Modelling Dynamic Volatility and Value-at-Risk Thresholds

Bernardo da Veiga
BCom (Hons) UWA

School of Economics and Commerce
University of Western Australia

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Abstract

Risk is paramount in life, and is especially so in the world of finance, where it is used, among others, in evaluating the costs of financial catastrophes. In finance, risk is defined as the variability of uncertain outcomes, such that the greater is the variability, the greater is the associated risk. Models of volatility can be used to estimate and forecast Value-at-Risk (VaR) thresholds for purposes of risk management. This thesis is concerned with the modelling and forecasting of dynamic volatility and VaR thresholds.

Chapter 2 provides a detailed overview of the VaR method, the Basel Accord and its subsequent two amendments which led Authorised Deposit-taking Institutions (ADIs) to be required to use VaR methods to calculate capital adequacy requirements as a protection against market risk.

Chapter 3 investigates the important issue of aggregation across financial assets. It is shown that portfolio VaR forecasts can be obtained by aggregating the portfolio into a single asset and directly calculating a VaR threshold, or by modelling the risk of each asset as well as the co-risks between asset, and using these to calculate a VaR threshold for the entire portfolio. The performance of each model is compared using various tests that largely reflect the concerns of regulators who would like ADIs to use models that display the appropriate statistical properties. The forecasting performance of the various models is compared using various models that are developed in this thesis.

Chapter 4 investigates the importance of including spillover effects in forecasting VaR thresholds. The forecasting performances of the VARMA-GARCH model of Ling and McAleer (2003), which...
includes spillover effects from all assets, the CCC model of Bollerslev (1990), which includes no spillovers, and the Portfolio Spillover GARCH (PS-GARCH) model, which accommodates aggregate spillovers parsimoniously, and hence avoids the so-called “curse of dimensionality”, are compared.

Chapter 5 analyses the importance of accommodating time-varying (or dynamic) conditional correlations in forecasting VaR thresholds. Chinese A and B share indices which, due to recent regulatory changes have shown an increase in correlation, are used to analyse this important issue. VaR forecasts produced by the Constant Conditional Correlation (CCC) model of Bollerslev (1990) are compared with those produced by the Dynamic Conditional Correlation (DCC) model of Engle. The empirical results show that accommodating dynamic correlations in the forecasting of VaR thresholds can lead to superior VaR threshold forecasts.

Chapter 6 assesses the ability of the Basel Accord penalties to align the interest of ADIs with that of regulators. Several popular conditional volatility models are used to forecast VaR threshold for a long series of S&P500. The empirical results show that the current Basel Accord penalty structure leads ADIs to choose models with excessive violations as it is presently not sufficiently severe. A new penalty structure is developed that leads to ADIs choosing models with the correct coverage.

In Chapter 7 the traditional VaR method is extended and applied to the analysis of country risk ratings, with the creation of Country Risk Bounds (CRBs). Such CRBs are a two-sided VaR analysis that can be used to provide valuable information to both lenders and borrowers. The results show that developing countries tend to have significantly wider bounds than do developed countries. This suggests that not only are developing countries deemed to be riskier, as reflected in a lower credit
rating, but they are also more likely to experience larger ratings changes, and hence incur substantial re-ratings risk.

The VaR technique is adapted and applied to the tourism literature in Chapter 8. As the Maldivian government relies heavily on the income generated from tourism, changes in tourism demand are analogous to financial returns as they translate directly to financial gains or losses. This chapter discusses the use of VaR methods in the management of tourism revenue. The chapter also outlines several ways in which this information can be used by various parties to improve the decision making process.
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Chapter 7 is based on a joint paper currently under review at Journal of Money, Credit and Banking.

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This thesis is dedicated to my mother, Claudia Sanchez, for her unfailing love and support that has made everything in my life possible.
Chapter One

1 Introduction

“All of life is the management of risk, not its elimination”

Walter Wriston, former chairman of Citicorp

Risk became a buzz word at the end of the 20th Century and at the beginning of the 21st Century. From financial disasters to terrorist attacks, natural catastrophes and deadly epidemics, it appears that risk can be found everywhere. In finance, risk is defined as the variability of outcomes, such that the greater is the variability the greater is the associated risk.

Financial theory has evolved to measure risk for the purpose of asset and derivative pricing. However, in the last three decades the sheer size of global equity, foreign exchange and derivatives markets, the trend towards deregulated banking systems, flexible exchange rate systems and the rapid increase in global financial integration, have led to a marked increase in global volatility (or risk) as the world experienced a series of financial disasters.

Consider for example, 19 October 1987, when the US stock market fell by 23% in a single day, wiping away over US$1 trillion in capital, or the Asian Financial crisis of 1997, in which 75% of the dollar capitalization of equities in Thailand, Malaysia, Korea and Indonesia were wiped out, or the Russian default of 1998, which led to a global

Although the cause of such disasters may differ, two features are always the same, namely that they are unpredictable and create significant financial losses. Disasters such those mentioned above have been largely responsible for the recent growth in the risk management industry, such that every major corporation now engages in some form of risk management, and most will have independent risk management divisions.

The systemic nature of the banking sector prompted regulators around the world to introduce capital adequacy requirements. This was done in order to mitigate the moral hazard problem associated with governments acting as lenders of last resort, and to force banks, or authorised deposit-taking institutions (ADIs), to internalise some of the burden that would otherwise be borne by taxpayers. Perhaps the most significant advance in international regulation of ADIs was the 1988 Basel Accord which, among other things, promoted uniform capital requirements among ADIs around the world.

However, the Group of Thirty (G-30) report, which was commissioned to study derivative industry practices, highlighted the fact that ADIs were holding increasingly larger equity and derivative trading portfolios. Such exposure meant that ADIs were becoming increasingly subject to market risk. In response to this report, the Basel accord was amended in 1995 to require ADIs to incorporate charges for market risk in their capital adequacy calculations.
In particular, the G-30 report and the 1995 amendment to the Basel Accord required ADIs to measure market risk through Value-at-Risk (VaR) methods. The original amendment required ADIs to use a standardised VaR approach, which was explicitly set out. This attracted widespread criticism from the international community as such an approach provided no incentive for more accurate and cost-reducing techniques. In response to this criticism, the Basel Accord was subsequently amended to allow ADIs to use internally developed models, provided these met a number of regulatory criteria. The VaR technique and the Basel accord are discussed in detail in Chapter 2.

The Basel Accord and its subsequent amendments have led to a plethora of research into more sophisticated and accurate VaR models. To date, research has followed broadly two directions, namely improvements in the estimation and forecasting of the variance of a returns series; and improvements in the estimation and forecasting of the distribution of the return series. Furthermore, tests of VaR accuracy have focused mainly on determining if VaR models accurately forecast a particular quantile of the returns series, which reflects the interests of regulators. However, ADIs may wish to select VaR models that not only satisfy regulatory constraints but also minimise costs.

The aim of this thesis is to investigate several important issues that have not previously been analysed in the literature. Chapter two provides an overview of the VaR method and a detailed discussion of the Basel Accord, with an emphasis on the Market Risk and Internal Models amendments.
One of the main criticisms of the standardised approach was that it failed to take into account the correlations between risk factors, and hence tended to provide conservative VaR forecasts. Conservative VaR forecasts lead to high capital charges. Furthermore, the standardised approach was inflexible and did not allow subsections of the portfolio to be analysed separately, and was not conductive to stress testing.

Andersen et al. (2005) point out that one of the most important issues in modern risk management is that of the aggregation level. The risk of a portfolio can be modelled as a Single Index (SI) by aggregating the portfolio and using an univariate modelling approach, or by modelling the portfolio at the individual asset level, which is called the Portfolio Method (PM). The PM requires models to capture the risk of each asset and the co-risks between assets. Andersen et al. (2005) assert that, while both approaches can be used in risk measuring, only the second approach can be used for risk management. Although the above discussion would seem to suggest that PM is superior to the SI approach, PM requires estimation of the entire covariance matrix. However, many existing risk models are not able to model the covariance for a large number of assets (see McAleer and da Veiga (2005) and Asai et al. (2005) for a detailed discussion).

Chapter 3 investigates the performance of SI and PM in forecasting VaR thresholds for two portfolios, the first equally weighted and the second value weighted, comprising 56 stocks that are listed in the Australian Stock Exchange. A number of popular univariate and multivariate conditional volatility models, including the GARCH model of Bollerslev
(1986), the GJR model of Glosten et al. (1992), the EGARCH model of Nelson (1994), the EWMA method proposed by Riskmetrics (1996), and a simple standard normal (SN) model based on historical variances and covariances. In the class of PM models, two correlation specifications are used, namely the Constant Conditional Correlation (CCC) model of Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) model of Engle (2002). For each model, the VaR threshold is calculated using three distributional assumptions, namely Normal, t distribution and the Generalised Error Distribution (GED).

The forecasting performance of the above models is compared using the Time Until First Failure (TUFF) test of Kupiec (1995), the Unconditional Coverage (UC), Serial Independence (Ind) and Conditional Coverage (CC) tests of Christoffersen (1998), and the logit-based test of da Veiga et al. (2005a). These tests reflect largely the concerns of regulators who would like ADIs to use models that display the correct statistical properties. In addition to the above tests, the forecasting performance of the various models is compared using the following measures which are developed in this thesis: 1) the mean daily capital charge, which captures the opportunity cost of using each model; 2) the absolute deviation of actual returns versus forecasted VaR thresholds (as VaR is a technique that is designed to manage risk, the magnitude of a violation is of paramount importance because large violations are of much greater concern than are small violations); and 3) the proportion of time spent out of the green zone, which gives an indication of the likely additional regulatory constraints that may be imposed upon an ADI.
The results suggest that the performance of each model is heavily influenced by the choice of distributional assumption, with the normal distribution generally leading to excessive violations and the t distribution leading to insufficient violations. The results of the empirical exercise do not show a clear distinction between SI and PM, with both classes of models leading to good performances in some cases and poor performances in others. Although the results of Chapter 3 do not offer support for a particular type of model, the PM has widespread applications and will, therefore, remain an important method.

Modern multivariate conditional volatility models often include spillover effects, such that the volatility of an asset depends dynamically on its own past volatility as well as on the volatility of other assets. However, the practical usefulness of these models can be affected by the computational difficulties in estimating such models for a large number of assets. Several models have been developed to deal with this so-called “curse of dimensionality”. The most common approach, as used by Bollerslev (1990) in the Constant Conditional Correlation (CCC) model, is to exclude spillover effects and to model a system of multiple univariate equations.

The aim of Chapter 4 is to investigate the importance of accommodating spillover effects in the forecasting of VaR thresholds. In this chapter, the forecasting performance of the CCC model, which has no spillover effects, is compared to the Vector Autoregressive Moving Average Conditional Heteroskedasticity (VARMA-GARCH) model of Ling and
McAleer (2003), which includes spillover effects from every asset in the portfolio. In addition, a parsimonious Portfolio Spillover (PS) GARCH model is developed that is able to model any number of assets while still including spillover effects. The empirical results suggest that spillover effects are statistically significant in both the VARMA-GARCH and PS-GARCH models.

The three models mentioned above are used to forecast the VaR thresholds for a portfolio comprising the S&P500, CAC40, FTSE100 and SMI indices. The forecasts are compared using the same measures as in Chapter 3. The results suggest that all three models lead to virtually identical VaR forecasts, so that the inclusion of spillover effects is not particularly important. As an appendix to Chapter 4 the Portfolio Single Index (PSI) multivariate conditional volatility and stochastic volatility models are developed.

An important development in multivariate conditional volatility modelling has been the creation of models that accommodate time-varying conditional correlations. The purpose of Chapter 5 is to compare the VaR forecasts produced by models that allow for dynamic conditional correlations with models that impose the assumption of constant conditional correlations. In order to investigate this issue, Chinese A and B share indices are used. The rationale for using such shares is that, prior to 28 February 2001, A shares could only be owned by Chinese investors while B shares could only be owned by foreign investors. This led to a lack of liquidity in the B share market and, as a result, such shares traded at a significant discount to their A share counterparts. However, on 28 February 2001, Chinese were permitted to own B shares and, as this represented a substantial arbitrage
opportunity, many Chinese investors included B shares in their portfolios. This market deregulation led to a significant increase in the correlation between the two classes of shares, as documented in Chiu et al. (2005).

The empirical results suggest that accommodating dynamic conditional correlations leads to superior VaR threshold forecasts, using the measures discussed in Chapter 3, and that the correlation between A and B shares are increased substantially, although this increase began well before the B share market reform. The results are of practical use for Chinese investors because it shows that, as the correlation between A and B shares approaches 1, investors should not be diversifying between different classes of shares, but rather should be specialising in choosing the class of shares that offers the highest expected returns.

Chapter 6 formulates the choice faced by ADIs as a constrained optimization problem, where ADIs wish to minimise the capital charges subject to meeting a series of regulatory and internal constraints. Five popular univariate conditional volatility models are used to forecast VaR thresholds for the S&P500 index under four distributional assumptions. The results show that, under the current guidelines of the Basel Accord, ADIs have an incentive to choose models that lead to twice the number of violations as is stipulated in the Basel Accord because the penalties imposed for excessive violations are not sufficiently severe. A new penalty structure is created, and it is shown that this simple penalty structure aligns the interests of ADIs and regulators by leading ADIs to choose models that lead to violations that are closer in number to the target of 1%.
Although VaR has traditionally been used to measure market risk, it can be readily applied to other areas. Chapter 7 applies the VaR method to the analysis of country risk ratings. Hoti and McAleer (2004, 2005a) suggest that country risk ratings have a direct impact on the cost of borrowing as they reflect the probability of debt default by a country. Therefore, rates of returns in country risk ratings are conceptually the same as financial returns. In this context, country risk ratings can be analysed using the same techniques as financial returns.

