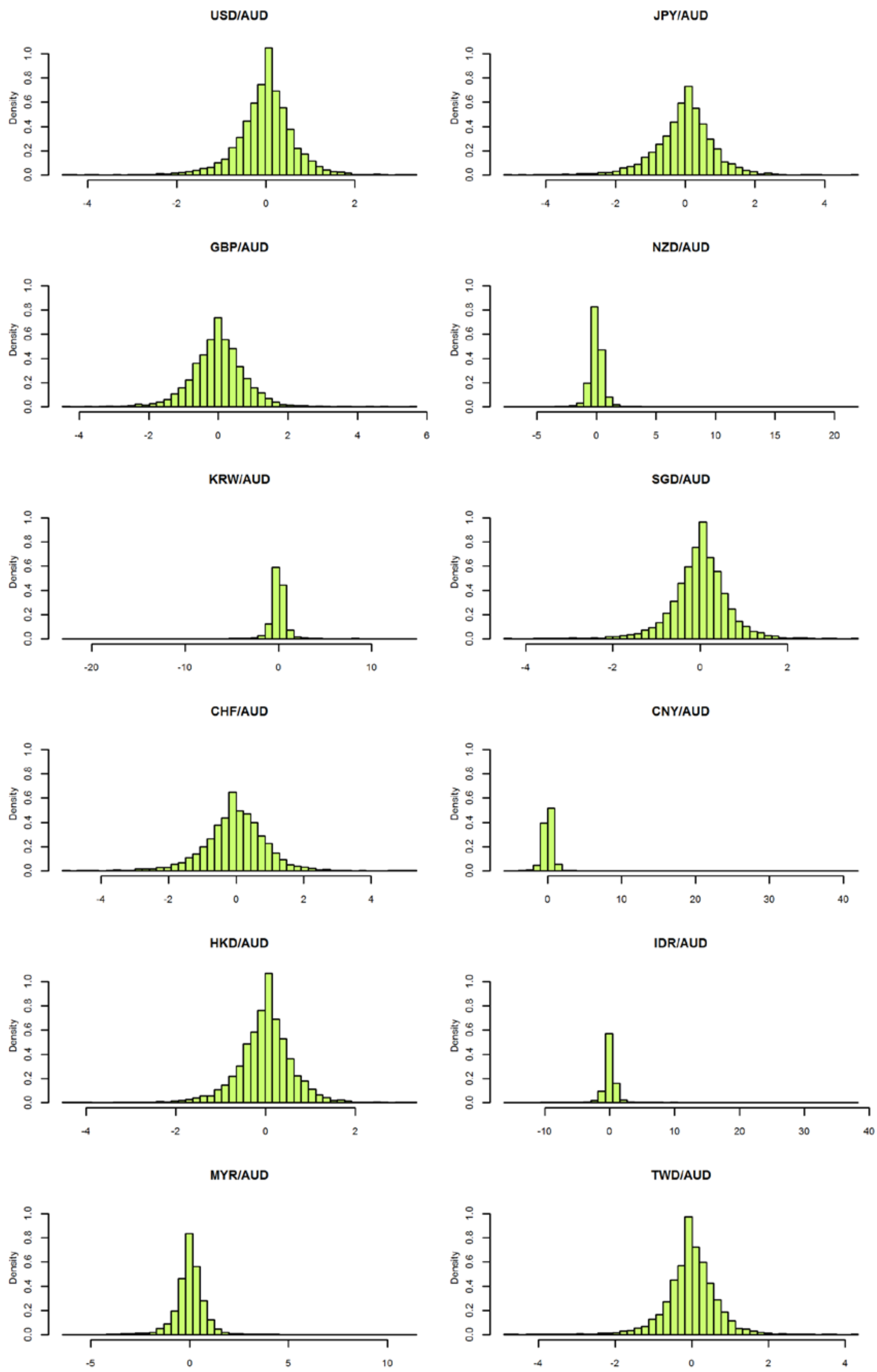


Figure 4.3 Histograms for Each Currency Returns during the Forecast Period

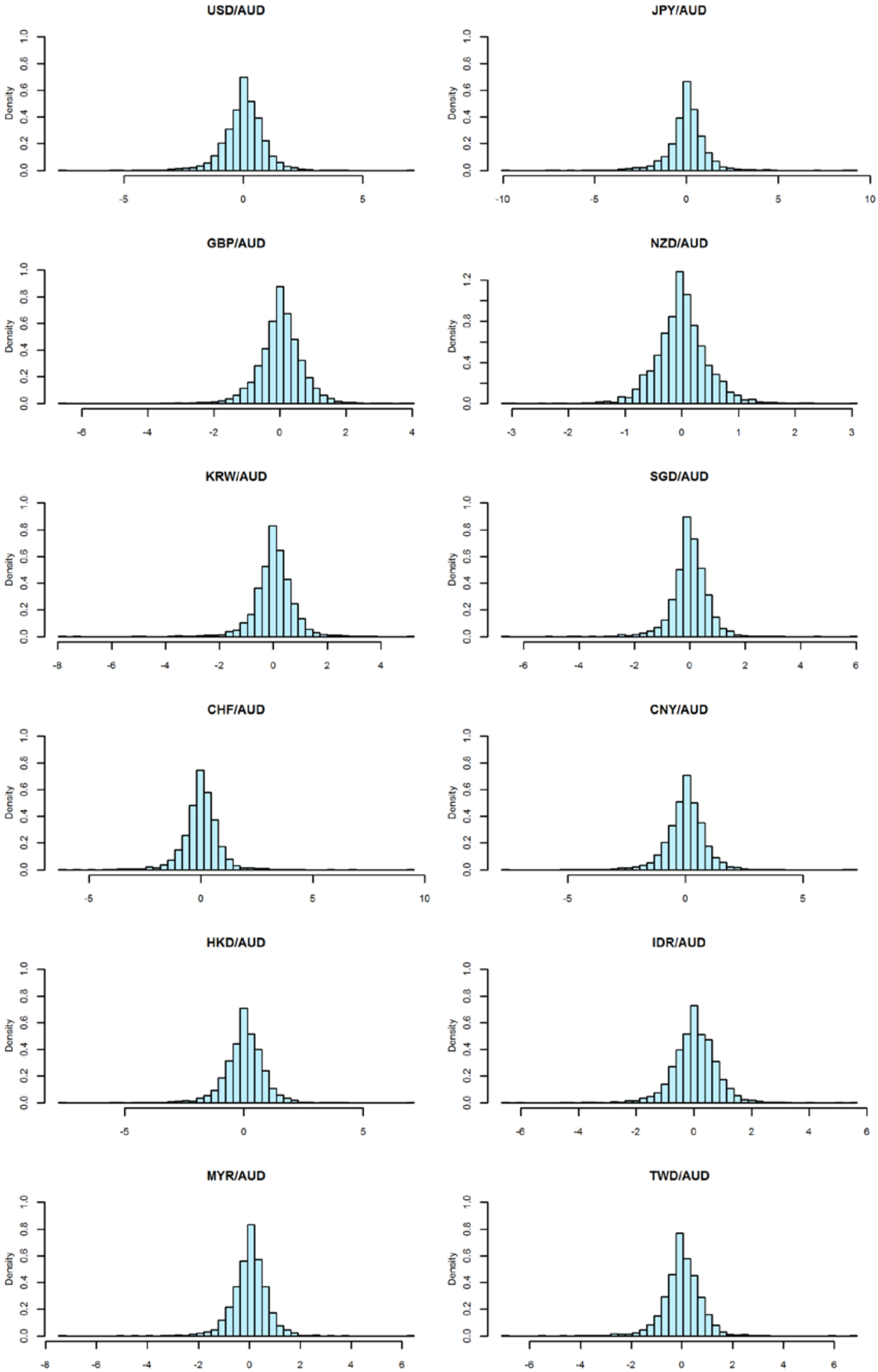


Figure 4.4 Daily Returns for Each Currency

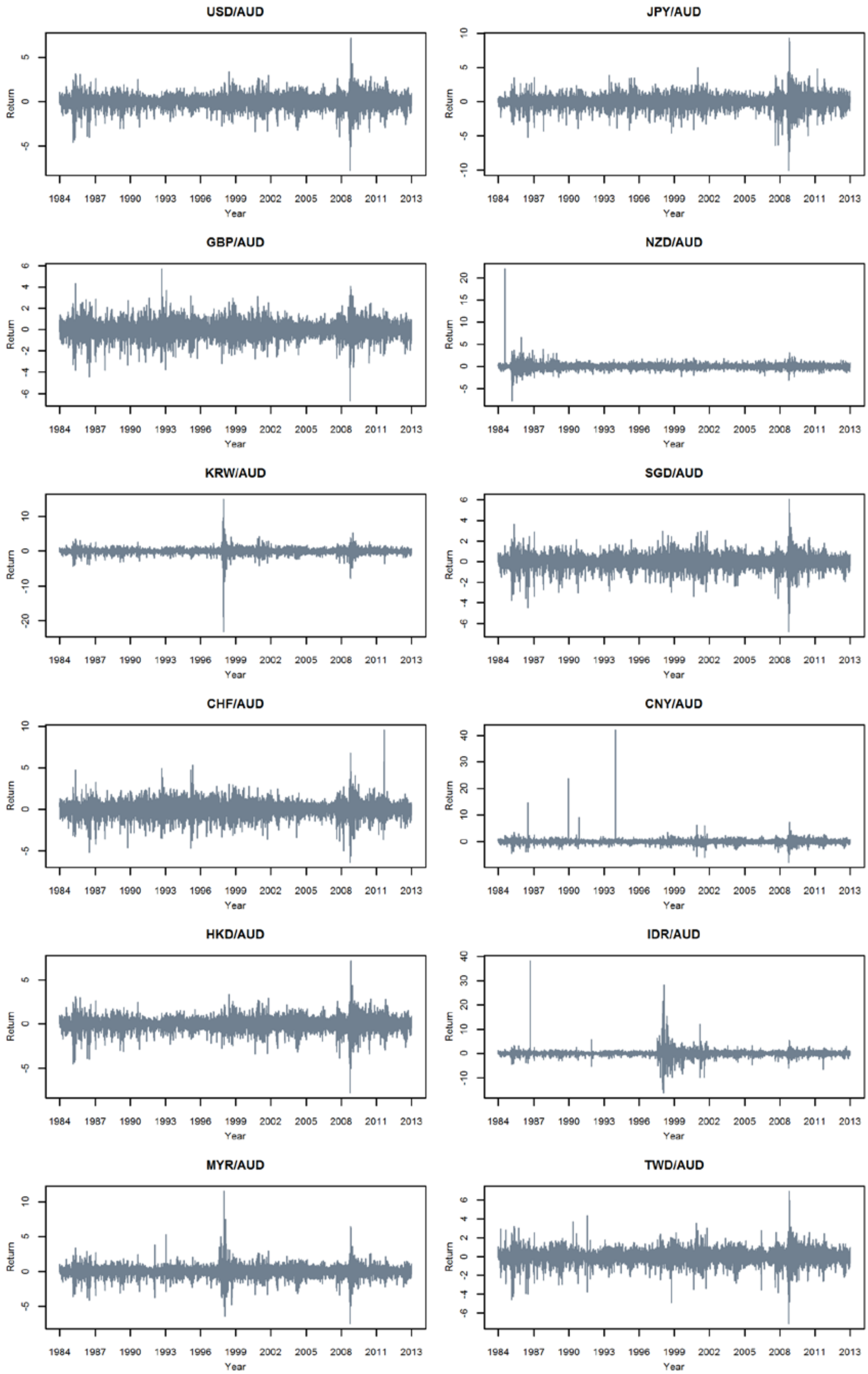


Figure 4.4 shows the daily returns for each respective currency. The volatility clustering of foreign exchange returns can be seen. All currencies displayed extreme movements during the periods of 2008 to 2009 due to the GFC. With exceptions for KRW for the periods from 1997 to 1998 due to Asian Financial Crisis, NZD in the year of 1984 due to constitutional crisis[5], IDR in the year of 1986 due to severe devaluation against USD; and CNY in the years of 1987 due to US stock market crash, 1990 and 1994 due to devaluation against USD.

Tables 4.4 and 4.5 report the parameter estimates of CCC models follow the GARCH(1,1) process. While Tables 4.6 and 4.7 report the parameter estimates of CCC models follow the GJR(1,1) process. These tables also provide the estimates under normal and student-t distributions. It is worth noting that the parameter estimates are not significantly different between normal and student-t distributions. The estimates for $\widehat{\omega}$, $\widehat{\alpha}$ and $\widehat{\beta}$ are positive for CCC-GARCH(1,1) and CCC-GJR(1,1) models. Moreover, the volatility persistence, $\widehat{\alpha}+\hat{\beta}<1$ for CCC-GARCH(1,1) model and $0<\widehat{\alpha}+\hat{\beta}+\frac{\hat{\gamma}}{2}<1$ for CCC-GJR(1,1) model indicating the sufficient conditions to ensure $\sigma_t^2 > 0$ are satisfied in these models. All currencies satisfy the second moment and the log-moment conditions, which are sufficient conditions for the QMLE to be consistent and asymptotically normal (see Ling and McAleer 2003).

[5] Prior 1984, NZD was pegged to a basket of currencies including USD, GBP, AUD, JPY and Deutsche Mark. In January 1984, NZD was allowed to float and suffered great devaluation against other major currencies. Source: Reserve Bank of New Zealand, http://www.rbnz.govt.nz

Table 4.4 Parameter Estimates for CCC-GARCH(1,1) model

	Normal Distribution											
	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
$\hat{\omega}$	**0.0055** *(0.0017)*	**0.0205** *(0.0067)*	**0.0190** *(0.0059)*	**0.0101** *(0.0015)*	**0.0067** *(0.0017)*	**0.0081** *(0.0025)*	**0.0482** *(0.0250)*	**0.0135** *(0.0051)*	**0.0057** *(0.0016)*	**0.0150** *(0.0055)*	**0.0117** *(0.0042)*	**0.0139** *(0.0046)*
$\hat{\alpha}$	**0.0715** *(0.0138)*	**0.1008** *(0.0181)*	**0.0656** *(0.0110)*	**0.1208** *(0.0106)*	**0.0903** *(0.0121)*	**0.0847** *(0.0170)*	**0.0900** *(0.0265)*	**0.1323** *(0.0282)*	**0.0724** *(0.0071)*	**0.1669** *(0.0367)*	**0.1142** *(0.0259)*	**0.0796** *(0.0150)*
$\hat{\beta}$	**0.9175** *(0.0150)*	**0.8746** *(0.0230)*	**0.9033** *(0.0183)*	**0.8478** *(0.0087)*	**0.9013** *(0.0114)*	**0.8990** *(0.0201)*	**0.8493** *(0.0560)*	**0.8519** *(0.0310)*	**0.9159** *(0.00970*	**0.8321** *(0.0325)*	**0.8693** *(0.0290)*	**0.8916** *(0.0204)*
Second Moment	0.9889	0.9754	0.9689	0.9686	0.9916	0.9837	0.9394	0.9842	0.9883	0.9990	0.9835	0.9712
Log-Moment	-0.0194	-0.0390	-0.0377	-0.0515	-0.0213	-0.0272	-0.0736	-0.0430	-0.0203	-0.0419	-0.0358	-0.0408

(1) Entries in bold denote 1% significant

(2) Standard errors are in *parenthesis*

Table 4.5 Parameter Estimates for CCC-GARCH(1,1) model

	Student-t Distribution											
	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
$\hat{\omega}$	**0.0056** *(0.0021)*	**0.0126** *(0.0045)*	**0.0173** *(0.0045)*	**0.0161** *(0.0044)*	**0.0080** *(0.0019)*	**0.0070** *(0.0019)*	**0.0372** *(0.0135)*	**0.0238** *(0.0018)*	**0.0057** *(0.0017)*	**0.0183** *(0.0036)*	**0.0100** *(0.0029)*	**0.0116** *(0.0030)*
$\hat{\alpha}$	**0.0774** *(0.0150)*	**0.0890** *(0.0147)*	**0.0624** *(0.0091)*	**0.1409** *(0.0250)*	**0.0952** *(0.0117)*	**0.0783** *(0.0124)*	**0.0768** *(0.0168)*	**0.1236** *(0.0180)*	**0.0785** *(0.0133)*	**0.1775** *(0.0174)*	**0.0921** *(0.0140)*	**0.0884** *(0.0142)*
$\hat{\beta}$	**0.9151** *(0.0148)*	**0.9010** *(0.0172)*	**0.9102** *(0.0139)*	**0.8143** *(0.0334)*	**0.8969** *(0.0117)*	**0.9094** *(0.0140)*	**0.8777** *(0.0311)*	**0.8402** *(0.0224)*	**0.9138** *(0.0137)*	**0.8215** *(0.0174)*	**0.8955** *(0.0184)*	**0.8933** *(0.0164)*
$\hat{\lambda}$	**4.4859** *(0.2323)*	**4.9669** *(0.3380)*	**6.1737** *(0.4958)*	**4.5052** *(0.3436)*	**4.4168** *(0.2794)*	**4.9232** *(0.3303)*	**6.3549** *(0.5232)*	**3.6847** *(0.1601)*	**4.4850** *(0.2565)*	**3.5207** *(0.1698)*	**4.2945** *(0.3248)*	**4.2950** *(0.2812)*
Second Moment	0.9925	0.9899	0.9726	0.9552	0.9921	0.9877	0.9545	0.9638	0.9923	0.9990	0.9876	0.9817
Log-Moment	-0.0215	-0.0455	-0.0346	-0.0512	-0.0214	-0.0310	-0.0553	-0.0186	-0.0227	-0.0413	-0.0367	-0.0418

(1) Entries in bold denote 1% significant

(2) Standard errors are in *parenthesis*

Table 4.6 Parameter Estimates for CCC-GJR(1,1) model

	Normal Distribution											
	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
$\hat{\omega}$	**0.0060** *(0.0019)*	**0.0235** *(0.0081)*	**0.0174** *(0.0055)*	**0.0101** *(0.0016)*	**0.0067** *(0.0018)*	**0.0091** *(0.0030)*	**0.0363** *(0.0183)*	**0.0074** *(0.0021)*	**0.0063** *(0.0018)*	**0.0147** *(0.0052)*	**0.0119** *(0.0043)*	**0.0142** *(0.0047)*
$\hat{\alpha}$	**0.0619** *(0.0136)*	**0.0707** *(0.0154)*	**0.0444** *(0.0120)*	**0.1180** *(0.0191)*	**0.0895** *(0.0147)*	**0.0676** *(0.0145)*	**0.0456** *(0.0210)*	**8.35E-06** *(9.03E-05)*	**0.0607** *(0.0093)*	**0.1567** *(0.0413)*	**0.1053** *(0.0282)*	**0.0723** *(0.0169)*
$\hat{\beta}$	**0.9157** *(0.0163)*	**0.8709** *(0.0257)*	**0.9103** *(0.0180)*	**0.8482** *(0.0091)*	**0.9011** *(0.0117)*	**0.8958** *(0.0218)*	**0.8827** *(0.0435)*	**0.9373** *(0.0102)*	**0.9140** *(0.0098)*	**0.8335** *(0.0324)*	**0.8681** *(0.0295)*	**0.8910** *(0.0207)*
$\hat{\gamma}$	-0.0183 *(0.0153)*	***-0.0531*** *(0.0213)*	**-0.0329** *(0.0121)*	-0.0053 *(0.0241)*	-0.0018 *(0.0182)*	***-0.0327*** *(0.0197)*	**-0.0488** *(0.0146)*	**-0.0956** *(0.0175)*	-0.0221 *(0.0143)*	-0.0175 *(0.0380)*	-0.0184 *(0.0218)*	-0.0135 *(0.0180)*
Second Moment	0.9867	0.9682	0.9711	0.9688	0.9915	0.9798	0.9527	0.9851	0.9857	0.9990	0.9826	0.9701
Log-Moment	-0.0193	-0.0234	-0.0340	-0.0773	-0.0245	-0.0232	-0.0556	-0.0678	-0.0197	-0.0491	-0.0288	-0.0338

(1) Entries in bold denote 1% significant

(2) Entries in bold and *Italic* denote 10% significant

(3) Standard errors are in *parenthesis*

Table 4.7 Parameter Estimates for CCC-GJR(1,1) model

	Student-t Distribution											
	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
$\hat{\omega}$	**0.0058**	**0.0136**	**0.0165**	**0.0017**	**0.0083**	**0.0074**	**0.0339**	**0.0086**	**0.0060**	**0.0183**	**0.0102**	**0.0117**
	(0.0022)	*(0.0051)*	*(0.0048)*	*(0.0003)*	*(0.0020)*	*(0.0021)*	*(0.0121)*	*(0.0048)*	*(0.0016)*	*(0.0035)*	*(0.0024)*	*(0.0030)*
$\hat{\alpha}$	**0.0724**	**0.0702**	**0.0470**	**5.35E-09**	**0.0904**	**0.0688**	**0.0491**	**8.68E-10**	**0.0722**	**0.1779**	**0.0856**	**0.0846**
	(0.0131)	*(0.0144)*	*(0.0114)*	*(0.0002)*	*(0.0125)*	*(0.0119)*	*(0.0158)*	*(0.0002)*	*(0.0127)*	*(0.0230)*	*(0.0129)*	*(0.0160)*
$\hat{\beta}$	**0.9144**	**0.9008**	**0.9141**	**0.9719**	**0.8958**	**0.9081**	**0.8891**	**0.9390**	**0.9129**	**0.8215**	**0.8945**	**0.8931**
	(0.0148)	*(0.0185)*	*(0.0158)*	*(0.0004)*	*(0.0124)*	*(0.0143)*	*(0.0286)*	*(0.0230)*	*(0.0134)*	*(0.0175)*	*(0.0165)*	*(0.0163)*
$\hat{\gamma}$	0.0093	***0.0297***	***0.0245***	**0.0481**	0.0099	0.0180	**0.0369**	**0.0890**	0.0118	-0.0008	0.0129	0.0068
	(0.0149)	*(0.0158)*	*(0.0114)*	*(0.0036)*	*(0.0165)*	*(0.0144)*	*(0.0139)*	*(0.0283)*	*(0.0129)*	*(0.0246)*	*(0.0153)*	*(0.0157)*
$\hat{\lambda}$	**4.4918**	**5.0298**	**6.2416**	**4.3169**	**4.4151**	**4.9359**	**6.4812**	**3.7383**	**4.4933**	**3.5211**	**4.2977**	**4.2953**
	(0.2185)	*(0.3481)*	*(0.5066)*	*(0.3311)*	*(0.2787)*	*(0.3308)*	*(0.5438)*	*(0.1972)*	*(0.2344)*	*(0.1702)*	*(0.3134)*	*(0.2800)*
Second Moment	0.9914	0.9858	0.9733	0.9960	0.9912	0.9858	0.9566	0.9835	0.9910	0.9990	0.9866	0.9811
Log-Moment	-0.0203	-0.0266	-0.0326	-0.0057	-0.0255	-0.0250	-0.0514	-0.0221	-0.0209	-0.0491	-0.0299	-0.0343

(1) Entries in bold denote 1% significant

(2) Entries in bold and *Italic* denote 10% significant

(3) Standard errors are in *parenthesis*

Table 4.8 Parameter Estimates for DCC-GARCH(1,1) and DCC-GJR(1,1) models

	Normal Distribution		Student-t Distribution	
	DCC-GARCH(1,1)	DCC-GJR(1,1)	DCC-GARCH(1,1)	DCC-GJR(1,1)
$\hat{\theta}_1$	**0.0468** *(0.0105)*	**0.0479** *(0.0109)*	**0.0382** *(0.0011)*	**0.0373** *(0.0010)*
$\hat{\theta}_2$	**0.8984** *(0.0281)*	**0.8997** *(0.0276)*	**0.9617** *(0.0011)*	**0.9626** *(0.0010)*
$\hat{\theta}_1 + \hat{\theta}_2$	0.9452	0.9476	0.9999	0.9999
$\hat{\lambda}$			**4.6796** *(0.1389)*	**4.5697** *(0.1304)*

(1) Entries in bold denote 1% significant

(2) Standard errors are in *parenthesis*

Table 4.8 summarizes the results for DCC estimates for all currencies. The estimated DCC parameters, $\hat{\theta}_1$ and $\hat{\theta}_2$, are statistically significant for all currencies, suggesting that the conditional correlations are not constant over time. Given that $\hat{\theta}_1 + \hat{\theta}_2 < 1$, the second moment condition is satisfied.

Tables 4.9 to 4.12 provide the conditional correlations estimated by CCC-GARCH(1,1) and CCC-GJR(1,1) models under normal and student-t distributions. Most of the time, all currencies are positively correlated and give similar estimates of conditional correlations between normal and student-t distributions. It can be seen that the currency pair of USD vs HKD displays the highest correlation at 0.9957, given that the currencies are pegged to each other, followed by USD vs TWD within a range of 0.9153 to 0.9158. While, the currency pair of NZD vs CNY has the lowest correlation within a range of 0.1955 to 0.2173.

Table 4.9 Conditional Correlations estimated by GARCH(1,1) model under Normal Distribution

	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
USD	1	0.5900	0.5816	0.3704	0.8778	0.8816	0.5028	0.4817	0.9957	0.5500	0.8537	0.9157
JPY	-	1	0.6217	0.3271	0.5839	0.7019	0.6716	0.3144	0.5930	0.3527	0.5958	0.5842
GBP	-	-	1	0.3159	0.5105	0.6428	0.7737	0.3010	0.5877	0.3016	0.5550	0.5532
NZD	-	-	-	1	0.3533	0.3837	0.2971	0.1955	0.3735	0.2378	0.3504	0.3507
KRW	-	-	-	-	1	0.8240	0.4526	0.4337	0.8787	0.5380	0.7965	0.8457
SGD	-	-	-	-	-	1	0.6058	0.4328	0.8840	0.5403	0.8645	0.8441
CHF	-	-	-	-	-	-	1	0.2625	0.5094	0.2504	0.5084	0.4887
CNY	-	-	-	-	-	-	-	1	0.4829	0.2725	0.3585	0.4365
HKD	-	-	-	-	-	-	-	-	1	0.5476	0.8521	0.9133
IDR	-	-	-	-	-	-	-	-	-	1	0.5372	0.5261
MYR	-	-	-	-	-	-	-	-	-	-	1	0.8148
TWD	-	-	-	-	-	-	-	-	-	-	-	1

Table 4.10 Conditional Correlations estimated by GARCH(1,1) model under Student-t Distribution

	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
USD	1	0.5894	0.5813	0.3718	0.8771	0.8817	0.5032	0.5181	0.9957	0.5471	0.8528	0.9153
JPY	-	1	0.6221	0.3283	0.5833	0.7023	0.6723	0.3363	0.5924	0.3508	0.5954	0.5821
GBP	-	-	1	0.3168	0.5107	0.6433	0.7744	0.3258	0.5873	0.3000	0.5560	0.5523
NZD	-	-	-	1	0.3544	0.3854	0.2984	0.2087	0.3750	0.2386	0.3517	0.3523
KRW	-	-	-	-	1	0.8238	0.4533	0.4644	0.8779	0.5350	0.7952	0.8451
SGD	-	-	-	-	-	1	0.6071	0.4649	0.8841	0.5371	0.8642	0.8433
CHF	-	-	-	-	-	-	1	0.2851	0.5098	0.2496	0.5094	0.4886
CNY	-	-	-	-	-	-	-	1	0.5194	0.2890	0.3887	0.4709
HKD	-	-	-	-	-	-	-	-	1	0.5447	0.8511	0.9128
IDR	-	-	-	-	-	-	-	-	-	1	0.5326	0.5236
MYR	-	-	-	-	-	-	-	-	-	-	1	0.8130
TWD	-	-	-	-	-	-	-	-	-	-	-	1

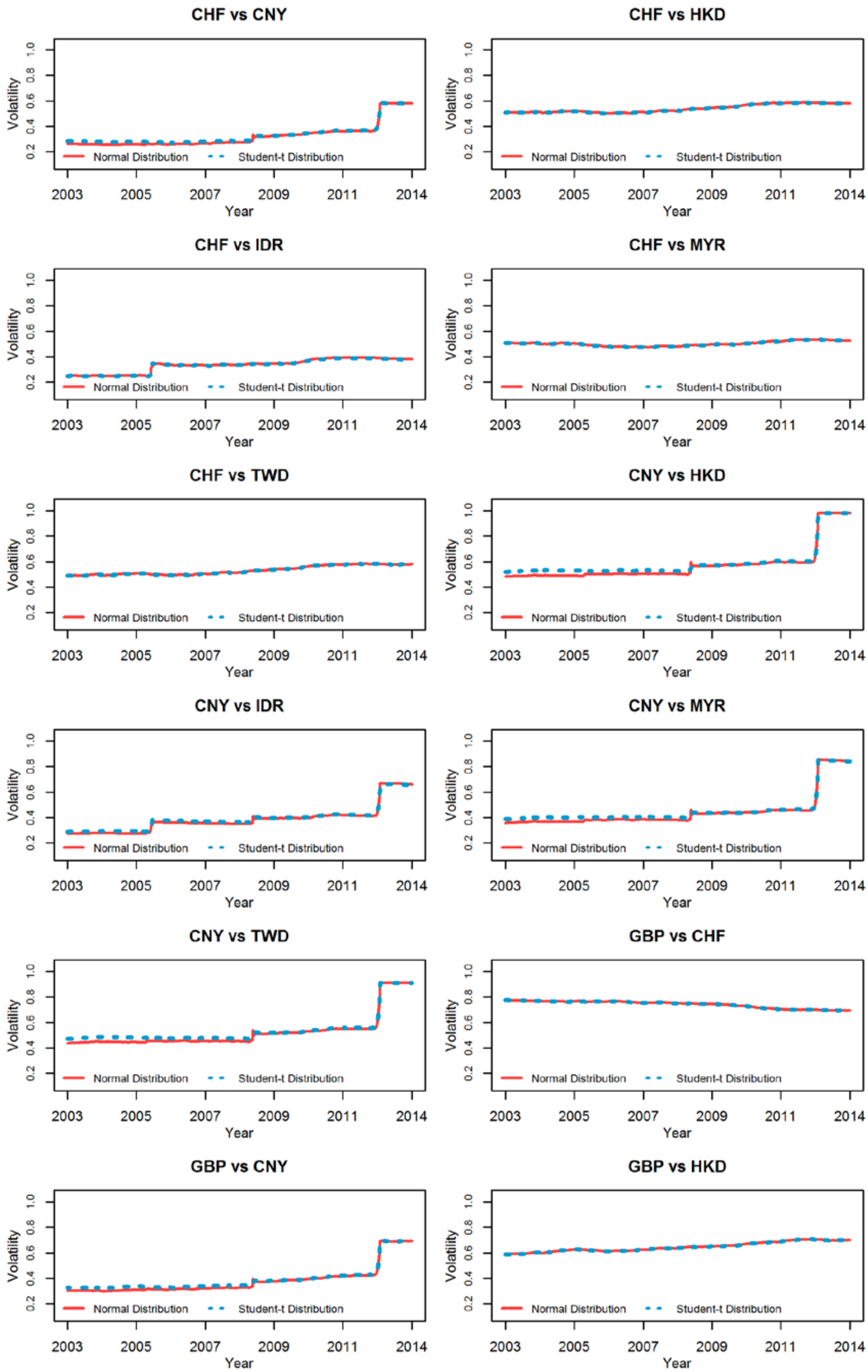
Table 4.11 Conditional Correlations estimated by GJR(1,1) model under Normal Distribution

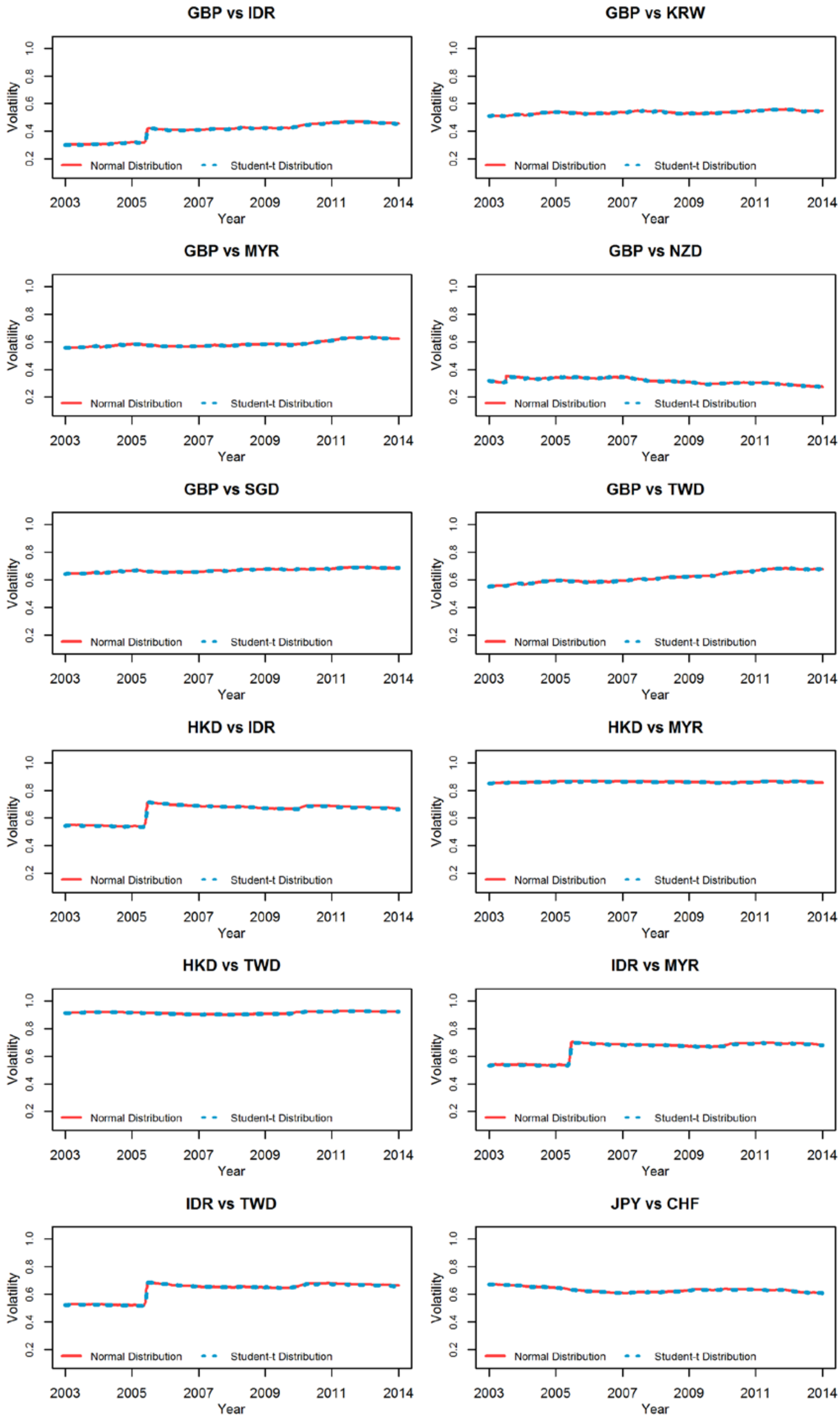
	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
USD	1	0.5886	0.5791	0.3696	0.8776	0.8814	0.5021	0.5392	0.9957	0.5485	0.8530	0.9158
JPY	-	1	0.6192	0.3260	0.5834	0.7008	0.6713	0.3504	0.5916	0.3509	0.5947	0.5839
GBP	-	-	1	0.3153	0.5087	0.6407	0.7717	0.3409	0.5852	0.2990	0.5528	0.5510
NZD	-	-	-	1	0.3531	0.3824	0.2966	0.2173	0.3725	0.2371	0.3494	0.3503
KRW	-	-	-	-	1	0.8233	0.4527	0.4849	0.8784	0.5366	0.7955	0.8455
SGD	-	-	-	-	-	1	0.6057	0.4860	0.8838	0.5387	0.8635	0.8440
CHF	-	-	-	-	-	-	1	0.2999	0.5087	0.2485	0.5078	0.4885
CNY	-	-	-	-	-	-	-	1	0.5408	0.2995	0.4090	0.4885
HKD	-	-	-	-	-	-	-	-	1	0.5461	0.8515	0.9135
IDR	-	-	-	-	-	-	-	-	-	1	0.5357	0.5243
MYR	-	-	-	-	-	-	-	-	-	-	1	0.8140
TWD	-	-	-	-	-	-	-	-	-	-	-	1

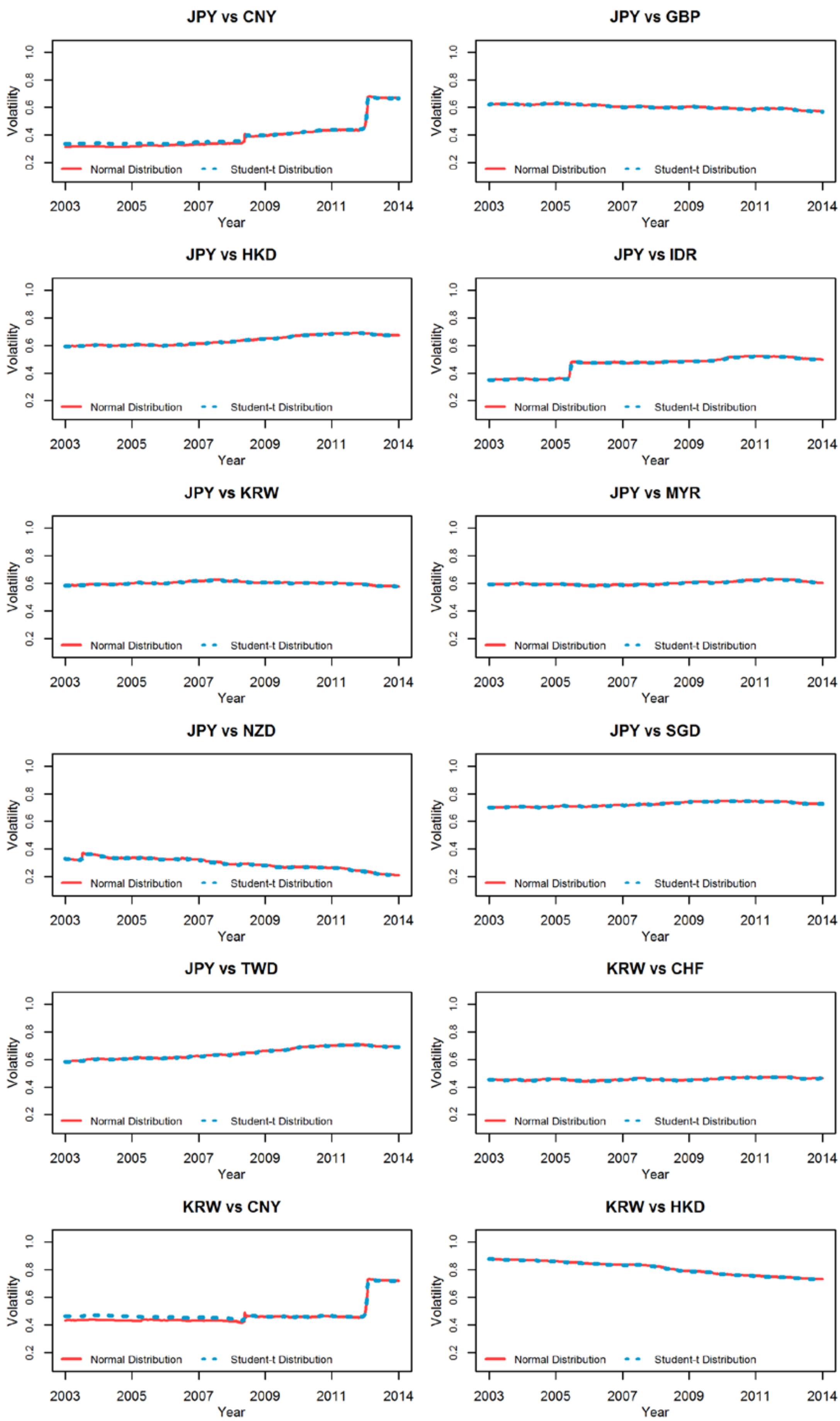
Table 4.12 Conditional Correlations estimated by GJR(1,1) model under Student-t Distribution