In this chapter the traditional VaR method is extended and the concept of Country Risk Bounds (CRBs) is created. CRBs are a two-sided VaR analysis that can be used to provide valuable information to both lenders and borrowers. The results show that developing countries tend to have significantly wider bounds than do developed countries. This suggests that, not only are developing countries deemed to be riskier, as reflected in a lower credit rating, but they are also more likely to experience larger ratings changes, and hence incur substantial re-ratings risk.

Finally, Chapter 8 introduces the VaR technique to the tourism literature. In this chapter, international tourist demand to the Maldives is analysed. The Maldives is chosen because the Maldivian Government depends heavily on tourism receipts, with tourism accounting for over-one third of GDP. As each tourist is required to pay a tax of US$10, for each night spent in the Maldives, changes in tourism demand are analogous to financial returns as they translate directly to financial gains or losses. The empirical results suggest that the models used are well suited for forecasting VaR in tourism demand to the Maldives.
The chapter also outlines several ways in which this information can be used by various parties to improve the decision making process. Finally, Chapter 9 summarises the main findings of the thesis and provides suggestions for future work.
2 **Overview of Value-at-Risk and the Basel Accord: Market Risk**

"Risk management is asking what might happen the other one percent
of the time."

Richard Felix, Morgan Stanley

2.1 **Value-at-Risk**

Value-at-Risk (VaR) is often described as a procedure that is designed to forecast the maximum expected negative return over a target horizon, given a (statistical) confidence limit (see Jorion (2000) for an excellent discussion). In other words, VaR measures an extraordinary loss on an ordinary day. VaR is used widely to manage the risk exposure of financial institutions and is a requirement of the Basel Capital Accord. The central idea underlying VaR is that, by forecasting the worst possible return for each day, institutions can be prepared for the worst case scenario. In the case of the banking industry, such an insurance policy can help avoid bank runs, which can be devastating to the economy if they result in widespread bank failures.

Formally, a VaR threshold is the lower bound of a confidence interval for the mean. Suppose that interest lies in modelling the random variable, $Y_t$, which can be decomposed as follows:
\[ Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t. \]  

(2.1)

This decomposition suggests that \( Y_t \) is comprised of a predictable component, \( E(Y_t \mid F_{t-1}) \), which is the conditional mean, and a random component, \( \varepsilon_t \). The variability of \( Y_t \), and hence its distribution, is determined entirely by the variability of \( \varepsilon_t \). If it is assumed that \( \varepsilon_t \) follows a distribution, such that:

\[ \varepsilon_t \sim D(\mu_t, \sigma_t) \]  

(2.2)

where \( \mu_t \) and \( \sigma_t \) are the unconditional mean and standard deviation of \( \varepsilon_t \), respectively, these can be estimated using a variety of parametric and/or non-parametric methods. The procedure used in this paper is discussed in Section 3. The VaR threshold for \( Y_t \) can be calculated as:

\[ VaR_t = E(Y_t \mid F_{t-1}) - z\sigma_t \]  

(2.3)

where \( z \) is the critical value from the distribution of \( \varepsilon_t \) to obtain the appropriate confidence level. Alternatively, \( \sigma_t \) can be replaced by alternative estimates of the conditional variance to obtain an appropriate VaR.
2.2 Base Accord: Historical Background

On June 26, 1974 Herstatt, a German bank, received large payments of DEM in Frankfurt in exchange for USD payments that were to be made in New York later that day, due to time zone differences. However, before the USD payments were made, Herstatt was forced into liquidation by German regulators. The Herstatt fiasco led the G-10 countries to form a committee in 1975 called the Basel Committee on Banking Supervision, which initially was intended to deal with the role of regulators in cross-jurisdictional situations and investigate ways of harmonizing international banking regulations. The Basel committee consists of senior representatives of bank supervising authorities and central banks from Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, Netherlands, Sweden, Switzerland, United Kingdom and the United States.

In 1988 the Basel Committee issued the Basel Capital Accord, which prescribed minimum capital requirements that Authorized Deposit Taking Institutions (ADI’s) must meet as a protection against credit risk. With the exception of Japan, where an extended transition period was granted, this became law in all G-10 countries by 1992. By January 2000, over 100 countries had formally adopted the Basel Accord. The Basel Committee identified two main objectives of the Basel Accord:

1) to establish a new framework to strengthen the soundness and stability of the international banking system; and

2) to diminish existing sources of competitive inequalities among international banks.
Minimum capital requirements are designed to mitigate the moral hazard problem, which the government’s role as a lender of last resort poses to the economy. Many commentators attribute the Asian financial crisis to the implicit guarantees many governments had made to ADI’s, which proceeded to engage in highly risky lending activities. By requiring banks to set aside capital to protect against default on loans, the Basel Accord internalises the burden that would otherwise be borne by taxpayers.

2.3 Market Risk and Internal models Amendments

“Derivatives are financial weapons of mass destruction, carrying dangers that, while now latent, are potentially lethal.”


The derivative market has experienced phenomenal growth in recent years. The global derivative market has grown more than 100 times in the last 30 years to a global total exceeding $200 trillion US dollars. The potential destabilizing nature of derivatives has been well documented (see Stulz (1994) for an excellent discussion of the dangers of derivatives), and commentators have placed the blame for several recent financial collapses, including Long Term Capital Management, Barings, and Enron to name but a few, on the poor use of derivatives. In 1992, Paul Volker, Chairman of the Group of Thirty (G-30), commissioned the Chairman of JP Morgan, Dennis Weatherstone, to undertake a study of derivative industry practices. The G-30 issued a report in 1993
outlining several recommendations for risk managers, regulators and legislators. In particular, Recommendation 5 pointed to the need to actively measure and manage market risk through the Value-at-Risk method.

Although the principle risk facing most ADI’s is credit risk, the Basel Accord was amended in 1995 to require ADI’s to apply capital charges to the market risk incurred by banks. The Basel Accord defines market risk as the: “Risk of loss in on and off-balance sheet positions arising from movements in market prices”. The four risks addressed in the Market Risk Amendment are: interest rate, equity position, foreign exchange and commodities risk. The aim of the Market Risk Amendment was to introduce the discipline that capital requirements impose on ADI’s and to provide a cushion to guard ADI’s against unexpected negative movements in their trading portfolios.

The original amendment to the Basel Accord set out a standardised methodology that ADI’s were required to follow when calculating the required capital charges. In particular, the standardised methodology stipulated how to measure each of the four risk exposures defined above, and that the overall capital charge should be based on the arithmetic sum of each risk factor.

With respect to Equity Position Risk under the Basel Accord, the standardised approach stipulates that the minimum capital charges are expressed in terms of two separately calculated charges for “specific risk” and “general risk”. “Specific risk” is defined as the sum of all long and short equity positions, while “general risk” is defined as the overall
net position in an equity market. The minimum capital charge for “specific risk” is 8%, unless the portfolio is deemed to be both liquid and well diversified, in which case the capital charges are 4%. It is worth noting that the Basel Accord is silent on what constitutes a liquid and well diversified portfolio. Hence, under the standardised method long portfolios will incur a minimum capital charge of 12% if well diversified and liquid, and 16% otherwise. These minimum capital requirements apply to both long and short positions in all instruments that display similar market behaviour to equities. However, non-convertible preference shares are covered under the interest rate risk requirements.

This approach attracted widespread criticism because it failed to recognise potential diversification benefits between the various risk factors and hence often led to excessively high capital charges. Furthermore, it was argued that the standardised approach did not provide an incentive for ADI’s to develop superior risk management techniques. Finally, many banks argued that the standardised approach was not sufficiently compatible with the measuring systems of most ADI’s.

In response to these criticisms, the Basel Committee issued an amendment to the Basel Accord in 1995 entitled: An Internal Model-Based Approach to Market Risk Capital Requirement. The principal aim of the internal models approach was to provide an alternative to the “general risk” component of the standardised approach. Several qualitative and quantitative criteria to be met by banks wishing to use internal models were proposed in the Basel Accord for the purpose of ensuring a minimum degree of prudence, transparency and consistency of capital requirements across ADI’s.
2.4 Qualitative Criteria (Basel II B.2)

a) The bank should have an independent risk control unit that is responsible for the design and implementation of the bank's risk management system. The unit should produce and analyse daily reports on the output of the bank's risk measurement model, including an evaluation of the relationship between measures of risk exposure and trading limits. This unit must be independent from business trading units and should report directly to senior management of the bank.

(b) The unit should conduct regular back-testing, that is, an ex post comparison of the risk measure generated by the model against actual daily changes in portfolio value over longer periods of time, as well as hypothetical changes based on static positions.

(c) The board of directors and senior management should be actively involved in the risk control process and must regard risk control as an essential aspect of the business to which significant resources need to be devoted. In this regard, the daily reports prepared by the independent risk control unit must be reviewed by a level of management with sufficient seniority and authority to enforce both reductions of positions taken by individual traders and reductions in the bank's overall risk exposure.

(d) The bank's internal risk measurement model must be closely integrated into the day-to-day risk management process of the bank. Its output should accordingly be an integral part of the process of planning, monitoring and controlling the bank's market risk profile.
(e) The risk measurement system should be used in conjunction with internal trading and exposure limits. In this regard, trading limits should be related to the bank's risk measurement model in a manner that is consistent over time and that is well understood by both traders and senior management.

(f) A routine and rigorous programme of stress testing should be in place to supplement the risk analysis based on the day-to-day output of the bank's risk measurement model. The results of stress testing should be reviewed periodically by senior management and should be reflected in the policies and limits set by management and the board of directors. Where stress tests reveal particular vulnerability to a given set of circumstances, prompt steps should be taken to manage those risks appropriately (for example, by hedging against that outcome or by reducing the size of the bank's exposures).

(g) Banks should have procedures in place for ensuring compliance with a documented set of internal policies, controls and procedures concerning the operation of the risk measurement system. The bank's risk measurement system must be well documented, for example, through a risk management manual that describes the basic principles of the risk management system and that provides an explanation of the empirical techniques used to measure market risk.
(h) An independent review of the risk measurement system should be carried out regularly in the bank's own internal auditing process. This review should include both the activities of the business trading units and the independent risk control unit. A review of the overall risk management process should take place at regular intervals (ideally not less than once a year) and should specifically address, at a minimum:

- the adequacy of the documentation of the risk management system and process;
- the organisation of the risk control unit;
- the integration of market risk measures into daily risk management;
- the approval process for risk pricing models and valuation systems used by front and back-office personnel;
- the validation of any significant change in the risk measurement process;
- the scope of market risks captured by the risk measurement model;
- the integrity of the management information system;
- the accuracy and completeness of position data;
- the verification of the consistency, timeliness and reliability of data sources used to run internal models, including the independence of such data sources;
- the accuracy and appropriateness of volatility and correlation assumptions;
- the accuracy of valuation and risk transformation;
the verification of the model's accuracy through the backtesting procedure described in (b) above and in the accompanying framework for the use of backtesting in conjunction approach to market risk capital requirements.

2.5 Quantitative Criteria (Basel II B.4)

(a) "Value-at-Risk" must be computed on a daily basis.

(b) In calculating the VaR, a 99th percentile, one-tailed confidence interval is to be used.

(c) In calculating VaR, an instantaneous price shock equivalent to a 10 day movement in prices is to be used, that is, the minimum "holding period" will be ten trading days. Banks may use VaR numbers calculated according to shorter holding periods scaled up to ten days by the square root of time (for the treatment of options, also see (h) below).

(d) The choice of historical observation period (sample period) for calculating value-at-risk will be constrained to a minimum length of one year. For banks that use a weighting scheme or other methods for the historical observation period, the "effective" observation period must be at least one year (that is, the weighted average time lag of the individual observations cannot be less than 6 months).

(e) Banks should update their data sets no less frequently than once every three months and should also reassess them whenever market prices are subject to material changes.
The supervisory authority may also require a bank to calculate its VaR using a shorter observation period if, in the supervisor's judgement, this is justified by a significant upsurge in price volatility.

(f) No particular type of model is prescribed. If each model used captures all the material risks run by the bank, as set out in B.3, banks will be free to use models based, for example, on variance-covariance matrices, historical simulations, or Monte Carlo simulations.

(g) Banks will have discretion to recognise empirical correlations within broad risk categories (for example, interest rates, exchange rates, equity prices and commodity prices, including related options volatilities in each risk factor category). The supervisory authority may also recognise empirical correlations across broad risk factor categories, provided that the supervisory authority is satisfied that the bank's system for measuring correlations is sound and implemented with integrity.

(h) Banks' models must accurately capture the unique risks associated with options within each of the broad risk categories. The following criteria apply to the measurement of options risk:

- banks' models must capture the non-linear price characteristics of options positions;
• banks are expected ultimately to move towards the application of a full 10 day price shock to options positions or positions that display option-like characteristics. In the interim, national authorities may require banks to adjust their capital measure for options risk through other methods, for example, periodic simulations or stress testing;

• each bank's risk measurement system must have a set of risk factors that captures the volatilities of the rates and prices underlying option positions, that is, vega risk. Banks with relatively large and/or complex options portfolios should have detailed specifications of the relevant volatilities. This means that banks should measure the volatilities of options positions broken down by different maturities.

(i) Each bank must meet, on a daily basis, a capital requirement expressed as the higher of (1) its previous day's VaR number measured according to the parameters specified in this section, and (2) an average of the daily VaR measures on each of the preceding sixty business days, multiplied by a suitable factor.

(j) The multiplication factor will be set by individual supervisory authorities on the basis of their assessment of the quality of the bank's risk management system, subject to an absolute minimum of 3. Banks will be required to add to this factor a "plus" directly related to the ex-post performance of the model, thereby introducing a built-in positive incentive to maintain the predictive quality of the model. The plus will range from 0 to 1 based on the outcome of so-called "backtesting." If the backtesting results are satisfactory and the bank meets all of the qualitative standards set out in B.2 above, the plus factor
could be zero. The accompanying document, *Supervisory framework for the use of backtesting in conjunction with the internal models approach to market risk capital requirements*, presents in detail the approach to be applied for backtesting and the plus factor.

(k) Banks using models will be subject to a separate capital charge to cover the *specific risk* of interest rate related instruments and equity securities, as defined in the standardised approach to the extent that this risk is not incorporated into their models. However, for banks using models, the total specific risk charge applied to interest rate related instruments or to equities should in no case be less than half the specific risk charges calculated under to the standardized methodology.

### 2.6 Backtesting

Although the amendment to the Basel Accord was designed to reward institutions with superior risk management systems, a backtesting procedure, whereby the realized returns are compared with the VaR forecasts, was introduced to assess the quality of the internal models. In cases where the internal models lead to a greater number of violations than could reasonably be expected, given the confidence level, the safety factor is increased by a penalty $k$, which is a function of the number of violations in the last 250 days (see Table 2.1 for the penalties recommended under the Basel Accord). The Basel Committee on Banking Supervision 1996 document *“Supervisory Framework for the Use of Backtesting” in Conjunction with the Internal Model Based Approach to Market Risk*
"Capital Requirements" defines three zones for backtesting results. These zones are given in Table 2.1. Section 3a of the above document states that:

‘The green zone corresponds to backtesting results that do not themselves suggest a problem with the quality or accuracy of a bank’s model. The yellow zone encompasses results that do raise questions in this regard, but where such a conclusion is not definitive. The red zone indicates a backtesting result that almost certainly indicates a problem with the bank’s risk model.’

Therefore, under the internal models amendment to the Basel Accord, the capital charge must be set at the higher of the previous day’s VaR or the average VaR over the last 60 days multiplied by (3+k). Finally, if a bank’s model is found to be inadequate in that it leads to an excessive number of violations, the bank may be required to adopt the standardized approach, which can lead to higher capital charges. Hence, it is vitally important that the model used does not lead to backtesting results that fall in the yellow and red zones, lest regulators find the model to be inadequate and require the bank to adopt the standardized approach.
<table>
<thead>
<tr>
<th>Zone</th>
<th>Number of Violations</th>
<th>Increase in $k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Green</td>
<td>0 to 4</td>
<td>0.00</td>
</tr>
<tr>
<td>Yellow</td>
<td>5</td>
<td>0.40</td>
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<td></td>
<td>6</td>
<td>0.50</td>
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<td>9</td>
<td>0.85</td>
</tr>
<tr>
<td>Red</td>
<td>10+</td>
<td>1.00</td>
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</tbody>
</table>

Note: The number of violations is given for 250 business days.
Chapter Three

3 Single Index and Portfolio Methods for Forecasting VaR Thresholds

3.1 Introduction

The central idea underlying VaR is that, by quantifying the size of potential losses, institutions can be prepared for the worst case scenario (see, for example, Allen et al. (2005)). For the banking industry, such an insurance policy can help avoid bank runs, which can be devastating to the economy if they result in widespread bank failures.

The 1995 market risk amendment to the Basel Accord requires that internationally active commercial banks with significant trading activities hold capital reserves to protect against adverse movements in their trading portfolios. Banks were originally required to use the standardised method in calculating the required capital charges. However, widespread criticism of the standardised approach led to a further amendment, whereby banks were permitted to measure market risk using internally generated VaR models, provided these models met a series of quantitative and qualitative criteria. The Basel Accord was discussed in detail in Chapter 2.
This chapter focuses on the calculation of capital charges for market risk arising from equity positions. Andersen et al. (2005) observe that one of the most important issues in modern risk management is that of aggregation level. For example, when modelling the risk of a bank’s trading portfolio, risk managers must choose whether to model the portfolio as (i) a Single Index (SI), by aggregating the portfolio into a single asset and using a univariate modelling approach, or as (ii) a Portfolio (PM), by modelling the portfolio at the asset level, thereby requiring a model that captures both individual asset risk and the co-risks between assets. Andersen et al. (2005) note that both approaches can be used for risk measurement, but only the portfolio approach can be used for risk management.

At first glance it would appear that the second approach would dominate the first as it is more versatile, conductive to stress testing, and helpful in the portfolio construction process. Moreover, the SI approach does not permit analysis of sub-sets of the overall portfolio, so that standard VaR methods, such as marginal VaR and component VaR, cannot be implemented. However, asset level modelling requires the estimation of the entire covariance matrix, and many existing risk models are not able to model the covariance matrix for large numbers of assets (see McAleer and da Veiga (2005) for a more detailed discussion).

Furthermore, Berkowitz and O’Brien (2002) provided evidence that the SI approach produces superior VaR forecasts than the models used by many commercial banks. They also found that models used by commercial banks typically underestimated the risk of the
trading portfolio and led to excessive violations, which were also found to cluster. da Veiga et al. (2005) found that models with an excessive number of violations often led to substantially lower capital charges than models with the correct number of violations. Their empirical results suggest that if banks wish to minimise the required capital charges, the current penalty structure of the Basel Accord would lead to the use of sub-optimal models from the point of view of regulators. This result may explain, at least in part, the findings of Berkowitz and O’Brien (2002).

The aim of this chapter is to compare the forecasting performance of the SI and portfolio methods in forecasting VaR thresholds for equally weighted and value weighted portfolios of 56 stocks that are listed on the Australian Stock Exchange. A number of popular univariate and multivariate conditional volatility models are estimated, including the GARCH model of Bollerslev (1986), the GJR model of Glosten et al. (1992), the EGARCH model of Nelson (1994), the EWMA method proposed by Riskmetrics (1996), and a simple standard normal (SN) model based on historical variances and covariances. In the class of PM models, two correlation specifications are used, namely the Constant Conditional Correlation (CCC) model of Bollerslev (1990) and the Dynamic Conditional Correlation (DCC) model of Engle (2002). These correlation specifications are chosen because they are parsimonious and able to model a large number of assets.

The models described above are compared using the Time Until First Failure (TUFF) test of Kupiec (1995), the Unconditional Coverage (UC), Serial Independence (Ind) and
Conditional Coverage (CC) tests of Christoffersen (1998), and the Logit-based test of da Veiga et al. (2005a). These tests are described in detail in Section 4.12.

In addition to the statistical tests described above, the forecasting performance of the various models considered is also evaluated by the following three measures: 1) mean daily capital charge, which captures the opportunity cost of using each model; 2) absolute deviation of actual returns versus forecasted VaR thresholds (as VaR is a technique that is designed to manage risk, the magnitude of a violation is of paramount importance since large violations are of much greater concern than are small violations); 3) proportion of time spent out of the green zone, which gives an indication of the likely additional regulatory constraints that may be imposed upon an ADI. This metric is also more informative than simply counting the number of violations, because a good VaR model should lead to the correct unconditional coverage at every point in time. Therefore, a poor model that underpredicts risk in turbulent times, and hence leads to excessive violations while overpredicting risk in tranquil times and leading to insufficient violations, and can still lead to the same number of violations as a good model. However, the poor model is likely to lead to substantially more time spent out of the green zone than will the good model.

Chapter 3 is outlined as follows. Section 3.2 describes the data and presents some summary statistics. Section 3.3 presents an overview of the various models that are used in the chapter. Section 3.4 describes alternative evaluation criteria for VaR forecasts.
Section 3.5 presents the empirical results and forecasting performance of the various models. Finally, Section 3.6 gives some concluding remarks.

3.2 Data

The data used in this chapter are daily returns for 56 stocks listed on the Australian Stock Exchange (ASX). The list of all stocks used is given in Table 3-1. These data represent, as at 30 June 2005, all the stocks currently in the ASX200 index that have been listed in the ASX since 1 January 1990. The sample period is from 1 January 1990 to 30 June 2005. All returns are expressed in Australian dollars.

As the purpose of the chapter is to investigate the performance of the single index and portfolio methods in forecasting VaR thresholds for the overall portfolio, two portfolios are constructed. The first portfolio uses equal weights and assumes daily rebalancing so that the weights remain equal and constant. The second portfolio is a value weighted portfolio, where the weights of a particular stock are given by the ratio of the total market capitalisation of that stock relative to the total market capitalization of all stocks considered. For the value weighted portfolio, the portfolio is also assumed to be rebalanced daily to reflect the changes in relative market capitalisations. This weighting structure is intended to mimic that of the market portfolio, where all stocks are held with weights given by their market capitalisation relative to the overall value of the market.
Figure 3-1 plots the daily returns and Figure 3-2 gives the histogram and descriptive statistics for the equally weighted portfolio; while Figure 3-3 plots the daily returns and Figure 3-4 gives the histogram and descriptive statistics for the value weighted portfolio. Both portfolios display means and medians close to zero. The equally weighted portfolio displays a greater range, with a maximum of 7.83% and a minimum of -8.63%, while the value weighted portfolio has a maximum of 5.21% and a minimum of -6.43%. Both portfolios are negatively skewed, display excess kurtosis, and are found to be highly non-normal, according to the Jarque-Bera Lagrange multiplier statistic for normality.
Table 3-1: List of Stocks

<table>
<thead>
<tr>
<th>Ticker</th>
<th>Name</th>
<th>Ticker</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABC</td>
<td>ADELAIDE BRIGHTON LIMITED</td>
<td>LEI</td>
<td>LEIGHTON HOLDINGS LIMITED</td>
</tr>
<tr>
<td>AGL</td>
<td>AUSTRALIAN GAS LIGHT COMPANY</td>
<td>LLC</td>
<td>LEND LEASE CORP LIMITED</td>
</tr>
<tr>
<td>ALS</td>
<td>ALESKO CORP LTD</td>
<td>NAB</td>
<td>NATIONAL AUSTRALIA BANK LTD</td>
</tr>
<tr>
<td>AMC</td>
<td>AMCOR LTD</td>
<td>NCM</td>
<td>NEWCREST MINING LIMITED</td>
</tr>
<tr>
<td>ANN</td>
<td>ANSELL LTD</td>
<td>NWS</td>
<td>NEWS CORP</td>
</tr>
<tr>
<td>ANZ</td>
<td>AUST AND NZ BANKING GROUP LTD</td>
<td>OMP</td>
<td>OAMPS LIMITED</td>
</tr>
<tr>
<td>AWC</td>
<td>ALUMINA LTD</td>
<td>ORG</td>
<td>ORIGIN ENERGY LIMITED</td>
</tr>
<tr>
<td>BHP</td>
<td>BHP BILLITON LTD</td>
<td>ORI</td>
<td>ORICA LTD</td>
</tr>
<tr>
<td>BIL</td>
<td>BRAMBLES INDUSTRIES LTD</td>
<td>OSH</td>
<td>OIL SEARCH LTD</td>
</tr>
<tr>
<td>BOQ</td>
<td>BANK OF QUEENSLAND LTD</td>
<td>OXR</td>
<td>OXIANA LTD</td>
</tr>
<tr>
<td>BPC</td>
<td>BURNS PHILP &amp; CO LTD</td>
<td>PBB</td>
<td>PACIFICA GROUP LIMITED</td>
</tr>
<tr>
<td>CCL</td>
<td>COCA-COLA AMATIL LIMITED</td>
<td>PBL</td>
<td>PUBLISHING &amp; BROADCASTING</td>
</tr>
<tr>
<td>CML</td>
<td>COLES MYER LTD</td>
<td>PPT</td>
<td>PERPETUAL TRUSTEES AUSTRALIA</td>
</tr>
<tr>
<td>CRG</td>
<td>CRANE GROUP LIMITED</td>
<td>PTD</td>
<td>PEPTECH LIMITED</td>
</tr>
<tr>
<td>CSR</td>
<td>CSR LIMITED</td>
<td>QBE</td>
<td>QBE INSURANCE GROUP LIMITED</td>
</tr>
<tr>
<td>CTX</td>
<td>CALTEX AUSTRALIA LIMITED</td>
<td>RIC</td>
<td>RIDLEY CORPORATION LIMITED</td>
</tr>
<tr>
<td>FCL</td>
<td>FUTURIS CORPORATION LIMITED</td>
<td>RIO</td>
<td>RIO TINTO LIMITED</td>
</tr>
<tr>
<td>FGL</td>
<td>FOSTER'S GROUP LTD</td>
<td>SBC</td>
<td>SOUTHERN CROSS BROADCASTING</td>
</tr>
<tr>
<td>GPT</td>
<td>GPT GROUP</td>
<td>SGP</td>
<td>STOCKLAND</td>
</tr>
<tr>
<td>GRD</td>
<td>GRD LTD</td>
<td>SHL</td>
<td>SONIC HEALTHCARE LTD</td>
</tr>
<tr>
<td>GUD</td>
<td>G.U.D. HOLDINGS LIMITED</td>
<td>SPT</td>
<td>SPOTLESS GROUP LIMITED</td>
</tr>
<tr>
<td>HDR</td>
<td>HARDMAN RESOURCES LTD</td>
<td>STO</td>
<td>SANTOS LTD</td>
</tr>
<tr>
<td>HIL</td>
<td>HILLS INDUSTRIES LIMITED</td>
<td>SUN</td>
<td>SUNCORP-METWAY LIMITED</td>
</tr>
<tr>
<td>HVN</td>
<td>HARVEY NORMAN HOLDINGS LTD</td>
<td>VSL</td>
<td>VISION SYSTEMS LIMITED</td>
</tr>
<tr>
<td>ILU</td>
<td>ILUKA RESOURCES LIMITED</td>
<td>WBC</td>
<td>WESTPAC BANKING CORPORATION</td>
</tr>
<tr>
<td>JBM</td>
<td>JUBILEE MINES NL</td>
<td>WES</td>
<td>WESFARMERS LIMITED</td>
</tr>
<tr>
<td>JHX</td>
<td>JAMES HARDIE INDUSTRIES NV</td>
<td>WPL</td>
<td>WOODSIDE PETROLEUM LTD</td>
</tr>
<tr>
<td>KCN</td>
<td>KINGSGATE CONSOLIDATED LTD</td>
<td>WYL</td>
<td>WATTYL LIMITED</td>
</tr>
</tbody>
</table>
Figure 3-1: Equally Weighted Portfolio Returns