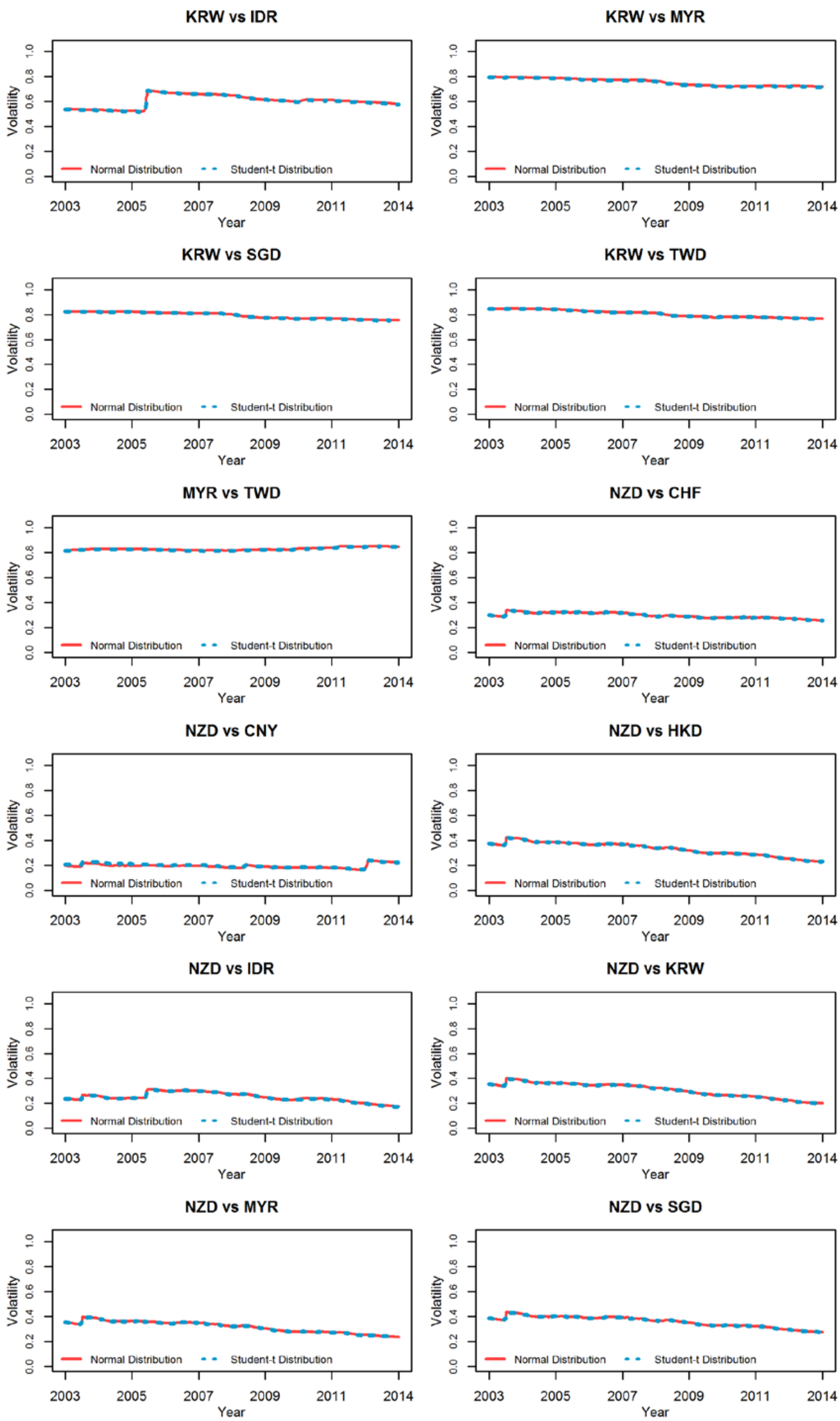
	USD	JPY	GBP	NZD	KRW	SGD	CHF	CNY	HKD	IDR	MYR	TWD
USD	1	0.5887	0.5794	0.3503	0.8765	0.8816	0.5022	0.5486	0.9957	0.5473	0.8519	0.9154
JPY	-	1	0.6204	0.3135	0.5831	0.7016	0.6718	0.3563	0.5917	0.3505	0.5946	0.5821
GBP	-	-	1	0.3068	0.5087	0.6418	0.7726	0.3479	0.5854	0.2992	0.5542	0.5507
NZD	-	-	-	1	0.3331	0.3648	0.2883	0.2059	0.3529	0.2211	0.3316	0.3313
KRW	-	-	-	-	1	0.8231	0.4524	0.4927	0.8774	0.5350	0.7940	0.8449
SGD	-	-	-	-	-	1	0.6066	0.4939	0.8840	0.5372	0.8635	0.8433
CHF	-	-	-	-	-	-	1	0.3059	0.5087	0.2489	0.5086	0.4881
CNY	-	-	-	-	-	-	-	1	0.5502	0.3024	0.4164	0.4980
HKD	-	-	-	-	-	-	-	-	1	0.5450	0.8504	0.9130
IDR	-	-	-	-	-	-	-	-	-	1	0.5326	0.5236
MYR	-	-	-	-	-	-	-	-	-	-	1	0.8124
TWD	-	-	-	-	-	-	-	-	-	-	-	1

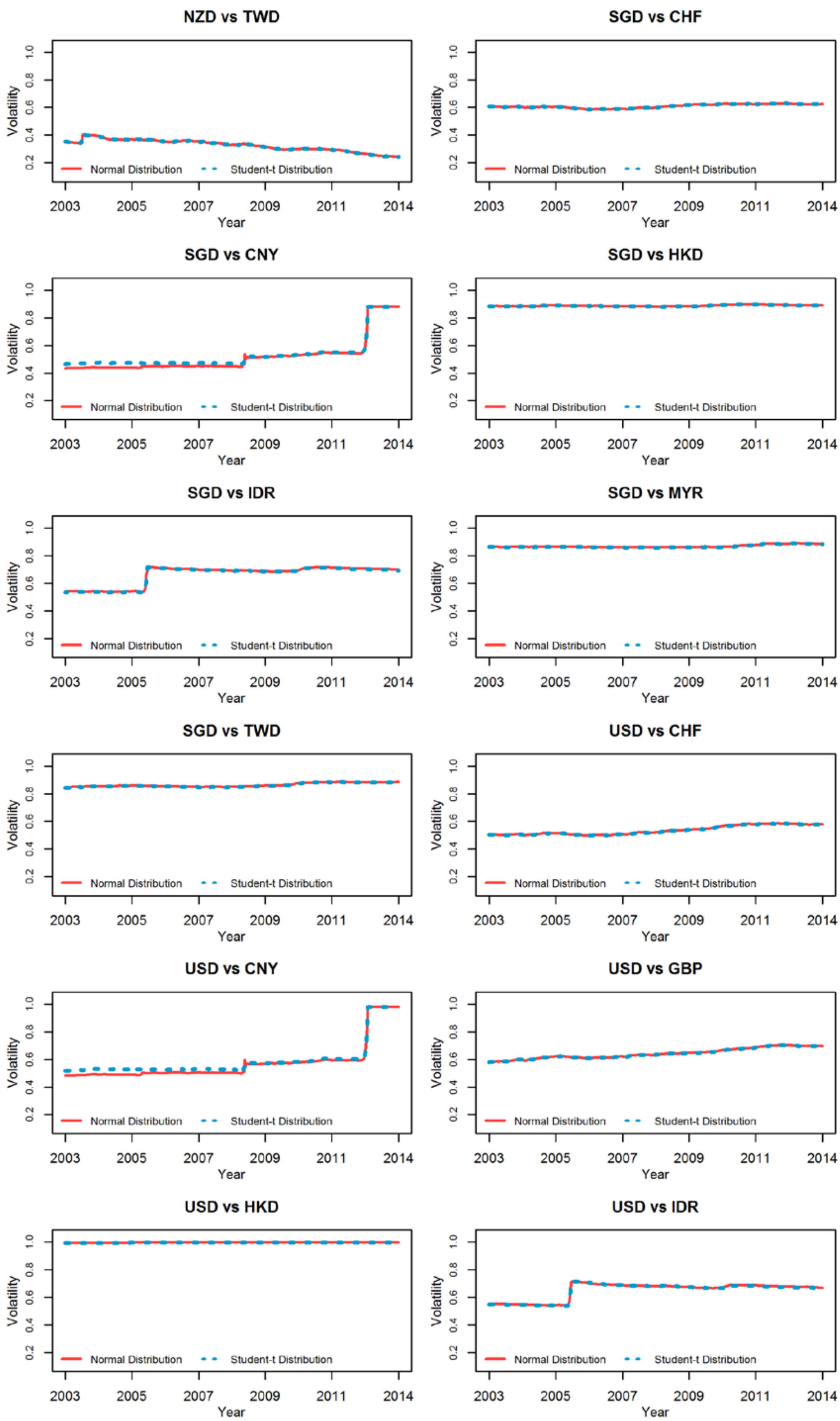
Figure 4.5 CCC Conditional Correlations for Each Pair of Currency




GBP vs IDR
GBP vs KRW
GBP vs MYR
GBP vs NZD
GBP vs SGD
GBP vs TWD
HKD vs IDR
HKD vs MYR
HKD vs TWD
IDR vs MYR
IDR vs TWD
JPY vs CHF
Volatility
0.2 0.4 0.6 0.8 1.0
Year
2003 2005 2007 2009 2011 2014
Normal Distribution
Student-t Distribution


JPY vs CNY
JPY vs GBP
JPY vs HKD
JPY vs IDR
JPY vs KRW
JPY vs MYR
JPY vs NZD
JPY vs SGD
JPY vs TWD
KRW vs CHF
KRW vs CNY
KRW vs HKD
Volatility
Year
Normal Distribution
Student-t Distribution
0.2
0.4
0.6
0.8
1.0
2003
2005
2007
2009
2011
2014


KRW vs IDR
KRW vs MYR
KRW vs SGD
KRW vs TWD
MYR vs TWD
NZD vs CHF
NZD vs CNY
NZD vs HKD
NZD vs IDR
NZD vs KRW
NZD vs MYR
NZD vs SGD
Volatility
Year
Normal Distribution
Student-t Distribution
0.0
0.2
0.4
0.6
0.8
1.0
2003
2005
2007
2009
2011
2014


NZD vs TWD
SGD vs CHF
SGD vs CNY
SGD vs HKD
SGD vs IDR
SGD vs MYR
SGD vs TWD
USD vs CHF
USD vs CNY
USD vs GBP
USD vs HKD
USD vs IDR
Volatility
0.2 0.4 0.6 0.8 1.0
2003 2005 2007 2009 2011 2014
Year
Normal Distribution
Student-t Distribution

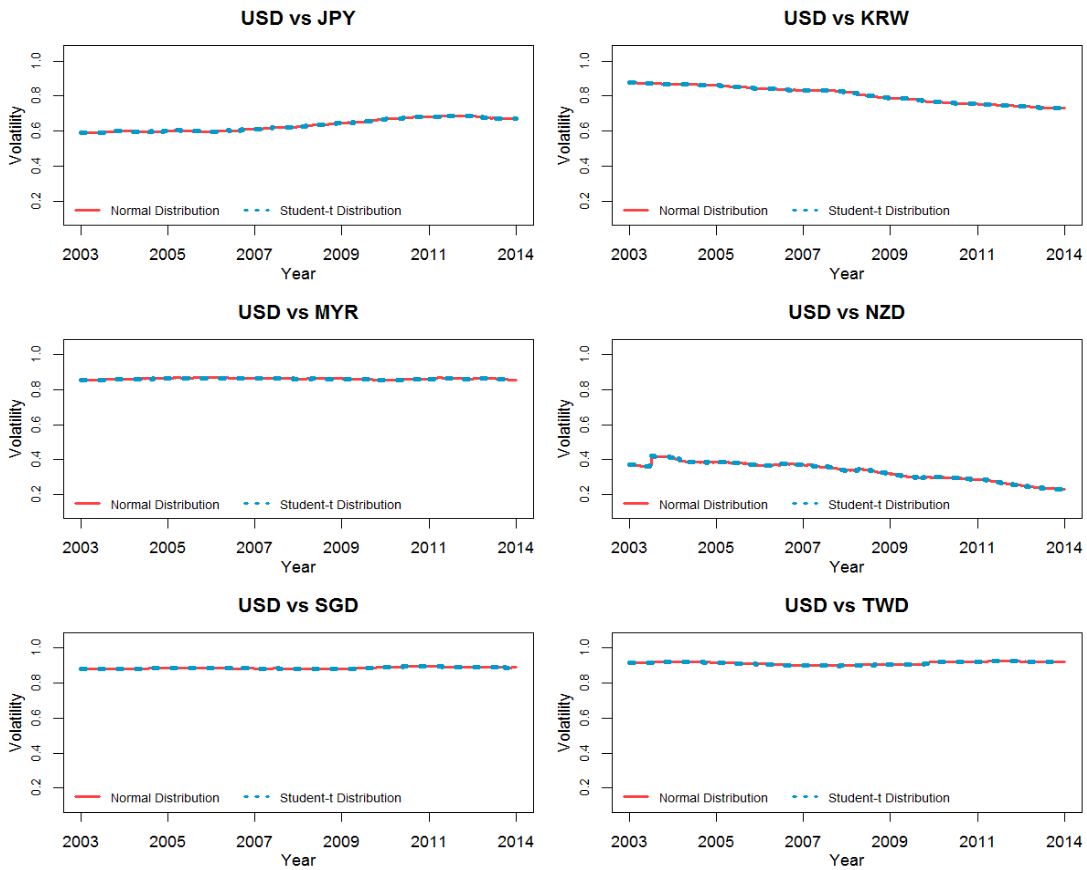
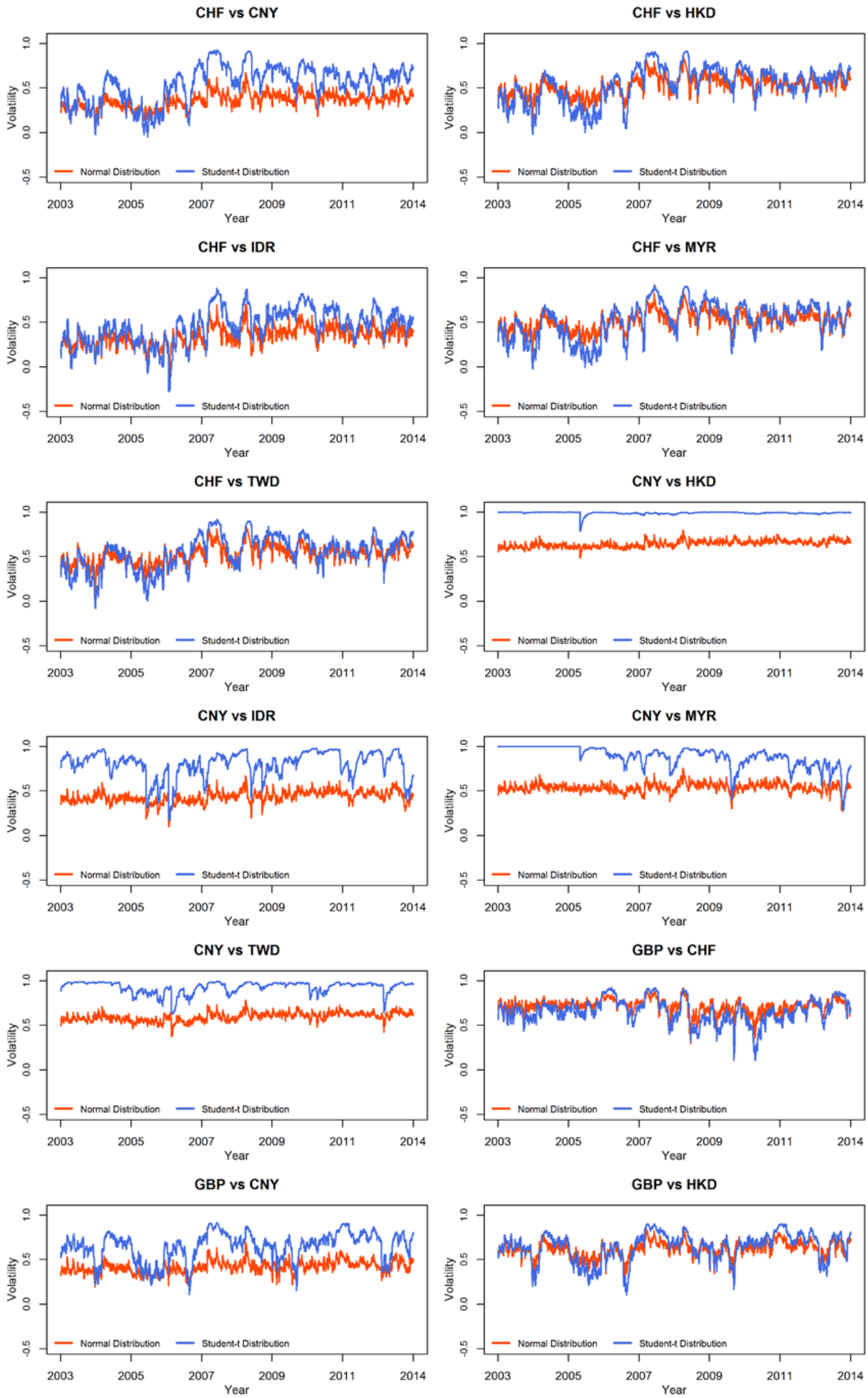
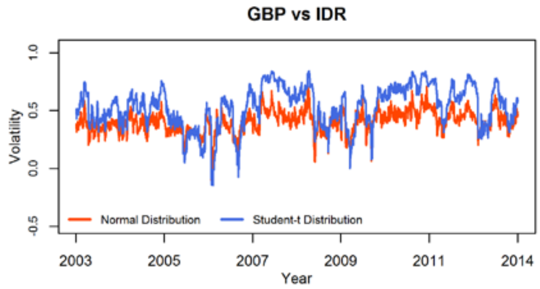
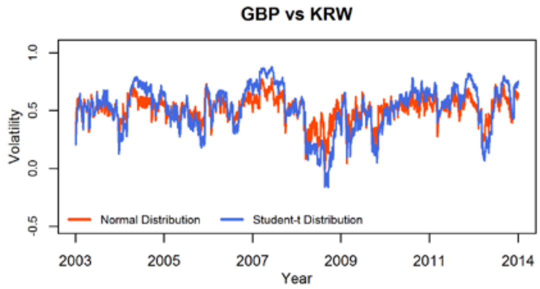
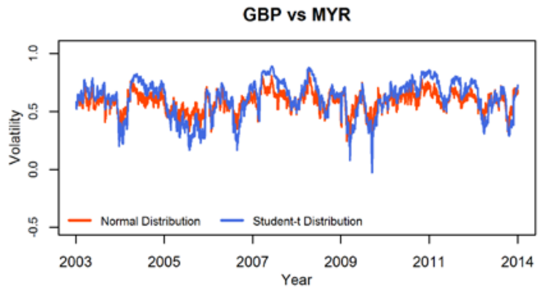
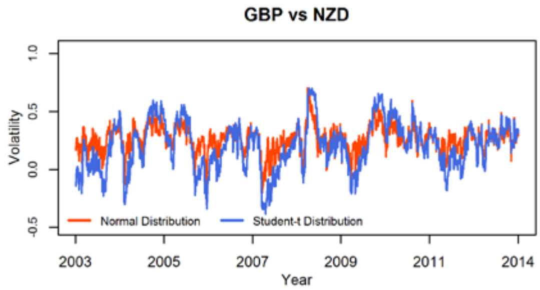
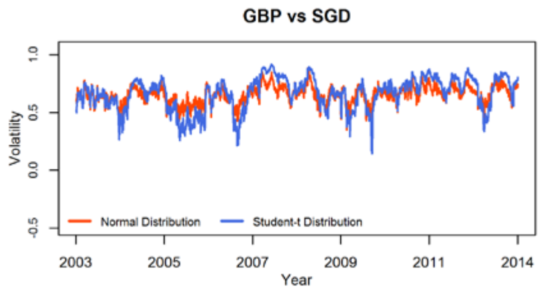
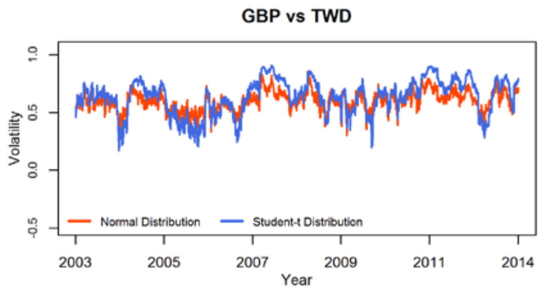
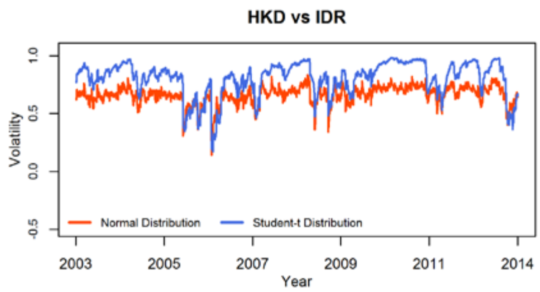
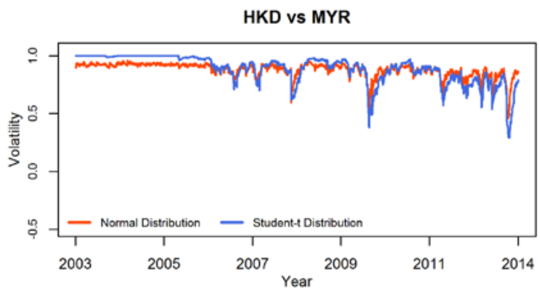
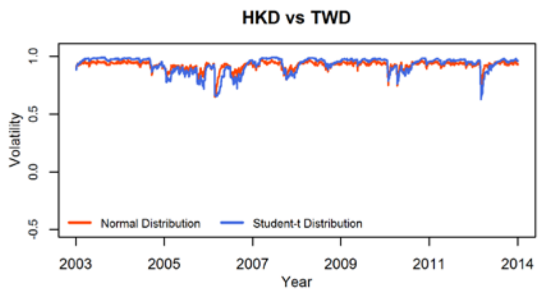
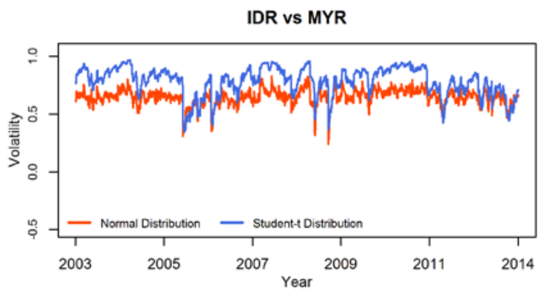
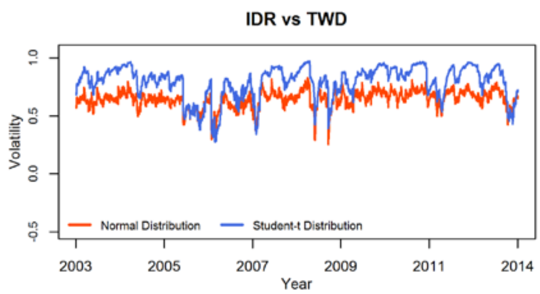
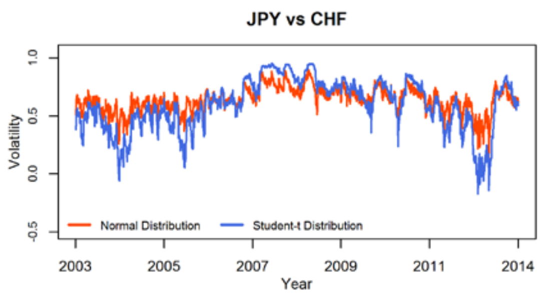
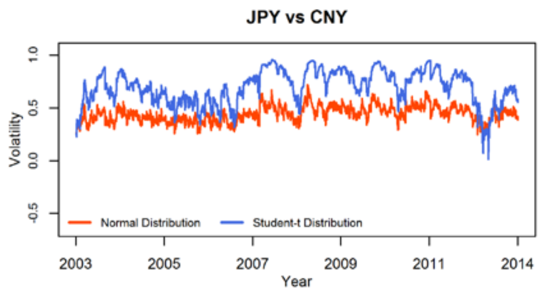
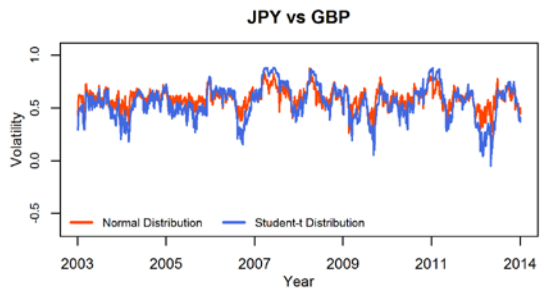
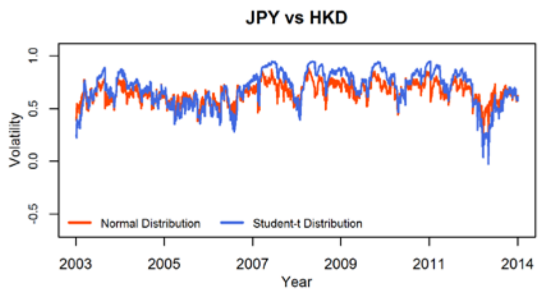
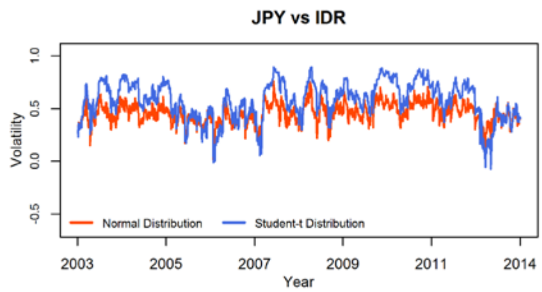
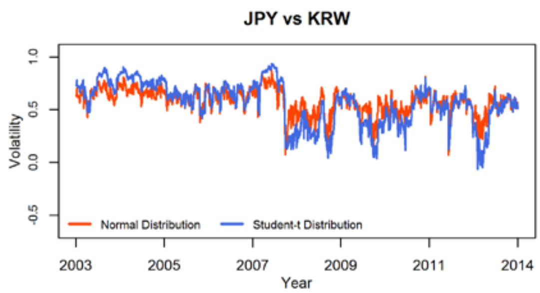
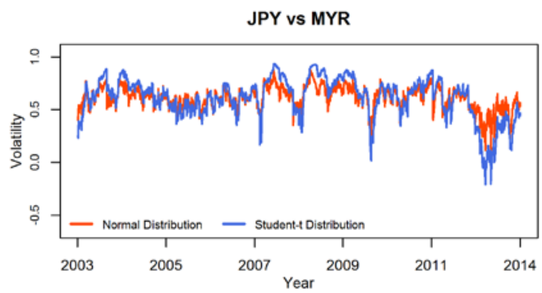


Figure 4.5 illustrates the conditional correlations for all 66 pairs of currencies from 2 January 2003 to 31 December 2013 with 2,871 observations. All currency pairs exhibit positive conditional correlations. The differences between normal and student-t distributions are barely distinguishable for all currency pairs. A constant perfect positive correlation is given by USD vs HKD since the currency pair is pegged. There are 12 currency pairs, namely, HKD vs MYR, HKD vs TWD, KRW vs HKD, KRW vs SGD, KRW vs TWD, MYR vs TWD, SGD vs HKD, SGD vs MYR, SGD vs TWD, USD vs KRW, USD vs MYR and USD vs SGD which display conditional correlations of higher than 0.8 consistently over the forecasting period. Some currency pairs, particularly those currency pairs with CNY, IDR, KRW, and NZD, include structural breaks that can also be seen at different points in time. Interestingly, those break points often shift to higher correlations after the structural breaks.

Figure 4.6 DCC Conditional Correlations for Each Pair of Currency




GBP vs IDR
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

GBP vs KRW
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

GBP vs MYR
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

GBP vs NZD
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

GBP vs SGD
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

GBP vs TWD
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

HKD vs IDR
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

HKD vs MYR
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

HKD vs TWD
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

IDR vs MYR
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

IDR vs TWD
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs CHF
Volatility
1.0 0.5 0.0 -0.5
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year


JPY vs CNY
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs GBP
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs HKD
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs IDR
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs KRW
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs MYR
Volatility
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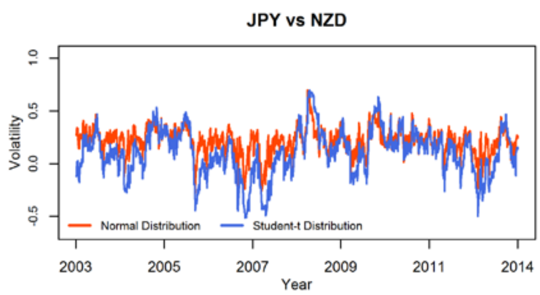
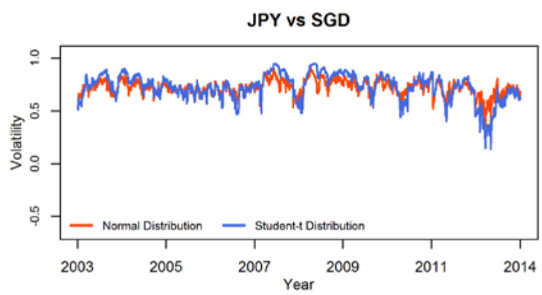
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs NZD
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs SGD
Volatility
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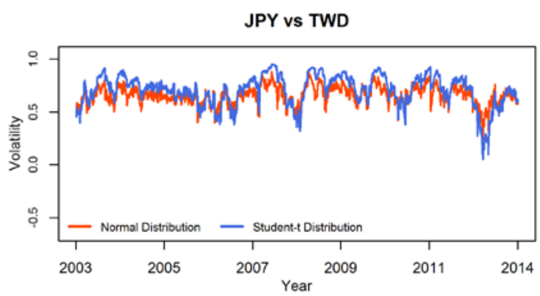
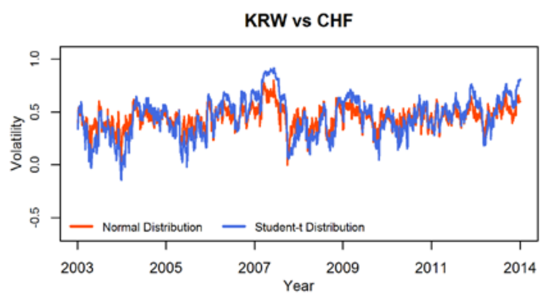
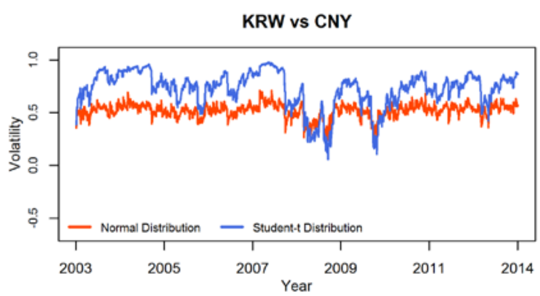
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

JPY vs TWD
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

KRW vs CHF
Volatility
-0.5 0.0 0.5 1.0
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

KRW vs CNY
Volatility
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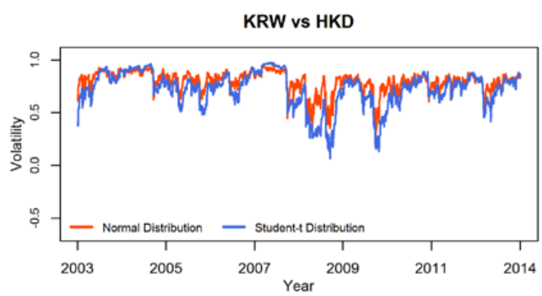
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year

KRW vs HKD
Volatility
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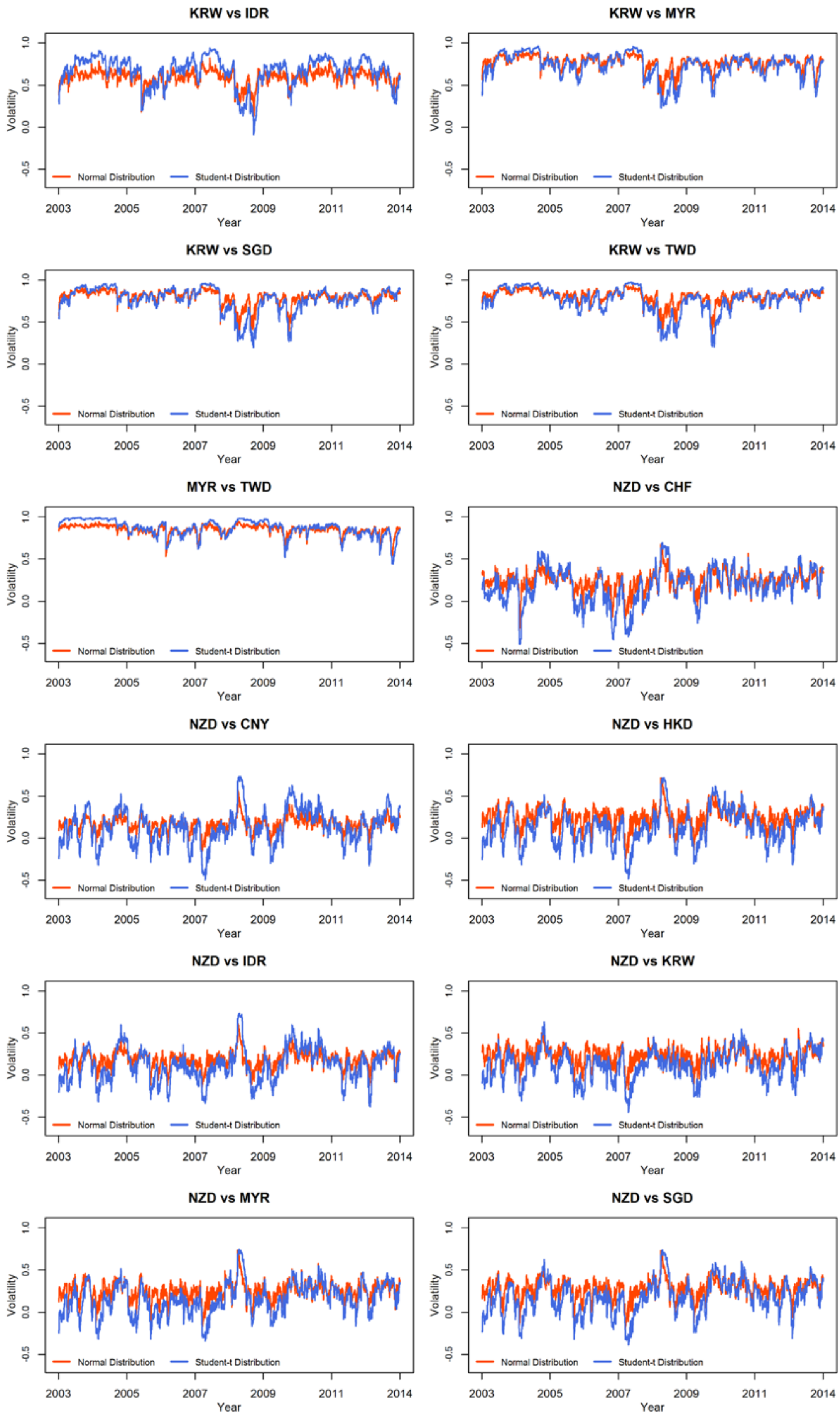
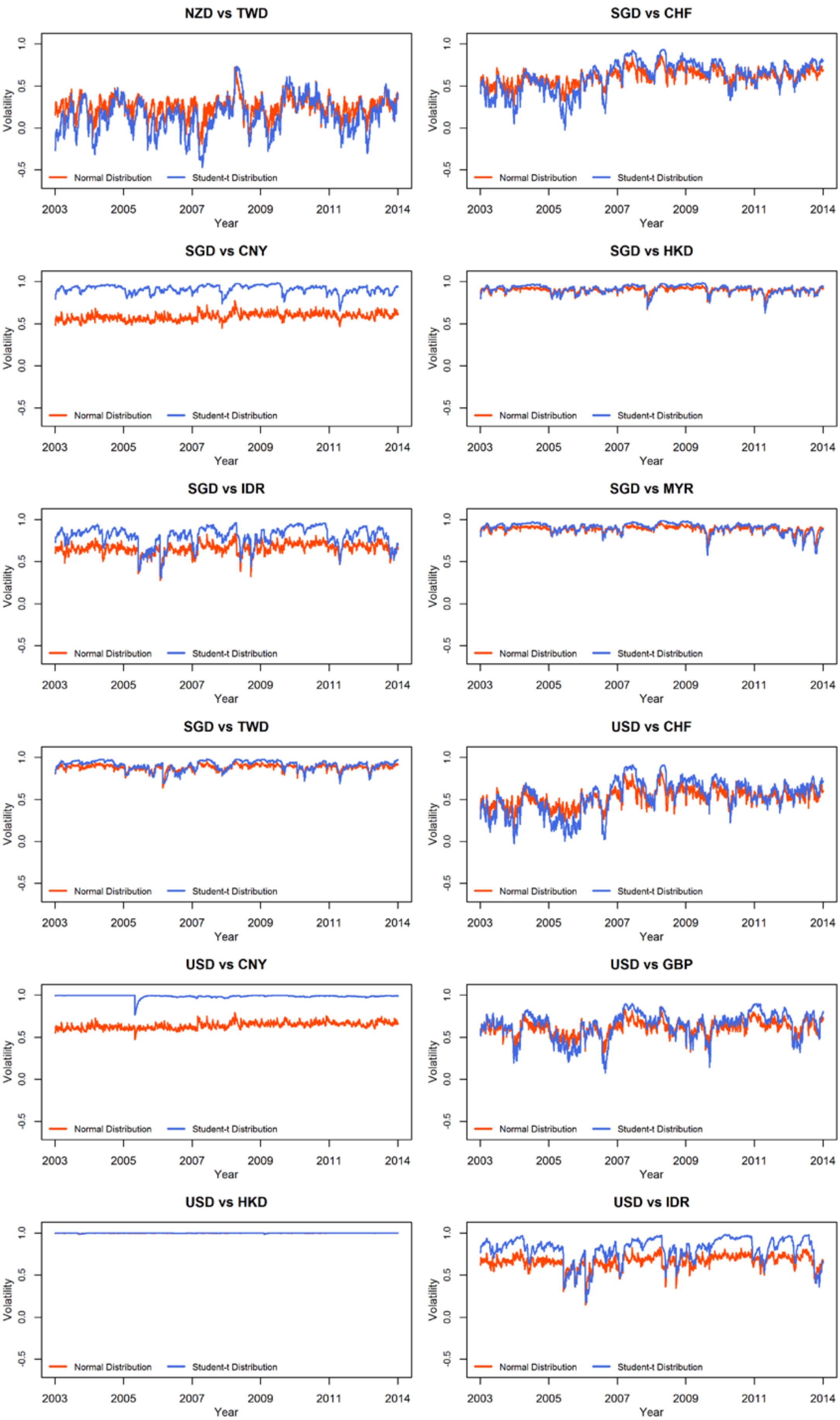
Normal Distribution
Student-t Distribution
2003 2005 2007 2009 2011 2014
Year


KRW vs IDR
KRW vs MYR
KRW vs SGD
KRW vs TWD
MYR vs TWD
NZD vs CHF
NZD vs CNY
NZD vs HKD
NZD vs IDR
NZD vs KRW
NZD vs MYR
NZD vs SGD
Volatility
Year
Normal Distribution
Student-t Distribution
2003
2005
2007
2009
2011
2014
-0.5
0.0
0.5
1.0


NZD vs TWD
SGD vs CHF
SGD vs CNY
SGD vs HKD
SGD vs IDR
SGD vs MYR
SGD vs TWD
USD vs CHF
USD vs CNY
USD vs GBP
USD vs HKD
USD vs IDR
Volatility
-0.5
0.0
0.5
1.0
Normal Distribution
Student-t Distribution
2003
2005
2007
2009
2011
2014
Year

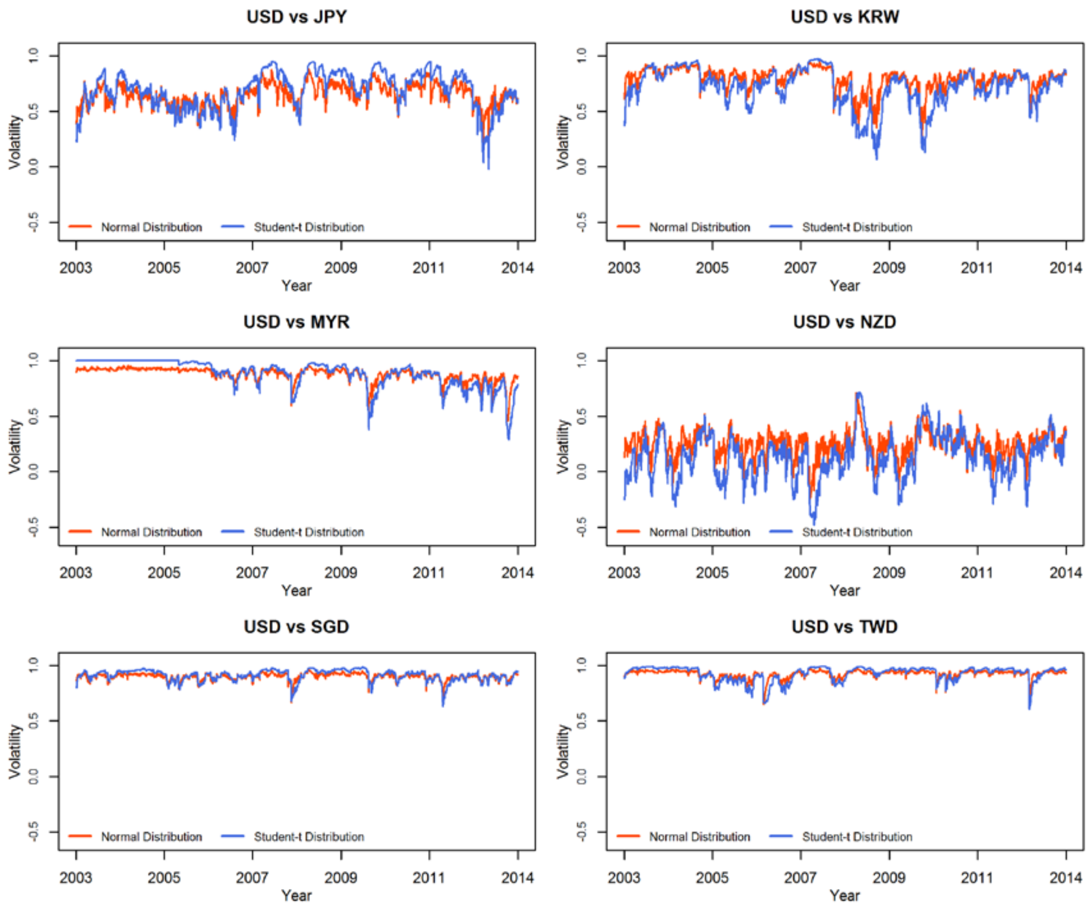
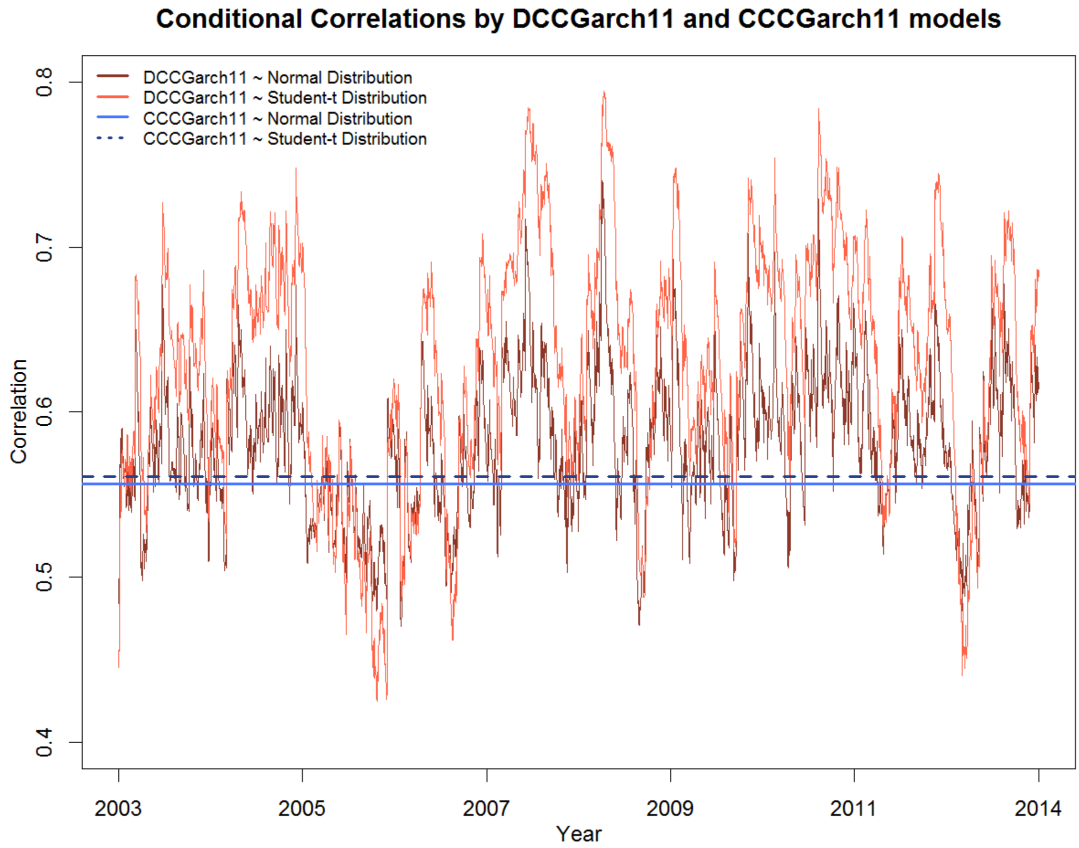


Figure 4.6 presents the dynamic conditional correlations for all 66 pairs of currencies. Each currency pair shows the different and dynamic structure of conditional correlations over the entire forecasting period, thereby suggesting that the assumption of constant conditional correlations may not be appropriate. This result is in line with the other empirical studies, see, for examples, Longin and Solnik (1995), Tse (2000), and Nakatani and Teräsvirta (2009). Similarly, all currency pairs exhibit positive time-varying conditional correlations. However, the conditional correlations assuming student-t distribution are smoother than those obtained under the normal distribution. While, a constant perfect positive correlation is given by USD vs HKD since the currency pair is pegged. Nevertheless, most currency pairs show sharp declines in conditional correlations during the periods of GFC, from 2008 to 2009.

Figure 4.7 Conditional Correlations for the Equally-weighted Portfolio



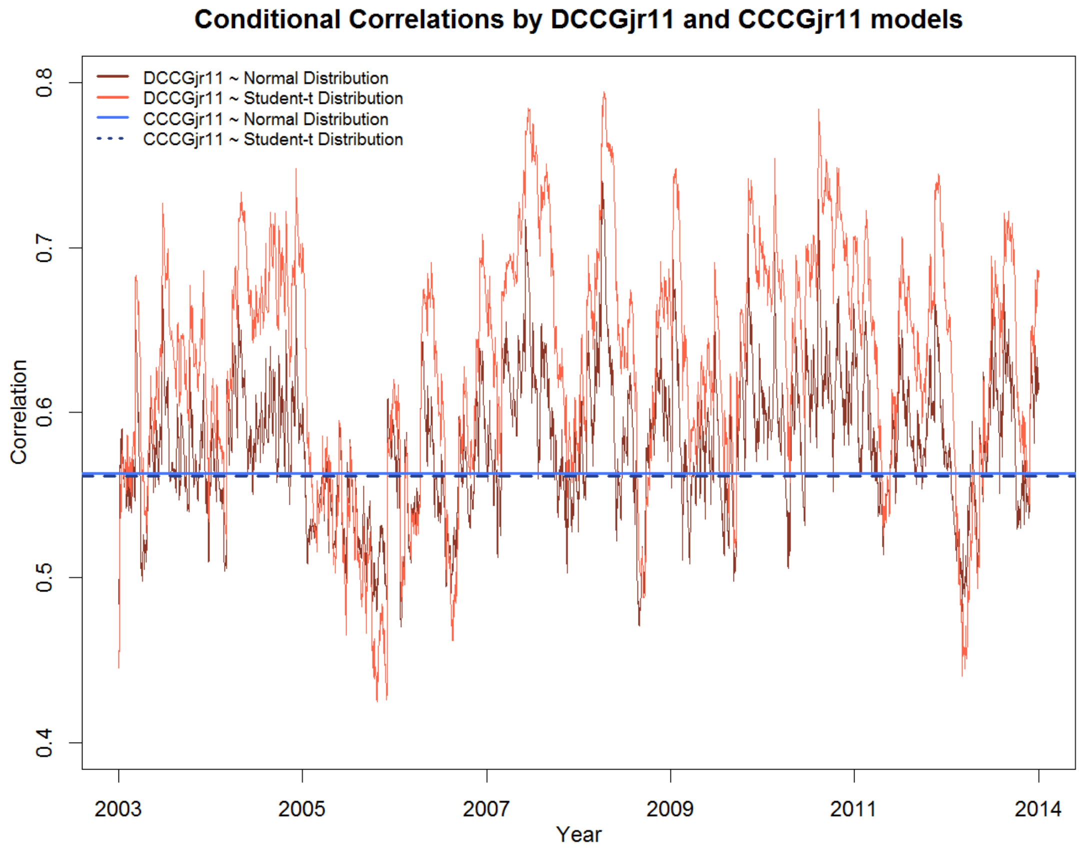


Figure 4.7 shows the conditional correlations for the equally-weighted portfolio derived from CCC and DCC models that follow GARCH(1,1) and GJR(1,1) processes. It can be seen that the portfolio exhibits positive conditional correlations. On average, the CCC conditional correlation is constantly estimated at 0.56. While, DCC conditional correlations are very erratic. The empirical evidence suggests that the conditional correlation is not constant over time which justifies the use of a model such as DCC to capture the time-varying conditional correlation structures in foreign exchange returns.

Figure 4.8 plots the conditional variances for the equally-weighted portfolio derived from CCC-GARCH(1,1), CCC-GJR(1,1), DCC-GARCH(1,1), and DCC-GJR(1,1) models. All models show similar dynamics of volatility. The GFC has a pronounced effect on the volatility of the portfolio returns, where a significant spike can be seen in the year 2008. Likewise, the level of volatility by DCC model displays a higher magnitude of 8 compared to CCC model at a magnitude of 6 during the GFC.

Figure 4.8 Conditional Variances for the Equally-weighted Portfolio

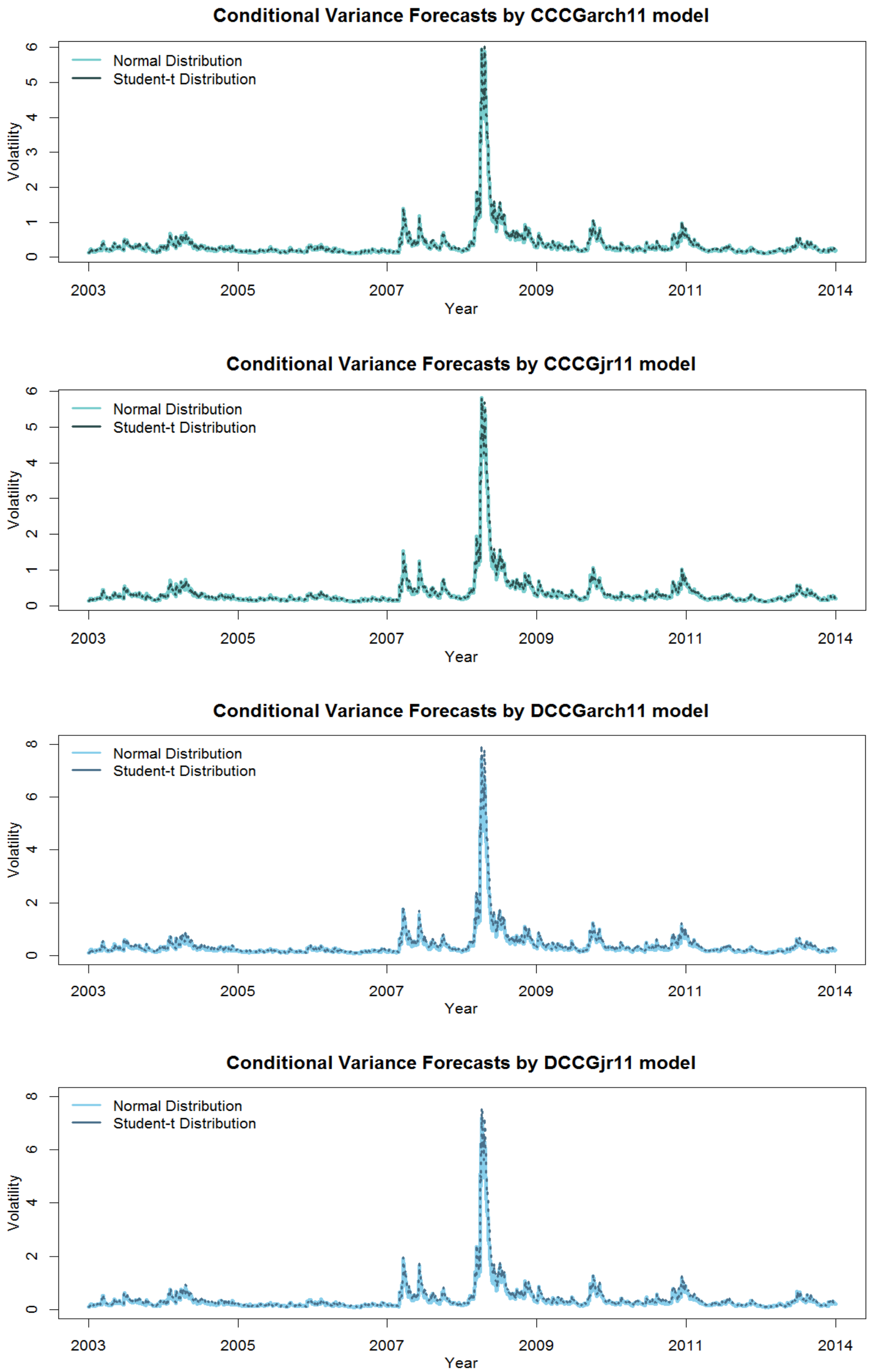


Table 4.13 VaR Forecasts at 1% level

Model	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	-1.2943 (1)	-1.1560	-5.6650	-0.7386	0.5336
$\widehat{VaR}_{norm}^{CCCGJR-N}$	-1.2956 (1)	-1.1520	-5.6090	-0.7479	0.5386
$\widehat{VaR}_{std}^{CCCGARCH-N}$	-1.5071 (2)	-1.3460	-6.5960	-0.8601	0.6214
$\widehat{VaR}_{std}^{CCCGJR-N}$	-1.5072 (2)	-1.3400	-6.5250	-0.8700	0.6265
$\widehat{VaR}_{std_\eta}^{CCCGARCH-N}$	-1.4636 (3)	-1.3060	-6.4560	-0.7665	0.6098
$\widehat{VaR}_{std_\eta}^{CCCGJR-N}$	-1.4635 (3)	-1.2980	-6.3890	-0.7811	0.6150
$\widehat{VaR}_{std}^{CCCGARCH-t}$	-1.5199 (4)	-1.3560	-6.5840	-0.8696	0.6287
$\widehat{VaR}_{std}^{CCCGJR-t}$	-1.5179 (4)	-1.3500	-6.4680	-0.8738	0.6326
$\widehat{VaR}_{std_\eta}^{CCCGARCH-t}$	-1.4877 (5)	-1.3250	-6.4870	-0.7814	0.6230
$\widehat{VaR}_{std_\eta}^{CCCGJR-t}$	-1.4853 (5)	-1.3200	-6.3890	-0.7860	0.6271
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	-1.3336 (1)	-1.1860	-6.3490	-0.7172	0.5896
$\widehat{VaR}_{norm}^{DCCGJR-N}$	-1.3353 (1)	-1.1800	-6.2380	-0.7264	0.5952
$\widehat{VaR}_{std}^{DCCGARCH-N}$	-1.5148 (2)	-1.3470	-7.2110	-0.8146	0.6697
$\widehat{VaR}_{std}^{DCCGJR-N}$	-1.5166 (2)	-1.3400	-7.0850	-0.8250	0.6761
$\widehat{VaR}_{std_\eta}^{DCCGARCH-N}$	-1.5080 (3)	-1.3370	-7.2360	-0.7530	0.6732
$\widehat{VaR}_{std_\eta}^{DCCGJR-N}$	-1.5085 (3)	-1.3310	-7.1050	-0.7654	0.6792
$\widehat{VaR}_{std}^{DCCGARCH-t}$	-1.6029 (4)	-1.4300	-7.4590	-0.7922	0.7249
$\widehat{VaR}_{std}^{DCCGJR-t}$	-1.6001 (4)	-1.4200	-7.2630	-0.8075	0.7288
$\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$	-1.5929 (5)	-1.4200	-7.4760	-0.7818	0.7286
$\widehat{VaR}_{std_\eta}^{DCCGJR-t}$	-1.5891 (5)	-1.4110	-7.2800	-0.7931	0.7324

(1) VaR forecasts are estimated from equation (4.6) based on a normal distribution

(2) VaR forecasts are estimated from equation (4.6) based on a normal distribution at the degrees of freedom set by t-density

(3) VaR forecasts are estimated from equation (4.6) based on a normal distribution at rolling degrees of freedom set by t-density

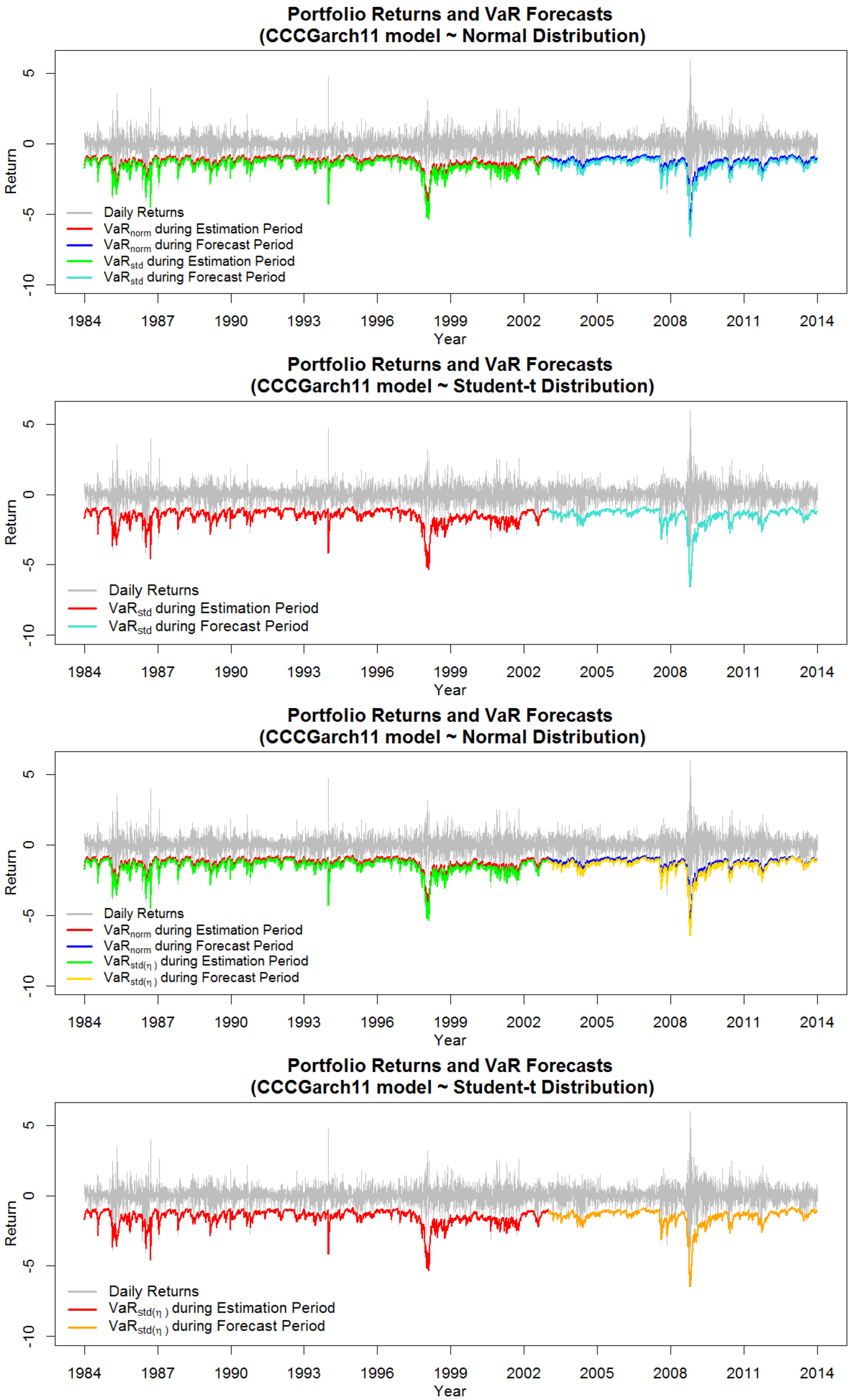
(4) VaR forecasts are estimated from equation (4.6) based on a student-t distribution at the degrees of freedom set by t-density

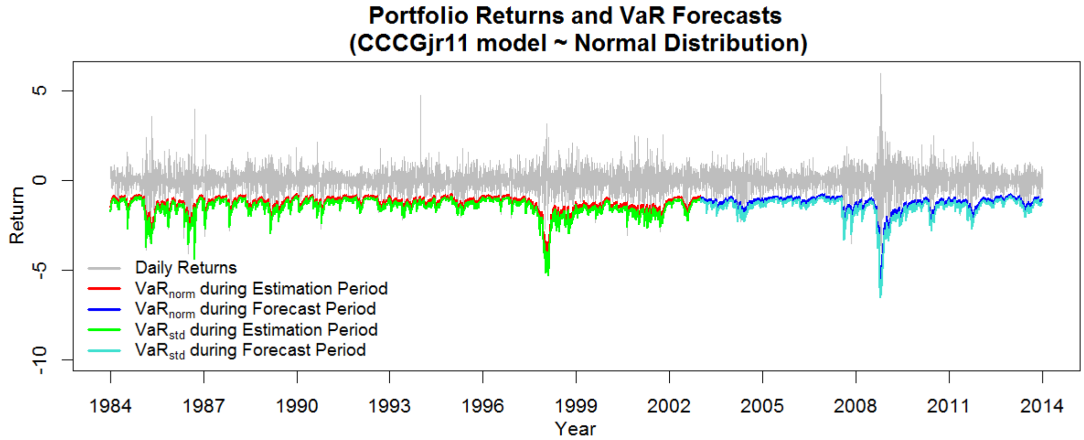
(5) VaR forecasts are estimated from equation (4.6) based on a student-t distribution at rolling degrees of freedom set by t-density

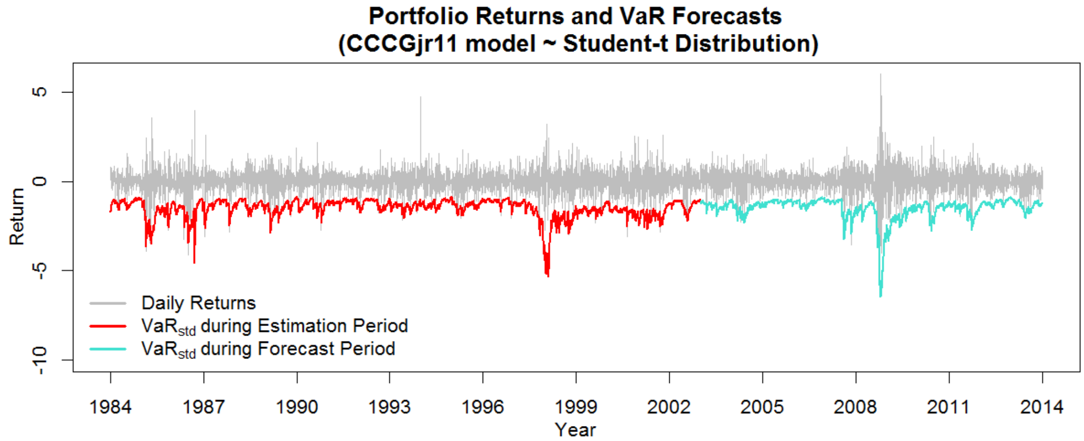
Table 4.13 summarizes the results for the 20 sets of VaR forecasts estimated by the CCC and DCC models. The means of VaR forecasts for the CCC and DCC models that utilized under student-t distribution appear to be lower than the means of VaR forecasts for the CCC and DCC models under the normal distribution. Hence, the student-t distribution provides more conservative VaR forecasts than a normal distribution. It can also be seen that the means of VaR forecasts estimated by the DCC models are mostly lower than the means of VaR forecasts estimated by the CCC models. In particular, $\widehat{VaR}_{std}^{DCCGARCH-t}$ shows the lowest mean of VaR forecasts at -1.6029 while $\widehat{VaR}_{norm}^{CCCGARCH-N}$ shows the highest mean of VaR forecasts at -1.2943. Hence, VaR forecasts estimated by the DCC models are crucial to improving the performance of VaR forecasts to accommodate the dynamic conditional correlations among foreign exchange returns.

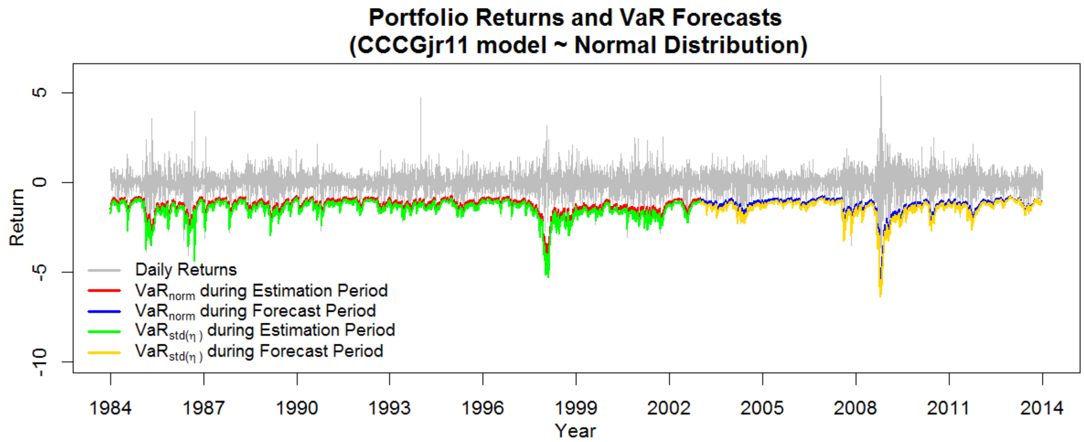
The time series of the daily portfolio returns together with VaR forecasts estimated by the CCC and DCC models are illustrated in Figure 4.9. It can be seen that the VaR forecasts based on student-t distribution are lower than the VaR forecasts based on normal distribution. The significant spikes of the portfolio returns indicated the events at which high volatility occurred, particularly in the periods from 1985 to 1987, from 1992 to 1994, from 1998 to 2000, from 2001 to 2002, and from 2008 to 2009 due to the US stock market crashes, EMS crisis, 9/11 events, Asian currency crisis and GFC, respectively.

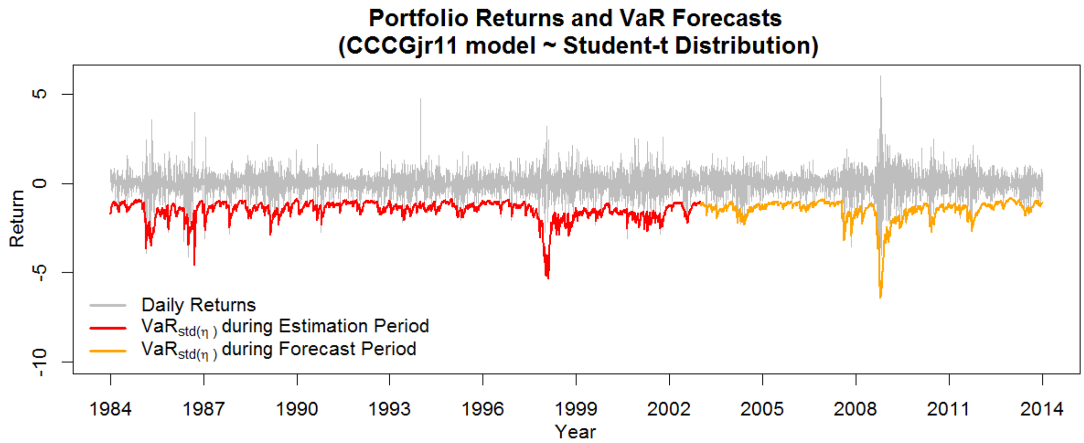
Figure 4.9 Portfolio Returns and VaR Forecasts at 1% Level

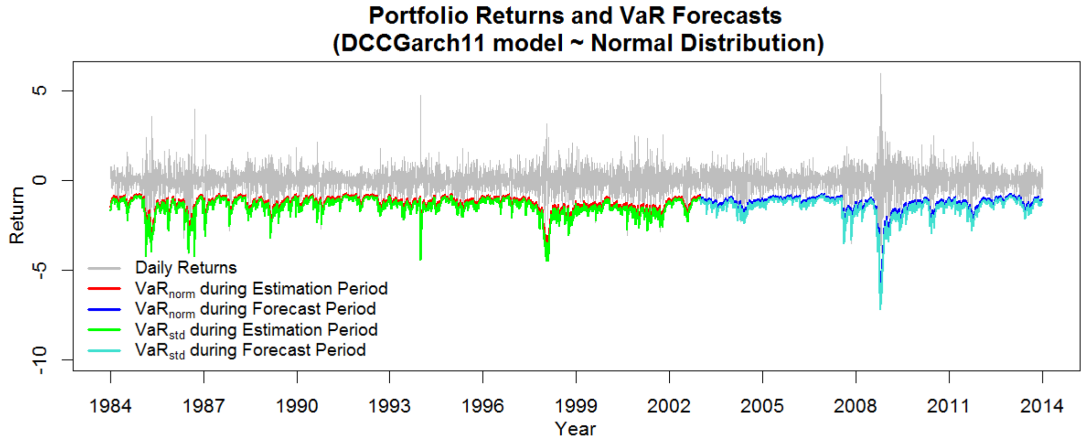


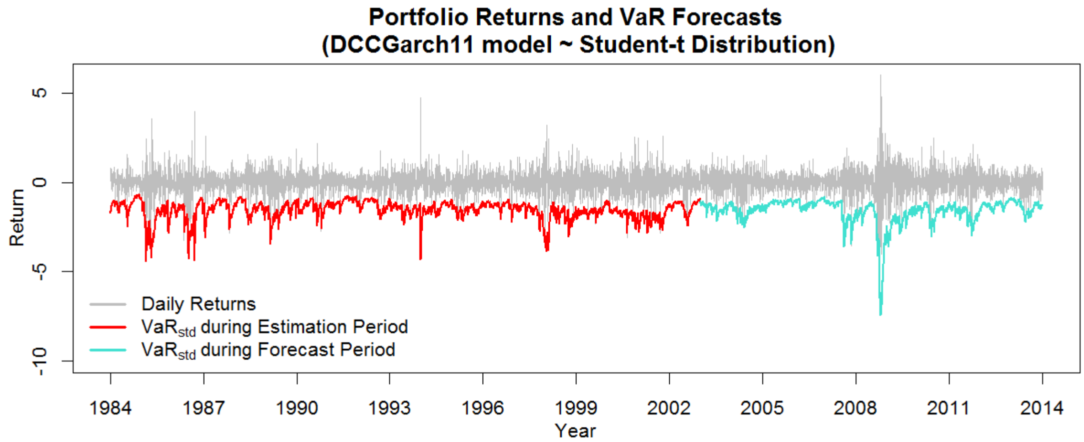

Portfolio Returns and VaR Forecasts
(CCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR_{norm} during Estimation Period
VaR_{norm} during Forecast Period
VaR_{std} during Estimation Period
VaR_{std} during Forecast Period
1984 1987 1990 1993 1996 1999 2002 2005 2008 2011 2014
Year

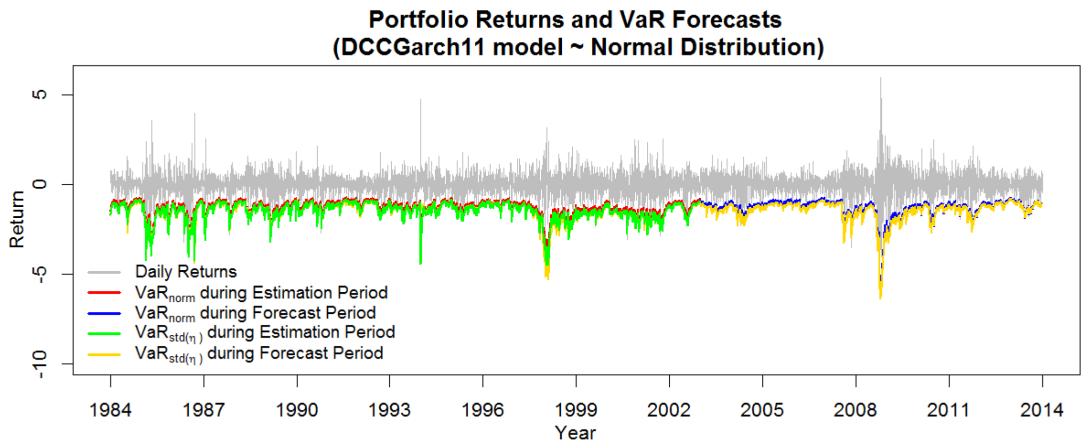

Portfolio Returns and VaR Forecasts
(CCCGjr11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
VaR_{std} during Estimation Period
VaR_{std} during Forecast Period
1984 1987 1990 1993 1996 1999 2002 2005 2008 2011 2014
Year

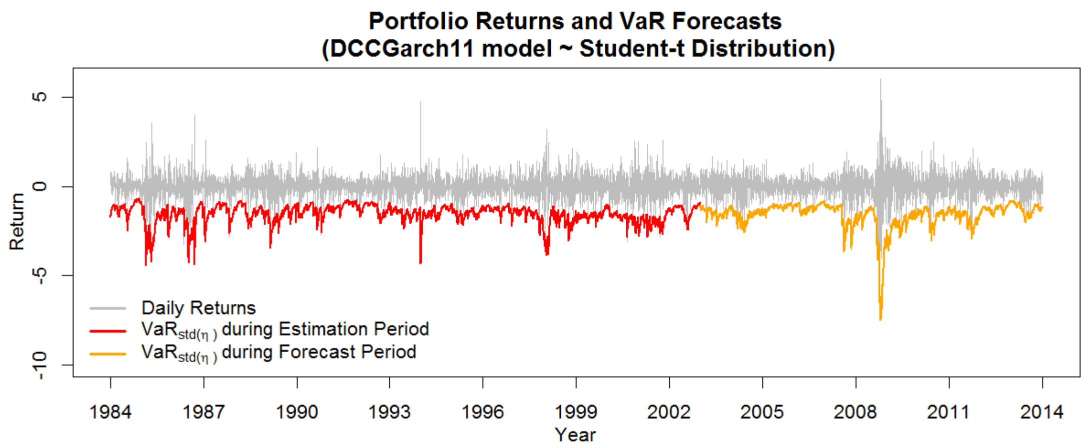

Portfolio Returns and VaR Forecasts
(CCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR_{norm} during Estimation Period
VaR_{norm} during Forecast Period
$VaR_{std(\eta)}$ during Estimation Period
$VaR_{std(\eta)}$ during Forecast Period
1984 1987 1990 1993 1996 1999 2002 2005 2008 2011 2014
Year