![Equally Weighted Portfolio Returns](image)

Figure 3-2: Histogram and Descriptive Statistics for Equally Weighted Portfolio Returns

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Series: Equally Weighted Portfolio</td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>1/01/1990 30/06/2005</td>
</tr>
<tr>
<td>Observations</td>
<td>4043</td>
</tr>
<tr>
<td>Mean</td>
<td>0.000369</td>
</tr>
<tr>
<td>Median</td>
<td>0.000349</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.076226</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.084055</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.006740</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.680426</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>16.42257</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>30662.31</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000000</td>
</tr>
</tbody>
</table>
3.3 Models

This section describes alternative models that can be used to estimate the conditional variance of a portfolio in one of two ways: (i) directly, by modelling the historical
portfolio returns (namely, the single index model); or (ii) indirectly, by modelling the conditional variance of each asset and the conditional correlation of each pair of assets (namely, the portfolio model). Financial returns are typically modelled as a stationary AR(1) process, although this can easily be relaxed.

Before discussing the various conditional variance models that are used in this chapter, it is useful to present Engle’s (1982) conditional volatility approach in which he suggested that a random process could be expressed as:

\[ Y_t = E(Y_t | F_{t-1}) + \varepsilon_t \]  

(3.1)

where \( E(Y_t | F_{t-1}) \) is the predictable component of \( Y_t \) given all the information at time \( t-1 \), \( F_{t-1} \), and \( \varepsilon_t \) is the unpredictable component of \( Y_t \). The error \( \varepsilon_t \) can be decomposed as:

\[ \varepsilon_t = \frac{1}{h_t} \eta_t \]  

(3.2)

where \( h_t \) is the conditional variance of \( Y_t \) and \( \eta_t \sim iid(O,1) \). Engle (1982) suggested the ARCH(1) model, in which \( h_t \) is modelled as:

\[ h_t = \omega + \alpha \varepsilon_{t-1}^2. \]  

(3.3)
Much of the subsequent work in the ARCH literature has focussed on developing more sophisticated models for $h_t$. In what follows, a variety of conditional variance models will be presented. The SI method only requires a conditional variance model, whereas the PM requires both a conditional variance and a conditional correlation model. The final two models to be discussed, namely the Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) models, are valid only for the PM. The models are presented in increasing order of complexity.

### 3.4 Standard Normal (SN)

The Standard Normal (SN) approach forecasts the conditional variance (correlation) at time $t$ as the historical variance (correlation) over a specified time interval. This approach is extremely simple and easy to implement computationally. In this chapter, the historical variance is calculated using a rolling window for the previous 250 business days, which is in accordance with the quantitative standards set out in the Basel Accord.

### 3.5 EWMA

Riskmetrics™ (1996) developed a model which estimates the conditional variances and covariances based on the exponentially weighted moving average (EWMA) method. In effect, this model is an integrated version of the ARCH$(\infty)$ model. This approach forecasts the conditional variance at time $t$ as a linear combination of the lagged
conditional variance and the squared unconditional shock at time \( t - 1 \). The EWMA model calibrates the conditional variance as:

\[
h_t = \lambda h_{t-1} + (1 - \lambda) \varepsilon_{t-1}^2
\]

(3.4)

where \( \lambda \) is a decay parameter. Riskmetrics\textsuperscript{TM} (1996) suggests that \( \lambda \) should be set at 0.94 for purposes of analysing daily data. In order to maintain compliance with the Basel Accord, an effective observation period of one year is used.

The PM version of the EWMA model is given by:

\[
h_{ij,t} = \lambda h_{ij,t-1} + (1 - \lambda) \varepsilon_{i,t-1} \varepsilon_{j,t-1}
\]

(3.5)

where \( h_{ij,t} \) denotes the covariance between the returns of asset \( i \) and \( j \), while \( \varepsilon_{i,t} \) and \( \varepsilon_{j,t} \) denote the shock to the returns of assets \( i \) and \( j \). The variance and covariance estimates can then be used to calculate the conditional variance of the overall portfolio.

### 3.6 GARCH

Bollerslev (1986) generalized ARCH(\( p \)) to the GARCH(\( p,q \)) model, which is given by:

\[
h_t = \omega + \sum_{j=1}^{p} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta h_{t-j}.
\]

(3.6)
For the case $p = q = 1$, $\omega > 0$, $\alpha_i > 0$, $\beta_i \geq 0$ are sufficient conditions to ensure a strictly positive conditional variance, $h_t > 0$. The ARCH (or $\alpha_i$) effect captures the short run persistence of shocks, and the GARCH (or $\beta_i$) effect indicates the contribution of shocks to long run persistence ($\alpha_i + \beta_i$).

For ARCH and GARCH models, the parameters are typically estimated using the maximum likelihood estimation (MLE) method. In the absence of normality of the standardized residuals, $\eta_t$, the parameters are estimated by the Quasi-Maximum Likelihood Estimation (QMLE) method (see, for example, Li, Ling and McAleer (2002)).

### 3.7 GJR

Glosten et al. (1992) extended the GARCH model to capture possible asymmetries between the effects of positive and negative shocks of a similar magnitude on the conditional variance. It is well known that a negative shock to financial returns tends to have a greater impact on volatility than does a positive shock. This phenomenon was first explained by Black (1976), who argued that a negative shock increases financial leverage through the debt-equity ratio, by decreasing equity, which, in turn, increases risk. The GJR($p,q$) model is given by:

$$h_t = \omega + \sum_{j=1}^{p} \alpha_j \epsilon_{t-j}^2 + \gamma I(\eta_{t-1}) \epsilon_{t-1}^2 + \sum_{i=1}^{q} \beta_i h_{t-i}$$

(3.7)
where the indicator variable, \( I(\eta_t) \), is defined as:

\[
I(\eta_t) = \begin{cases} 
1, & \eta_t \leq 0 \\
0, & \eta_t > 0
\end{cases}
\]  

(3.8)

For the case \( p = 1, \omega > 0, \alpha_1 > 0, \alpha_1 + \gamma_1 > 0, \beta_1 \geq 0 \) are sufficient conditions to ensure a strictly positive conditional variance, \( h_t > 0 \). The indicator variable distinguishes between positive and negative shocks, where the asymmetric effect \( (\gamma_1 > 0) \) measures the contribution of shocks to both short run persistence \( (\alpha_1 + \gamma_1 / 2) \) and long run persistence \( (\alpha_1 + \beta_1 + \gamma_1 / 2) \).

Several important theoretical results are relevant for the GARCH model. Ling and McAleer (2002a, 2002b) established the necessary and sufficient conditions for strict stationarity and ergodicity, as well as for the existence of all moments, for the univariate GARCH(\( p,q \)) model. Ling and McAleer (2003) demonstrated that the QMLE for GARCH(\( p,q \)) is consistent if the second moment is finite, \( E(\varepsilon_t^2) < \infty \), and asymptotically normal if the fourth moment is finite, \( E(\varepsilon_t^4) < \infty \). The necessary and sufficient condition for the existence of the second moment of \( \varepsilon_t \) for the GARCH(1,1) model is \( \alpha_1 + \beta_1 < 1 \).
Another important result is that the log-moment condition for the QMLE of GARCH(1,1), which is a weak sufficient condition for the QMLE to be consistent and asymptotically normal, is given by $E(\log(\alpha_i \eta_i^2 + \beta_i)) < 0$. The log-moment condition was derived in Elie and Jeantheau (1995) and Jeantheau (1998) for consistency, and in Boussama (2000) for asymptotic normality. In practice, it is more straightforward to verify the second moment condition than the weaker log-moment condition, as the latter is a function of unknown parameters and the mean of the logarithmic transformation of a random variable.

The GJR model has also had some important theoretical developments. In the case of symmetry of $\eta_t$, the regularity condition for the existence of the second moment of GJR(1,1) is $\alpha_t + \beta_t + \gamma_t / 2 < 1$ (see Ling and McAleer (2002b)). Moreover, the weak log-moment condition for GJR(1,1), $E(\log((\alpha_t + \gamma_t I(\eta_t)\eta_t^2 + \beta_t)) < 0$, is sufficient for the consistency and asymptotic normality of the QMLE (see McAleer, Chan and Marinova (2002)).

### 3.8 EGARCH

Nelson (1991) proposed the Exponential GARCH (EGARCH) model, which is given as:

$$\log(h_t) = \omega + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}} + \sum_{j=1}^{q} \beta_j \log(h_{t-j}).$$  \hspace{1cm} (3.9)
As the range of $\log(h_t)$ is the real number line, the EGARCH model does not require any parametric restrictions to ensure that the conditional variances are positive. Furthermore, the EGARCH specification is able to capture several stylised facts, such as small positive shocks having a greater impact on conditional volatility than small negative shocks, and large negative shocks having a greater impact on conditional volatility than large positive shocks. Such features in financial returns and risk are often cited in the literature to support the use of EGARCH to model the conditional variances.

Unlike the EWMA, ARCH, GARCH and GJR models, EGARCH uses the standardized rather than the unconditional shocks. Moreover, as the standardized shocks have finite moments, the moment conditions of EGARCH are straightforward and may be used as diagnostic checks of the underlying models. However, the statistical properties of EGARCH have not yet been developed formally. If the standardized shocks are independently and identically distributed, the statistical properties of EGARCH are likely to be natural extensions of (possibly vector) ARMA time series processes (for further details, see McAleer (2005)).

### 3.9 Constant Conditional Correlation

The constant conditional correlation (CCC) GARCH model of Bollerslev (1990) is given by:

$$\varepsilon_t = D_t \eta_t$$  \hspace{1cm} (3.10)
\[ H_t = W + \sum_{k=1}^{r} A_k \tilde{e}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l} \quad (3.11) \]

where \( F_t \) is the past information available to time \( t \), \( H_t = (h_{1t}, \ldots, h_{mt})' \), \( W = (\omega_1, \ldots, \omega_m)' \), \( D_t = \text{diag}(h_{i,t}^{1/2}) \), \( \eta_t = (\eta_{1t}, \ldots, \eta_{mt})' \), \( \tilde{e}_t = (e_{1t}^2, \ldots, e_{mt}^2) \), and \( A_k \) and \( B_l \) are \( m \times m \) diagonal matrices with typical elements \( \alpha_{ij} \) and \( \beta_{ij} \), respectively, for \( i = j \).

The CCC model specifies the conditional correlations of the conditional (or standardized) shocks as \( E(\eta_t, \eta_t') = \Gamma \), where \( \Gamma \) is the constant conditional correlation matrix of the conditional shocks. This matrix is equivalent to the constant conditional correlation matrix of the conditional shocks. Although Bollerslev (1990) only considered a GARCH conditional variance specification in his original paper, the CCC method can be used with any conditional volatility model that can produce standardised residuals \( \eta_t \).

### 3.10 Dynamic Conditional Correlation

Empirical results have often found that the assumption of constant conditional correlation is too restrictive (see, for example, McAlleer and da Veiga (2005)). Moreover, these restrictions are often rejected in practice, so that the incorrect specification of the conditional correlation matrix may have important practical implications in many financial applications. For this reason, Engle (2002) extended the CCC model to the
Dynamic Conditional Correlation (DCC) model, where the conditional correlation matrix, \( E(\eta_t, \eta_t' | F_{t-1}) = \Gamma_t \), is assumed to be given as:

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

(3.12)

\[
Q_t = (ii' - \theta_1 - \theta_2) \circ Q + \theta_1 \circ \eta_{t-1} \eta_{t-1}' + \theta_2 \circ Q_{t-1}
\]

(3.13)

where \( \circ \) denotes the Hadamard element-by-element product, \( i \) denotes an \( m \times 1 \) vector of unit elements, and \( Q, \theta_1 \) and \( \theta_2 \) are \( m \times m \) symmetric matrices. If \( \theta_1 \) and \( \theta_2 \) are restricted to be the null matrix, then (3.13) collapses to \( Q_t = Q \), which implies that the conditional correlations are constant.