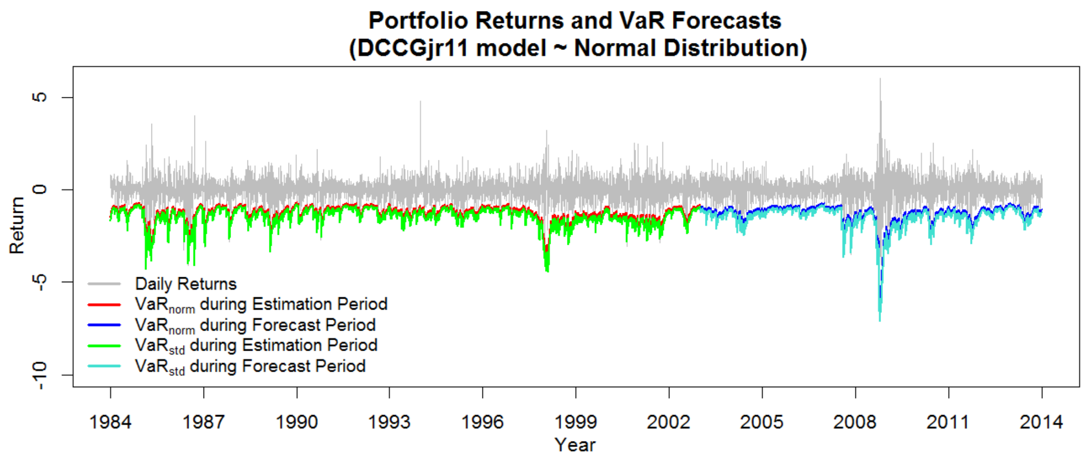

Portfolio Returns and VaR Forecasts
(CCCGjr11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
$VaR_{std(\eta)}$ during Estimation Period
$VaR_{std(\eta)}$ during Forecast Period
1984 1987 1990 1993 1996 1999 2002 2005 2008 2011 2014
Year

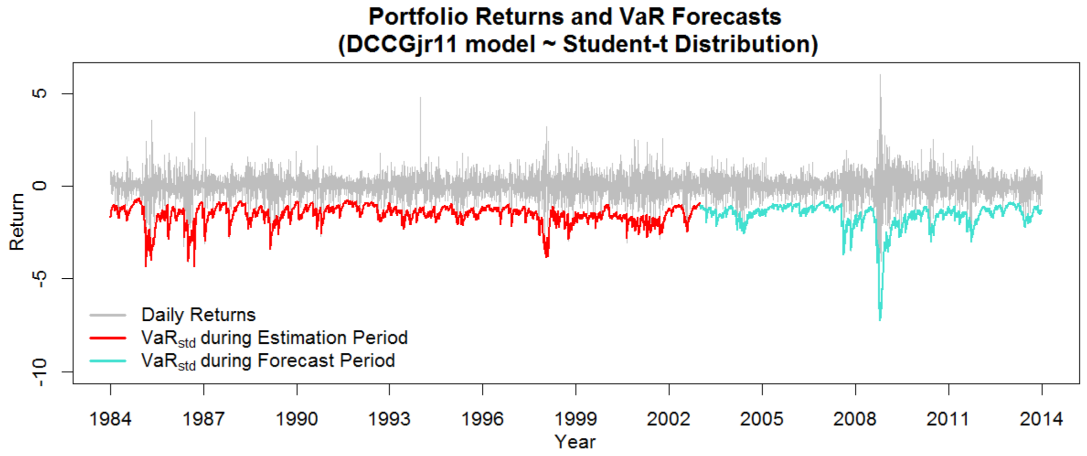

Portfolio Returns and VaR Forecasts
(DCCGarch11 model ~ Normal Distribution)
Return
Year
Daily Returns
VaR_{norm} during Estimation Period
VaR_{norm} during Forecast Period
VaR_{std} during Estimation Period
VaR_{std} during Forecast Period

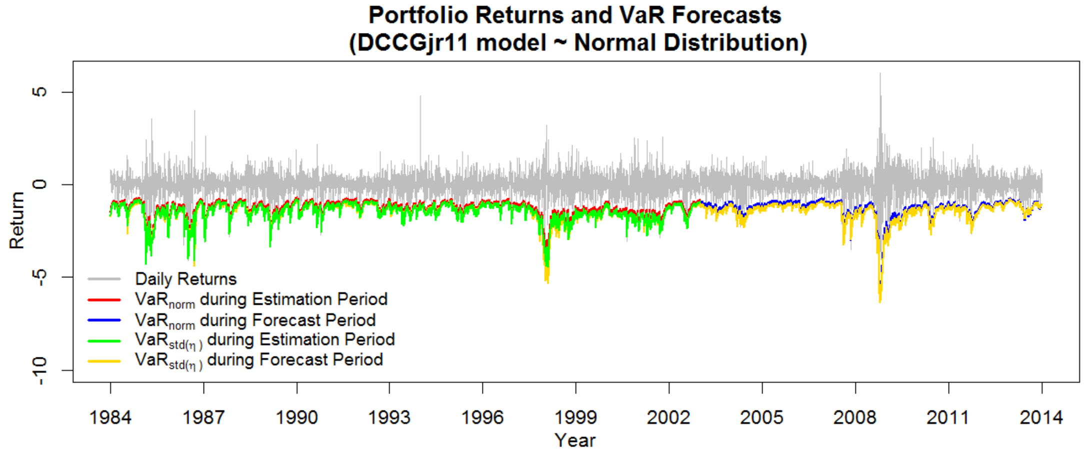

Portfolio Returns and VaR Forecasts
(DCCGarch11 model ~ Student-t Distribution)
Return
Year
Daily Returns
VaR_{std} during Estimation Period
VaR_{std} during Forecast Period


Portfolio Returns and VaR Forecasts
(DCCGarch11 model ~ Normal Distribution)
Return
Year
Daily Returns
VaR_{norm} during Estimation Period
VaR_{norm} during Forecast Period
$VaR_{std(\eta)}$ during Estimation Period
$VaR_{std(\eta)}$ during Forecast Period


Portfolio Returns and VaR Forecasts
(DCCGarch11 model ~ Student-t Distribution)
Return
Year
Daily Returns
$VaR_{std(\eta)}$ during Estimation Period
$VaR_{std(\eta)}$ during Forecast Period


Portfolio Returns and VaR Forecasts
(DCCGjr11 model ~ Normal Distribution)
Return
Year
Daily Returns
VaR_{norm} during Estimation Period
VaR_{norm} during Forecast Period
VaR_{std} during Estimation Period
VaR_{std} during Forecast Period


Portfolio Returns and VaR Forecasts
(DCCGjr11 model ~ Student-t Distribution)
Return
Year
Daily Returns
VaR_{std} during Estimation Period
VaR_{std} during Forecast Period


Portfolio Returns and VaR Forecasts
(DCCGjr11 model ~ Normal Distribution)
Return
Year
Daily Returns
VaR_{norm} during Estimation Period
VaR_{norm} during Forecast Period
$VaR_{std(\eta)}$ during Estimation Period
$VaR_{std(\eta)}$ during Forecast Period

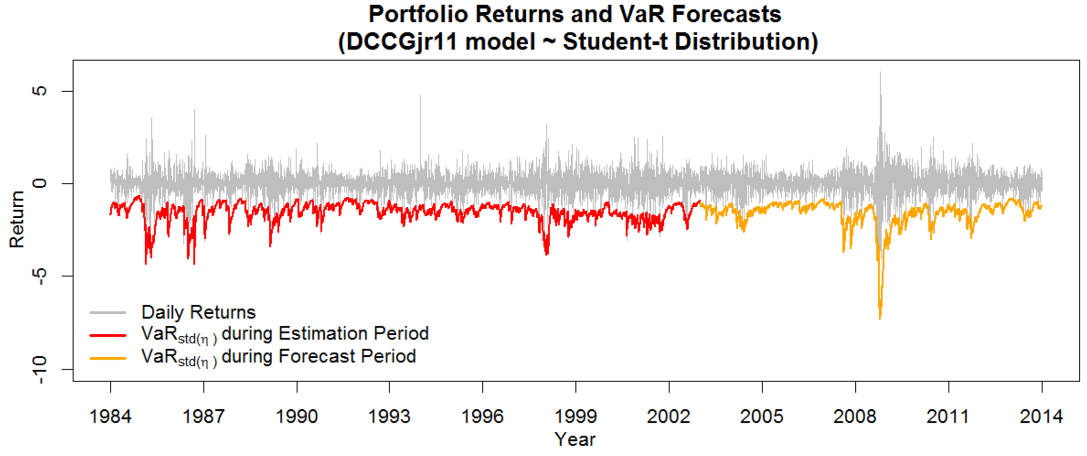

Portfolio Returns and VaR Forecasts
(DCCGjr11 model ~ Student-t Distribution)
Return
Year
Daily Returns
$VaR_{std(\eta)}$ during Estimation Period
$VaR_{std(\eta)}$ during Forecast Period

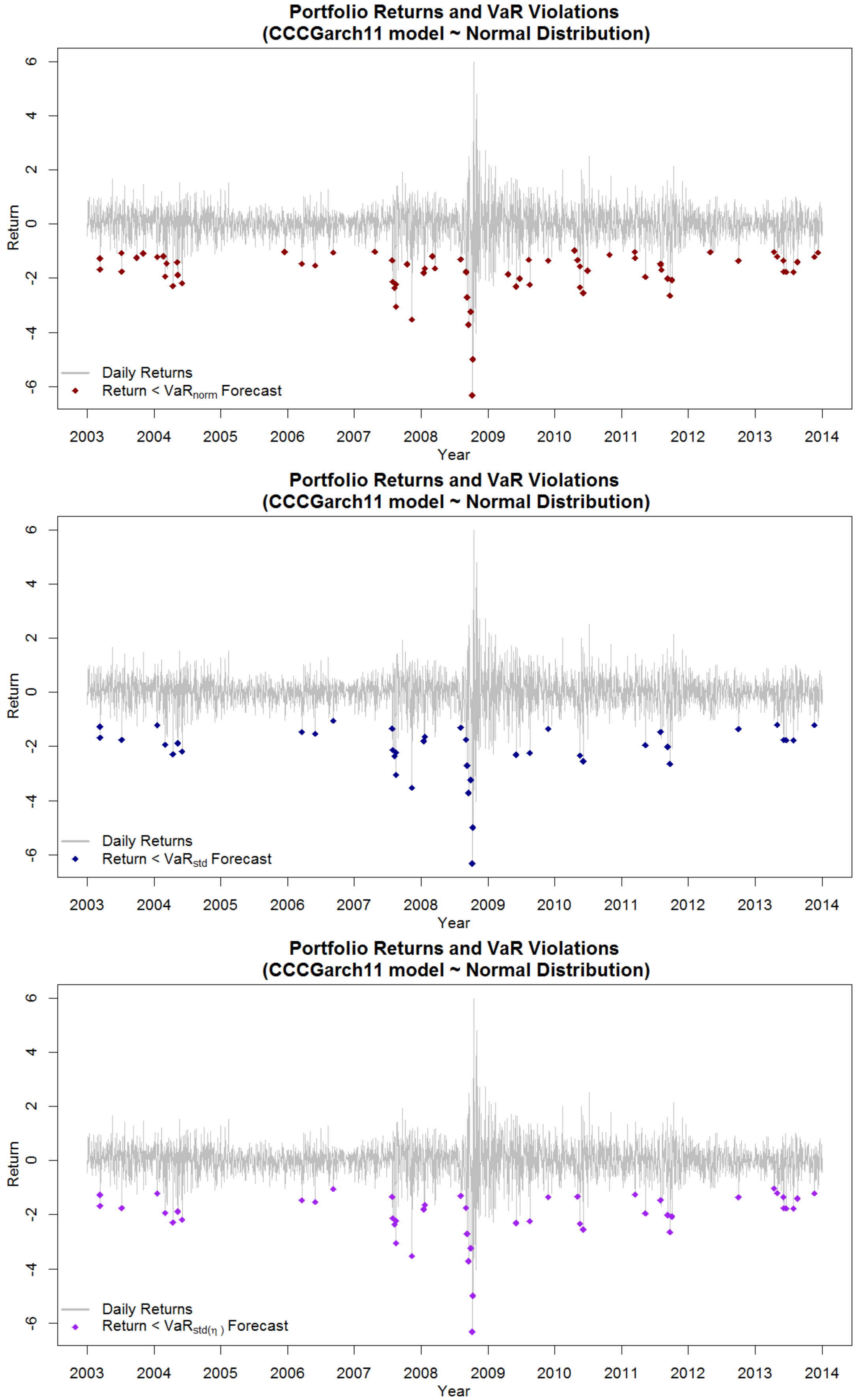
Table 4.14 Number and Percentage of Violations for VaR Forecasts at 1% Level

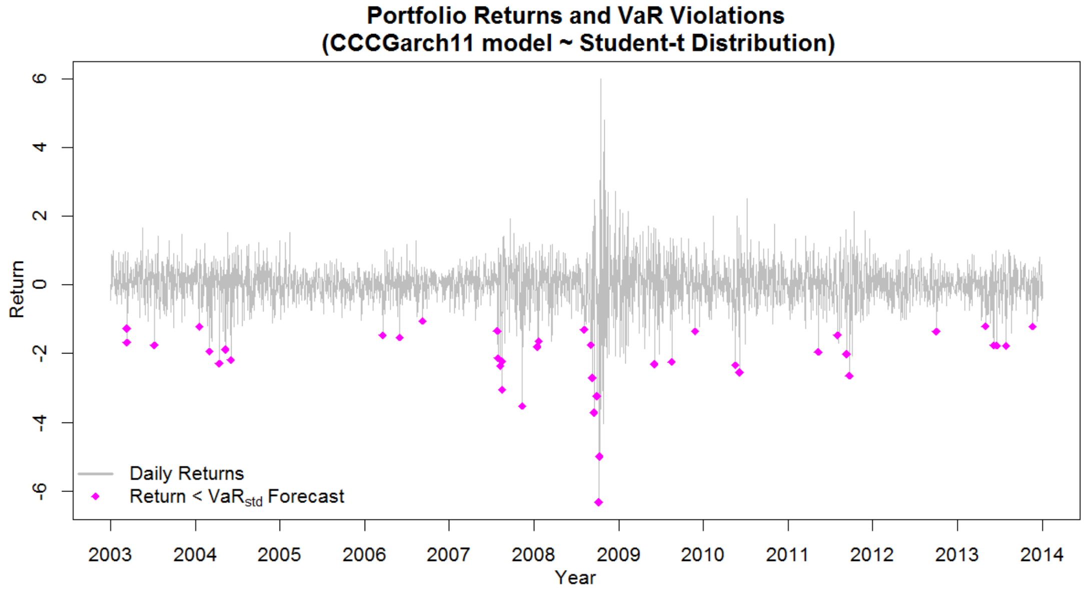
Model	No. of Violation	% of Violation	Ranking
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	71	2.47%	20
$\widehat{VaR}_{norm}^{CCCGJR-N}$	69	2.40%	19
$\widehat{VaR}_{std}^{CCCGARCH-N}$	41	1.43%	8
$\widehat{VaR}_{std}^{CCCGJR-N}$	39	1.36%	5
$\widehat{VaR}_{std_\eta}^{CCCGARCH-N}$	47	1.64%	16
$\widehat{VaR}_{std_\eta}^{CCCGJR-N}$	45	1.57%	12
$\widehat{VaR}_{std}^{CCCGARCH-t}$	41	1.43%	8
$\widehat{VaR}_{std}^{CCCGJR-t}$	40	1.39%	7
$\widehat{VaR}_{std_\eta}^{CCCGARCH-t}$	45	1.57%	12
$\widehat{VaR}_{std_\eta}^{CCCGJR-t}$	45	1.57%	12
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	68	2.37%	18
$\widehat{VaR}_{norm}^{DCCGJR-N}$	64	2.23%	17
$\widehat{VaR}_{std}^{DCCGARCH-N}$	41	1.43%	8
$\widehat{VaR}_{std}^{DCCGJR-N}$	39	1.36%	5
$\widehat{VaR}_{std_\eta}^{DCCGARCH-N}$	41	1.43%	8
$\widehat{VaR}_{std_\eta}^{DCCGJR-N}$	41	1.43%	8
$\widehat{VaR}_{std}^{DCCGARCH-t}$	35	1.22%	2
$\widehat{VaR}_{std}^{DCCGJR-t}$	33	1.15%	1
$\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$	37	1.29%	4
$\widehat{VaR}_{std_\eta}^{DCCGJR-t}$	35	1.22%	2

Table 4.14 reports the number and percentage of violations for VaR forecasts. The ranking starts from 1 is the best model, i.e., the model that correctly forecasts market risk, and 20 is the worst model with a percentage of violation more than one percent, i.e., the model that underestimates market risk. High percentages of violations for $\widehat{VaR}_{norm}^{CCCGARCH-N}$ and $\widehat{VaR}_{norm}^{CCCGJR-N}$ are given at 2.47% and 2.40%, respectively. Similarly, $\widehat{VaR}_{norm}^{DCCGARCH-N}$ and $\widehat{VaR}_{norm}^{DCCGJR-N}$ present high percentages of violations at 2.37% and 2.23%, respectively. The best model is given by $\widehat{VaR}_{std}^{DCCGJR-t}$ at 1.15%, followed by $\widehat{VaR}_{std}^{DCCGARCH-t}$ and $\widehat{VaR}_{std_{\eta}}^{DCCGJR-t}$ at 1.22%. The highest percentage of violations at the lowest ranking is given by $\widehat{VaR}_{norm}^{CCCGARCH-N}$ at 2.47%. It is worth noting that among the student-distribution models, the DCC models are preferred to the CCC models with the DCC models present the percentages of VaR violations that are closer to one percent.

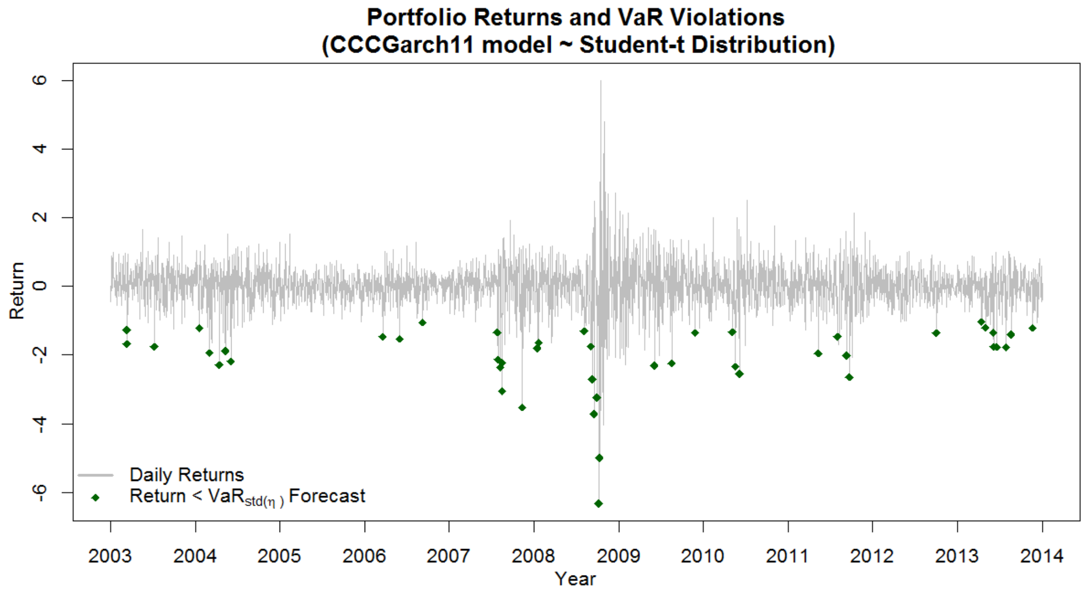
Figure 4.10 shows the time series of the daily portfolio returns during the forecast period and the time at which VaR violations occurred. A violation is recorded when an actual loss exceeds the VaR forecast. The episodes of VaR violations are often centralized during the periods of high volatility. The events of VaR violations under student-t distribution always give fewer violations than VaR violations under the normal distribution.

Figure 4.10 Portfolio Returns and VaR Violations

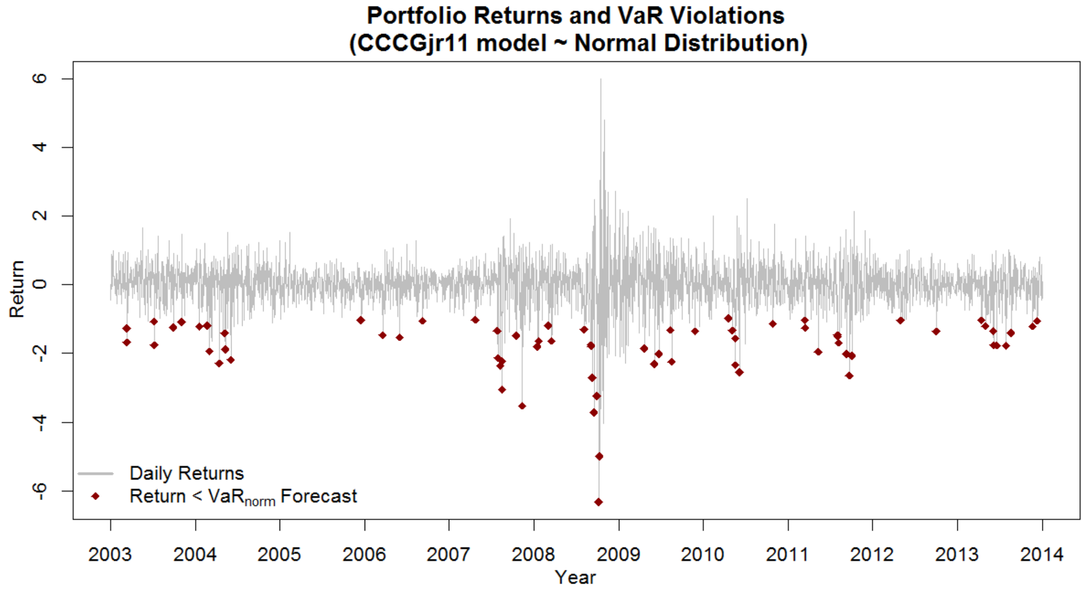


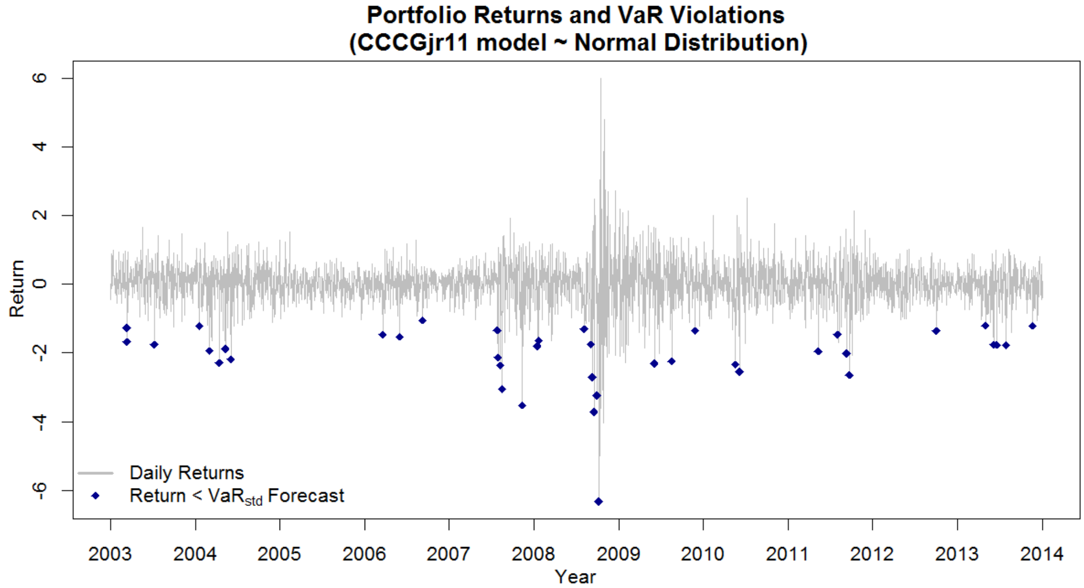


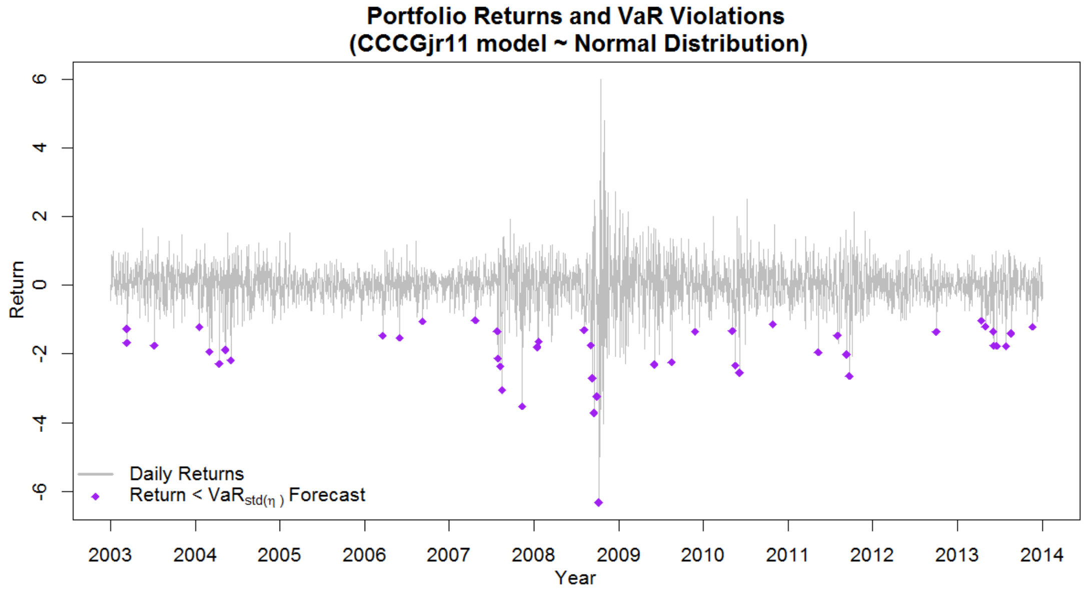
Portfolio Returns and VaR Violations
(CCCGarch11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd Forecast
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

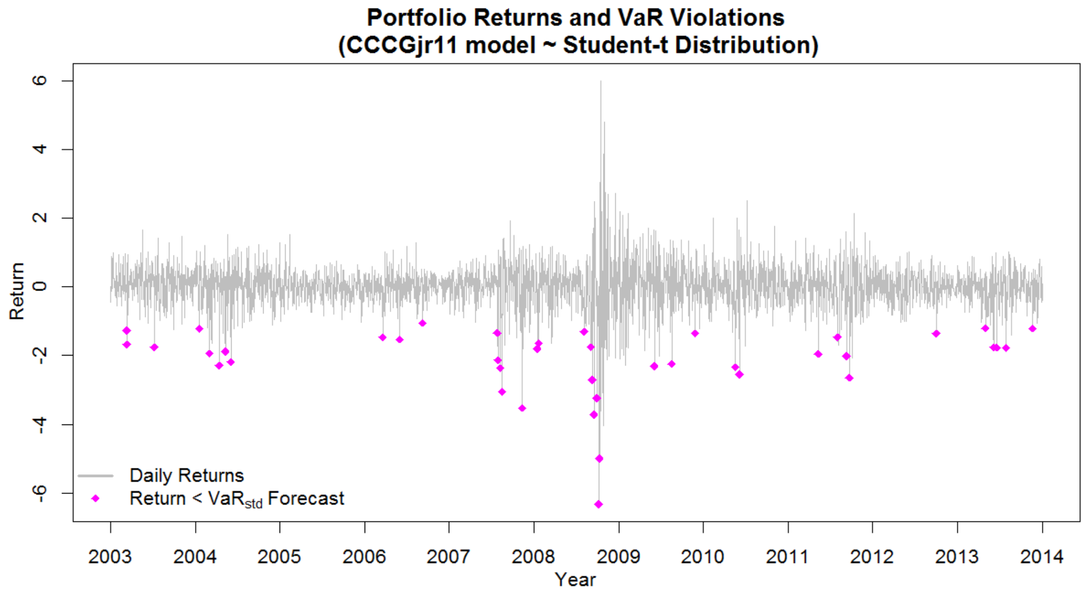


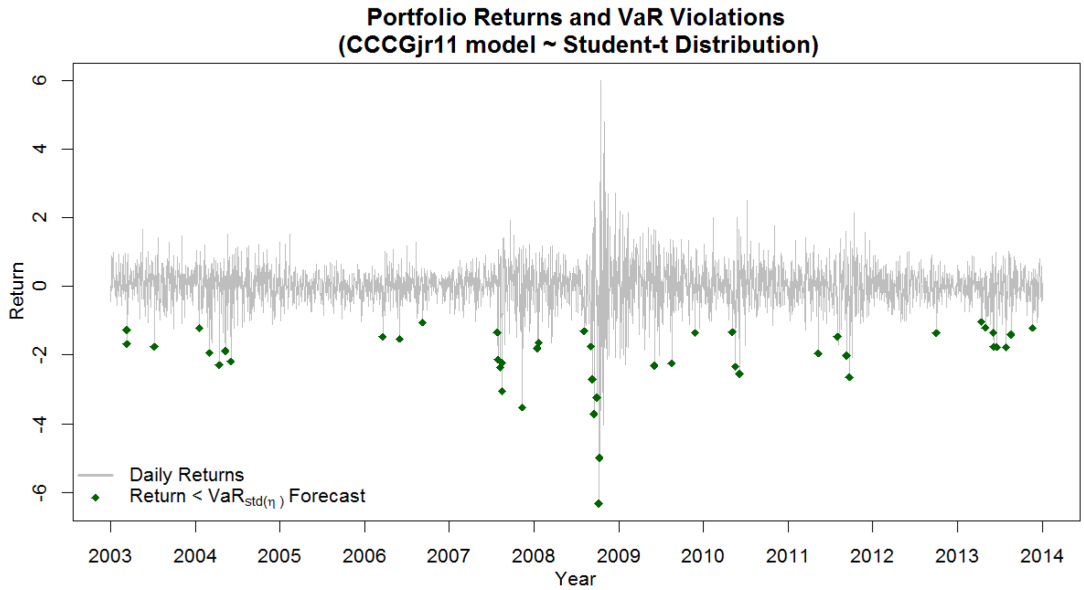
Portfolio Returns and VaR Violations
(CCCGarch11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd(η) Forecast
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

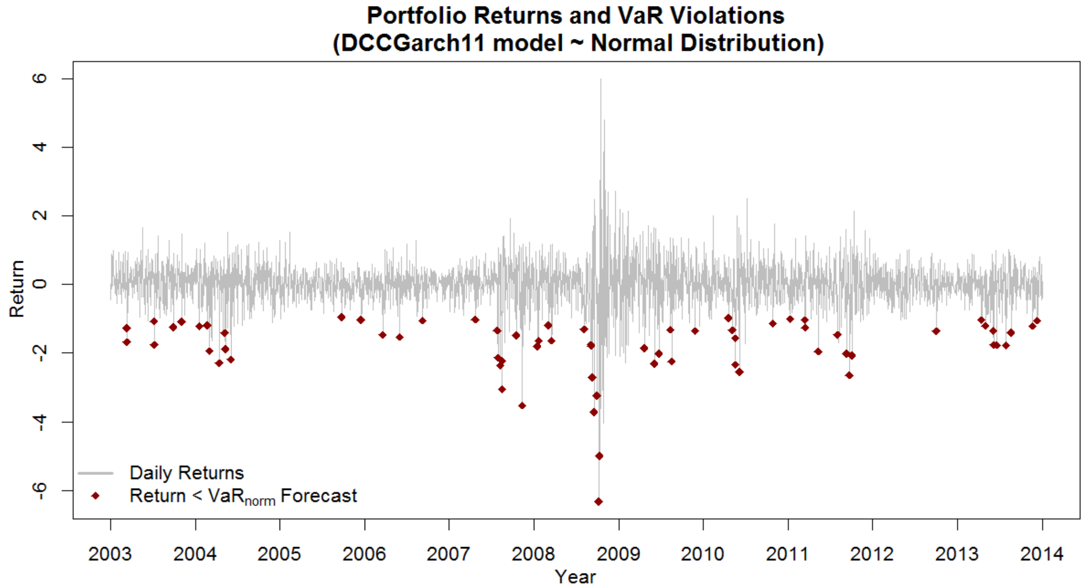

Portfolio Returns and VaR Violations
(CCCGjr11 model ~ Normal Distribution)
Return
Year
Daily Returns
Return < VaR_{norm} Forecast


Portfolio Returns and VaR Violations
(CCCGjr11 model ~ Normal Distribution)
Return
Year
Daily Returns
Return < VaR_{std} Forecast

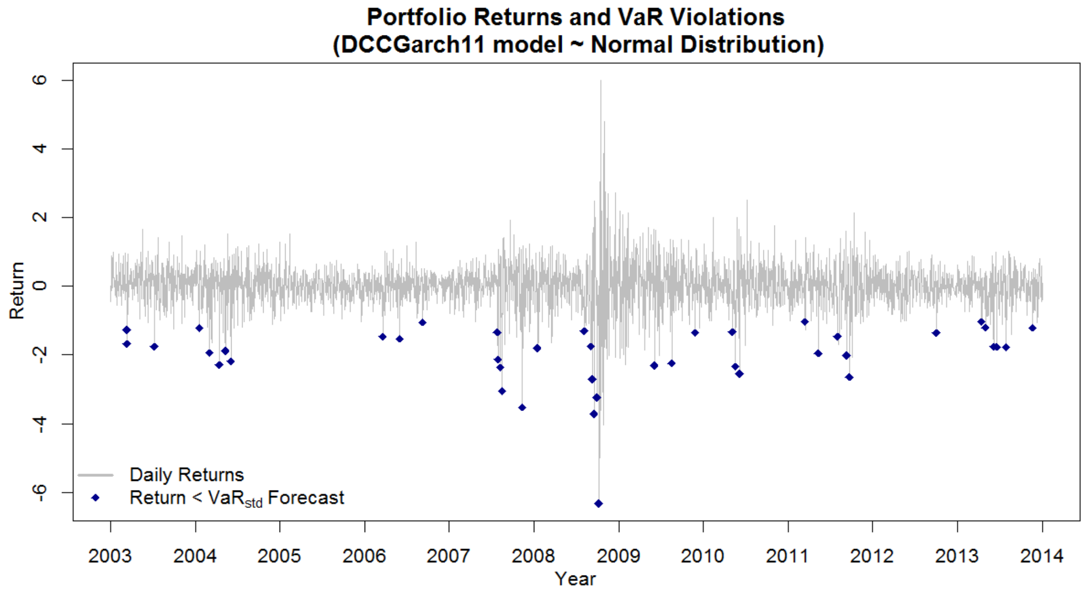

Portfolio Returns and VaR Violations
(CCCGjr11 model ~ Normal Distribution)
Return
Year
Daily Returns
Return < $VaR_{std(\eta)}$ Forecast


Portfolio Returns and VaR Violations
(CCCGjr11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd Forecast

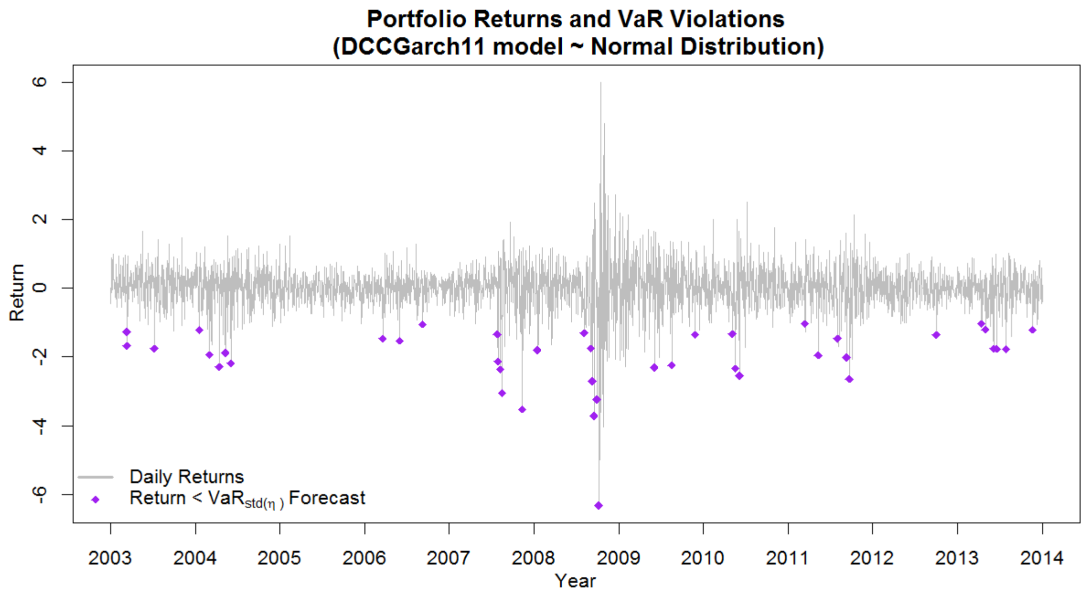

Portfolio Returns and VaR Violations
(CCCGjr11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd(η) Forecast



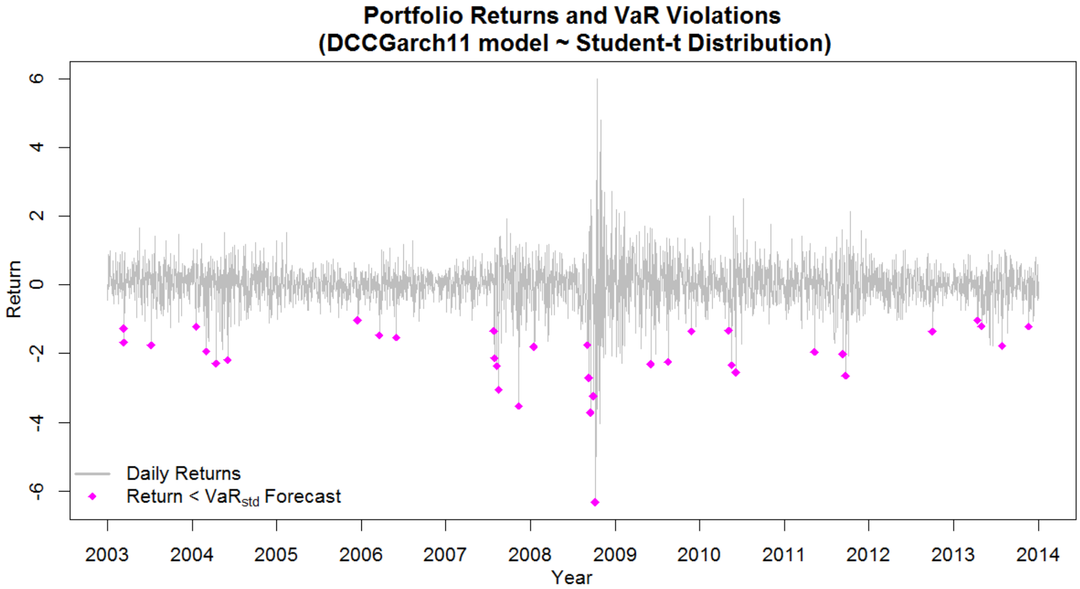
Portfolio Returns and VaR Violations
(DCCGarch11 model ~ Normal Distribution)
Return
Year
Daily Returns
Return < VaR$_{norm}$ Forecast
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