Given the dynamic conditional correlations and the conditional variances, the time-varying conditional covariance matrix, \( \Omega_t \), can then be estimated as follows:

\[
\hat{\Omega}_t = \hat{D}_t \hat{\Gamma}_t \hat{D}_t.
\]

(3.14)

The parameters in the CCC and DCC models, as defined in (3.1), (3.2) and (3.11), and (3.1), (3.2), (3.11), (3.12), (3.13) and (3.13), respectively, can be estimated by maximizing the likelihood function, that is:
\[ \hat{\lambda} = \max_{\lambda} l(\lambda) = \max_{\lambda} \left( -\frac{1}{2} \sum_{t=1}^{T} \log|\Omega_t| + \epsilon_t' \Omega_t^{-1} \epsilon_t \right) \quad (3.15) \]

where \( \lambda \) denotes the vector of unknown parameters. If \( \eta_t \) follows a conditional PM normal distribution, then \( \hat{\lambda} \) is the Maximum Likelihood Estimator (MLE); otherwise, it is the Quasi MLE (QMLE).

It is straightforward to show that the likelihood function, \( l(\lambda) \), can be rewritten as:

\[ l(\lambda) = l_1(\lambda_1) + l_2(\lambda_1, \lambda_2), \quad (3.16) \]

where \( \lambda_1 \) denotes the vector of unknown parameters in the conditional mean and the conditional variance equations, and \( \lambda_2 \) denotes the vector of unknown parameters in the conditional correlation matrix for CCC, and the vector of unknown parameters in (3.12) and (3.13) for DCC. Furthermore,

\[ l_1(\lambda_1) = -\frac{1}{2} \sum_{t=1}^{T} \log |D_t^2| + \epsilon_t' D_t^{-2} \epsilon_t, \quad (3.17) \]

so that for CCC:

\[ l_2(\lambda_1, \lambda_2) = -\frac{1}{2} \sum_{t=1}^{T} \log |\Gamma| + \eta_t' \Gamma^{-1} \eta_t - \eta_t' \eta_t, \quad (3.18) \]
whereas for DCC, it is given as:

\[ l_2(\lambda_1, \lambda_2) = -\frac{1}{2} \sum_{t=1}^{T} \log |\Gamma_t| + \eta_t' \Gamma_t^{-1} \eta_t - \eta_t' \eta_t. \] (3.19)

Using the invariance principle, Bollerslev (1990) and Engle (2002) argued that the parameters in the models can be estimated in two stages for CCC and DCC, respectively. The first stage involves estimating the parameters of the conditional mean and conditional variance only. Given the parameters estimated in the first stage, the second stage estimates the parameters in the conditional correlation matrix for CCC, and the parameters in the conditional correlation equation as defined in (3.12)-(3.13) for DCC.

Formally, \( \hat{\lambda}_1 = \max_{\lambda_1} l_1(\lambda_1) \) and \( \hat{\lambda}_2 = \max_{\lambda_2} l_2(\lambda_2 | \hat{\lambda}_1) \).

Given that \( A_i \) and \( B_j \) are both diagonal matrices, \( l_1(\lambda_i) \) can then be rewritten as:

\[ l_1(\lambda_i) = \sum_{t=1}^{m} \left[ -\frac{1}{2} \sum_{t=1}^{T} \log h_{it} + \frac{\varepsilon_{it}^2}{h_{it}} \right], \] (3.20)

which is the sum of the \( m \) likelihood functions corresponding to the GARCH process for each asset. Therefore,
\[ \hat{\lambda}_t = \max_{\lambda_t} l_{\lambda_t}(\hat{\lambda}_t) \]  
\[ = \max_{\lambda_t} \sum_{j=1}^{m} \frac{1}{2} \sum_{t=1}^{T} \log h_{it} + \frac{\hat{\varepsilon}_{it}^2}{h_{it}} \]  
\[ = \sum_{j=1}^{m} \max_{\lambda_t} \frac{1}{2} \sum_{t=1}^{T} \log h_{it} + \frac{\hat{\varepsilon}_{it}^2}{h_{it}}. \]

Hence, the parameters in the conditional variance can be estimated as a multiple of univariate GARCH models. This is useful as the structural and statistical properties of univariate GARCH models have been fully established. In particular, Elie and Jeantheau (1995) and Jeantheau (1998) showed that the QMLE is consistent for a GARCH(1,1) model if the log-moment condition is satisfied, namely,

\[ E(\log(\alpha_{ii} \eta_{it}^2 + \beta_{ii})) < 0. \]

Boussama (1995) showed that the log-moment condition is sufficient for QMLE to be asymptotically normal. Therefore, verifying the empirical log-moment condition can be viewed as a diagnostic check on the validity of the model.

The practical advantage of Engle’s (2002) model over some other dynamic conditional correlation alternatives, such as the Varying Conditional Correlation (VCC) model of Tse and Tsui (2002), is that the parameters in the conditional variance and correlation
equations can be estimated separately using a two stage procedure. This allows a large number of assets to be included without imposing many of the numerical problems suffered by other PM GARCH-type models.

Unless otherwise stated, the DCC estimates reported in this chapter will be obtained through the two stage procedure, as described in Engle (2002), using the EViews 5 econometric software package. Similar estimates can be obtained using the RATS 6 econometric software package.

3.11 Evaluation Methods for VaR Forecasts

Christoffersen (1998) derived likelihood ratio (LR) tests of unconditional coverage (UC), serial independence (Ind) and conditional coverage (CC). Subsequently, Lopez (1998) adapted these tests to evaluate VaR threshold forecasts. These tests are widely used in practice to evaluate competing risk models. An adequate VaR model should exhibit the property that the unconditional coverage (which is calculated as the number of observed violations divided by \( T \)) should equal \( \delta \), where \( \delta \) is the level of significance chosen for the VaR, and \( T \) is the number of trading days in the evaluation period. The probability of observing \( x \) violations in a sample of size \( T \), under the null hypothesis, is given by:

\[
Pr(x) = C_x^T (\delta)^x (1-\delta)^{T-x}
\]

(3.24)

---

where $\delta$ is the desired proportion of observations that should be lower than the forecasted VaR thresholds, typically set at 1%. These observations are known as violations. $C^T_x = \frac{T!}{x!(T-x)!}$ where $!$ denotes the factorial operator such that $T! = \prod_{i=0}^{T-1} T - i$.

Therefore, the LR statistic for testing whether the number of observed violations, divided by $T$, is equal to $\delta$ is:

$$LR_{UC} = 2[\log(\hat{\delta}^x(1-\hat{\delta})^{N-x}) - \log(\delta^x(1-\delta)^{N-x})],$$ \hspace{1cm} (3.25)

where $\hat{\delta} = x/N$, where $x$ is the number of violations, and $N$ is the number of forecasts. The LR statistic is asymptotically distributed as $\chi^2(1)$ under the null hypothesis of correct UC.

However, a model that leads to the correct unconditional coverage may still be suboptimal. For example, models that exhibit serially dependant violations, implying that unexpected extraordinary trading losses are clustered, may lead to bank failures. The Basel Accord explicitly states that the backtesting procedure implicitly assumes that violations are not serially dependent (see Basel (1996), Section 2). The test of independence proposed by Christoffersen (1998) is the LR statistic for the null hypothesis of serial independence against the alternative of first-order Markov dependence.
Finally, Christoffersen (1998) proposed the conditional coverage test, which is a joint test of unconditional coverage and independence. The conditional coverage LR statistic is given as the sum of the unconditional coverage LR statistic and the independence LR statistic, which is asymptotically distributed as $\chi^2(2)$ under the joint null hypothesis.

However, the serial independence test of Christoffersen (1998) has been shown to have low power. Lopez (1998) showed that the unconditional coverage, serial independence and conditional coverage tests can have low power against reasonable alternative VaR models. In order to establish an alternative to the serial independence test of Christoffersen (1998), da Veiga et al. (2005a) proposed a logit-based test for the predictability of violations.

The logit-based test models the probability of violations as a function of previously available information. As violations should be independently and identically distributed, violations produced by adequate models should not be predictable, and past information should not provide any information concerning the probability of future violations. The basic framework of the logit-based test is as follows. The dependent variable of interest is given by:

$$P(R_t < \text{VaR}_t),$$  \hspace{1cm} (3.26)

which denotes the probability of the observed return, $R_t$, being lower than the forecasted VaR threshold.
da Veiga et al. (2005a) identify three variables that might be able to predict the probability of a violation at time $t$: (i) a binary variable that takes the value $1$ if $R_t < VaR_t$, and $0$ otherwise; (ii) the deviation of the observed return from the VaR threshold, which is calculated as $R_t - VaR_t$; and (iii) the duration between violations, which is calculated as the number of trading days between violations. The logistic equation that is estimated by da Veiga et al. (2005a) is given by:

$$
P(R_t < VaR_t) = \frac{e^{X \beta + \varepsilon}}{1 + e^{X \beta + \varepsilon}},$$

(3.27)

where $X$ is a $T \times K$ matrix, $T$ is the number of observations, $K$ is the number of regressors, including a constant; $\beta$ is a $K \times 1$ vector of parameters to be estimated, and $\varepsilon$ is a $T \times 1$ vector of i.i.d. random shocks. If the estimated coefficients of any of the regressors are found to be significant, the null hypothesis of no predictability of violations is rejected. All the estimates for the logit-based method to be presented below were obtained using the quadratic hill-climbing technique.

Kupiec (1995) developed the Time Until First Failure (TUFF) test, which is based on the number of observations until the first violation. The null hypothesis is the same as for the UC test, for which the observed proportion of violations is given by $\hat{\delta} = x / N$. The TUFF LR statistic, which is asymptotically distributed as $\chi(1)$, is given by:
\[ LR_{TUFF} = -2 \ln[\hat{\delta}(1-\hat{\delta})^{-1}] + 2 \ln[\frac{1}{\tau}(1-\frac{1}{\tau})^{-1}] \] (3.28)

where \( \tau \) denotes the number of observations before the first violation.

da Veiga et al. (2005b) suggested that ADIs, in essence, face a constrained optimisation problem. The ADIs wish to minimise the required capital charges with respect to a choosing a model and critical value, subject to a series of regulatory constraints. Hence, in addition to the statistical tests described above, the forecasting performance of the various models considered are also evaluated according to: 1) proportion of time spent out of the green zone, which gives an indication of the likely additional regulatory constraints that may be imposed upon a bank; 2) mean daily capital charge, which captures the opportunity cost of using each model; and 3) absolute deviation of actual returns versus forecasted VaR thresholds. As VaR is a technique that is designed to manage risk, the magnitude of a violation is of paramount importance since large violations are of much greater concern than are small violations (see Lopez (1998) for a detailed discussion).

3.12 Forecasting Performance

This section compares the SI and PM approaches, as well as the constant and dynamic conditional correlation approaches to forecasting VaR thresholds. The data used in this chapter range from 1 January 1990 to 30 June 2005, which corresponds to 4043 observations. In order to evaluate the VaR forecasting performance of the various models
described in Section 4, a rolling window approach is used to forecast the 1-day ahead 99% VaR thresholds for the equally weighted and value weighted portfolios, as described in Section 3. In order to arrive at a balance between a viable number of rolling windows and an efficient number of observations for estimation, we set the rolling window size to 2043, which creates a forecasting period from 31 October 1997 to 30 June 2005, giving 2000 forecasts. In the empirical example presented here, estimation starts with observations 1 to 2043 of the data set, and the estimated parameters are then used to forecast the 1-day ahead VaR threshold. Then, using observations 2 to 2044, estimation is undertaken again, and the estimated parameters are used to forecast the next 1-day ahead forecast, and so on, until the last rolling sample at the end of the total number of observations.

Figures 3-5 to 3-13 plot the conditional variance forecasts produced by each model considered for the equally weighted portfolio, while Figures 3-14 to 3-22 plot the conditional variance forecasts for the value weighted portfolio.
Figure 3-13: DCC Conditional Variance Forecasts for the Equally Weighted Portfolio.

Figure 3-14: SI Standard Normal Conditional Variance Forecasts for the Value Weighted Portfolio

Figure 3-15: SI Riskmetrics\(^{TM}\) Conditional Variance Forecasts for the Value Weighted Portfolio.

Figure 3-16: SI GARCH Conditional Variance Forecasts for the Value Weighted Portfolio.

Figure 3-17: SI GJR Conditional Variance Forecasts for the Value Weighted Portfolio.

Figure 3-18: SI EGARCH Conditional Variance Forecasts for the Value Weighted Portfolio.
As the returns are found to be highly non-normal, all VaR thresholds are calculated assuming that the returns follow: 1) a Normal distribution; 2) a Generalised Error Distribution (GED), where the appropriate GED parameter is estimated for every rolling window; and 3) a t distribution, where the degrees of freedom are estimated for every rolling window. Figures 3-23 to 3-28 plot the rolling critical values. As can be seen, the empirically estimated critical values vary substantially, with the critical value based on the t distribution always exceeding the critical values from the GED which, in turn, is always greater than the critical values from the Normal distribution. Figures 3-29 to 3-37 and Figures 3-38 to 3-46 plot the realised returns and VaR forecasts for the equally weighted and value weighted portfolios respectively.
Figure 3-29: Equally Weighted Portfolio Realized Returns and SI Standard Normal VaR Forecasts

Figure 3-30: Equally Weighted Portfolio Realized Returns and SI Riskmetrics™ VaR Forecasts

Figure 3-31: Equally Weighted Portfolio Realized Returns and SI GARCH VaR Forecasts

Figure 3-32: Equally Weighted Portfolio Realized Returns and SI GJR VaR Forecasts

Figure 3-33: Equally Weighted Portfolio Realized Returns and SI EGARCH VaR Forecasts

Figure 3-34: Equally Weighted Portfolio Realized Returns and PM Standard Normal VaR Forecasts
The results from the UC, Ind and CC tests are given in Tables 3-2 to 3-4. For the VaR forecasts of the equally weighted portfolio obtained under the normal distribution, the SI standard normal (SN), SI Riskmetrics™, SI GARCH, PM SN and PM Riskmetrics™ models all fail the UC test, as they lead to excessive violations. For the value weighted portfolio, the SI SN, SI Riskmetrics™, PM SN, PM Riskmetrics™ and DCC models all fail the UC test due to excessive violations.

Table 3-2: Tests of VaR Thresholds using the Normal Distribution

<table>
<thead>
<tr>
<th>Model</th>
<th>Equally Weighted Portfolio</th>
<th>Value Weighted Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UC</td>
<td>Ind</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>10.450*</td>
<td>2.924</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>5.233*</td>
<td>4.961</td>
</tr>
<tr>
<td>SI GJR</td>
<td>0.760</td>
<td>1.801</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>0.434</td>
<td>11.703*</td>
</tr>
<tr>
<td>PM SN</td>
<td>10.450*</td>
<td>18.114*</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>10.450*</td>
<td>2.924</td>
</tr>
<tr>
<td>CCC</td>
<td>0.434</td>
<td>29.332*</td>
</tr>
<tr>
<td>DCC</td>
<td>1.170</td>
<td>23.947*</td>
</tr>
</tbody>
</table>

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

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

(3) Entries in **bold** denote significance at the 95% level, and * denotes significance at the 99% level.
Table 3-3: Tests of VaR Thresholds using GED

<table>
<thead>
<tr>
<th>Model</th>
<th>UC</th>
<th>Ind</th>
<th>CC</th>
<th>TUFF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Equally Weighted Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>2.230</td>
<td>7.556</td>
<td>9.786*</td>
<td>0.366</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>2.230</td>
<td>7.556</td>
<td>9.786*</td>
<td>0.366</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>0.479</td>
<td>0.018</td>
<td>0.497</td>
<td>0.545</td>
</tr>
<tr>
<td>SI GJR</td>
<td>1.382</td>
<td>0.114</td>
<td>1.496</td>
<td>0.695</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>2.031</td>
<td>8.442</td>
<td>10.473*</td>
<td>0.782</td>
</tr>
<tr>
<td>PM SN</td>
<td>2.230</td>
<td>7.556</td>
<td>9.786*</td>
<td>0.366</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>2.230</td>
<td>0.013</td>
<td>2.243</td>
<td>0.366</td>
</tr>
<tr>
<td>CCC</td>
<td>0.479</td>
<td>5.157</td>
<td>5.636</td>
<td>0.523</td>
</tr>
<tr>
<td>DCC</td>
<td>0.209</td>
<td>21.429*</td>
<td>21.638*</td>
<td>0.460</td>
</tr>
<tr>
<td><strong>Value Weighted Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>0.434</td>
<td>2.091</td>
<td>2.525</td>
<td>1.299</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>1.661</td>
<td>1.329</td>
<td>2.990</td>
<td>5.190</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>0.050</td>
<td>0.061</td>
<td>0.111</td>
<td>3.588</td>
</tr>
<tr>
<td>SI GJR</td>
<td>3.772</td>
<td>0.073</td>
<td>3.845</td>
<td>0.325</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>2.031</td>
<td>0.099</td>
<td>2.130</td>
<td>4.976</td>
</tr>
<tr>
<td>PM SN</td>
<td>0.434</td>
<td>2.091</td>
<td>2.525</td>
<td>1.299</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>2.875</td>
<td>0.968</td>
<td>3.843</td>
<td>0.710</td>
</tr>
<tr>
<td>CCC</td>
<td>6.187</td>
<td>18.370*</td>
<td>24.557*</td>
<td>0.016</td>
</tr>
<tr>
<td>DCC</td>
<td>2.875</td>
<td>6.796</td>
<td>9.671*</td>
<td>2.026</td>
</tr>
</tbody>
</table>

(1) The Unconditional Coverage (UC) and Time Until First Failure (TUFF) tests are asymptotically distributed as $\chi^2(1)$.
(2) The Serial Independence (Ind) and Conditional Coverage (CC) tests are asymptotically distributed as $\chi^2(2)$.
(3) Entries in **bold** denote significance at the 95% level, and * denotes significance at the 99% level.

The UC test for the VaR forecasts from the equally weighted portfolio, assuming the returns follow GED, suggest that all models lead to the correct conditional coverage, but the same test for the value weighted portfolio suggests that the CCC leads to excessive violations. Finally, for the VaR forecasts assuming a t distribution, all the models, with the exception of the SI and PM Riskmetrics™ models, fail the UC test. For the value weighted portfolio, all the models, except for the SI and PM SN model, the SI and PM Riskmetrics™ and the CCC models, fail the UC test. However, for the VaR forecasts calculated using a t distribution, all the models that fail the UC test do so as they lead to too few violations.
Table 3-4: Tests of VaR Thresholds using the t Distribution

<table>
<thead>
<tr>
<th>Model</th>
<th>UC</th>
<th>Ind</th>
<th>CC</th>
<th>TUFF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Equally Weighted Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>4.888</td>
<td>0.061</td>
<td>4.949</td>
<td>0.017</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>2.031</td>
<td>0.099</td>
<td>2.130</td>
<td>0.012</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>13.651*</td>
<td>5.157</td>
<td>18.808*</td>
<td>0.436</td>
</tr>
<tr>
<td>SI GJR</td>
<td>16.250*</td>
<td>0.013</td>
<td>16.263*</td>
<td>0.642</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>19.253*</td>
<td>0.008</td>
<td>19.261*</td>
<td>0.068</td>
</tr>
<tr>
<td>PM SN</td>
<td>4.888</td>
<td>0.061</td>
<td>4.949</td>
<td>0.017</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>2.031</td>
<td>0.099</td>
<td>2.130</td>
<td>0.012</td>
</tr>
<tr>
<td>CCC</td>
<td>13.651*</td>
<td>0.018</td>
<td>13.669*</td>
<td>0.436</td>
</tr>
<tr>
<td>DCC</td>
<td>13.651*</td>
<td>0.019</td>
<td>13.670*</td>
<td>0.542</td>
</tr>
<tr>
<td><strong>Value Weighted Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>1.382</td>
<td>7.121</td>
<td>8.503</td>
<td>1.763</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>1.382</td>
<td>7.121</td>
<td>8.503</td>
<td>3.640</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>13.651*</td>
<td>0.018</td>
<td>13.669*</td>
<td>0.540</td>
</tr>
<tr>
<td>SI GJR</td>
<td>11.388*</td>
<td>0.025</td>
<td>11.413*</td>
<td>0.603</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>11.388*</td>
<td>0.025</td>
<td>11.413*</td>
<td>0.603</td>
</tr>
<tr>
<td>PM SN</td>
<td>0.867</td>
<td>6.045</td>
<td>6.912</td>
<td>2.031</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>1.382</td>
<td>0.032</td>
<td>1.414</td>
<td>3.640</td>
</tr>
<tr>
<td>CCC</td>
<td>13.651*</td>
<td>0.018</td>
<td>13.669*</td>
<td>0.540</td>
</tr>
<tr>
<td>DCC</td>
<td>0.867</td>
<td>6.045</td>
<td>6.912</td>
<td>2.097</td>
</tr>
</tbody>
</table>

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

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

(3) Entries in **bold** denote significance at the 95% level, and * denotes significance at the 99% level.

The results of the Ind test for the VaR forecasts for the equally weighted portfolio, assuming a normal distribution, suggest that all models, except for the SI and PM Riskmetrics™, SI GARCH and SI EGARCH models, have serially dependent violations. For the value weighted portfolio, the CCC model lead to serially dependent violations. In terms of forecasting the VaR for the equally weighted portfolio using GED, the SI and PM SN, SI Riskmetrics™, SI EGARCH and DCC models all lead to serially dependent violations. For the value weighted portfolio, the CCC and DCC models all lead to serially dependent violations. Finally, using the t distribution, no models lead to serially dependent violations.
dependent violations for the equally weighted portfolio, while the SI and PM SN, SI Riskmetrics™ and DCC models lead to serially dependent violations.

The CC test of the joint null hypothesis of correct UC and Ind for the VaR forecasts, under a normal distribution for the equally weighted portfolio, suggests that all models except SI GJR fail the test. The results for the value weighted portfolio suggest that all the models, except for the SI GARCH, GJR and EGARCH models, fail the test.

In the case of the VaR forecasts for the equally weighted portfolio obtained under the assumption that the returns follow GED, all models with the exception of SI GARCH and GJR, PM SN and PM Riskmetrics™, fail the CC test. For the value weighted portfolio, the CCC and DCC models fail the CC test. Finally, for the VaR forecasts for the equally weighted portfolio under a t distribution, all models fail the CC test, with the exception of the SI and PM SN and Riskmetrics™ models. For the value weighted portfolio, all models except PM Riskmetrics™, fail the CC test.

The results of the TUFF test are also given in Table 3-4: Tests of VaR Thresholds using the t Distribution and tests of VaR thresholds using the t distribution are in Table 3-6. The results suggest that all models perform well for the equally weighted portfolio. For the value weighted portfolio under the assumption of normality, SI GARCH and EGARCH and CCC fail the TUFF test. In the case of the results obtained under the assumption of GED, no models fail the TUFF test for the equally weighted portfolio, while the SI Riskmetrics™ and EGARCH models fail for the value weighted portfolio.
Finally, no models fail the TUFF test for both portfolios under the assumption that the returns follow a t distribution.

As an alternative to the UC, Ind, CC and TUFF tests, da Veiga et al. (2005a) proposed a logit-based test of VaR forecasts. The logic behind this test is that if violations are iid, then past information should not be able to predict the probability of future violations. The results of the logit-based test are presented in Table 3-5 for the equally weighted portfolio and Table 3-6 for the value weighted portfolio. As can be seen for all models, only the constant and past deviations are found to be significant. Furthermore, when significant, the deviation parameter is always negative, suggesting that when the return is greater than the VaR forecast, the probability of future violations increases.

For the equally weighted portfolio under the assumption of normality, all models except for SI EGARCH fail the logit-based test. For the value weighted portfolio, the SI Riskmetrics™ and SN, and PM Riskmetrics™ and SN, all fail the logit-based test. When the VaR is calculated assuming that the returns follow GED, the results for the equally weighted portfolio show that all models, with the exception of the SI GARCH, GJR and EGARCH, and the PM Riskmetrics™ models, fail the logit-based test. For the value weighted portfolio, both the SI and PM Riskmetrics™ models fail the logit-based test. Finally, for the results obtained under the assumption that the returns follow a t distribution for the equally weighted portfolio, the SI SN, SI Riskmetrics™, PM SN, PM Riskmetrics™ and DCC models, all fail the logit-based test. In the case of the value weighted portfolio, no model fails the logit-based test.
Table 3-5: Tests of VaR Thresholds for the Equally Weighted Portfolio using the logit test

<table>
<thead>
<tr>
<th>Model</th>
<th>Normal distribution</th>
<th>GED</th>
<th>t distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>c Vio(-1) Dev(-1) Dur(-1)</td>
<td>c Vio(-1) Dev(-1) Dur(-1)</td>
<td>c Vio(-1) Dev(-1) Dur(-1)</td>
</tr>
<tr>
<td>Equally Weighted Portfolio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>-2.863 0.019 -88.347 -0.001 -2.760 -1.111 -117.829 0.002 -2.574 -33.746 -173.813 0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-6.967) (0.022) (-3.558) (-0.111) (-5.622) (-0.891) (-3.926) (0.445) (-3.176) (-0.001) (-3.489) (0.464)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>-2.772 (-1.792) -143.777 (-0.001) -2.805 -1.230 -138.485 0.005 -1.510 -7.693 -61.231 0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.431) (-4.839) (-5.333) (-0.946) (-4.210) (1.206) (-4.723) (-0.001) (-3.367) (-0.382)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI GARCH</td>
<td>-2.542 -0.930 -94.580 -0.004 -4.188 0.859 -60.824 0.004 -5.218 -29.203 -50.134 0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.429) (-0.847) (-3.233) (-1.395) (-5.532) (0.550) (-1.575) (1.159) (-3.554) (-0.003) (-0.791) (0.840)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI GJR</td>
<td>-3.140 -0.706 -85.240 -0.001 -2.109 -6.104 -21.153 0.001 -7.964 -24.911 41.663 0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.741) (-0.507) (-2.488) (-0.399) (-7.348) (-0.001) (-1.374) (0.233) (-5.154) (-0.002) (1.045) (1.438)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>-3.903 1.253 -43.973 0.001 -4.472 1.513 -48.392 0.002 -9.099 -27.150 53.074 0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-6.604) (1.128) (-1.349) (0.103) (-5.451) (0.962) (-1.179) (0.664) (-4.283) (-0.007) (0.995) (1.615)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PM SN</td>
<td>-2.863 0.019 -88.347 -0.001 -2.761 -1.111 -117.829 0.002 -2.574 -33.746 -173.813 0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-6.967) (0.023) (-3.558) (-0.111) (-5.622) (-0.891) (-3.926) (0.445) (-3.176) (-0.001) (-3.489) (0.464)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>-2.272 -2.198 -143.777 -0.001 -5.178 -26.687 -69.22 -0.003 -1.510 -7.693 -61.231 0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.431) (-4.839) (-5.333) (-0.946) (-4.210) (1.206) (-4.723) (-0.001) (-3.367) (-0.382)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC</td>
<td>-3.399 0.834 -78.042 0.001 -2.974 -1.135 -115.652 0.001 -4.263 -30.946 -102.039 0.002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DCC</td>
<td>-3.436 (0.757) (-2.434) (0.158) (-4.252) (-0.660) (-2.996) (0.360) (-2.971) (-0.001) (-1.627) (1.046)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.702) (0.941) (-2.187) (-0.368) (-5.317) (0.531) (-2.422) (0.231) (-2.840) (-0.001) (-2.829) (0.721)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(1) Vio denotes the parameter corresponding to a binary variable that takes the value 1 for a violation, and zero otherwise. Dev denotes the parameter corresponding to the deviation of returns from the forecasted VaR, which is computed as (return-VaR). Dur denotes the parameter corresponding to the duration, in days, between consecutive violations.