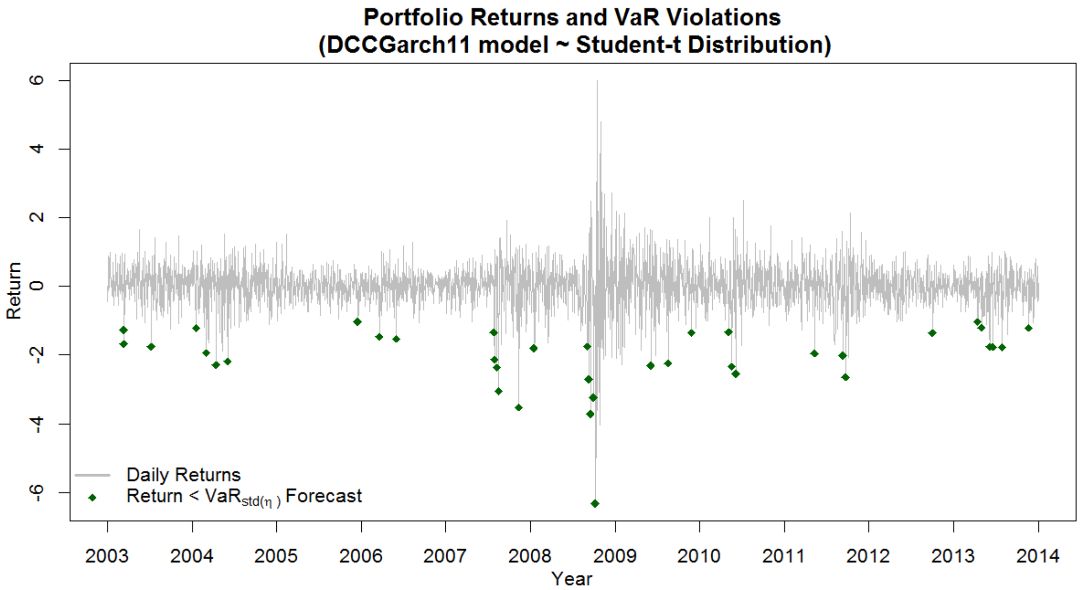


Portfolio Returns and VaR Violations
(DCCGarch11 model ~ Normal Distribution)
Return
Year
Daily Returns
Return < VaR$_{std}$ Forecast
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

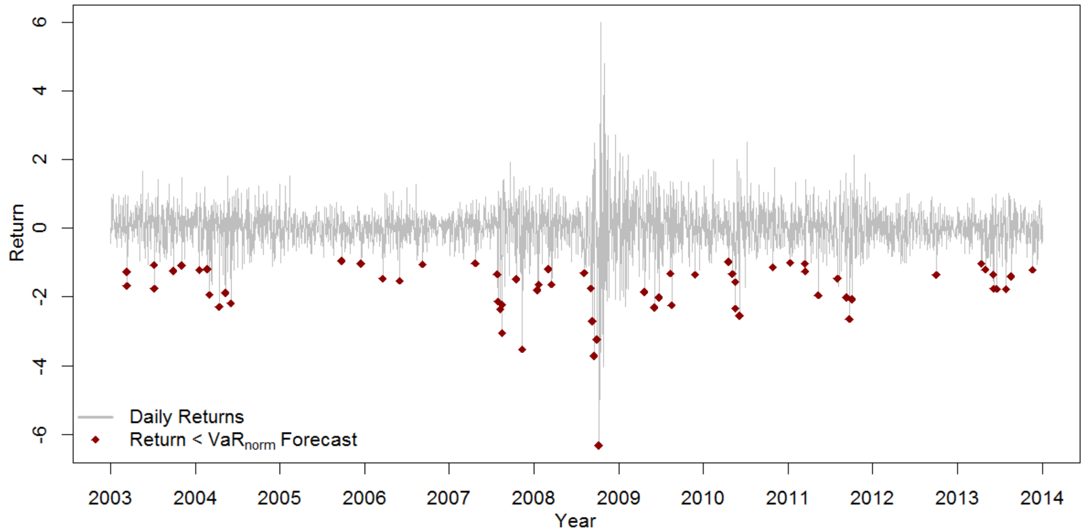


Portfolio Returns and VaR Violations
(DCCGarch11 model ~ Normal Distribution)
Return
Year
Daily Returns
Return < VaR$_{std(\eta)}$ Forecast
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

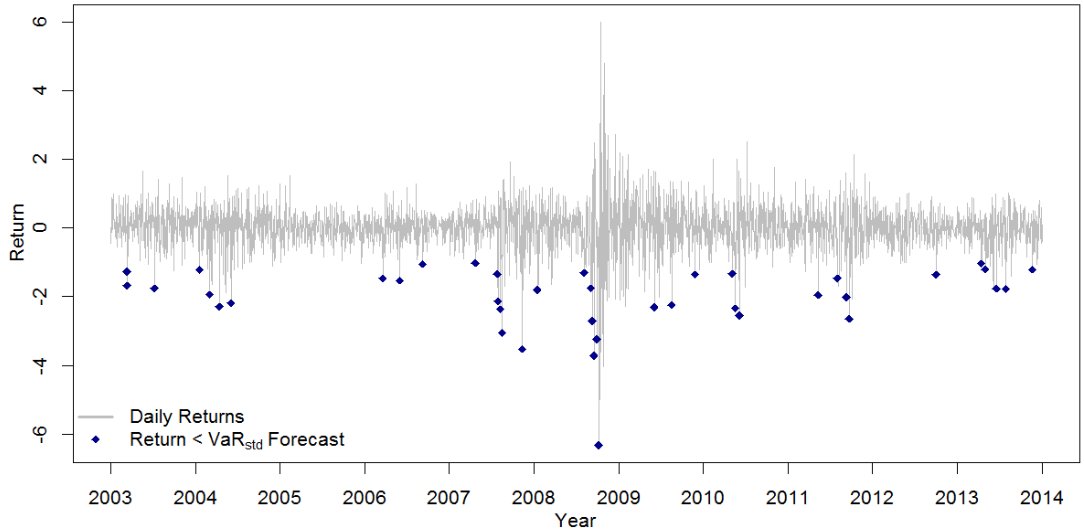

Portfolio Returns and VaR Violations
(DCCGarch11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd Forecast
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014
6 4 2 0 -2 -4 -6


Portfolio Returns and VaR Violations
(DCCGarch11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd(η) Forecast
2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014
6 4 2 0 -2 -4 -6

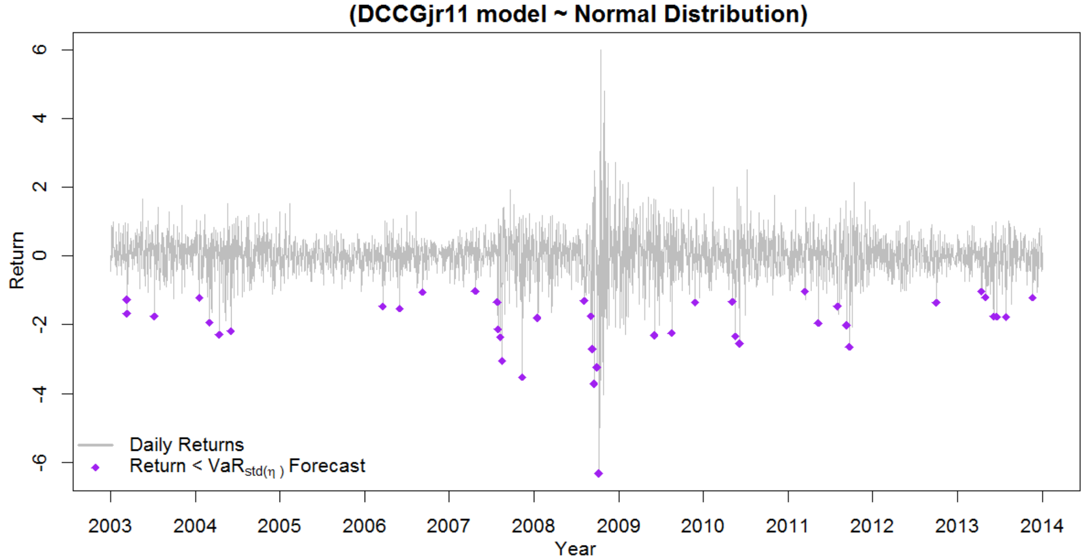
**Portfolio Returns and VaR Violations
(DCCGjr11 model ~ Normal Distribution)**

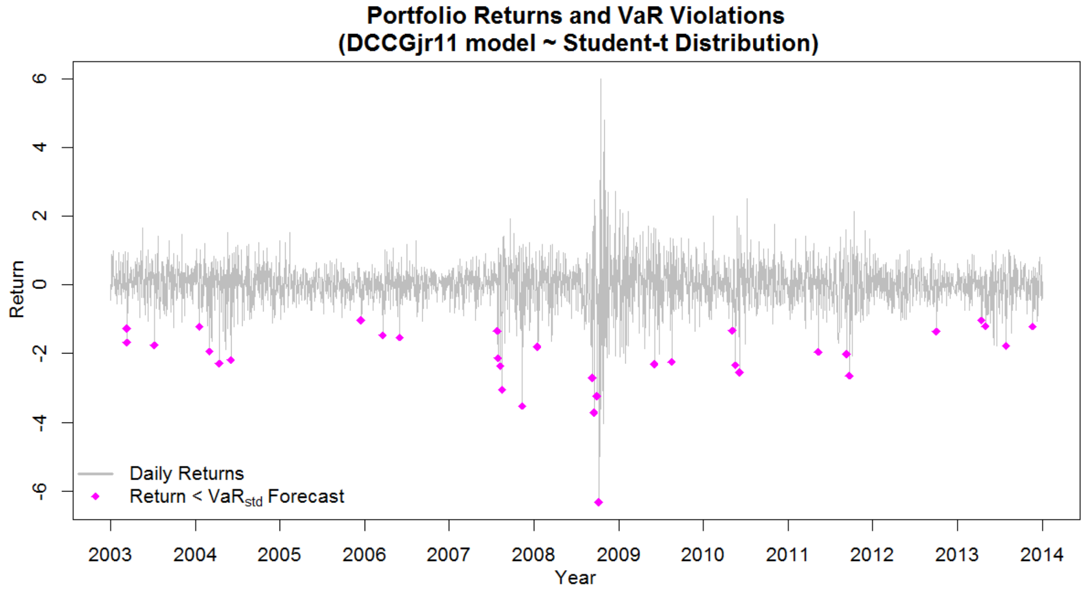


**Portfolio Returns and VaR Violations
(DCCGjr11 model ~ Normal Distribution)**



**Portfolio Returns and VaR Violations
(DCCGjr11 model ~ Normal Distribution)**




Portfolio Returns and VaR Violations
(DCCGjr11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd Forecast
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

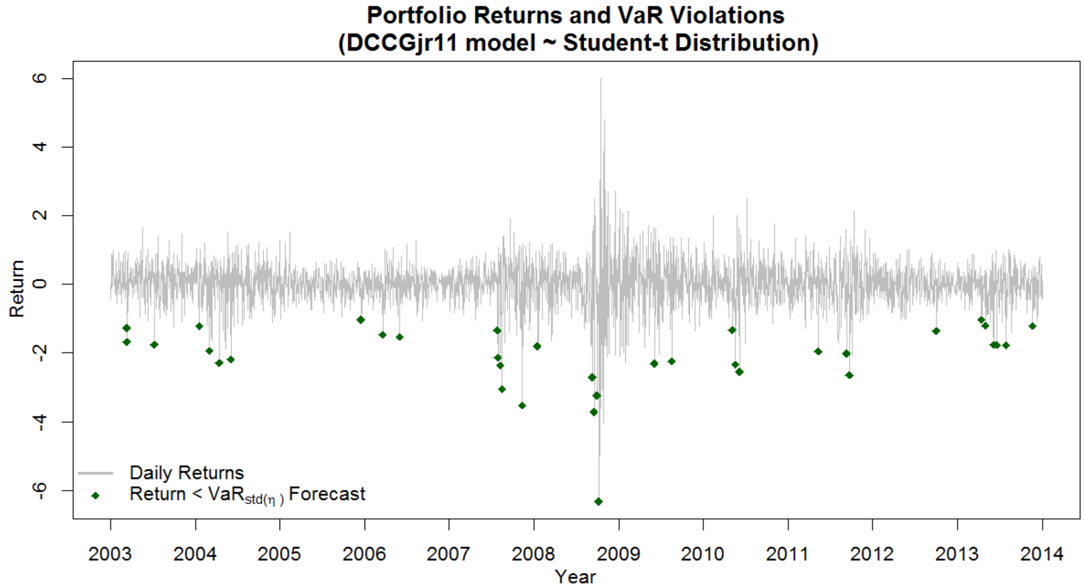

Portfolio Returns and VaR Violations
(DCCGjr11 model ~ Student-t Distribution)
Return
Year
Daily Returns
Return < VaRstd(η) Forecast
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014

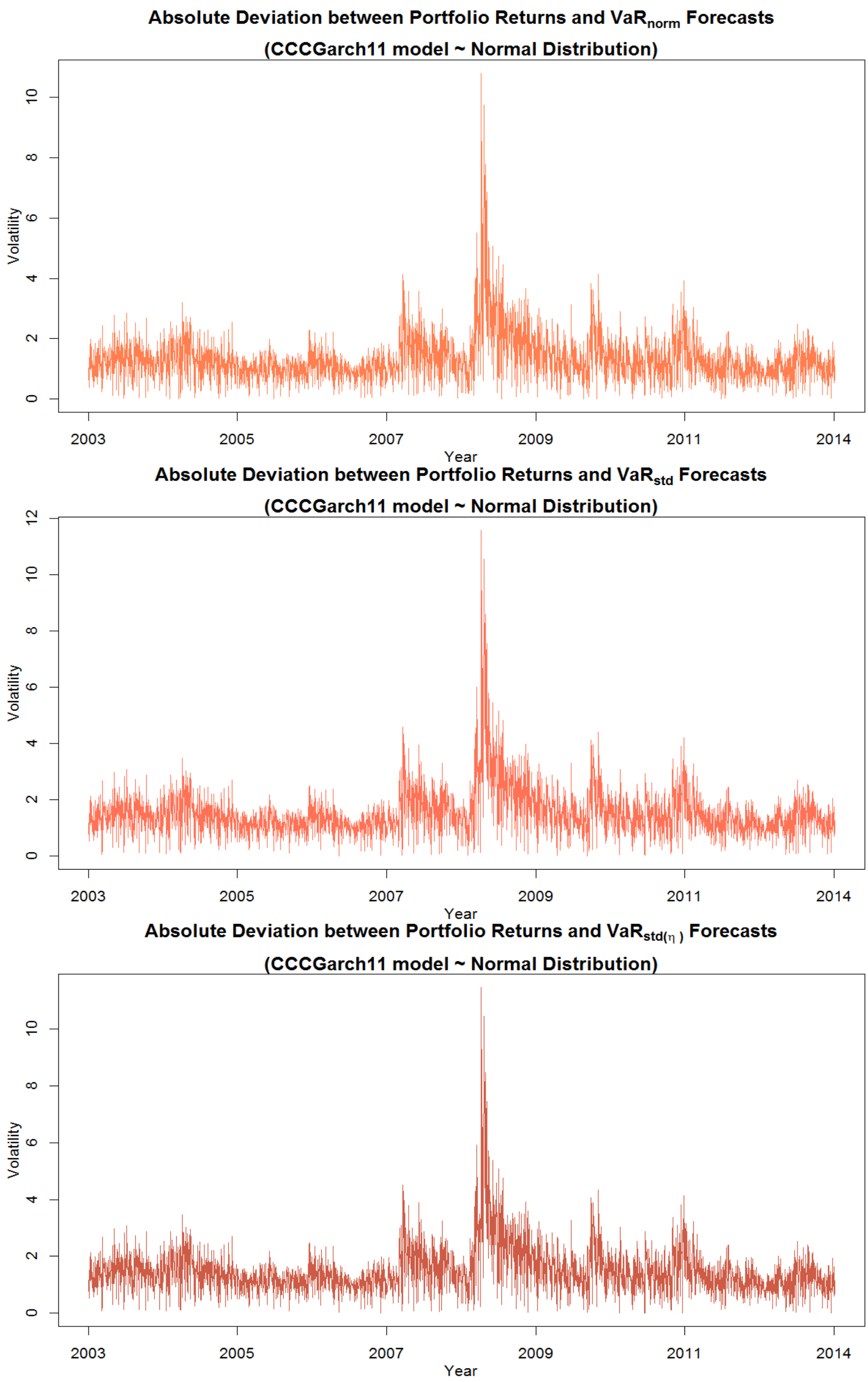
Table 4.15 Ratios for Absolute Deviation between Portfolio Returns and VaR Forecasts at 1% level

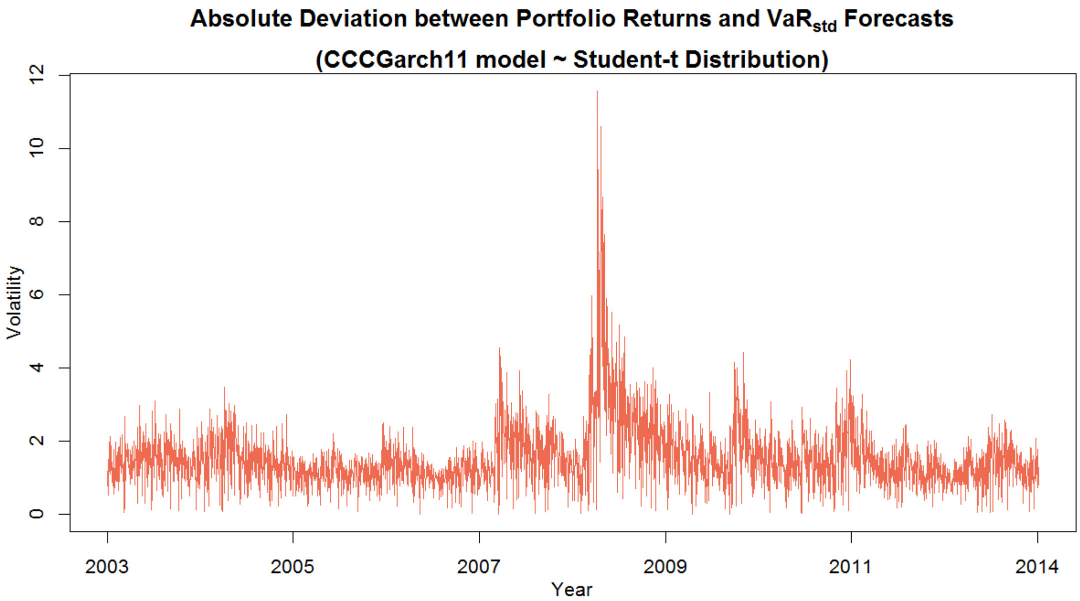
Model	Mean	Median	Minimum	Maximum
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	1.024	1.009	0.00095	2.747
$\widehat{VaR}_{norm}^{CCCGJR-N}$	1.024	1.009	0.00271	2.683
$\widehat{VaR}_{std}^{CCCGARCH-N}$	1.015	1.008	0.00229	2.500
$\widehat{VaR}_{std}^{CCCGJR-N}$	1.015	1.008	0.00103	2.447
$\widehat{VaR}_{std_\eta}^{CCCGARCH-N}$	1.017	1.008	0.00017	2.550
$\widehat{VaR}_{std_\eta}^{CCCGJR-N}$	1.016	1.008	0.00073	2.494
$\widehat{VaR}_{std}^{CCCGARCH-t}$	1.016	1.008	0.00496	2.478
$\widehat{VaR}_{std}^{CCCGJR-t}$	1.015	1.008	0.00164	2.447
$\widehat{VaR}_{std_\eta}^{CCCGARCH-t}$	1.016	1.008	0.00049	2.512
$\widehat{VaR}_{std_\eta}^{CCCGJR-t}$	1.016	1.008	0.00245	2.480
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	1.022	1.009	0.00271	2.734
$\widehat{VaR}_{norm}^{DCCGJR-N}$	1.022	1.009	0.00356	2.667
$\widehat{VaR}_{std}^{DCCGARCH-N}$	1.015	1.008	0.00315	2.441
$\widehat{VaR}_{std}^{DCCGJR-N}$	1.015	1.007	0.00183	2.467
$\widehat{VaR}_{std_\eta}^{DCCGARCH-N}$	1.015	1.008	0.00114	2.539
$\widehat{VaR}_{std_\eta}^{DCCGJR-N}$	1.015	1.007	0.00087	2.480
$\widehat{VaR}_{std}^{DCCGARCH-t}$	1.013	1.007	0.00046	2.527
$\widehat{VaR}_{std}^{DCCGJR-t}$	1.013	1.007	0.01378	2.399
$\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$	1.013	1.007	0.00065	2.452
$\widehat{VaR}_{std_\eta}^{DCCGJR-t}$	1.013	1.007	0.00707	2.410
(1) The ratio is calculated by (VaR Forecast minus Actual Return) divided by Actual Return				

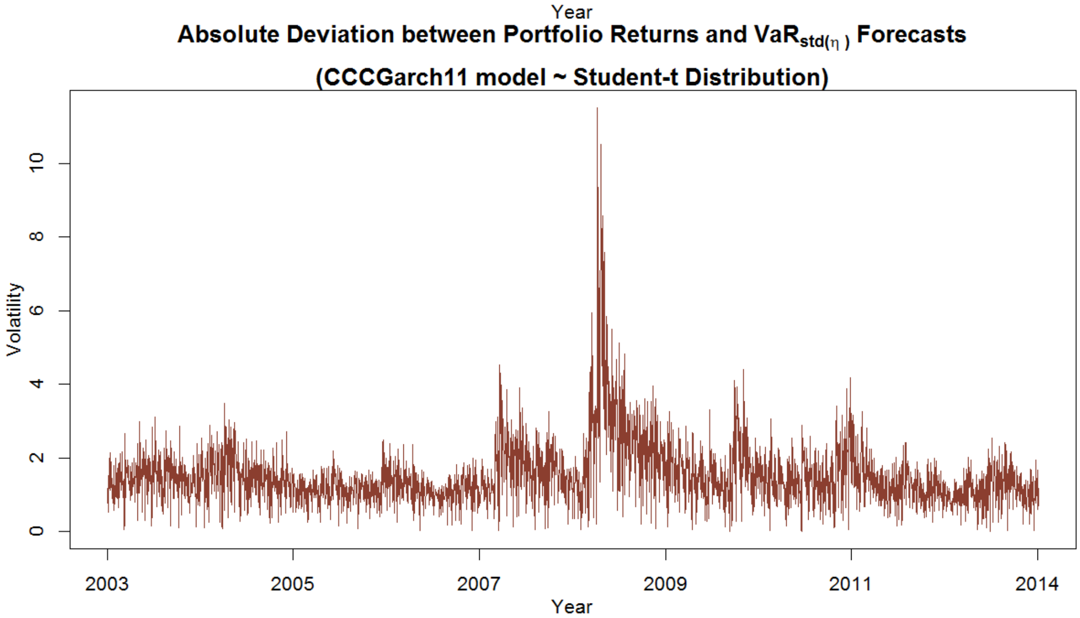
The magnitude of violations can be assessed by the ratios of absolute deviation between the actual returns and VaR forecasts. The regulator is concerned with whether the VaR forecasts are large enough to cover banks' unexpected trading losses. Hence, the size of large losses can be determined by the magnitude of violations. Table 4.15 summarizes the ratios of actual losses to the length of VaR forecasts for all models. The highest mean ratio at 1.024 is given by $\widehat{VaR}_{norm}^{CCCGARCH-N}$ and $\widehat{VaR}_{norm}^{CCCGJR-N}$, followed by $\widehat{VaR}_{norm}^{DCCGARCH-N}$ and $\widehat{VaR}_{norm}^{DCCGJR-N}$ at a mean ratio of 1.022. While, the lowest mean ratio is shown by $\widehat{VaR}_{std}^{DCCGARCH-t}$, $\widehat{VaR}_{std}^{DCCGJR-t}$, $\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$ and $\widehat{VaR}_{std_\eta}^{DCCGJR-t}$ at a mean ratio of 1.013.

Figure 4.11 plots the ratios of actual returns to the length of VaR forecasts during the forecast period. A smaller magnitude of violations can be seen during periods of low volatility. Whereas, the highest magnitude of violations, i.e. the largest size of losses, occurred in the year of 2008.

Figure 4.11 Absolute Deviation between Portfolio Returns and VaR Forecasts

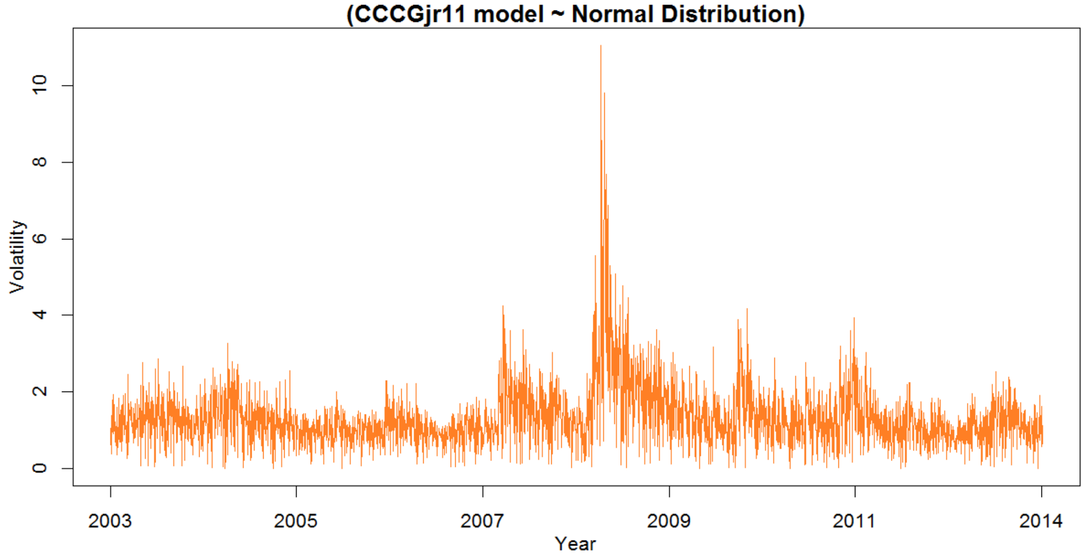



Absolute Deviation between Portfolio Returns and VaR_{std} Forecasts
(CCCGarch11 model ~ Student-t Distribution)
Volatility
0
2
4
6
8
10
12
2003
2005
2007
2009
2011
2014
Year


Absolute Deviation between Portfolio Returns and $VaR_{std(\eta)}$ Forecasts
(CCCGarch11 model ~ Student-t Distribution)
Volatility
0
2
4
6
8
10
2003
2005
2007
2009
2011
2014
Year

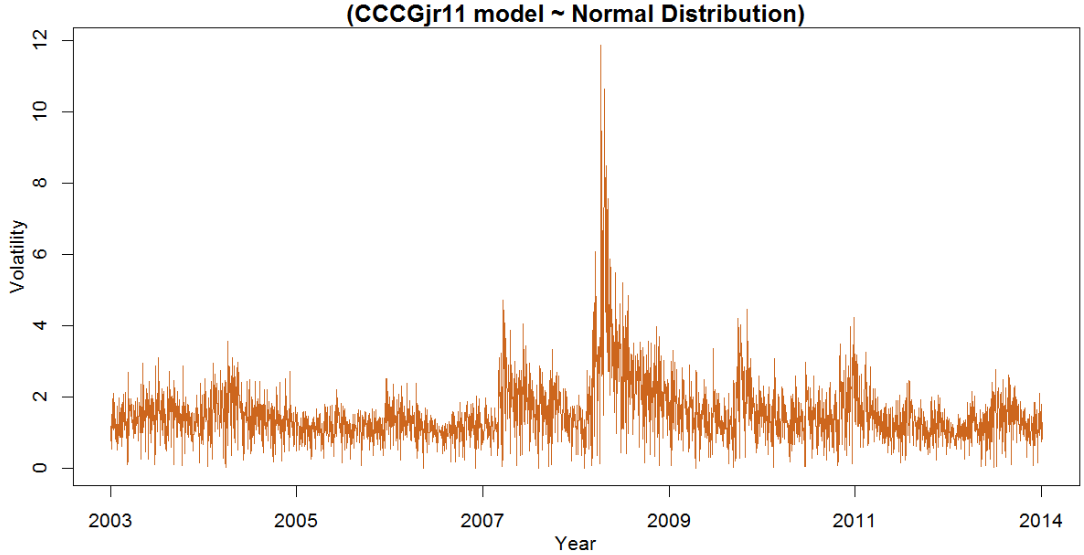
Absolute Deviation between Portfolio Returns and VaR_{norm} Forecasts

(CCCGjr11 model ~ Normal Distribution)



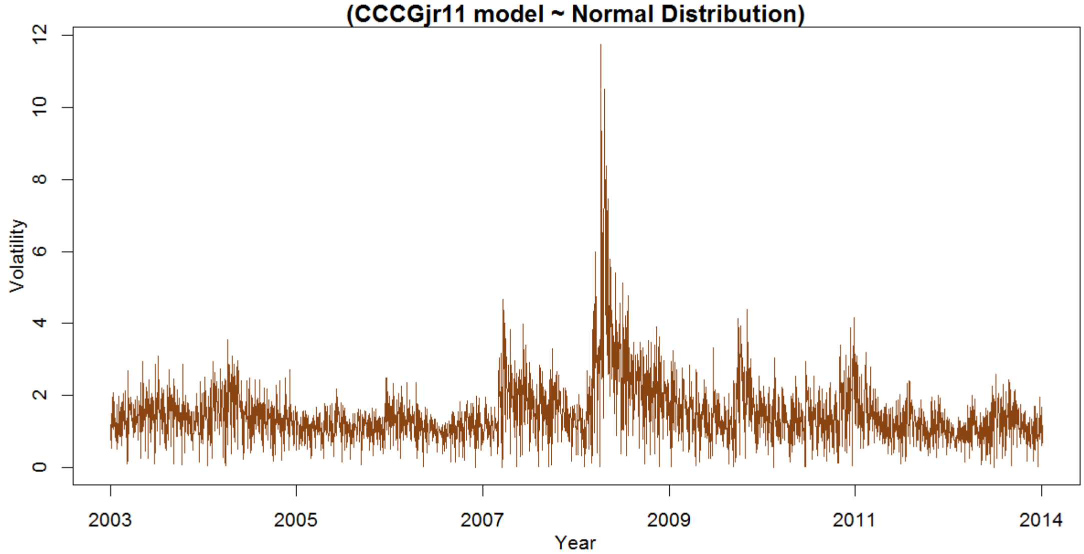
Absolute Deviation between Portfolio Returns and VaR_{std} Forecasts

(CCCGjr11 model ~ Normal Distribution)



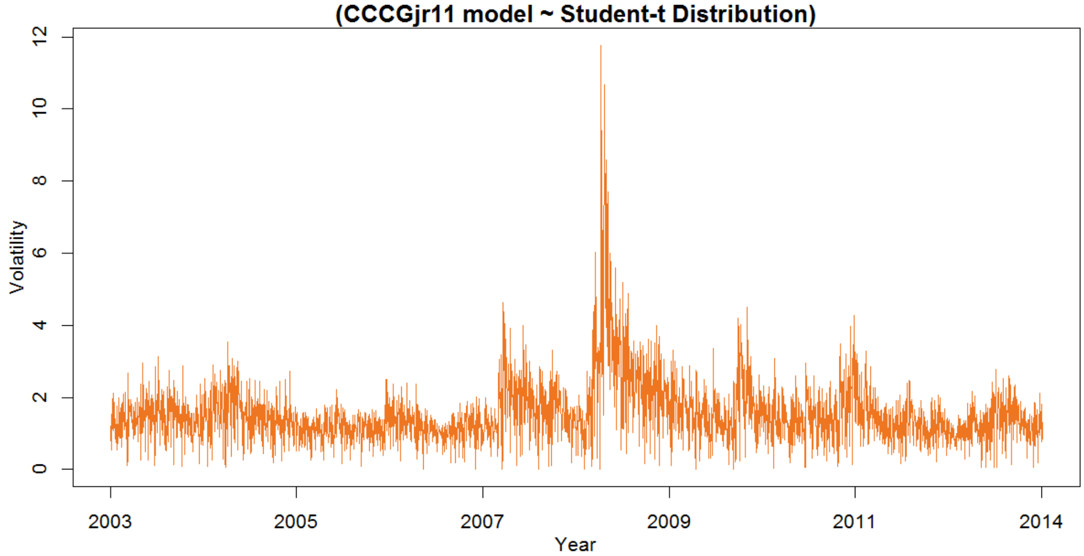
Absolute Deviation between Portfolio Returns and $VaR_{std(\eta)}$ Forecasts

(CCCGjr11 model ~ Normal Distribution)



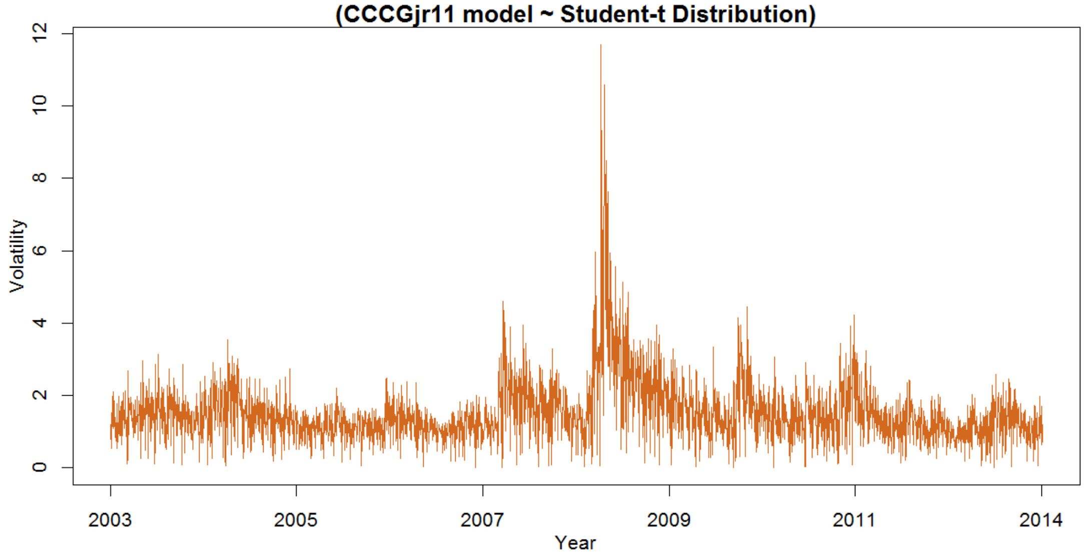
Absolute Deviation between Portfolio Returns and VaR_{std} Forecasts

(CCCGjr11 model ~ Student-t Distribution)

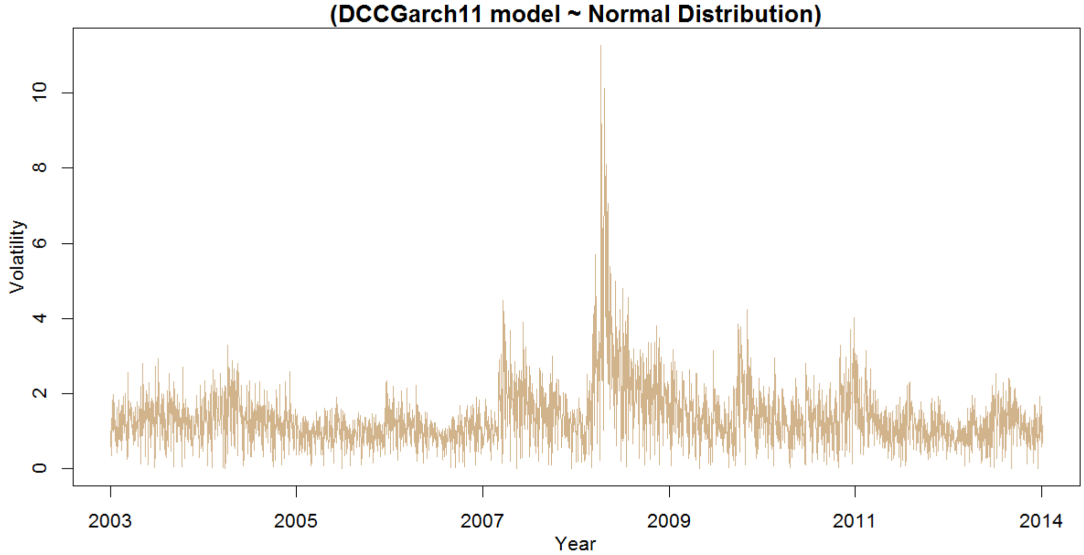


Absolute Deviation between Portfolio Returns and $VaR_{std(\eta)}$ Forecasts

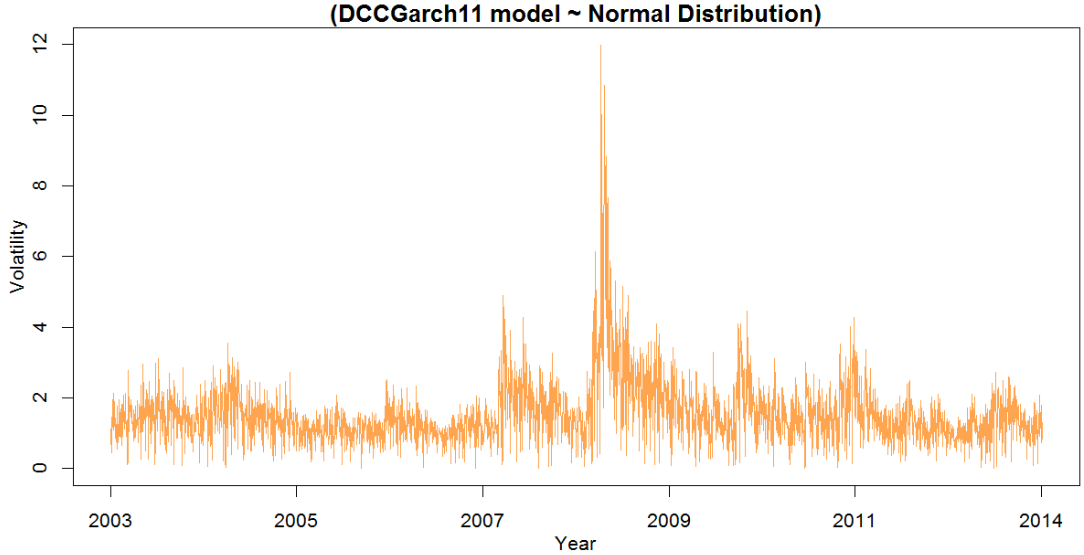
(CCCGjr11 model ~ Student-t Distribution)