(2) The two entries for each parameter are its estimated coefficient and t-ratio, respectively. Entries in bold are significant at the 1% level.
Table 3-6: Tests of VaR Thresholds for the Value Weighted Portfolio using the logit test

<table>
<thead>
<tr>
<th>Model</th>
<th>Normal distribution</th>
<th>GED</th>
<th>t distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>c</td>
<td>Vio(-1)</td>
<td>Dev(-1)</td>
</tr>
<tr>
<td>Value Weighted Portfolio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>-3.586</td>
<td>0.578</td>
<td>-46.450</td>
</tr>
<tr>
<td></td>
<td>(-7.463)</td>
<td>(0.602)</td>
<td>(-2.177)</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>-3.224</td>
<td>-0.558</td>
<td>-52.833</td>
</tr>
<tr>
<td></td>
<td>(-7.322)</td>
<td>(-0.477)</td>
<td>(-2.442)</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>-4.350</td>
<td>-28.693</td>
<td>-13.179</td>
</tr>
<tr>
<td></td>
<td>(-6.704)</td>
<td>(-0.001)</td>
<td>(-0.501)</td>
</tr>
<tr>
<td></td>
<td>(-7.464)</td>
<td>(-0.002)</td>
<td>(-0.110)</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>-5.022</td>
<td>-28.893</td>
<td>10.296</td>
</tr>
<tr>
<td></td>
<td>(-7.693)</td>
<td>(-0.005)</td>
<td>(0.424)</td>
</tr>
<tr>
<td>PM SN</td>
<td>-3.289</td>
<td>0.145</td>
<td>-56.298</td>
</tr>
<tr>
<td></td>
<td>(-7.321)</td>
<td>(0.153)</td>
<td>(-2.674)</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>-3.016</td>
<td>-0.892</td>
<td>-66.164</td>
</tr>
<tr>
<td></td>
<td>(-6.929)</td>
<td>(-0.751)</td>
<td>(-2.943)</td>
</tr>
<tr>
<td>CCC</td>
<td>-4.881</td>
<td>2.173</td>
<td>-29.984</td>
</tr>
<tr>
<td></td>
<td>(-5.459)</td>
<td>(1.407)</td>
<td>(-0.800)</td>
</tr>
<tr>
<td>DCC</td>
<td>-3.181</td>
<td>0.455</td>
<td>-18.829</td>
</tr>
<tr>
<td></td>
<td>(-8.279)</td>
<td>(0.602)</td>
<td>(-1.032)</td>
</tr>
</tbody>
</table>

(1) Vio denotes the parameter corresponding to a binary variable that takes the value 1 for a violation, and zero otherwise. Dev denotes the parameter corresponding to the deviation of returns from the forecasted VaR, which is computed as (return-VaR). Dur denotes the parameter corresponding to the duration, in days, between consecutive violations.

(2) The two entries for each parameter are its estimated coefficient and t-ratio, respectively. Entries in **bold** are significant at the 1% level.
The results of the four statistical tests described above provide mixed evidence regarding
the performance of the SI versus the PM models. Furthermore, the performance of each
conditional volatility model appears to vary substantially, depending on the way in which
the portfolio is constructed. The results also suggest that the distributional assumptions
are far more important than the choice of model.

Table 3-7: Evaluating VaR Thresholds using the Normal Distribution

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Violations</th>
<th>Proportion of Time out of the Green Zone</th>
<th>Daily Capital Charge</th>
<th>AD of Violations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equally Weighted Portfolio</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>36</td>
<td>25.45%</td>
<td>4.76%</td>
<td>1.058%</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>36</td>
<td>24.62%</td>
<td>4.56%</td>
<td>0.972%</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>31</td>
<td>12.63%</td>
<td>4.77%</td>
<td>0.691%</td>
</tr>
<tr>
<td>SI GJR</td>
<td>24</td>
<td>12.90%</td>
<td>4.67%</td>
<td>0.586%</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>23</td>
<td>8.51%</td>
<td>4.64%</td>
<td>0.605%</td>
</tr>
<tr>
<td>PM SN</td>
<td>36</td>
<td>25.45%</td>
<td>4.76%</td>
<td>1.058%</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>36</td>
<td>24.62%</td>
<td>4.56%</td>
<td>0.976%</td>
</tr>
<tr>
<td>CCC</td>
<td>23</td>
<td>3.00%</td>
<td>5.06%</td>
<td>0.642%</td>
</tr>
<tr>
<td>DCC</td>
<td>25</td>
<td>1.71%</td>
<td>4.85%</td>
<td>0.943%</td>
</tr>
<tr>
<td>Value Weighted Portfolio</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>32</td>
<td>16.23%</td>
<td>5.79%</td>
<td>1.083%</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>33</td>
<td>15.10%</td>
<td>5.78%</td>
<td>1.123%</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>21</td>
<td>0.20%</td>
<td>5.67%</td>
<td>0.714%</td>
</tr>
<tr>
<td>SI GJR</td>
<td>21</td>
<td>0.00%</td>
<td>5.64%</td>
<td>0.6995</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>20</td>
<td>0.00%</td>
<td>5.64%</td>
<td>0.785%</td>
</tr>
<tr>
<td>PM SN</td>
<td>34</td>
<td>22.86%</td>
<td>5.86%</td>
<td>1.106%</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>33</td>
<td>11.94%</td>
<td>5.76%</td>
<td>1.085%</td>
</tr>
<tr>
<td>CCC</td>
<td>13</td>
<td>0.00%</td>
<td>6.21%</td>
<td>0.9099%</td>
</tr>
<tr>
<td>DCC</td>
<td>45</td>
<td>48.68%</td>
<td>5.41%</td>
<td>0.993%</td>
</tr>
</tbody>
</table>

(1) The daily capital charge is given as the negative of the higher of the previous day’s VaR, or the average VaR over the last 60 business days times (3+k), where k is the penalty. The capital charge represents the proportion of the portfolio that must be kept in reserves.
(2) AD denotes absolute deviation, which is computed as (absolute value of the actual returns minus the forecasted VaR threshold) divided by the forecasted VaR threshold.
(3) As there are 2000 days in our forecasting period, the expected number of violations at the 1% level of significance is 20.

Tables 3-7 and 3-8 give the proportion of time spent out of the green zone, the mean
daily capital charge and its standard deviation, and the maximum and mean absolute
deviations of the violations, expressed as a percentage of the VaR forecast for each model. These results also provide some mixed evidence regarding the relative performance of the SI and the PM. For the equally weighted portfolio, the SI and PM Riskmetrics™ model always lead to the lowest mean daily capital charges, for all distributions considered. In the case of the value weighted portfolio, the lowest capital charges are always obtained for the DCC-GARCH model.

### Evaluating VaR Thresholds using GED

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Violations</th>
<th>Proportion of Time out of the Green Zone</th>
<th>Daily Capital Charge Mean</th>
<th>StDev</th>
<th>Maximum</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Equally Weighted Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>27</td>
<td>2.17%</td>
<td>5.07%</td>
<td>1.062%</td>
<td>195%</td>
<td>42%</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>27</td>
<td>3.90%</td>
<td>4.91%</td>
<td>0.934%</td>
<td>193%</td>
<td>39%</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>17</td>
<td>0.50%</td>
<td>5.21%</td>
<td>0.472%</td>
<td>182%</td>
<td>36%</td>
</tr>
<tr>
<td>SI GJR</td>
<td>15</td>
<td>0.00%</td>
<td>5.12%</td>
<td>0.435%</td>
<td>170%</td>
<td>31%</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>14</td>
<td>0.00%</td>
<td>5.10%</td>
<td>0.461%</td>
<td>164%</td>
<td>32%</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>27</td>
<td>2.17%</td>
<td>5.07%</td>
<td>1.062%</td>
<td>195%</td>
<td>42%</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>27</td>
<td>3.90%</td>
<td>4.91%</td>
<td>0.938%</td>
<td>193%</td>
<td>38%</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>21</td>
<td>0.23%</td>
<td>5.67%</td>
<td>0.745%</td>
<td>123%</td>
<td>26%</td>
</tr>
<tr>
<td>SI GJR</td>
<td>12</td>
<td>0.00%</td>
<td>6.04%</td>
<td>0.748%</td>
<td>93%</td>
<td>27%</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>14</td>
<td>0.00%</td>
<td>6.04%</td>
<td>0.846%</td>
<td>91%</td>
<td>24%</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>27</td>
<td>2.17%</td>
<td>5.07%</td>
<td>1.062%</td>
<td>195%</td>
<td>42%</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>28</td>
<td>3.03%</td>
<td>5.99%</td>
<td>1.223%</td>
<td>134%</td>
<td>26%</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>28</td>
<td>0.00%</td>
<td>6.65%</td>
<td>0.958%</td>
<td>85%</td>
<td>28%</td>
</tr>
<tr>
<td>SI GJR</td>
<td>28</td>
<td>9.20%</td>
<td>5.35%</td>
<td>0.896%</td>
<td>147%</td>
<td>31%</td>
</tr>
</tbody>
</table>

(1) The daily capital charge is given as the negative of the higher of the previous day’s VaR, or the average VaR over the last 60 business days times (3+k), where k is the penalty. The capital charge represents the proportion of the portfolio that must be kept in reserves.

(2) AD denotes absolute deviation, which is computed as (absolute value of the actual returns minus the forecasted VaR threshold) divided by the forecasted VaR threshold.

(3) As there are 2000 days in our forecasting period, the expected number of violations at the 1% level of significance is 20.
Table 3-8: Evaluating VaR Thresholds using the t Distribution

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Violations</th>
<th>Proportion of Time out of the Green Zone</th>
<th>Daily Capital Charge</th>
<th>AD of Violations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td>StDev</td>
</tr>
<tr>
<td><strong>Equally Weighted Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>11</td>
<td>0.00%</td>
<td>6.21%</td>
<td>1.357%</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>14</td>
<td>0.00%</td>
<td>6.02%</td>
<td>1.234%</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>6</td>
<td>0.00%</td>
<td>6.45%</td>
<td>0.561%</td>
</tr>
<tr>
<td>SI GJR</td>
<td>5</td>
<td>0.00%</td>
<td>6.37%</td>
<td>0.557%</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>4</td>
<td>0.00%</td>
<td>6.37%</td>
<td>0.666%</td>
</tr>
<tr>
<td>PM SN</td>
<td>11</td>
<td>0.00%</td>
<td>6.21%</td>
<td>1.357%</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>14</td>
<td>0.00%</td>
<td>6.02%</td>
<td>1.239%</td>
</tr>
<tr>
<td>CCC</td>
<td>6</td>
<td>0.00%</td>
<td>6.99%</td>
<td>0.924%</td>
</tr>
<tr>
<td>DCC</td>
<td>6</td>
<td>0.00%</td>
<td>6.75%</td>
<td>1.514%</td>
</tr>
<tr>
<td><strong>Value Weighted Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SI SN</td>
<td>15</td>
<td>0.00%</td>
<td>6.60%</td>
<td>1.352%</td>
</tr>
<tr>
<td>SI Riskmetrics™</td>
<td>15</td>
<td>0.00%</td>
<td>6.44%</td>
<td>1.324%</td>
</tr>
<tr>
<td>SI GARCH</td>
<td>6</td>
<td>0.00%</td>
<td>6.72%</td>
<td>0.830%</td>
</tr>
<tr>
<td>SI GJR</td>
<td>7</td>
<td>0.00%</td>
<td>6.69%</td>
<td>0.819%</td>
</tr>
<tr>
<td>SI EGARCH</td>
<td>7</td>
<td>0.00%</td>
<td>6.69%</td>
<td>0.936%</td>
</tr>
<tr>
<td>PM SN</td>
<td>16</td>
<td>0.00%</td>
<td>6.63%</td>
<td>1.370%</td>
</tr>
<tr>
<td>PM Riskmetrics™</td>
<td>15</td>
<td>0.00%</td>
<td>6.46%</td>
<td>1.334%</td>
</tr>
<tr>
<td>CCC</td>
<td>6</td>
<td>0.00%</td>
<td>7.36%</td>
<td>1.002%</td>
</tr>
<tr>
<td>DCC</td>
<td>16</td>
<td>0.00%</td>
<td>5.71%</td>
<td>0.947%</td>
</tr>
</tbody>
</table>

(1) The daily capital charge is given as the negative of the higher of the previous day’s VaR, or the average VaR over the last 60 business days times (3+k), where k is the penalty. The capital charge represents the proportion of the portfolio that must be kept in reserves.