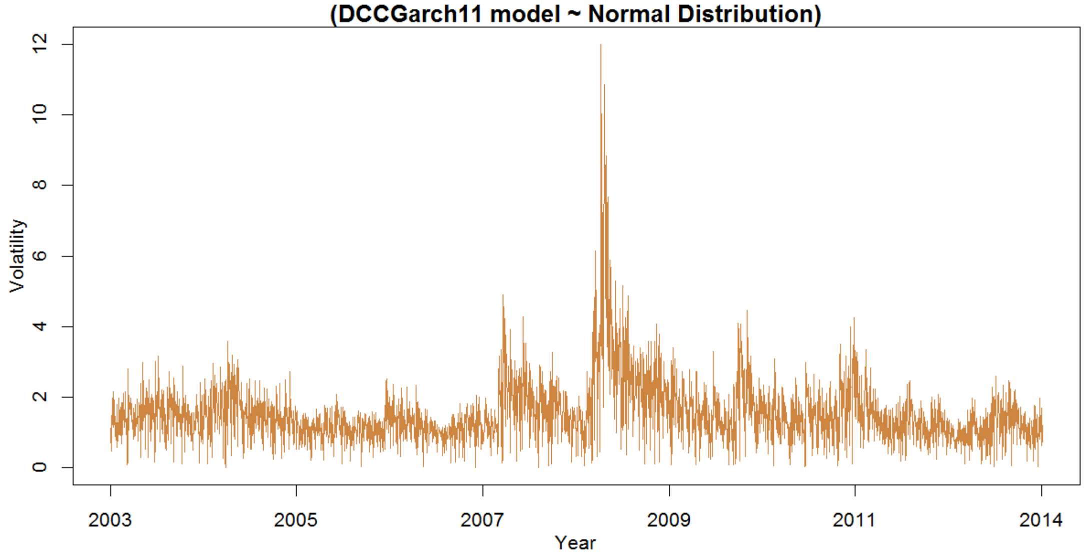
Absolute Deviation between Portfolio Returns and VaR_{norm} Forecasts (DCCGarch11 model ~ Normal Distribution)

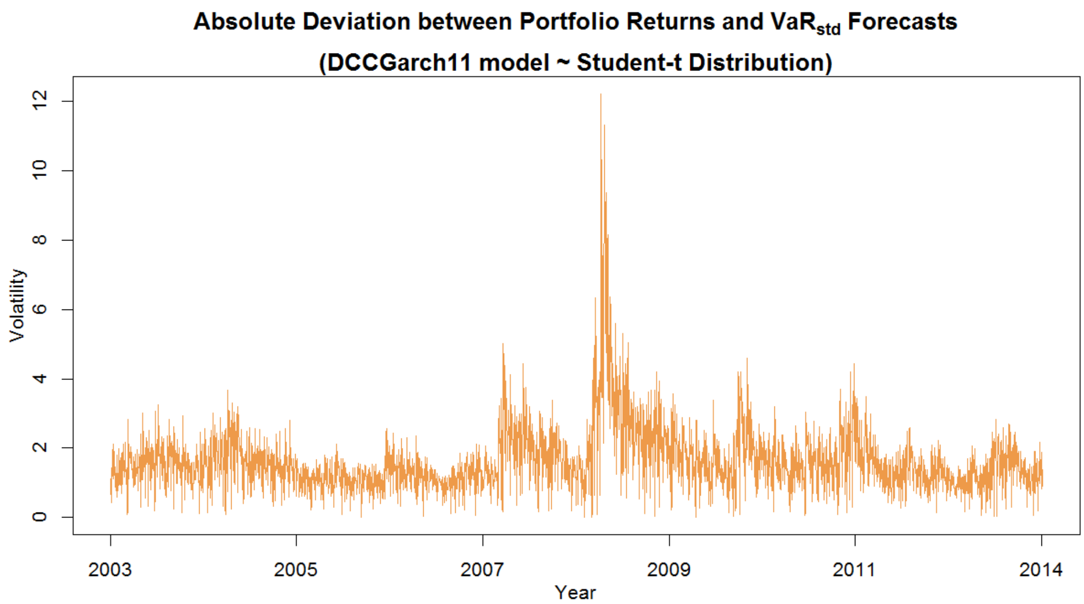


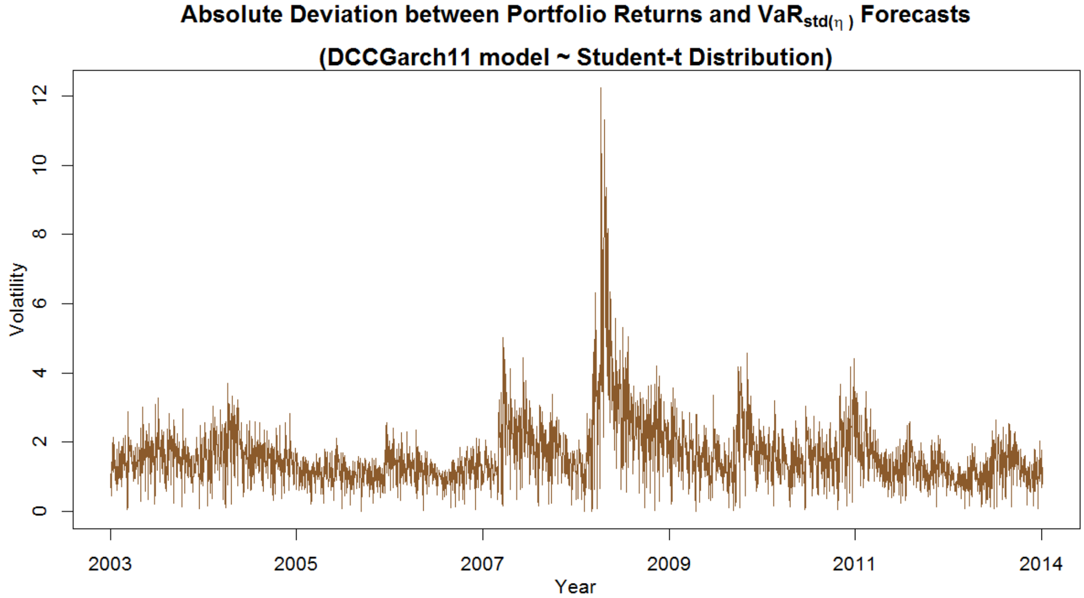
Absolute Deviation between Portfolio Returns and VaR_{std} Forecasts (DCCGarch11 model ~ Normal Distribution)

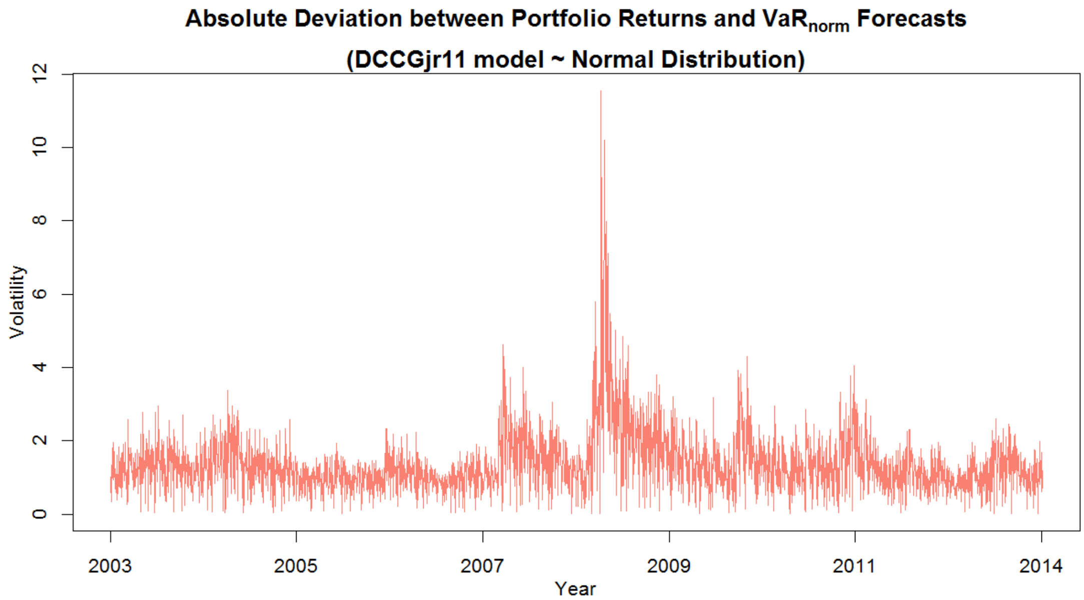


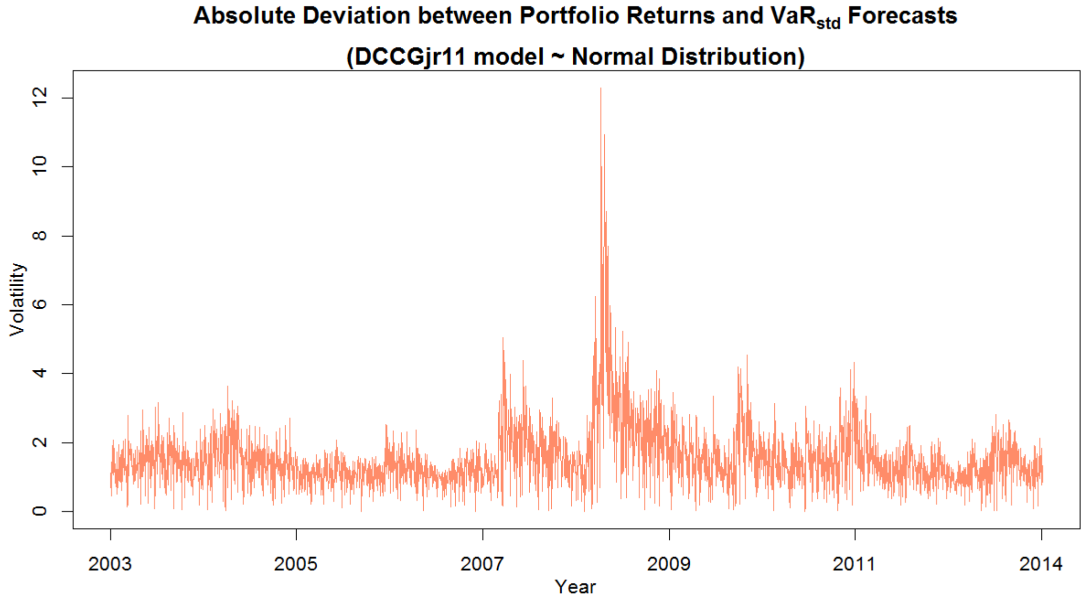
Absolute Deviation between Portfolio Returns and $VaR_{std(\eta)}$ Forecasts (DCCGarch11 model ~ Normal Distribution)

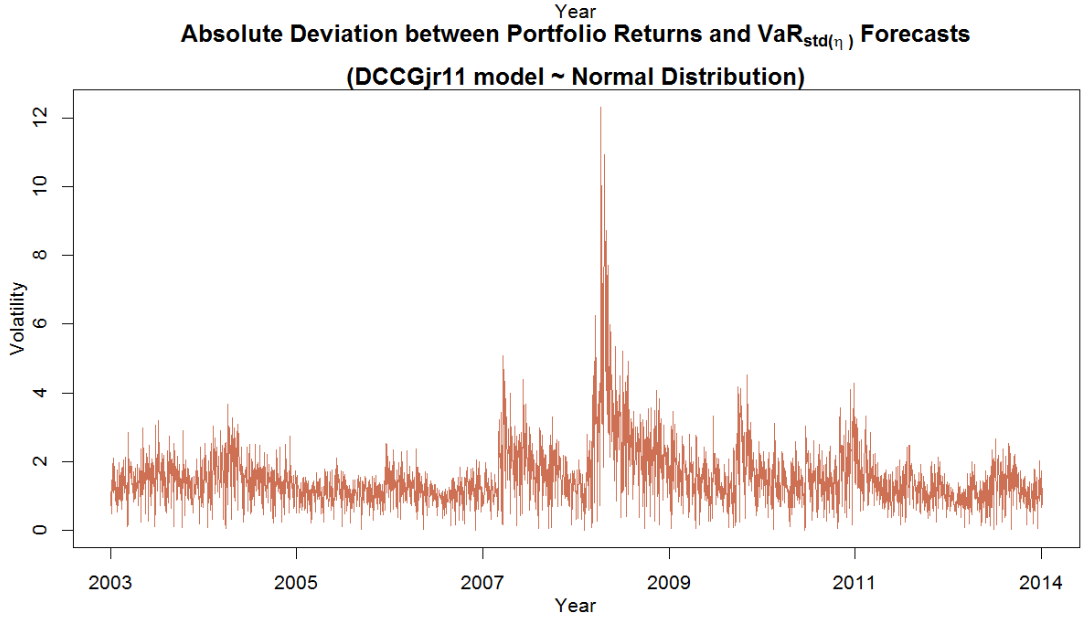



Absolute Deviation between Portfolio Returns and VaRstd Forecasts
(DCCGarch11 model ~ Student-t Distribution)
Volatility
0
2
4
6
8
10
12
2003
2005
2007
2009
2011
2014
Year


Absolute Deviation between Portfolio Returns and VaRstd(η) Forecasts
(DCCGarch11 model ~ Student-t Distribution)
Volatility
0
2
4
6
8
10
12
2003
2005
2007
2009
2011
2014
Year

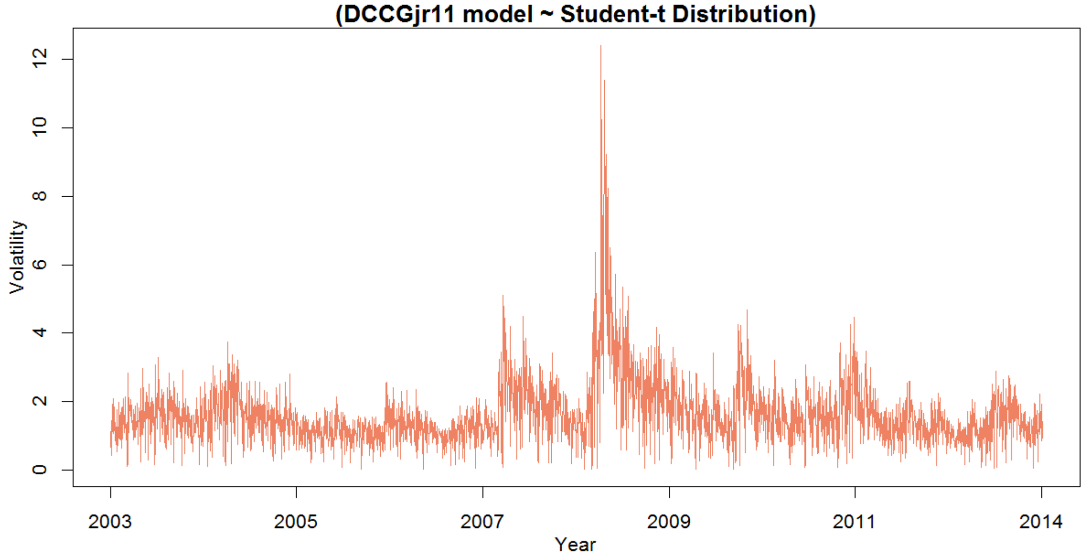

Absolute Deviation between Portfolio Returns and VaR_{norm} Forecasts
(DCCGjr11 model ~ Normal Distribution)
Volatility
0
2
4
6
8
10
12
2003
2005
2007
2009
2011
2014
Year


Absolute Deviation between Portfolio Returns and VaR_{std} Forecasts
(DCCGjr11 model ~ Normal Distribution)
Volatility
0
2
4
6
8
10
12
2003
2005
2007
2009
2011
2014
Year


Absolute Deviation between Portfolio Returns and $VaR_{std(\eta)}$ Forecasts
(DCCGjr11 model ~ Normal Distribution)
Volatility
0
2
4
6
8
10
12
2003
2005
2007
2009
2011
2014
Year

Absolute Deviation between Portfolio Returns and VaR_{std} Forecasts

(DCCGjr11 model ~ Student-t Distribution)



Absolute Deviation between Portfolio Returns and $VaR_{std(\eta)}$ Forecasts

(DCCGjr11 model ~ Student-t Distribution)

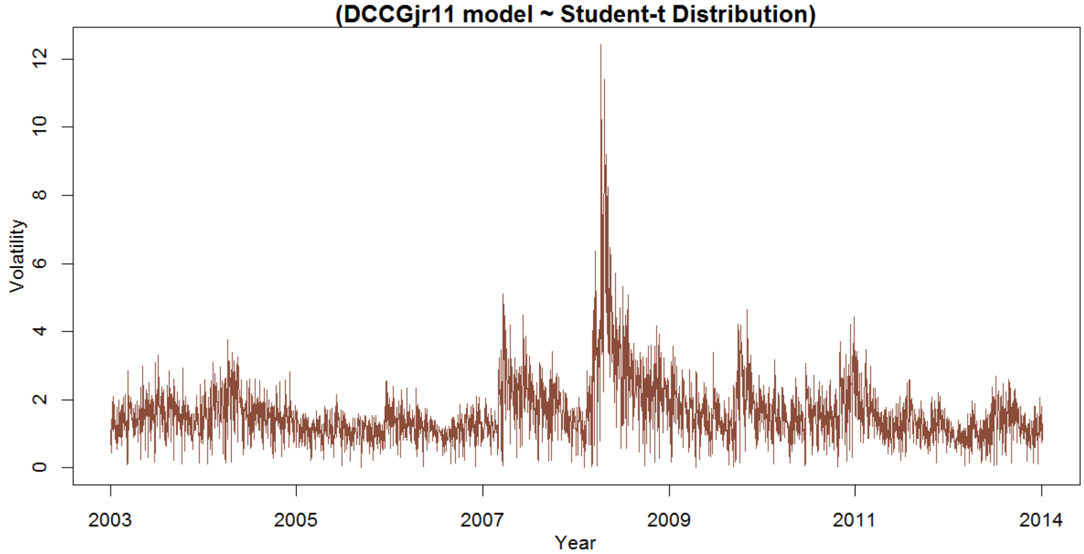


Table 4.16 Backtesting Results for VaR Forecasts at 1% level

Model	TUFF (1)	UC (1)	Ind (2)	CC (2)
$\widehat{VaR}^{CCCGARCH-N}_{norm}$	0.3715	**44.6241**	**12.9469**	**57.5710**
$\widehat{VaR}^{CCCGJR-N}_{norm}$	0.3715	**41.0007**	**13.7388**	**54.7394**
$\widehat{VaR}^{CCCGARCH-N}_{std}$	0.3715	**4.6920**	5.2691	**9.9611**
$\widehat{VaR}^{CCCGJR-N}_{std}$	0.3715	3.3500	2.4869	5.8368
$\widehat{VaR}^{CCCGARCH-N}_{std_\eta}$	0.3715	**9.8707**	**7.1900**	**17.0607**
$\widehat{VaR}^{CCCGJR-N}_{std_\eta}$	0.3715	**7.9611**	4.3391	**12.3002**
$\widehat{VaR}^{CCCGARCH-t}_{std}$	0.3715	**4.6920**	5.2691	**9.9611**
$\widehat{VaR}^{CCCGJR-t}_{std}$	0.3715	**3.9956**	2.3324	**6.3280**
$\widehat{VaR}^{CCCGARCH-t}_{std_\eta}$	0.3715	**7.9611**	**7.7980**	**15.7591**
$\widehat{VaR}^{CCCGJR-t}_{std_\eta}$	0.3715	**7.9611**	**7.7980**	**15.7591**
$\widehat{VaR}^{DCCGARCH-N}_{norm}$	0.3715	**39.2333**	**10.6979**	**49.9312**
$\widehat{VaR}^{DCCGJR-N}_{norm}$	0.3715	**32.4696**	**8.7800**	**41.2496**
$\widehat{VaR}^{DCCGARCH-N}_{std}$	0.3715	**4.6920**	2.1846	**6.8766**
$\widehat{VaR}^{DCCGJR-N}_{std}$	0.3715	3.3500	2.4869	5.8368
$\widehat{VaR}^{DCCGARCH-N}_{std_\eta}$	0.3715	**4.6920**	2.1846	**6.8766**
$\widehat{VaR}^{DCCGJR-N}_{std_\eta}$	0.3715	**4.6920**	2.1846	**6.8766**
$\widehat{VaR}^{DCCGARCH-t}_{std}$	0.3715	1.3011	3.1780	4.4791
$\widehat{VaR}^{DCCGJR-t}_{std}$	0.3715	0.6178	3.5724	4.1901
$\widehat{VaR}^{DCCGARCH-t}_{std_\eta}$	0.3715	2.2160	2.8172	5.0331
$\widehat{VaR}^{DCCGJR-t}_{std_\eta}$	0.3715	1.3011	3.1780	4.4791

(1) The Unconditional Coverage (UC) and Time Until First Failure (TUFF) tests are asymptotically distributed as χ^2 (1).

(2) The Serial Independence (Ind) and Conditional Coverage (CC) tests are asymptotically distributed as χ^2 (2).

(3) Entries in bold denote rejection of the tests.

The results from TUFF, UC, Ind and CC tests are presented in Table 4.16. The TUFF results for all models lead to correct acceptance of the test at a constant value of 0.3715. It can be seen that both CCC and DCC models under a normal distribution, fail UC, Ind and CC tests. This suggests that the VaR violations performed by these models are serially dependent. On the other hand, $\widehat{VaR}_{std}^{CCCGJR-N}$, $\widehat{VaR}_{std}^{DCCGJR-N}$, $\widehat{VaR}_{std}^{DCCGARCH-t}$, $\widehat{VaR}_{std}^{DCCGJR-t}$, $\widehat{VaR}_{std_{\eta}}^{DCCGARCH-t}$ and $\widehat{VaR}_{std_{\eta}}^{DCCGJR-t}$ pass UC, Ind and CC tests. This shows that the VaR violations are likely to be independent and that a VaR violation today should not provide any information about whether or not a VaR violation will occur tomorrow. While, $\widehat{VaR}_{norm}^{CCCGARCH-N}$, $\widehat{VaR}_{std_{\eta}}^{CCCGJR-N}$, $\widehat{VaR}_{std}^{CCCGARCH-t}$, $\widehat{VaR}_{std}^{CCCGJR-t}$, $\widehat{VaR}_{std}^{DCCGARCH-N}$, $\widehat{VaR}_{std_{\eta}}^{DCCGARCH-N}$, and $\widehat{VaR}_{std_{\eta}}^{DCCGJR-N}$ fail the UC and CC tests but pass Ind test.

Table 4.17 summarizes the results for VaR^{min} at 1% level. It represents the lower VaR of the previous day or the average VaR on the previous 60 days. These VaR values are used to verify the VaR forecasts from Table 4.13.

Table 4.17 VaR^{min} at 1% level

Model	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	-1.3913	-1.2220	-5.6650	-0.8125	0.5869
$\widehat{VaR}_{norm}^{CCCGJR-N}$	-1.3949	-1.2170	-5.6090	-0.8183	0.5921
$\widehat{VaR}_{std}^{CCCGARCH-N}$	-1.6201	-1.4230	-6.5960	-0.9461	0.6834
$\widehat{VaR}_{std}^{CCCGJR-N}$	-1.6227	-1.4150	-6.5250	-0.9520	0.6964
$\widehat{VaR}_{std_{\eta}}^{CCCGARCH-N}$	-1.5741	-1.3790	-6.4560	-0.9067	0.6704
$\widehat{VaR}_{std_{\eta}}^{CCCGJR-N}$	-1.5767	-1.3730	-6.3890	-0.9035	0.6759
$\widehat{VaR}_{std}^{CCCGARCH-t}$	-1.6335	-1.4340	-7.0850	-0.9096	0.6919
$\widehat{VaR}_{std}^{CCCGJR-t}$	-1.6330	-1.4340	-7.0850	-0.9096	0.6964
$\widehat{VaR}_{std_{\eta}}^{CCCGARCH-t}$	-1.5998	-1.4000	-6.4870	-0.9120	0.6853
$\widehat{VaR}_{std_{\eta}}^{CCCGJR-t}$	-1.5990	-1.3910	-6.3890	-0.9042	0.6899
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	-1.4454	-1.2620	-6.3490	-0.7953	0.6460
$\widehat{VaR}_{norm}^{DCCGJR-N}$	-1.4496	-1.2630	-6.2380	-0.8009	0.6518
$\widehat{VaR}_{std}^{DCCGARCH-N}$	-1.6418	-1.4340	-7.2110	-0.9034	0.7337
$\widehat{VaR}_{std}^{DCCGJR-N}$	-1.6464	-1.4340	-7.0850	-0.9096	0.7402
$\widehat{VaR}_{std_{\eta}}^{DCCGARCH-N}$	-1.6355	-1.4280	-7.2360	-0.8912	0.7373
$\widehat{VaR}_{std_{\eta}}^{DCCGJR-N}$	-1.6386	-1.4250	-7.1050	-0.8877	0.7434
$\widehat{VaR}_{std}^{DCCGARCH-t}$	-1.7400	-1.5300	-7.4590	-0.9254	0.7947
$\widehat{VaR}_{std}^{DCCGJR-t}$	-1.7382	-1.5190	-7.2630	-0.9356	0.7993
$\widehat{VaR}_{std_{\eta}}^{DCCGARCH-t}$	-1.7303	-1.5200	-7.4760	-0.8934	0.7984
$\widehat{VaR}_{std_{\eta}}^{DCCGJR-t}$	-1.7274	-1.5070	-7.2800	-0.8877	0.8030

(1) VaR^{min} is calculated as the negative of the higher VaR of the previous day or the average VaR over the past 60 days

Table 4.18 Number and Percentage of Violations for Rolling VaR Violations

Model	No. of Violation	% of Violation	Ranking
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	60	2.09%	20
$\widehat{VaR}_{norm}^{CCCGJR-N}$	58	2.02%	19
$\widehat{VaR}_{std}^{CCCGARCH-N}$	36	1.25%	8
$\widehat{VaR}_{std}^{CCCGJR-N}$	34	1.18%	5
$\widehat{VaR}_{std_\eta}^{CCCGARCH-N}$	43	1.50%	16
$\widehat{VaR}_{std_\eta}^{CCCGJR-N}$	38	1.32%	13
$\widehat{VaR}_{std}^{CCCGARCH-t}$	36	1.25%	8
$\widehat{VaR}_{std}^{CCCGJR-t}$	35	1.22%	7
$\widehat{VaR}_{std_\eta}^{CCCGARCH-t}$	40	1.39%	14
$\widehat{VaR}_{std_\eta}^{CCCGJR-t}$	40	1.39%	14
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	52	1.81%	18
$\widehat{VaR}_{norm}^{DCCGJR-N}$	50	1.74%	17
$\widehat{VaR}_{std}^{DCCGARCH-N}$	36	1.25%	8
$\widehat{VaR}_{std}^{DCCGJR-N}$	34	1.18%	5
$\widehat{VaR}_{std_\eta}^{DCCGARCH-N}$	36	1.25%	8
$\widehat{VaR}_{std_\eta}^{DCCGJR-N}$	36	1.25%	8
$\widehat{VaR}_{std}^{DCCGARCH-t}$	28	0.97%	2
$\widehat{VaR}_{std}^{DCCGJR-t}$	29	1.01%	1
$\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$	32	1.11%	3
$\widehat{VaR}_{std_\eta}^{DCCGJR-t}$	32	1.11%	3

Table 4.18 reports the number and percentage of VaR^{min} violations on the previous 250 days. The regulator is concerned with whether the internal VaR models adopted by banks provide correct coverage for losses. Notice that the ranking presented in Table 4.18 is similar to the ranking listed in Table 4.14. The best model presented in this case is $\widehat{VaR}_{std}^{DCCGJR-t}$ at 1.01%, given that it is the closest to one percent, followed by $\widehat{VaR}_{std}^{DCCGARCH-t}$ at 0.97%. While, $\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$ and $\widehat{VaR}_{std_\eta}^{DCCGJR-t}$ show similar percentages of violations at 1.11%. The highest percentage of VaR violations is given by $\widehat{VaR}_{norm}^{CCCGARCH-N}$ at 2.09%. These results have an important consequence in forecasting VaR as the normal distribution can potentially underestimate market risk with the higher amount of capital charges. This may substantially increase a bank's cost that cannot be used for other profitable purposes. An alternative solution is to use other distributions such as student-t distribution to accommodate large movements of asset returns in the market (see, for example, Bauwens and Laurent 2005).

Table 4.19 shows the scaling factors as required by the Basel Committee. Of particular interest, $\widehat{VaR}_{norm}^{CCCGARCH-N}$ gives the highest mean of scaling factor at a level of 3.4, while $\widehat{VaR}_{std}^{DCCGJR-t}$ and $\widehat{VaR}_{std_\eta}^{DCCGJR-t}$ give the lowest mean of scaling factor at a level of 3.0. It can be seen that the median and the minimum scaling factor for all models present at a level of 3.0. While, a maximum level of 4.0 is observed for $\widehat{VaR}_{norm}^{CCCGARCH-N}$, $\widehat{VaR}_{norm}^{CCCGJR-N}$, and $\widehat{VaR}_{norm}^{DCCGARCH-N}$.

Table 4.19 Scaling Factors

Model	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	3.4	3.4	3.0	4.0	0.3450
$\widehat{VaR}_{norm}^{CCCGJR-N}$	3.3	3.4	3.0	4.0	0.3364
$\widehat{VaR}_{std}^{CCCGARCH-N}$	3.1	3.0	3.0	3.8	0.2321
$\widehat{VaR}_{std}^{CCCGJR-N}$	3.1	3.0	3.0	3.7	0.1944
$\widehat{VaR}_{std_{\eta}}^{CCCGARCH-N}$	3.2	3.0	3.0	3.9	0.2691
$\widehat{VaR}_{std_{\eta}}^{CCCGJR-N}$	3.1	3.0	3.0	3.7	0.2159
$\widehat{VaR}_{std}^{CCCGARCH-t}$	3.1	3.0	3.0	3.8	0.2321
$\widehat{VaR}_{std}^{CCCGJR-t}$	3.1	3.0	3.0	3.8	0.2208
$\widehat{VaR}_{std_{\eta}}^{CCCGARCH-t}$	3.2	3.0	3.0	3.8	0.2478
$\widehat{VaR}_{std_{\eta}}^{CCCGJR-t}$	3.2	3.0	3.0	3.8	0.2478
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	3.3	3.0	3.0	4.0	0.3193
$\widehat{VaR}_{norm}^{DCCGJR-N}$	3.2	3.0	3.0	3.9	0.2860
$\widehat{VaR}_{std}^{DCCGARCH-N}$	3.1	3.0	3.0	3.7	0.1997
$\widehat{VaR}_{std}^{DCCGJR-N}$	3.1	3.0	3.0	3.7	0.1776
$\widehat{VaR}_{std_{\eta}}^{DCCGARCH-N}$	3.1	3.0	3.0	3.7	0.1976
$\widehat{VaR}_{std_{\eta}}^{DCCGJR-N}$	3.1	3.0	3.0	3.7	0.1776
$\widehat{VaR}_{std}^{DCCGARCH-t}$	3.1	3.0	3.0	3.7	0.1548
$\widehat{VaR}_{std}^{DCCGJR-t}$	3.0	3.0	3.0	3.5	0.1245
$\widehat{VaR}_{std_{\eta}}^{DCCGARCH-t}$	3.1	3.0	3.0	3.7	0.1742
$\widehat{VaR}_{std_{\eta}}^{DCCGJR-t}$	3.0	3.0	3.0	3.5	0.1245

(1) The scaling factor is calculated as 3+*k*, where *k* is the violation penalty

Table 4.20 Capital Charges for VaR^{min} at 1% level

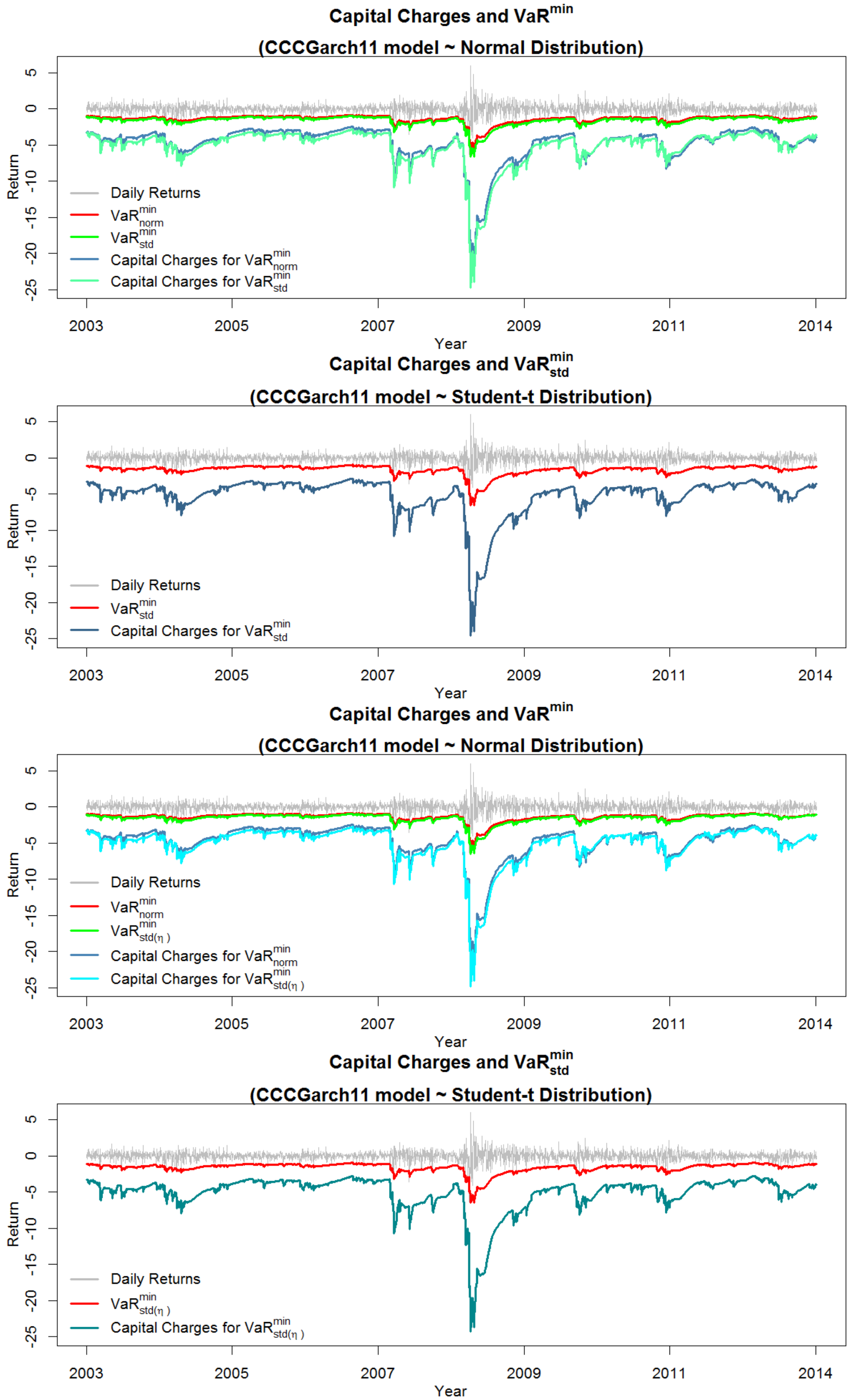
Model	Mean	Median	Minimum	Maximum	Standard Deviation
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	-4.79	-4.06	-22.66	-2.44	2.5215
$\widehat{VaR}_{norm}^{CCCGJR-N}$	-4.77	-4.01	-22.43	-2.46	2.5406
$\widehat{VaR}_{std}^{CCCGARCH-N}$	-5.18	-4.38	-24.74	-2.84	2.6551
$\widehat{VaR}_{std}^{CCCGJR-N}$	-5.12	-4.36	-23.82	-2.86	2.5406
$\widehat{VaR}_{std_\eta}^{CCCGARCH-N}$	-5.13	-4.32	-24.86	-2.72	2.6680
$\widehat{VaR}_{std_\eta}^{CCCGJR-N}$	-5.01	-4.28	-23.32	-2.71	2.4855
$\widehat{VaR}_{std}^{CCCGARCH-t}$	-5.22	-4.41	-24.61	-2.84	2.6874
$\widehat{VaR}_{std}^{CCCGJR-t}$	-5.19	-4.38	-24.26	-2.88	2.6821
$\widehat{VaR}_{std_\eta}^{CCCGARCH-t}$	-5.15	-4.36	-24.31	-2.74	2.6518
$\widehat{VaR}_{std_\eta}^{CCCGJR-t}$	-5.15	-4.35	-23.96	-2.71	2.6684
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	-4.87	-4.05	-25.39	-2.39	2.7387
$\widehat{VaR}_{norm}^{DCCGJR-N}$	-4.81	-4.01	-24.02	-2.40	2.6061
$\widehat{VaR}_{std}^{DCCGARCH-N}$	-5.19	-4.45	-26.32	-2.71	2.6897
$\widehat{VaR}_{std}^{DCCGJR-N}$	-5.15	-4.34	-25.86	-2.73	2.7088
$\widehat{VaR}_{std_\eta}^{DCCGARCH-N}$	-5.15	-4.38	-26.41	-2.67	2.6938
$\widehat{VaR}_{std_\eta}^{DCCGJR-N}$	-5.13	-4.31	-25.93	-2.66	2.7201
$\widehat{VaR}_{std}^{DCCGARCH-t}$	-5.41	-4.63	-26.10	-2.78	2.7875
$\widehat{VaR}_{std}^{DCCGJR-t}$	-5.31	-4.59	-24.69	-2.81	2.5191
$\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$	-5.41	-4.65	-26.17	-2.68	2.7925
$\widehat{VaR}_{std_\eta}^{DCCGJR-t}$	-5.28	-4.56	-24.75	-2.67	2.5316

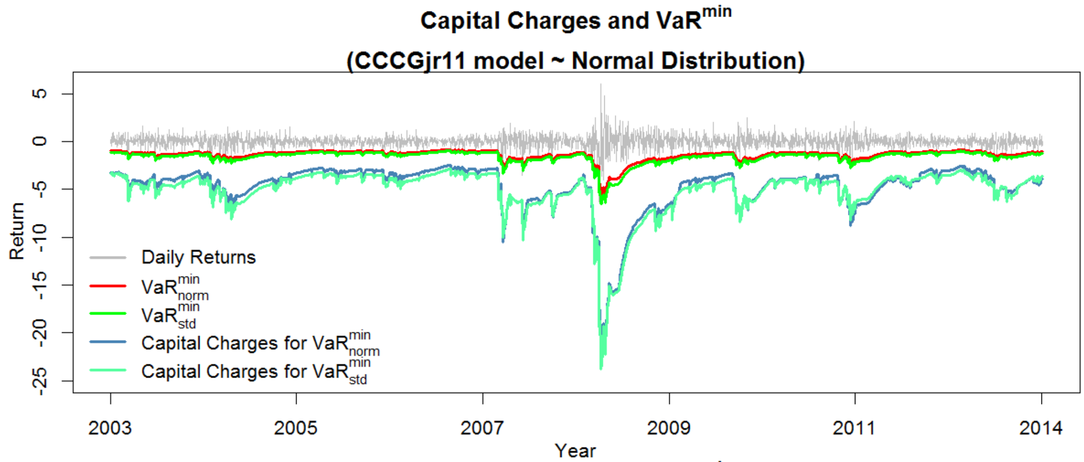
(1) The capital charge is calculated as the lower VaR of the previous day or the average VaR on the previous 60 days (VaR^{min}), multiplied by a scaling factor of (3+*k*), where *k* is the violation penalty

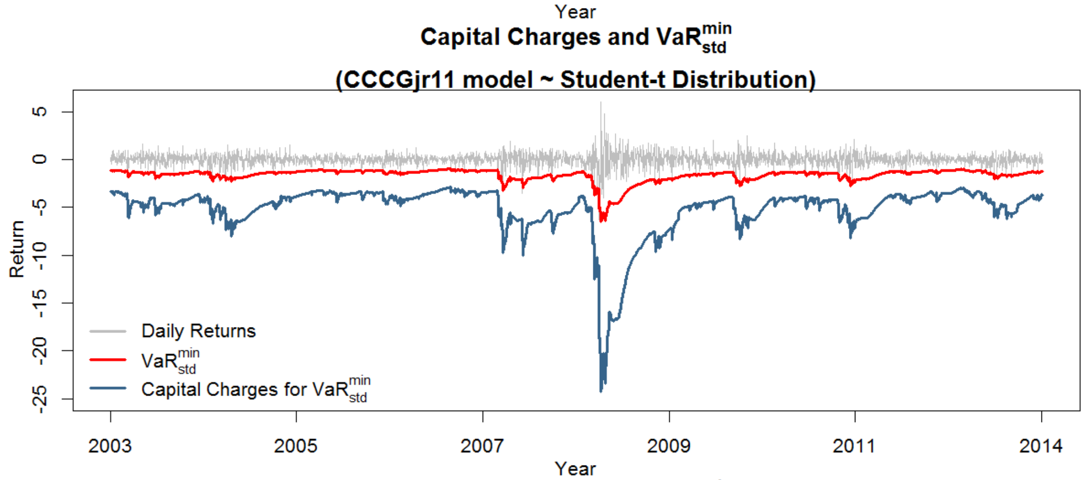
Table 4.20 shows the market risk capital charges that are a product of VaR^{min} (Table 4.17) multiplied by a scaling factor (Table 4.19). It represents the capital requirements established by the Basel Accord. Berkowitz and O'Brien (2002) and Pérignon, Deng, and Wang (2008) showed that banks tend to report high VaR forecasts that lead to an excessive amount of capital charges. In any case, there is an opportunity cost of misestimating VaR. Hence, pursuing a correct VaR model that can lead to the precision of determining minimum capital requirements is crucial for banks and the regulator (see Santos et al. 2012). In this case, $\widehat{VaR}_{std}^{DCCGARCH-t}$ and $\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$ provide the lowest mean of capital charges at -5.41. $\widehat{VaR}_{std}^{DCCGJR-t}$ and $\widehat{VaR}_{std}^{CCCGARCH-t}$ give a mean of capital charges at -5.31 and -5.22, respectively. The lowest capital charge is given by $\widehat{VaR}_{std_\eta}^{DCCGARCH-N}$ at -26.41, followed by $\widehat{VaR}_{std}^{DCCGARCH-N}$ at -26.32, and $\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$ at -26.17. These capital costs are mostly charged during the GFC, where sharp negative spikes of capital charges are shown in Figure 4.12. On the contrary, the highest capital charge is presented by $\widehat{VaR}_{norm}^{DCCGARCH-N}$ at – 2.39, followed by $\widehat{VaR}_{norm}^{DCCGJR-N}$ at -2.40. This occurs during periods of low volatility in the foreign exchange market.

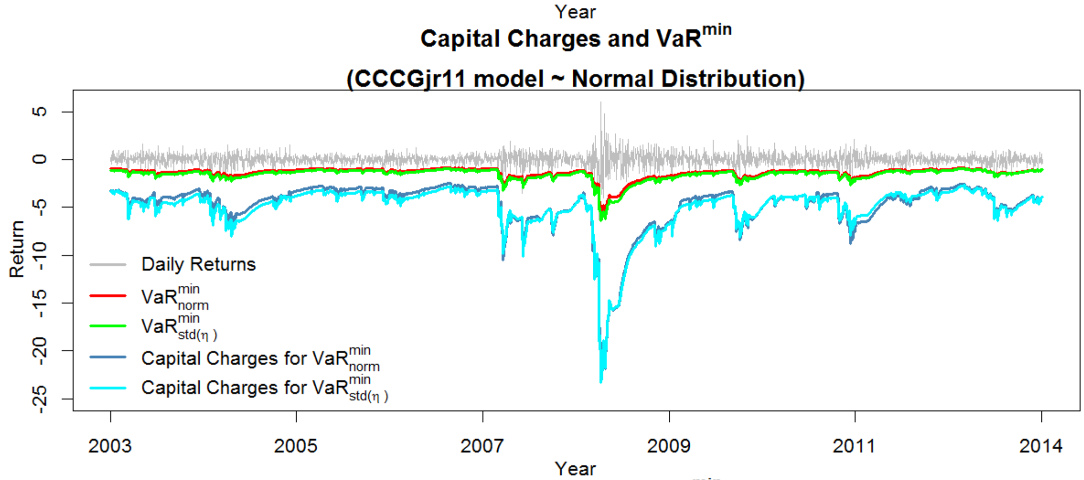
Figure 4.12 demonstrates the episodes at which capital charges are most likely to occur. It can be seen that due to extreme negative returns during the GFC of 2008, the capital charges are imposed at the highest costs. This is mostly expected during extreme market conditions where higher capital charges are imposed to protect banks from the worst possible trading losses.

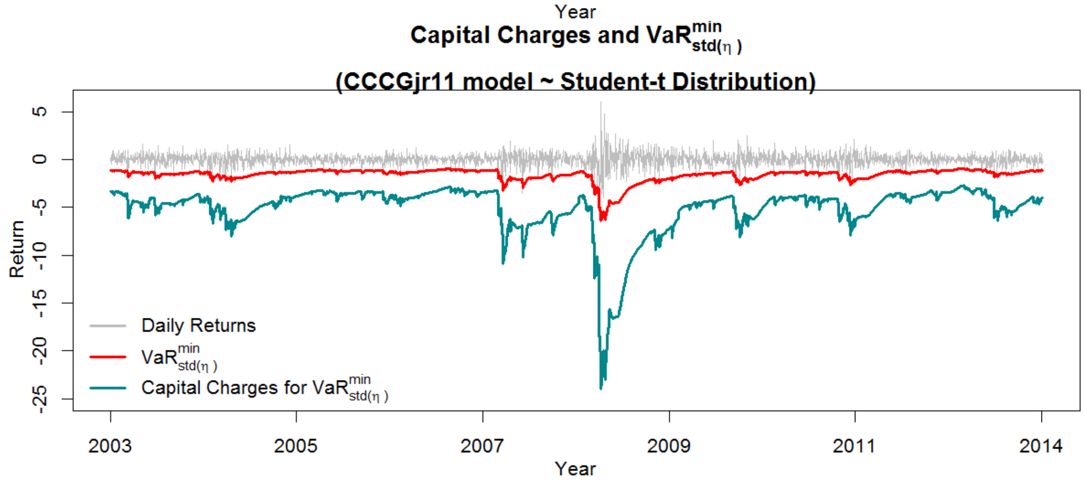
Figure 4.12 Capital Charges and VaR^{min} at 1% level

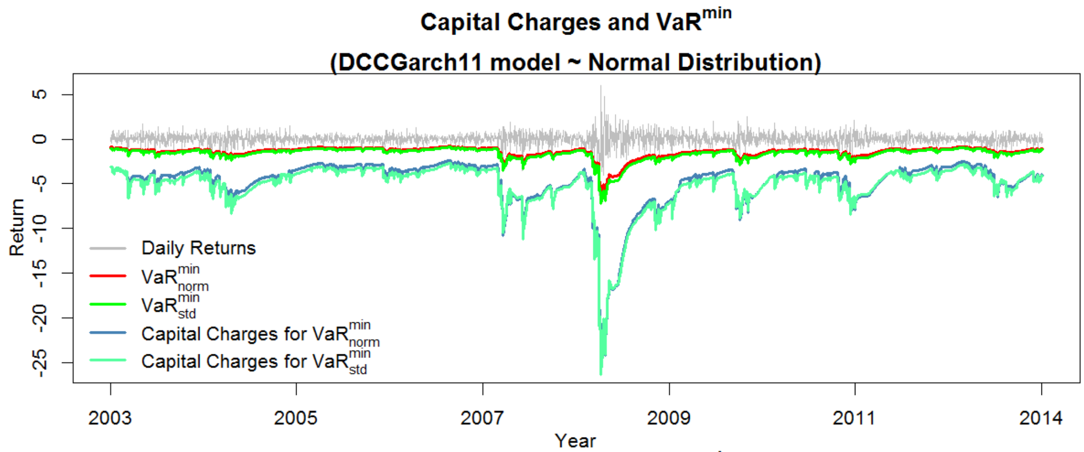


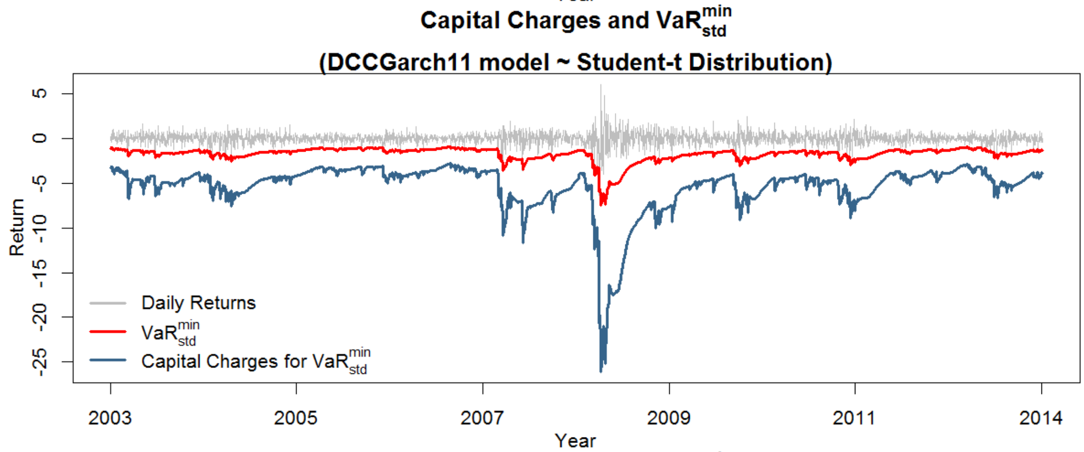

Capital Charges and VaR^{min}
(CCCGjr11 model ~ Normal Distribution)
Return
Daily Returns
VaR^{min}_{norm}
VaR^{min}_{std}
Capital Charges for VaR^{min}_{norm}
Capital Charges for VaR^{min}_{std}
5
0
-5
-10
-15
-20
-25
2003
2005
2007
2009
2011
2014
Year

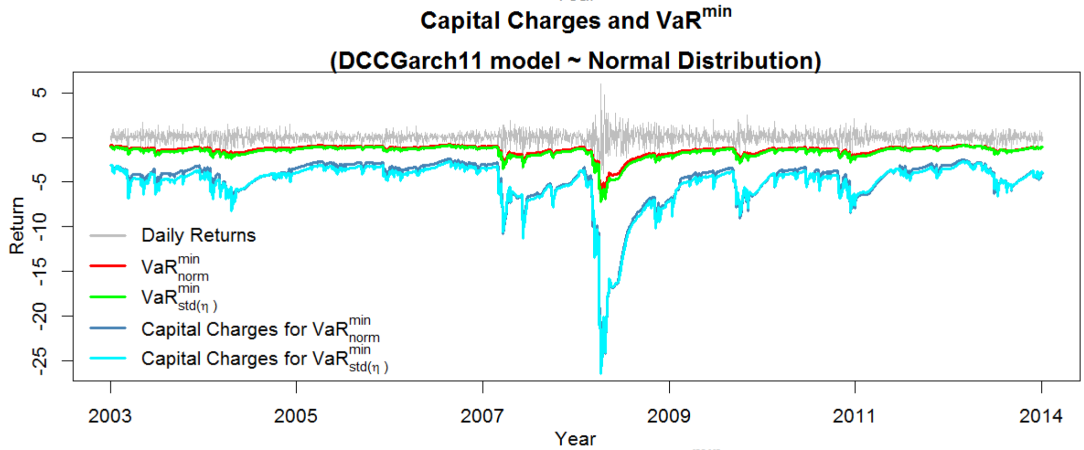

Capital Charges and VaR^{min}_{std}
(CCCGjr11 model ~ Student-t Distribution)
Return
Daily Returns
VaR^{min}_{std}
Capital Charges for VaR^{min}_{std}
5
0
-5
-10
-15
-20
-25
2003
2005
2007
2009
2011
2014
Year

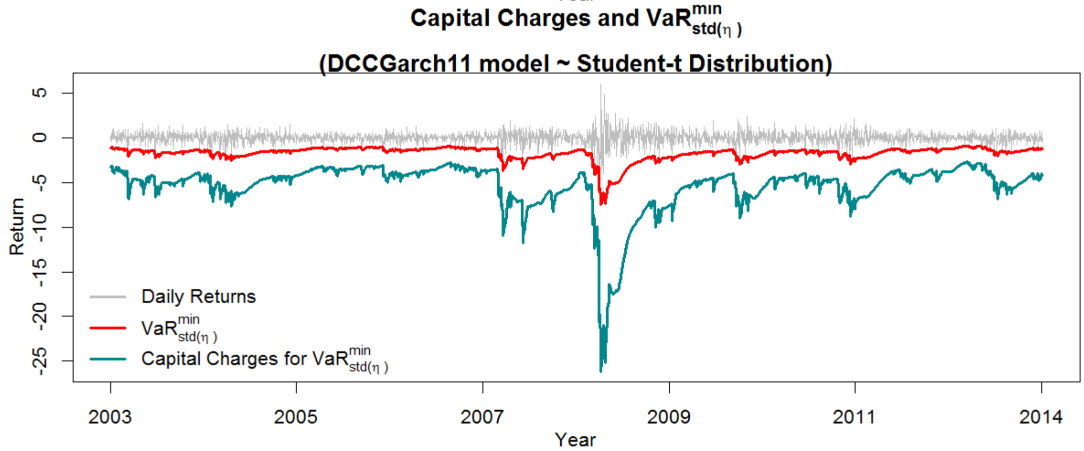

Capital Charges and VaR^{min}
(CCCGjr11 model ~ Normal Distribution)
Return
Daily Returns
VaR^{min}_{norm}
$VaR^{min}_{std(\eta)}$
Capital Charges for VaR^{min}_{norm}
Capital Charges for $VaR^{min}_{std(\eta)}$
5
0
-5
-10
-15
-20
-25
2003
2005
2007
2009
2011
2014
Year

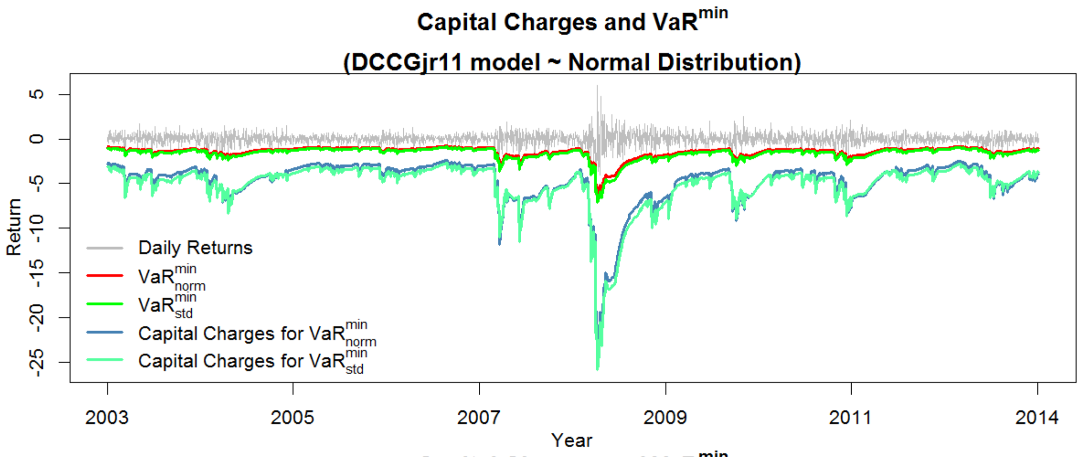

Capital Charges and $VaR^{min}_{std(\eta)}$
(CCCGjr11 model ~ Student-t Distribution)
Return
Daily Returns
$VaR^{min}_{std(\eta)}$
Capital Charges for $VaR^{min}_{std(\eta)}$
5
0
-5
-10
-15
-20
-25
2003
2005
2007
2009
2011
2014
Year

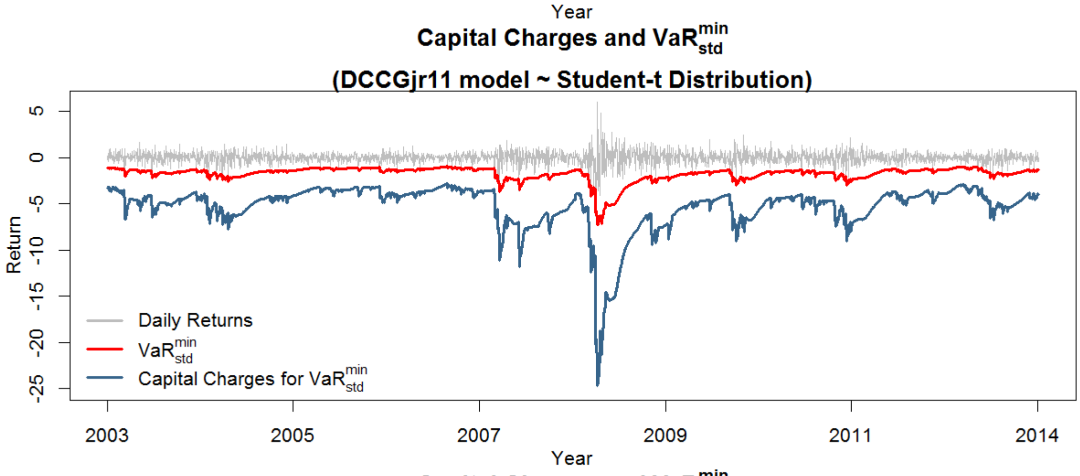

Capital Charges and VaR^{min}
(DCCGarch11 model ~ Normal Distribution)
Return
Year
2003 2005 2007 2009 2011 2014
5 0 -5 -10 -15 -20 -25
Daily Returns
VaR^{min}_{norm}
VaR^{min}_{std}
Capital Charges for VaR^{min}_{norm}
Capital Charges for VaR^{min}_{std}

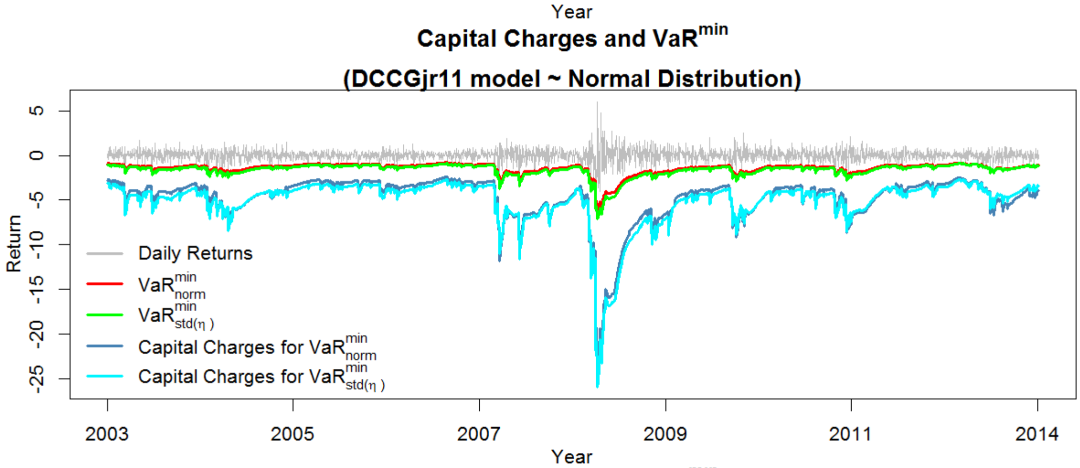

Capital Charges and VaR^{min}_{std}
(DCCGarch11 model ~ Student-t Distribution)
Return
Year
2003 2005 2007 2009 2011 2014
5 0 -5 -10 -15 -20 -25
Daily Returns
VaR^{min}_{std}
Capital Charges for VaR^{min}_{std}


Capital Charges and VaR^{min}
(DCCGarch11 model ~ Normal Distribution)
Return
Year
2003 2005 2007 2009 2011 2014
5 0 -5 -10 -15 -20 -25
Daily Returns
VaR^{min}_{norm}
$VaR^{min}_{std(\eta)}$
Capital Charges for VaR^{min}_{norm}
Capital Charges for $VaR^{min}_{std(\eta)}$


Capital Charges and $VaR^{min}_{std(\eta)}$
(DCCGarch11 model ~ Student-t Distribution)
Return
Year
2003 2005 2007 2009 2011 2014
5 0 -5 -10 -15 -20 -25
Daily Returns
$VaR^{min}_{std(\eta)}$
Capital Charges for $VaR^{min}_{std(\eta)}$


Capital Charges and VaR^min
(DCCGjr11 model ~ Normal Distribution)
Return
Daily Returns
VaR^min_norm
VaR^min_std
Capital Charges for VaR^min_norm
Capital Charges for VaR^min_std
2003 2005 2007 2009 2011 2014
Year


Capital Charges and VaR^min_std
(DCCGjr11 model ~ Student-t Distribution)
Return
Daily Returns
VaR^min_std
Capital Charges for VaR^min_std
2003 2005 2007 2009 2011 2014
Year


Capital Charges and VaR^min
(DCCGjr11 model ~ Normal Distribution)
Return
Daily Returns
VaR^min_norm
VaR^min_std(η)
Capital Charges for VaR^min_norm
Capital Charges for VaR^min_std(η)
2003 2005 2007 2009 2011 2014
Year

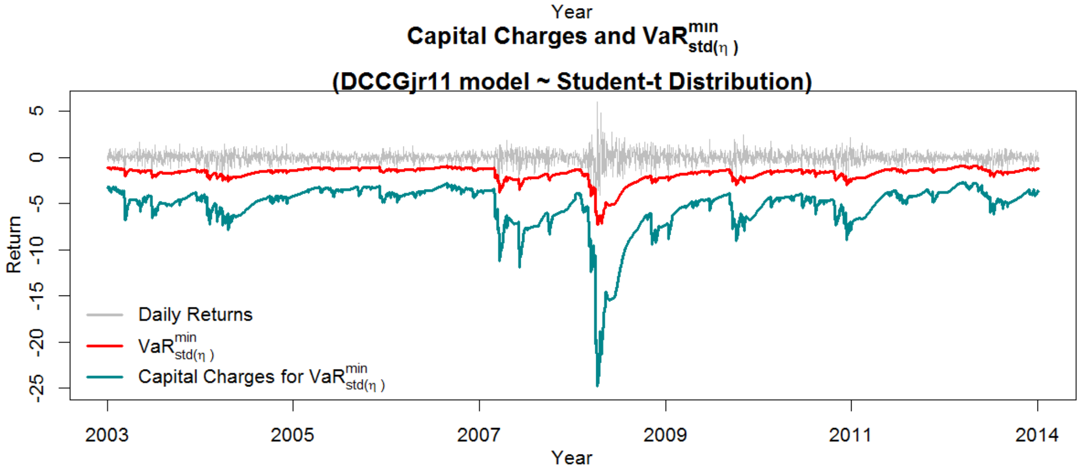
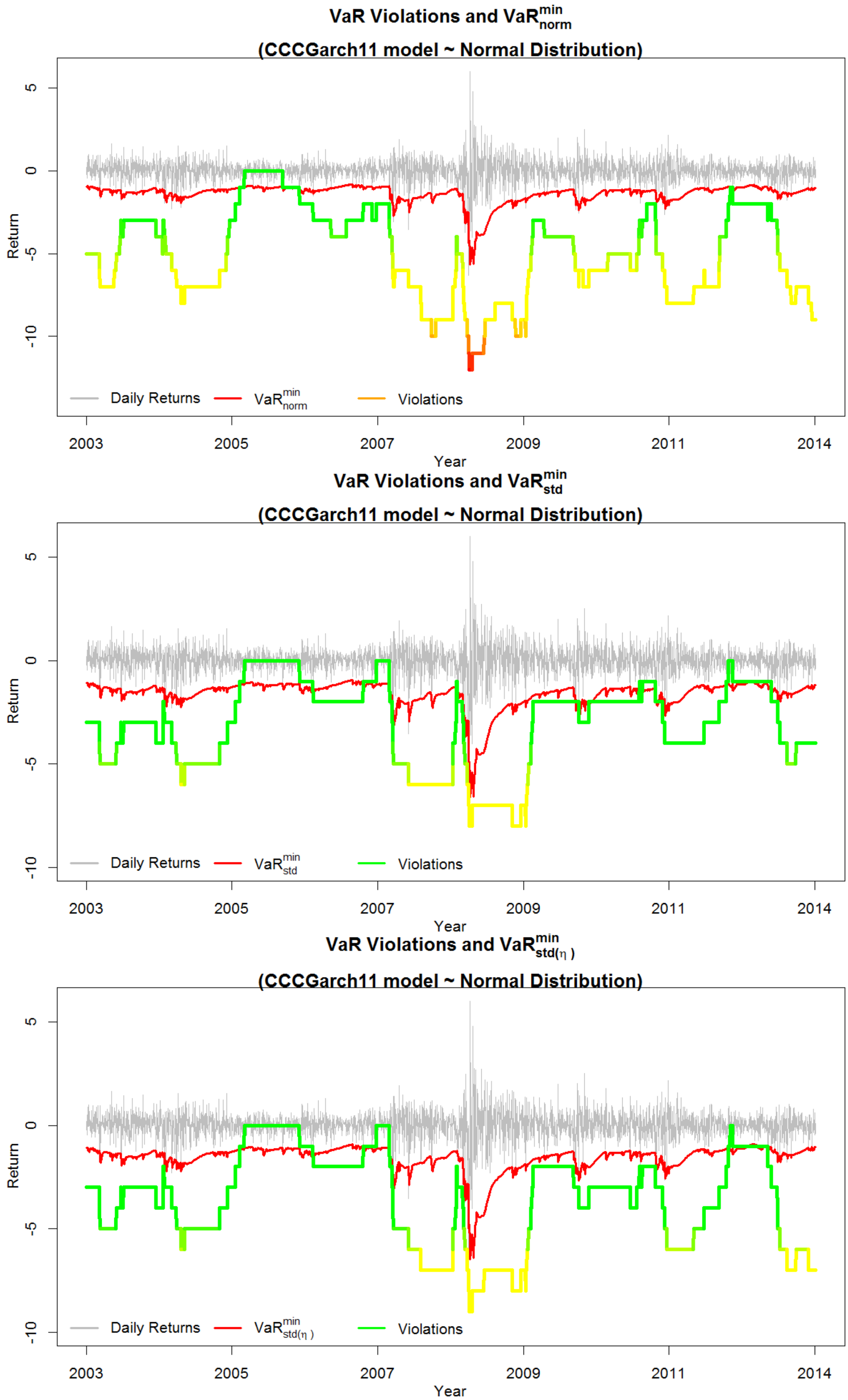
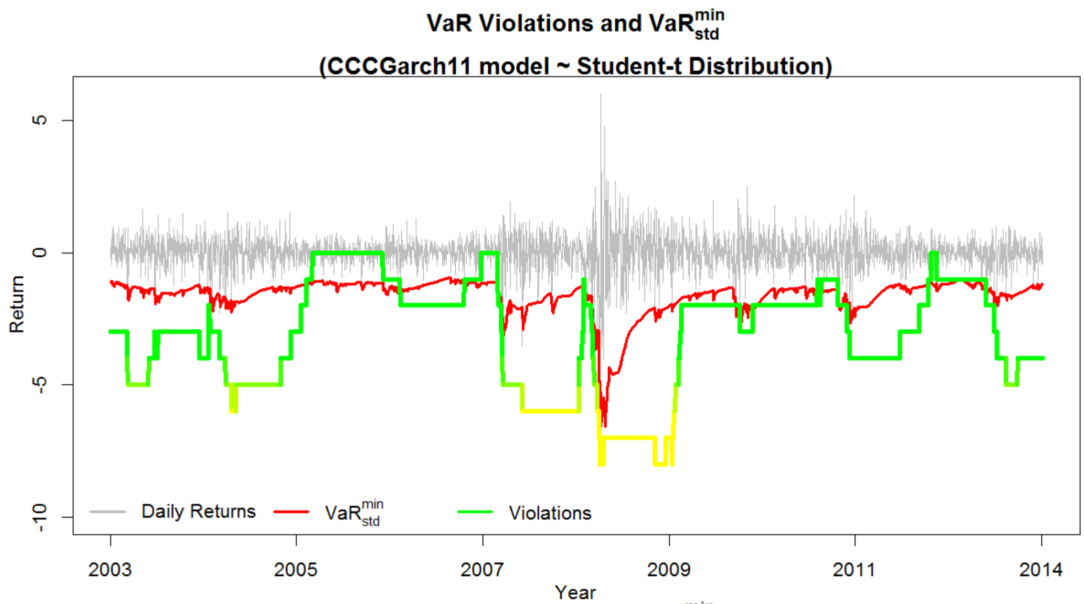

Capital Charges and VaR^min_std(η)
(DCCGjr11 model ~ Student-t Distribution)
Return
Daily Returns
VaR^min_std(η)
Capital Charges for VaR^min_std(η)
2003 2005 2007 2009 2011 2014
Year

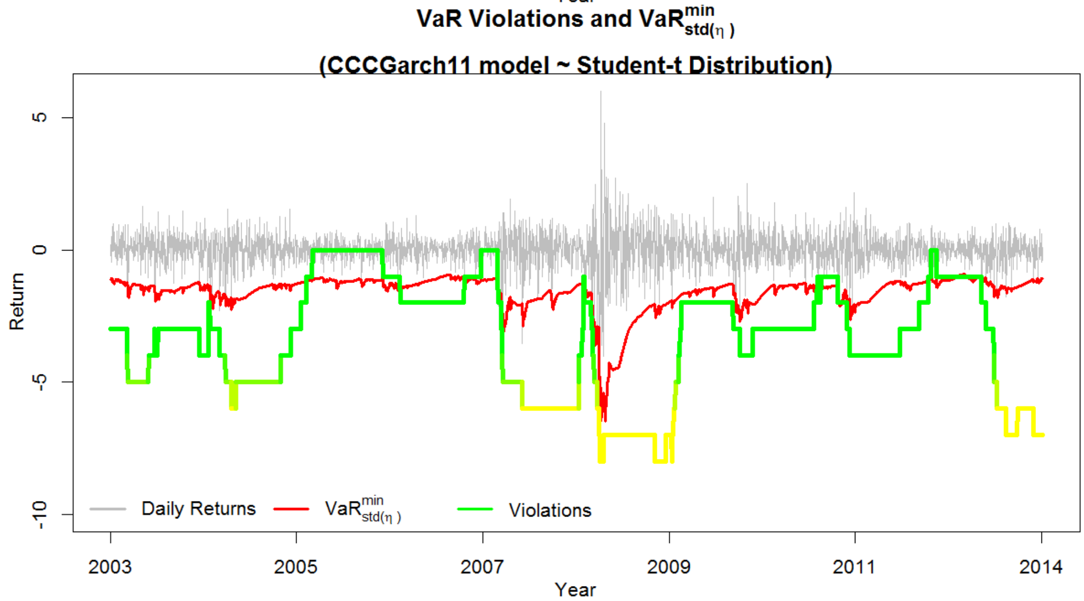
Table 4.21 Proportion of Time Staying in a Color Zone

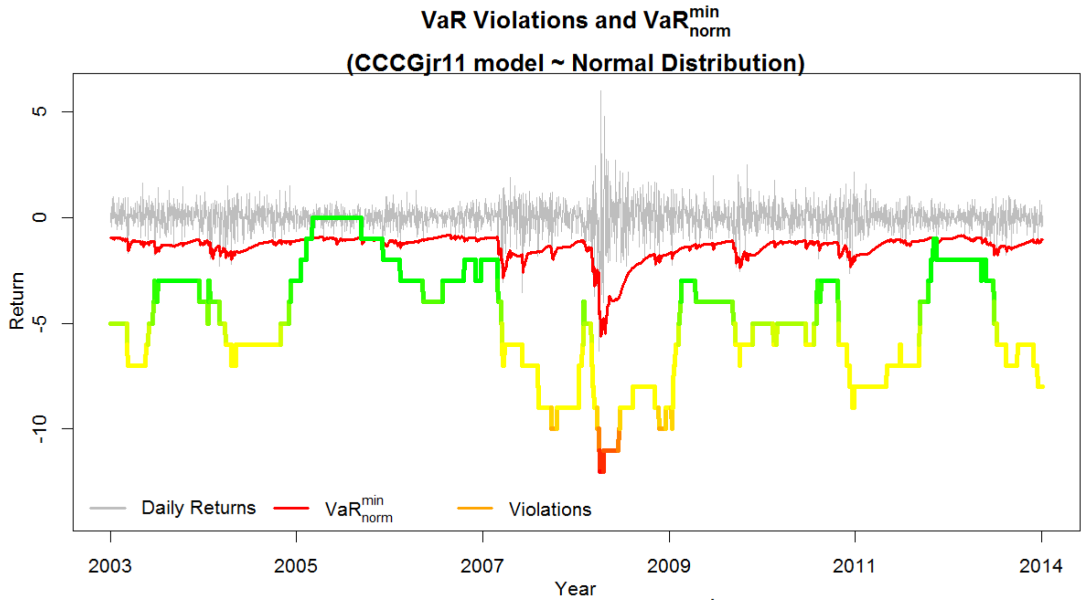
Model	Green	Yellow	Red
$\widehat{VaR}_{norm}^{CCCGARCH-N}$	44.83%	51.45%	3.76%
$\widehat{VaR}_{norm}^{CCCGJR-N}$	45.87%	50.40%	3.76%
$\widehat{VaR}_{std}^{CCCGARCH-N}$	73.35%	26.68%	0%
$\widehat{VaR}_{std}^{CCCGJR-N}$	75.86%	24.17%	0%
$\widehat{VaR}_{std_\eta}^{CCCGARCH-N}$	63.50%	36.54%	0%
$\widehat{VaR}_{std_\eta}^{CCCGJR-N}$	71.86%	28.18%	0%
$\widehat{VaR}_{std}^{CCCGARCH-t}$	73.35%	26.68%	0%
$\widehat{VaR}_{std}^{CCCGJR-t}$	75.51%	24.52%	0%
$\widehat{VaR}_{std_\eta}^{CCCGARCH-t}$	69.35%	30.69%	0%
$\widehat{VaR}_{std_\eta}^{CCCGJR-t}$	69.35%	30.69%	0%
$\widehat{VaR}_{norm}^{DCCGARCH-N}$	53.54%	43.61%	2.89%
$\widehat{VaR}_{norm}^{DCCGJR-N}$	55.83%	44.20%	0%
$\widehat{VaR}_{std}^{DCCGARCH-N}$	74.82%	25.22%	0%
$\widehat{VaR}_{std}^{DCCGJR-N}$	82.79%	17.24%	0%
$\widehat{VaR}_{std_\eta}^{DCCGARCH-N}$	77.60%	22.43%	0%
$\widehat{VaR}_{std_\eta}^{DCCGJR-N}$	82.79%	17.24%	0%
$\widehat{VaR}_{std}^{DCCGARCH-t}$	83.63%	16.41%	0%
$\widehat{VaR}_{std}^{DCCGJR-t}$	89.31%	10.73%	0%
$\widehat{VaR}_{std_\eta}^{DCCGARCH-t}$	78.75%	21.28%	0%
$\widehat{VaR}_{std_\eta}^{DCCGJR-t}$	89.31%	10.73%	0%

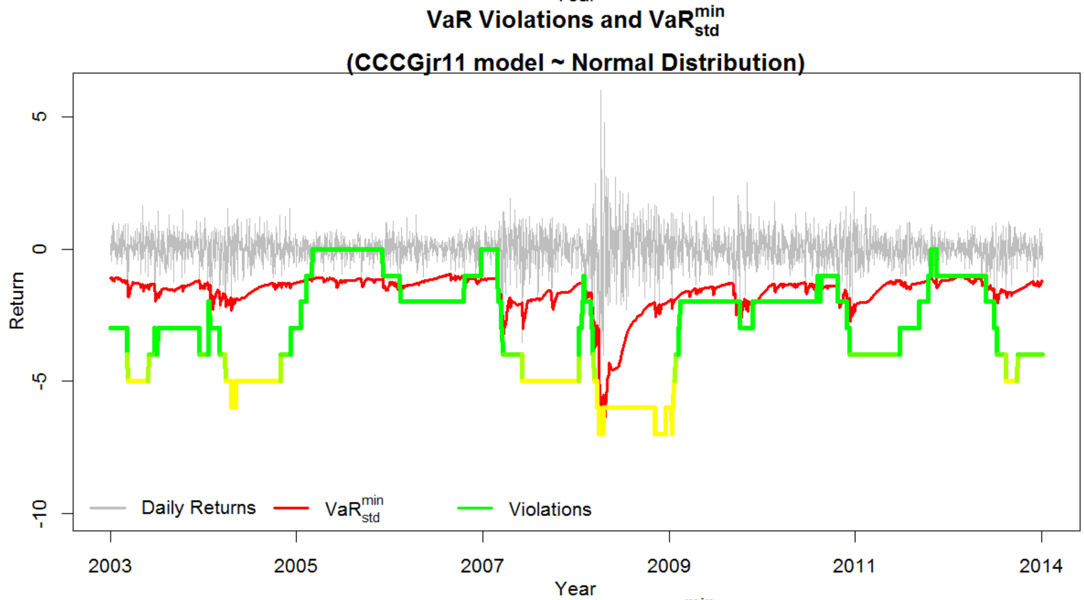
Figure 4.13 VaR Violations and VaR^{min} at 1% level

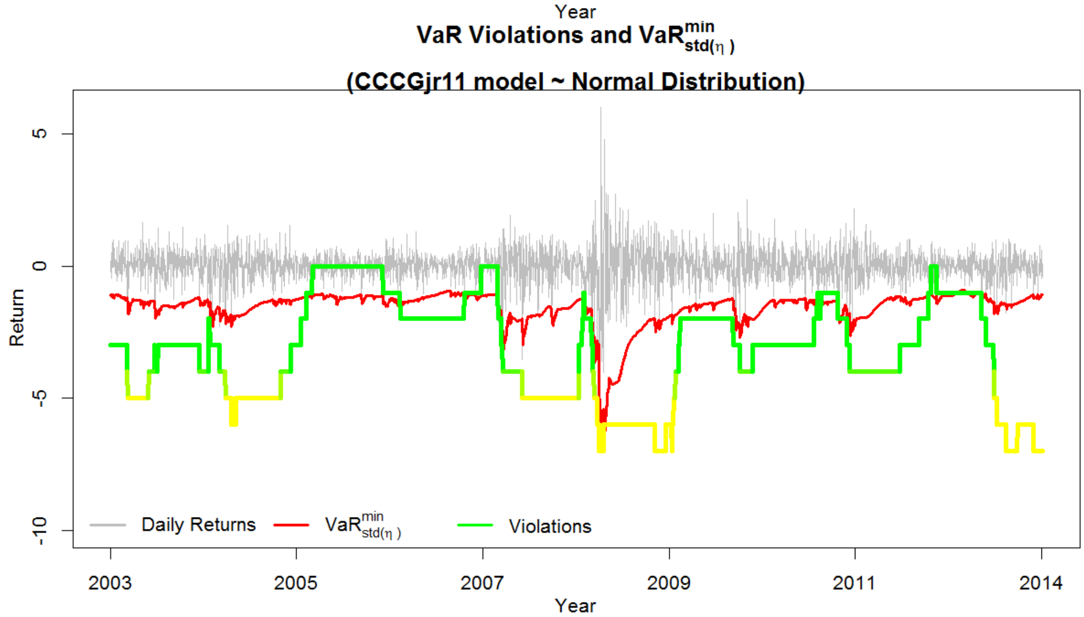



VaR Violations and VaR_{std}^{min}
(CCCGarch11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
VaR_{std}^{min}
Violations
2003
2005
2007
2009
2011
2014
Year


VaR Violations and $VaR_{std(\eta)}^{min}$
(CCCGarch11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
$VaR_{std(\eta)}^{min}$
Violations
2003
2005
2007
2009
2011
2014
Year

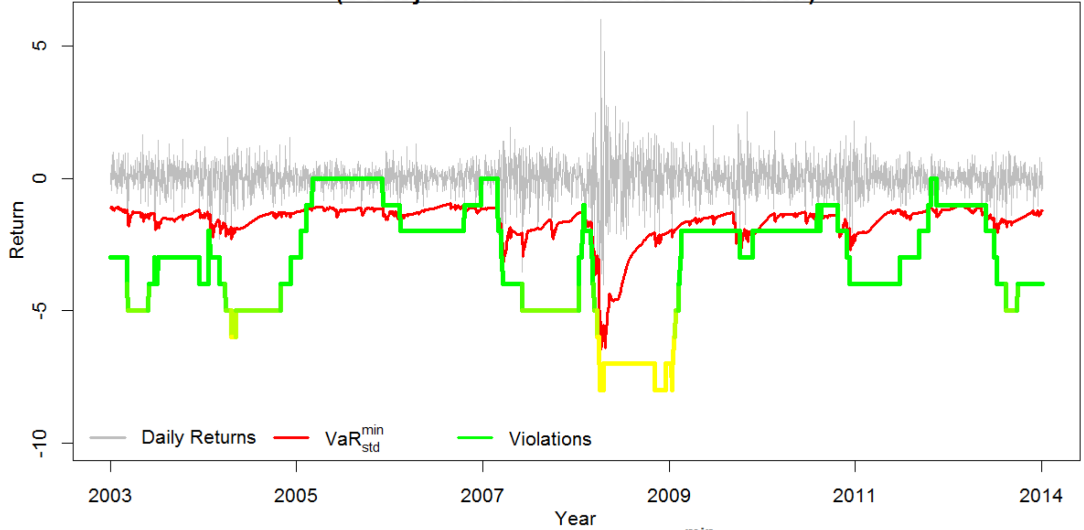

VaR Violations and VaR$^{min}_{norm}$
(CCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR$^{min}_{norm}$
Violations
2003
2005
2007
2009
2011
2014
Year


VaR Violations and VaR$^{min}_{std}$
(CCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR$^{min}_{std}$
Violations
2003
2005
2007
2009
2011
2014
Year


VaR Violations and VaR$^{min}_{std(\eta)}$
(CCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR$^{min}_{std(\eta)}$
Violations
2003
2005
2007
2009
2011
2014
Year

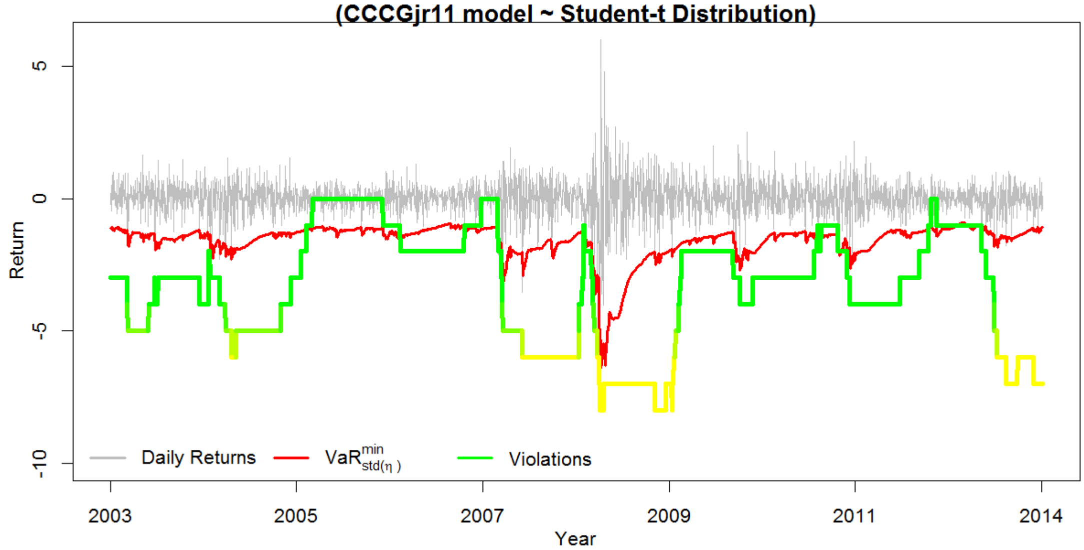
VaR Violations and VaR_{std}^{min}

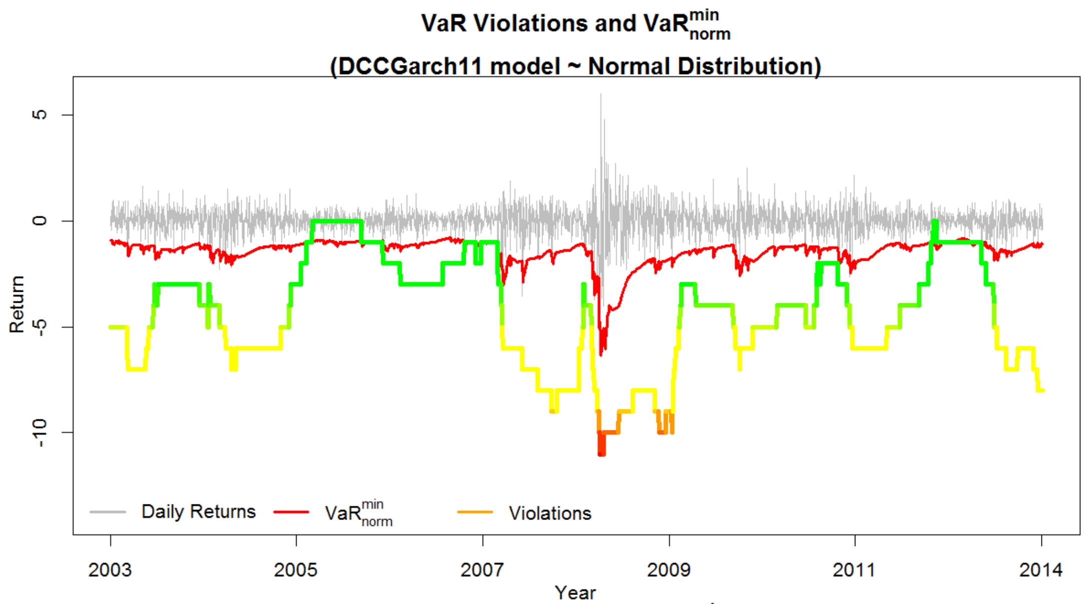
(CCCGjr11 model ~ Student-t Distribution)

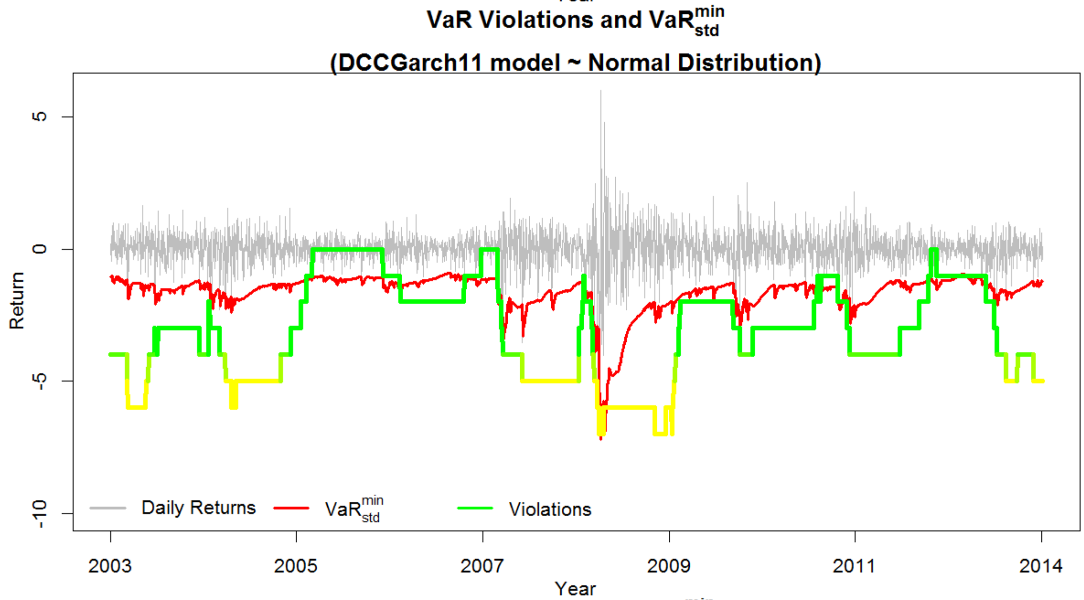


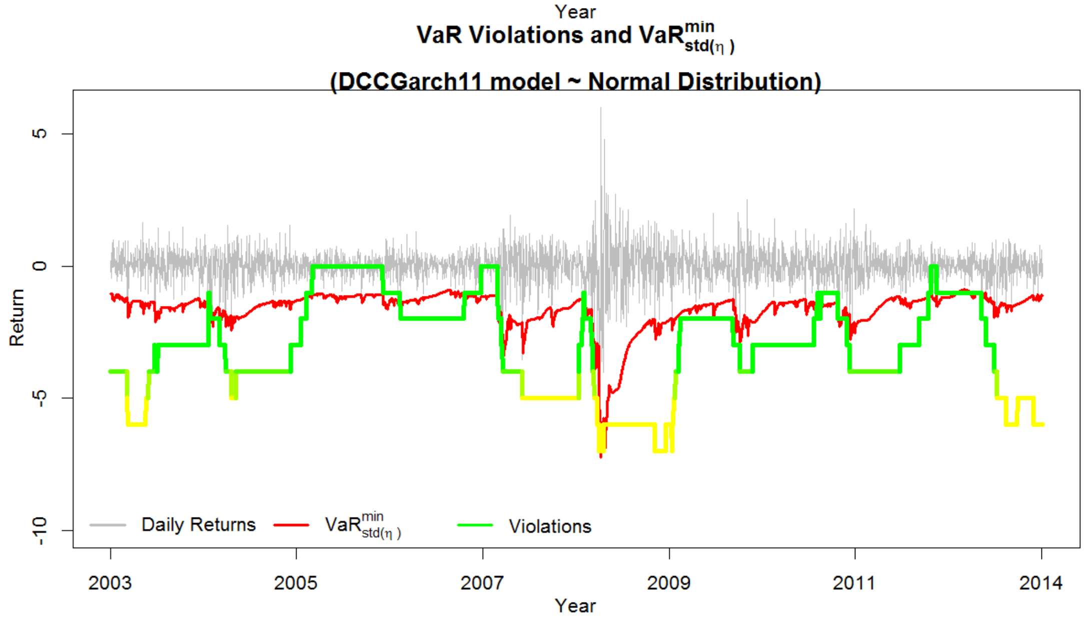
VaR Violations and $VaR_{std(\eta)}^{min}$

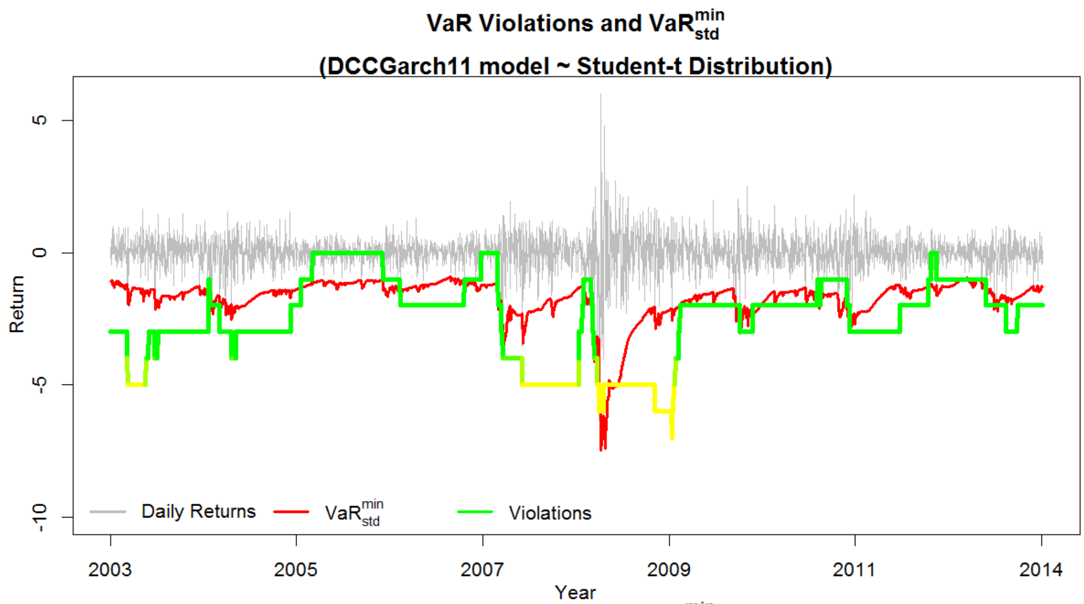
(CCCGjr11 model ~ Student-t Distribution)

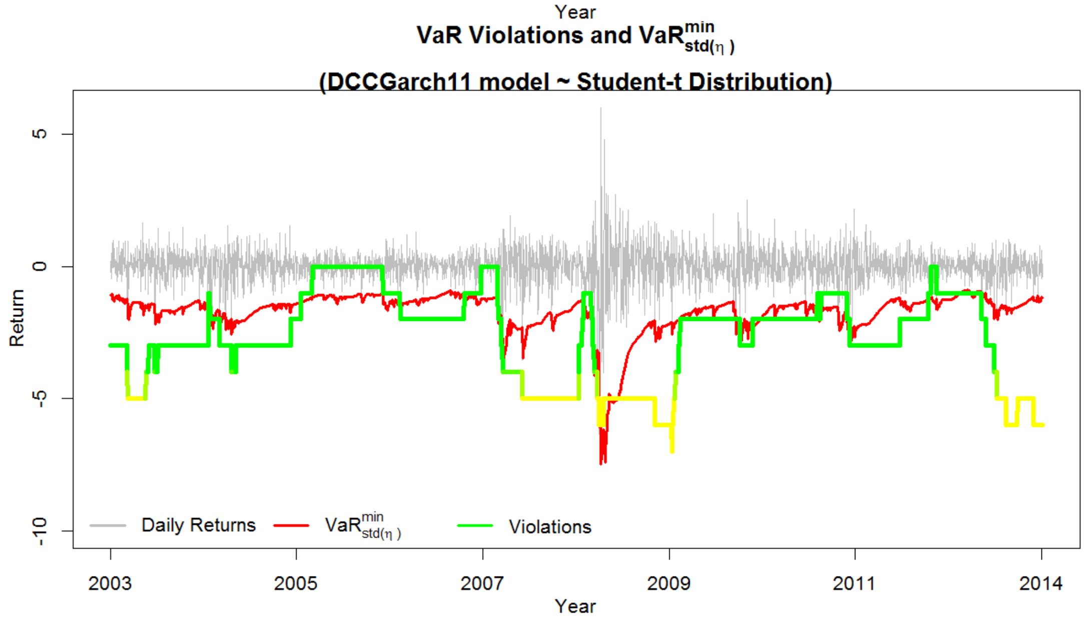


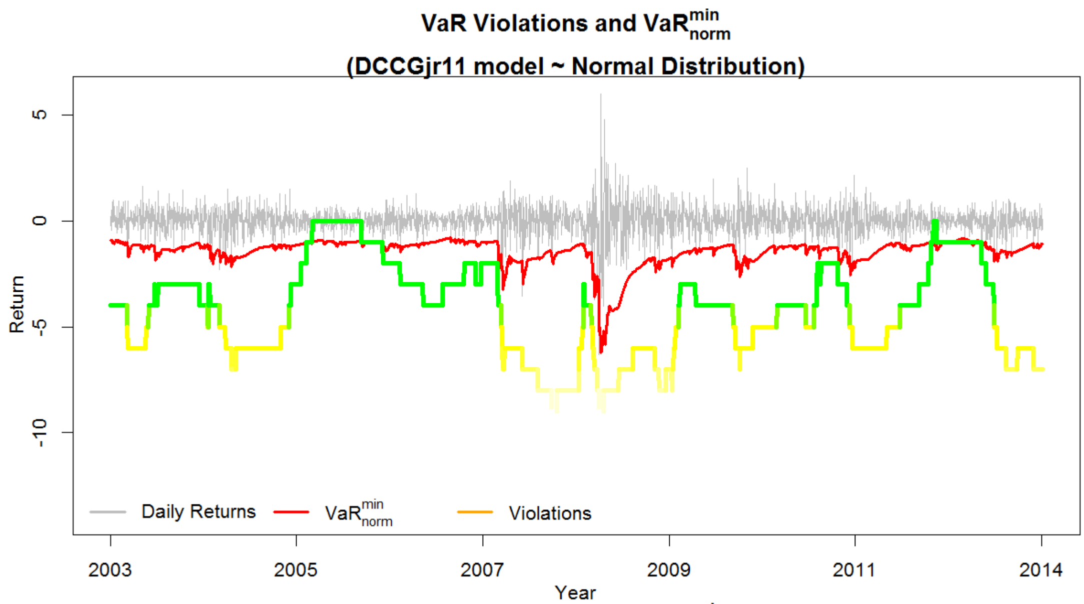

VaR Violations and VaR^{min}_{norm}
(DCCGarch11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR^{min}_{norm}
Violations
2003
2005
2007
2009
2011
2014
Year

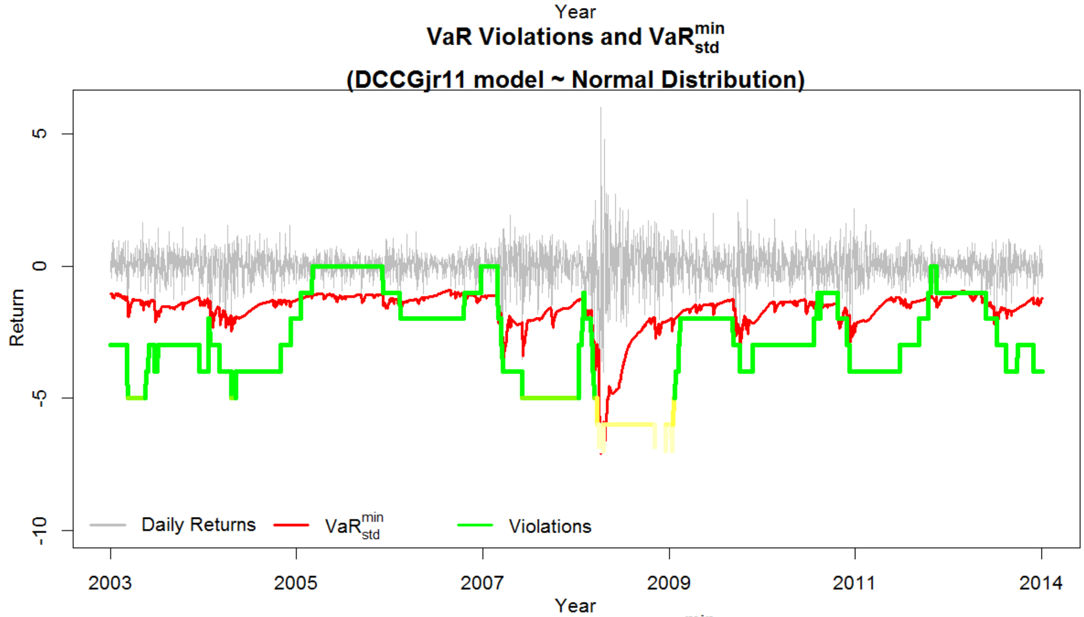

VaR Violations and VaR^{min}_{std}
(DCCGarch11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR^{min}_{std}
Violations
2003
2005
2007
2009
2011
2014
Year

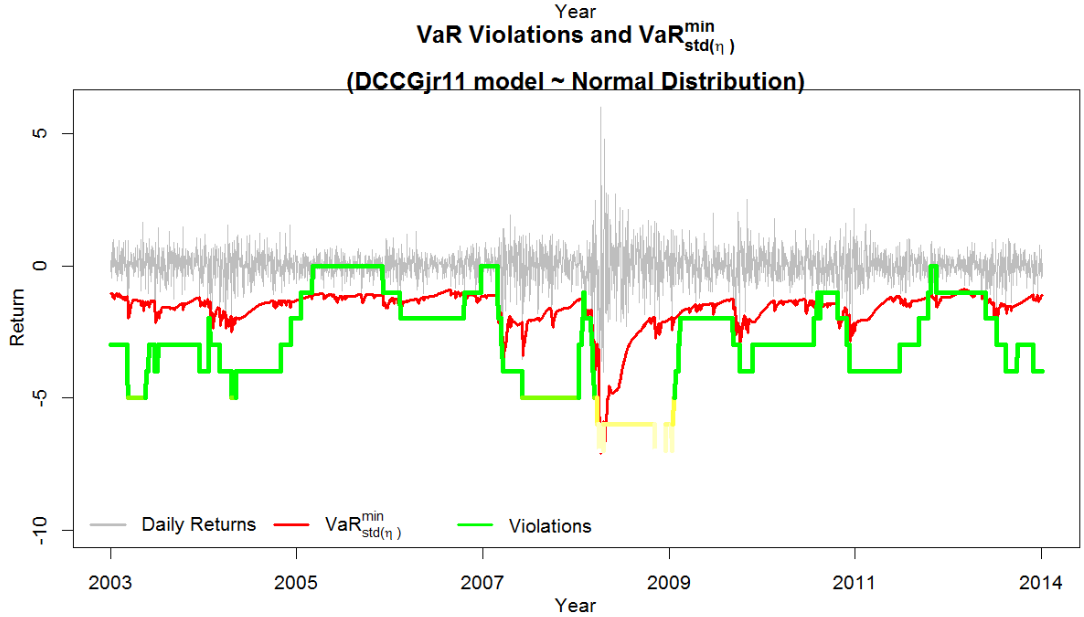

VaR Violations and $VaR^{min}_{std(\eta)}$
(DCCGarch11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
$VaR^{min}_{std(\eta)}$
Violations
2003
2005
2007
2009
2011
2014
Year

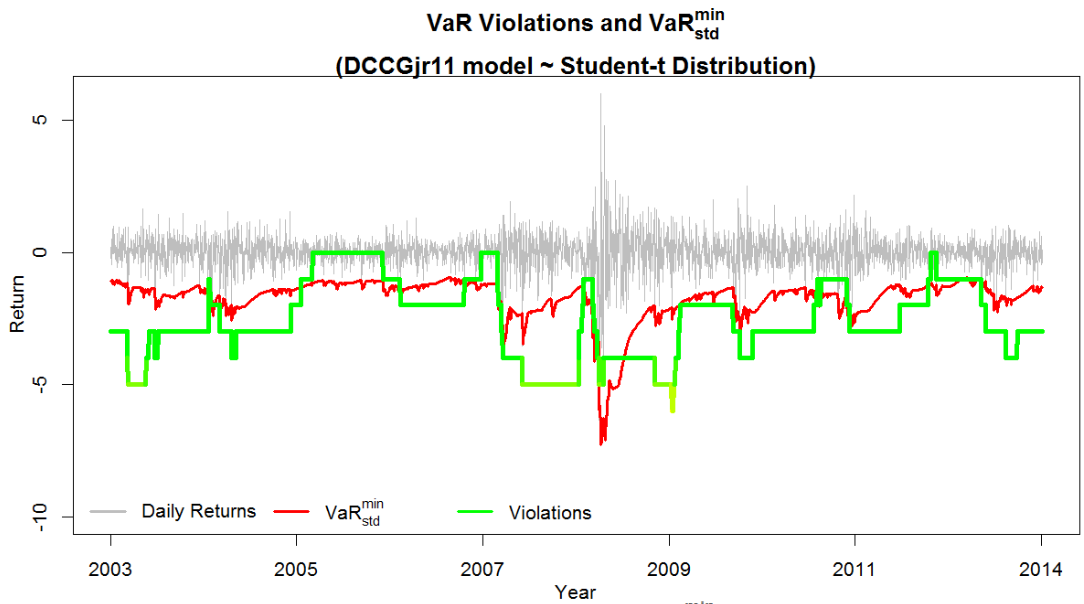

VaR Violations and VaR^{min}_{std}
(DCCGarch11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
VaR^{min}_{std}
Violations
2003
2005
2007
2009
2011
2014
Year


VaR Violations and $VaR^{min}_{std(\eta)}$
(DCCGarch11 model ~ Student-t Distribution)
Return
5
0
-5
-10
Daily Returns
$VaR^{min}_{std(\eta)}$
Violations
2003
2005
2007
2009
2011
2014
Year


VaR Violations and VaR^{min}_{norm}
(DCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR^{min}_{norm}
Violations
2003
2005
2007
2009
2011
2014
Year


VaR Violations and VaR^{min}_{std}
(DCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
VaR^{min}_{std}
Violations
2003
2005
2007
2009
2011
2014
Year


VaR Violations and $VaR^{min}_{std(\eta)}$
(DCCGjr11 model ~ Normal Distribution)
Return
5
0
-5
-10
Daily Returns
$VaR^{min}_{std(\eta)}$
Violations
2003
2005
2007
2009
2011
2014
Year



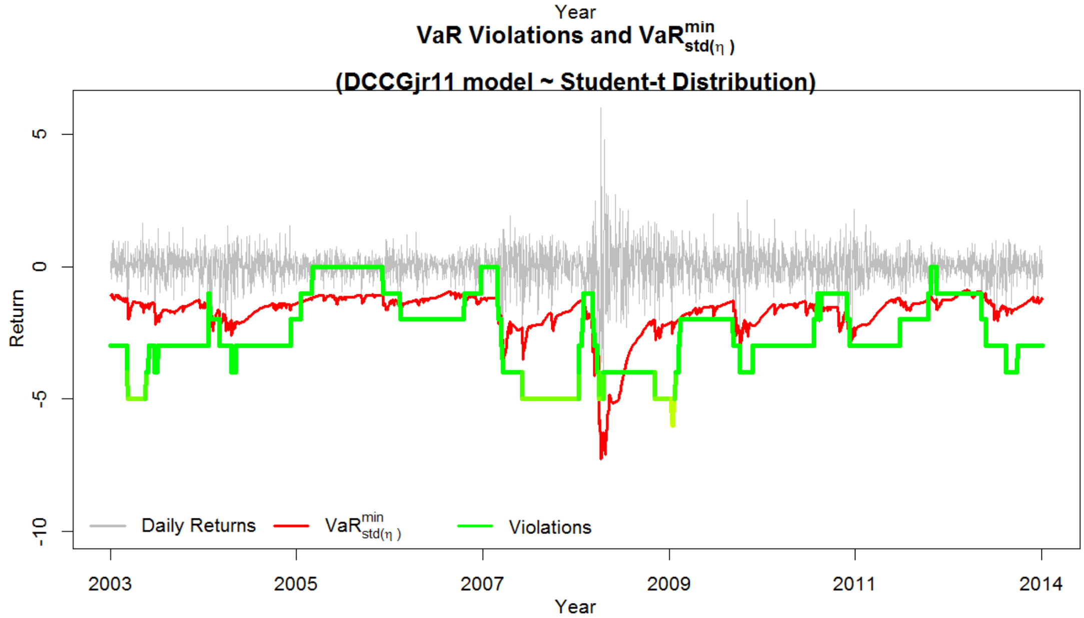


Table 4.21 provides the proportion of time staying in the green, yellow and red zones. The green zone is desirable by all banks, as this indicates that no excessive violations occur. A bank is categorized in the red zone if its VaR model is not appropriate, and will be required to pay a greater amount of capital charges. Figure 4.13 exhibits the periods of when the green, yellow and red zones are likely to occur for all VaR models. In most cases, the models tend to stay in the green and yellow zones during periods of low volatility with fewer VaR violations. With exception to $\widehat{VaR}_{norm}^{CCCGARCH-N}$, $\widehat{VaR}_{norm}^{CCCGJR-N}$, and $\widehat{VaR}_{norm}^{DCCGARCH-N}$, these models spend some time

in the red zone due to excessive negative movements during the GFC. $\widehat{VaR}_{std}^{DCCGJR-t}$, $\widehat{VaR}_{std}^{DCCGARCH-t}$, and $\widehat{VaR}_{std}^{DCCGJR-N}$ models spend a very large proportion of time in the green zone, and substantially spending less time in the yellow zone.

4.4 CONCLUSION

This chapter emphasizes the importance of accommodating time-varying conditional correlations in forecasting VaR. These findings are crucial for banks and the regulator since a correct VaR model leads to increase efficiency in measuring market risk, hence leading to determine minimum capital requirements. In this chapter, two multivariate volatility models, namely CCC and DCC models, are considered to forecast VaR. These models are estimated by GARCH(1,1) and GJR1,1) processes under normal and student-t distributions. The results show that a student-t distribution gives a more robust estimation of VaR forecasts than a normal distribution, given that the foreign exchange returns exhibit heavy tails (see, Lee, Chiou, and Lin 2006, and, Pesaran and Pesaran 2010). The results also find that the VaR forecasts based on DCC models are superior to VaR forecasts based on the CCC models with the DCC models have lower numbers and percentages of VaR violations that are closer to one percent. Consequently, the time-varying conditional correlation highlights the importance of accommodating significant changes in the correlation between asset returns in forecasting VaR. Also, CCC models deliver a higher amount of capital charges compared to the DCC models. These results are consistent with the empirical findings by da Veiga, Chan, and McAleer (2008).

From the above discussions, $\widehat{VaR}_{std}^{DCCGJR-t}$ has always represented the most appropriate model given that it provides the lowest number of violations and a percentage of violation that is very close to one percent. Also, the model has the lowest mean ratio of absolute deviation for VaR violations. $\widehat{VaR}_{std}^{DCCGJR-t}$ has correctly accepted all statistical tests including TUFF, UC, Ind and CC tests. Based on the backtesting procedures as outlined by the Basel Accord, the model has consistently stayed in the green zone with no excessive violations occur in the red zone thus, no severe violation penalty is imposed. While, the mean and median of scaling factor are also maintained at a level of 3.0, with an exception of the highest scaling factor at 3.5 during the GFC of 2008. This implies that the scaling factors are consistently kept at a level of 3.0, which is mostly desirable by banks without suffering additional penalty charges. It is worth noting that the model leads to a mean of capital charges at -5.31 with VaR^{min} at -1.7382.

In most cases, $\widehat{VaR}_{norm}^{CCCGARCH-N}$ presents the least appropriate model given that it has the highest number and percentage of violations. The model fails all statistical tests with serial dependent and excessive violations. The model also has the highest mean ratio of absolute deviation for VaR violations. It can be seen that the model has a maximum scaling factor of 4 with the mean and median of scaling factor at a level of 3.4. However, the model has the lowest mean of capital charges at -4.79 with VaR^{min} at -1.3913. Therefore, the assumption of normality has a tendency of providing less conservative VaR forecasts and often with excessive violations but at a lower amount of capital charges. While, student-t distribution inclines to provide lower VaR forecasts with fewer violations, but usually at a higher amount of capital charges. Given that a higher amount of capital charge represents an additional cost to the banks, these results show that banks should exercise great care in selecting an optimal VaR model.

Incorporating multivariate volatility in VaR models is not straightforward where there are many other factors to be considered. These models raise some difficulties in practice, where banks trade with relatively large and complex portfolios that are unlikely to change daily. This implies that each day, the banks would have to compute a series of historical data for the new portfolios to estimate VaR. This may create additional costs to the banks. Instead of using these models, banks appear to be taking less computationally demanding alternatives. Banks prefer to use a simple VaR model that aggregates all of the risks of a portfolio into a single number, which is suitable for use in the boardroom, reporting to the regulator and disclosure in their financial reports. Nonetheless, multivariate volatility models play a significant role in the study of VaR as they are very useful to measure and manage market risk.

Chapter 5

A Critical Analysis of the Market Risk Regulatory Framework under Basel III

[THIS CHAPTER IS PERMANENTLY EXEMPTED FROM THE THESIS INDEFINITELY]

Chapter 6

CONCLUSION

This thesis examines the tale of two perspectives in the context of Australian risk management in theory and in practice. Value-at-Risk (VaR) is established as an important risk measure to control and manage market risk. The popularity of VaR models is partly due to their conceptual simplicity and partly from the requirements of Basel Accord to the regulation of the banking system. Basel III explicitly recognizes the role of VaR where the banks must implement and report to monitor their market risk exposure and to determine the amount of regulatory capital requirements. Consequently, the Basel Accord also establishes the penalties for inadequate VaR models, hence, there are incentives to pursue practical approaches to forecasting VaR.

Following the recent regulatory changes in Basel III, the need to understand the risk management practices in Australia is becoming more urgent and pronounced. The thesis begins with an overview of the regulatory changes to Basel III with an emphasis on the influence of these regulations on market risk exposure. The Basel Accord requires Authorised Deposit-taking Institutions (ADIs) to measure their VaR forecasts on a daily basis using one or more risk models. To further evaluate and improve VaR procedures, this thesis concentrates on developing an alternative model to forecast VaR. The risk estimates of these models that are used to determine the capital charges and associated costs of ADIs depending on the number of previous VaR violations. At 99 percent confidence level, if an ADI's internal model leads to a greater number of violations than reasonably expected, a violation penalty at a multiplication factor of $3+k$ will be imposed. Then, the ADI will be required to hold a greater amount of capital charges including the penalty charges.

The thesis provides new information about how VaR models can be improved by estimating market risk and suggest a superior forecasting model to produce an optimal risk measure for assessing market risk. The study will proceed by the application of VaR to optimize capital charges for Australian authorized deposit-taking institutions (ADIs) in accommodating market risk to an acceptable level.

This thesis proposes a consistent estimator of the tail index for the asymmetric extension of Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) error by Glosten, Jagannathan, and Runkle (1993). The thesis then applies the proposed estimator to forecast VaR for a portfolio of the Australian dollar with twelve other currencies and compares its performance with the more traditional approaches based on conditional and unconditional variances. The results suggest that the proposed method performed reasonably well against the traditional approaches, and it has the advantage of accommodating information from the time-varying volatility without the need for computing the conditional variances on a regular basis. Thus, it provides a more computationally efficient approach to forecasting VaR.

This thesis compares the performance of univariate and multivariate conditional volatility models in forecasting VaR. The thesis considers the Constant Conditional Correlation (CCC) model of Bollerslev (1990); and models that allow dynamic conditional correlation such as the Dynamic

Conditional Correlation (DCC) model of Engle (2002) and the Time-Varying Conditional Correlation (TVC) model of Tse and Tsui (2002). While the underlying assumptions vary between these models, their common objective is to model the volatility of multiple assets by capturing their possible interactions. Thus, they provide more information about the underlying assets that could not be recovered by univariate models. However, the practical usefulness of these models is limited by their complexity as the number of asset increases. The results found that VaR forecasts based on the DCC models are superior to VaR forecasts based on the CCC models. The time-varying conditional correlation highlights the importance of accommodating significant changes in the correlation between asset returns in forecasting VaR. Furthermore, the results also find that a student-t distribution gives a more robust estimation of VaR forecasts than a normal distribution. Hence, the selection of a distribution assumption proves to be a more important consideration than the choice of a model to improve the performance of VaR forecasts.

This thesis examines the information content of reported VaR forecasts on ADI's trading revenues in a simple linear regression framework. The idea is that if the reported VaR forecasts are adequate, then they should be related to ADI's future trading revenues. The results support this hypothesis for some ADIs. Due to data limitation on the number of observations and the frequency of data, the thesis cannot utilize more sophisticated techniques that are standard in financial econometrics. One of the main objectives for Basel III is to strengthen banks' transparency and disclosures. The thesis finds that the current financial reporting environment in Australia does not provide academic researchers and the regulator enough information to assess the quality of VaR forecasts reported by ADIs. It is also worth noting that the requirements for banks to disclose information more completely can sometimes be very costly and may not necessary increase transparency.

This thesis has significant theoretical and practical implications. In theory, the proposed VaR models may be preferred for risk forecasting to accommodate for dynamic volatility in situations when very large and extreme returns occurred in a high volatility period. In practice, the ability to model VaR may be constrained by limited data availability, computational burdens and subsequent increase of costs. Most of these criticisms have been stressed by banks and the regulator. While the current regulatory framework implements a set of standards to manage and control the market risk exposure, the framework has yet to develop an alternative approach that can satisfy all practical and regulatory objectives. In reality, the role of academic researchers is crucial to enable feedback and to provide continuous engagement with the banks and the regulator. This, in effect, means that the academic researchers need to become more relevant to the regulatory process if banks and the regulator are to engage with them. Similarly, banks and the regulator should seek an increased level of engagement with the academic researchers. Subsequently, a more rigorous research to the understanding and the practice of VaR can be connected between banks and the regulator with the academic researchers.

The research undertaken in this thesis can be extended in the following manners. First, a wider selection of distributional assumptions can be used. These include the asymmetric distributions, for example, Generalized Error Distribution (GED) by Nelson (1991). Second, a large and more complex portfolio can be constructed assuming different weight structures, for example, the application of optimal weights in a portfolio in evaluating the performance of VaR forecast. Third, alternative univariate and multivariate conditional volatility models can also be considered, for example, the Exponential GARCH model of Nelson (1991), and Baba, Engle, Kraft and Kroner (BEKK) model described by Engle and Kroner (1995). Lastly, the use of ultra-frequency data, for example, 1-hour, 5-minute and 1-minute data can be applied to produce daily VaR forecasts.

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Appendix I

AUSTRALIAN PRUDENTIAL REGULATION AUTHORITY (APRA) CONFIDENTIALITY AGREEMENT

[THIS APPENDIX IS PERMANENTLY EXEMPTED FROM THE THESIS INDEFINITELY]

Appendix II

ETHICS APPROVAL BY CURTIN UNIVERSITY

[THIS APPENDIX IS PERMANENTLY EXEMPTED FROM THE THESIS INDEFINITELY]