(2) AD denotes absolute deviation, which is computed as (absolute value of the actual returns minus the forecasted VaR threshold) divided by the forecasted VaR threshold.

(3) As there are 2000 days in our forecasting period, the expected number of violations at the 1% level of significance is 20.

The rolling backtesting results for each model are given in Figures 3-47 to 3-55 for the equally weighted portfolio, and in Figures 3-56 to 3-64 for the value weighted portfolio.

The backtesting results show that the majority of models perform well. Only the SI GARCH, SI SN and PM SN models, under the assumption of normality, lead to backtesting results that fall in the Red zone. For the value weighted portfolio, only the DCC model leads to backtesting results that fall in the Red zone under the assumption of normality.
Figure 3-47: Rolling Backtest for the Equally Weighted Portfolio using the SI Standard Normal Model

Figure 3-48: Rolling Backtest for the Equally Weighted Portfolio using the SI Riskmetrics™ Model

Figure 3-49: Rolling Backtest for the Equally Weighted Portfolio using the SI GARCH Model

Figure 3-50: Rolling Backtest for the Equally Weighted Portfolio using the SI GJR Model

Figure 3-51: Rolling Backtest for the Equally Weighted Portfolio using the SI EGARCH Model

Figure 3-52: Rolling Backtest for the Equally Weighted Portfolio using the PM Standard Normal Model
Figure 3-53: Rolling Backtest for the Equally Weighted Portfolio using the PM Riskmetrics™ Model

Figure 3-54: Rolling Backtest for the Equally Weighted Portfolio using the CCC Model

Figure 3-55: Rolling Backtest for the Equally Weighted Portfolio using the DCC Model

Figure 3-56: Rolling Backtest for the Value Weighted Portfolio using the SI Standard Normal Model

Figure 3-57: Rolling Backtest for the Value Weighted Portfolio using the SI Riskmetrics™ Model

Figure 3-58: Rolling Backtest for the Value Weighted Portfolio using the SI GARCH Model
It is natural to ask whether the reported daily capital charges are statistically different from each other. Diebold and Mariano (1995) propose a method for testing the null hypothesis of no difference in the accuracy of two competing forecasts. The original test compares the errors \((e_{1,t}, e_{2,t}), \ t = 1,...,n\), produced by two competing forecasts. Such forecasts are evaluated using a loss function, \(f(e)\), and the null hypothesis refers to the equality of the expected forecast performance, namely, \(E[f(e_{1,t}) - f(e_{2,t})] = 0\).

In this chapter, the relevant loss function is the calculated capital charges produced by each model. Figures 3-65 to 3-73 give the daily capital charges for the equally weighted portfolio and Figures 3-74 to 3-82 give the daily capital charges for the value weighted portfolio. The original statistic proposed by Diebold and Mariano (1995) is given as follows:

\[
S_t = \left[\frac{1}{V(\bar{d})}\right]^{\frac{1}{2}} \bar{d},
\]

where

\[
d_t = f(e_{1,t}) - f(e_{2,t}), \ t = 1,...,n,
\]

\[
\bar{d} = n^{-1} \sum_{t=1}^{n} d_t,
\]
\[ V(\tilde{d}) \approx n^{-1} \left[ \xi_0 + 2 \sum_{k=1}^{h-1} \xi_k \right], \]

where \( \xi_k \) is the \( k'\)th autocovariance of \( d_i \), and \( h \) is the number of steps ahead used for forecasting. However, Harvey et al. (1997) showed that the original statistic proposed by Diebold and Mariano (1995) can be over-sized, and proposed the following adjusted statistic:

\[ S_1^* = \left[ \frac{n + 1 - 2h + n^{-1}h(h-1)}{n} \right]^{\frac{1}{2}} S_1. \]

The adjusted test statistic follows a t distribution with \( n - 1 \) degrees of freedom. Table 3-9 and 3-10 give the results of the adjusted Diebold and Mariano test. As can be seen, almost all pairs of models yield capital charges that are statistically different from each other. This result suggests that the choice of model used to forecast the VaR threshold is important as it can lead to substantially different capital charges.
Figure 3-65: Rolling Capital Charge for the Equally Weighted Portfolio Using the SI Standard Normal Model.

Figure 3-66: Rolling Capital Charge for the Equally Weighted Portfolio Using the SI Riskmetrics™ Model.

Figure 3-67: Rolling Capital Charge for the Equally Weighted Portfolio Using the SI GARCH Model.

Figure 3-68: Rolling Capital Charge for the Equally Weighted Portfolio Using the SI GJR Model.

Figure 3-69: Rolling Capital Charge for the Equally Weighted Portfolio Using the SI EGARCH Model.

Figure 3-70: Rolling Capital Charge for the Equally Weighted Portfolio Using the PM Standard Normal Model.
Figure 3-71: Rolling Capital Charge for the Equally Weighted Portfolio Using the PM Riskmetrics™ Model

Figure 3-72: Rolling Capital Charge for the Equally Weighted Portfolio Using the CCC Model.

Figure 3-73: Rolling Capital Charge for the Equally Weighted Portfolio Using the DCC Normal Model.

Figure 3-74: Rolling Capital Charge for the Value Weighted Portfolio Using the SI Standard Normal Model.

Figure 3-75: Rolling Capital Charge for the Value Weighted Portfolio Using the SI Riskmetrics™ Model.

Figure 3-76: Rolling Capital Charge for the Value Weighted Portfolio Using the SI GARCH Model.
Figure 3-77: Rolling Capital Charge for the Value Weighted Portfolio Using the SI GJR Model.

Figure 3-78: Rolling Capital Charge for the Value Weighted Portfolio Using the SI EGARCH Model.

Figure 3-79: Rolling Capital Charge for the Value Weighted Portfolio Using the PM Standard Normal Model.

Figure 3-80: Rolling Capital Charge for the Value Weighted Portfolio Using the PM Riskmetrics™ Model

Figure 3-81: Rolling Capital Charge for the Value Weighted Portfolio Using the CCC Model.

Figure 3-82: Rolling Capital Charge for the Equally Weighted Portfolio Using the DCC Normal Model.
### Table 3-9: Adjusted Diebold and Mariano Test for the Equally Weighted Portfolio

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<td>31.57</td>
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</table>
Table 3-10: Adjusted Diebold and Mariano Test for the Value Weighted Portfolio
Model

SI SN - N

SI SN - N

SI SN - GED

-25.84

SI SN - GED
SI SN - T
TM - N

SI Riskmetrics

TM -GED

SI Riskmetrics

TM

SI Riskmetrics

-T

SI GARCH - N
SI GARCH - GED
SI GARCH - T
SI GJR - N
SI GJR - GED

SI SN - T

-65.74
-88.27

SI
SI
SI
RiskmetricsT RiskmetricsT RiskmetricsT SI GARCH - SI GARCH - SI GARCH M-N
M -GED
M
N
GED
T
-T

1.06
18.17
52.89

-19.09
2.53
52.13
-26.01

-57.50
-56.91
34.30
-48.46
-44.88

10.33
24.67
54.43
8.80
23.20
48.05

-24.18 -83.24
-3.14 -59.88
34.85
-8.45
-22.52 -69.25
-5.05 -55.99
26.16 -21.79
-126.23 -194.50
-224.56

SI GJR - N

SI GJR GED

SI GJR - T

SI EGARCH SI EGARCH SI EGARCH
-N
- GED
-T

12.60 -21.17 -79.30
-1.04 -54.04
26.03
53.72
34.15
-5.77
11.35 -20.64 -68.74
25.08
-3.02 -53.55
48.07
26.39 -18.15
12.31 -114.47 -205.08
127.86
11.78 -207.58
186.59 158.42
11.97
-210.92 -234.32
-231.52

SI GJR - T
SI EGARCH - N
SI EGARCH - GED
SI EGARCH - T
PM SN - N
PM SN - GED
PM SN - T
TM

PM Riskmetrics

TM

PM Riskmetrics

-N

-21.28
-1.38
38.49
-20.36
-3.45
30.15
-71.48
6.61
210.29
-81.01
-0.89
268.18
-193.33

-74.01
-57.24
-6.87
-64.25
-54.56
-21.30
-130.78
-106.12
6.64
-134.18
-103.64
-1.03
-210.30
-207.79

-20.06
15.71
55.05
-8.64
13.60
48.02
-15.92
16.99
71.40
-17.99
14.58
69.18
-17.90
14.48
63.92

PM SN GED

-28.29
-16.85
80.53
-20.53
-4.89
51.24
-25.73
1.13
54.50
-26.96
-0.79
49.51
-29.00
-0.61
51.85
-18.13

PM SN - T

-67.80
-91.63
-16.78
-55.84
-54.17
-37.44
-55.03
-35.60
6.23
-54.23
-34.97
3.83
-60.05
-39.02
4.59
-57.21
-88.36

PM
PM
PM
RiskmetricsT RiskmetricsT RiskmetricsT
M
M
M
-N
- GED
-T

2.80
20.65
57.01
2.84
31.52
53.69
-8.00
27.58
84.00
-11.01
25.89
85.55
-11.21
26.27
80.32
9.63
22.49
58.77

-19.09
3.15
52.11
-26.31
0.79
46.13
-23.26
5.46
55.87
-24.62
3.41
53.10
-26.08
3.83
53.74
-12.76
5.75
55.72
-30.54

- GED

TM

PM Riskmetrics

12.68
28.26
59.96
11.19
26.71
54.32
8.54
140.73
259.20
-0.78
156.39
341.70

PM SN - N

-T

CCC-N
CCC- GED
CCC- T
DCC- N
DCC- GED
DCC- T

(1)
(2)
(3)
(4)

Each entry corresponds to the adjusted Diebold and Mariano test statistic.
The test statistic tests the null hypothesis that the forecasts given by the model listed in the collum are the same as the forecasts given by the model listed in the row.
The test statistic follows a t-distribution with n-1 degrees of freedom.
Entries in bold are significant at the 1% level.

79

-59.05
-58.26
29.98
-50.61
-46.74
-15.38
-48.50
-26.71
20.32
-48.49
-26.98
16.92
-54.58
-30.66
19.70
-49.68
-53.68
34.97
-55.22
-48.88

CCC - N

-29.63
-11.06
19.64
-43.93
-15.65
12.21
-52.52
-13.21
38.08
-57.25
-16.30
37.67
-49.70
-13.58
31.99
-26.40
-9.55
21.01
-39.42
-15.55
12.96

CCC - GED

-64.36
-39.87
-2.49
-97.68
-52.99
-11.78
-94.06
-53.48
5.29
-98.62
-57.85
3.13
-88.63
-50.10
2.95
-63.91
-38.23
-1.06
-84.00
-50.93
-11.09
-272.30

CCC - T

-130.39
-97.58
-45.55
-195.37
-131.25
-58.92
-168.00
-127.25
-54.17
-171.38
-132.44
-58.79
-161.34
-119.09
-50.57
-135.45
-95.34
-43.94
-171.11
-121.57
-58.35
-291.62
-290.64

DCC - N

38.05
48.20
81.75
33.10
50.57
80.85
28.89
76.23
153.62
24.10
73.62
156.77
29.02
84.98
158.78
44.47
49.11
82.49
33.64
50.24
82.06
59.25
95.26
163.34

DCC - GED

34.69
50.30
84.33
33.57
51.28
80.31
36.51
90.64
179.17
31.88
82.76
171.27
37.63
93.65
170.05
38.52
49.95
83.22
40.48
51.92
79.85
61.07
94.66
158.26
6.84

DCC - T

7.24
25.23
62.89
6.19
24.28
53.72
-3.33
36.07
98.48
-6.28
31.01
90.49
-6.07
30.18
81.82
13.09
26.11
62.78
4.63
23.20
53.78
41.25
82.07
159.79
-21.86
-38.50


3.13 Conclusions

The aim of this chapter was to compare the performance of the Single Index and Portfolio models in forecasting VaR thresholds for two portfolios comprising 56 stocks from the Australian Stock Exchange. Alternative SI and PM conditional volatility models were used to forecast the VaR thresholds under three distributional assumptions. The performance of each model was evaluated using the Unconditional Coverage, Serial Independence and Conditional Coverage tests of Christoffersen (1998), the Time Until First Failure (TUFF) test of Kupiec (1995), and the logit-based test of da Veiga et al. (2005a). The results of these tests provide mixed evidence concerning the performance of the Single Index relative to the Portfolio models. However, it is interesting to note that the daily capital charges given by all models are lower than what they would have been under the standardised Basel Accord approach, suggesting that ADIs can benefit from using internal models.

The performance of each model was shown to be very sensitive to the distributional assumptions. The assumption of normality led to the least conservative VaR forecasts, while the t distribution led to the most conservative VaR forecasts. The results presented in this chapter are consistent with the results of da Veiga et al. (2005), where it was found that the assumption of normality led to excessive violations and the lowest daily capital charges. This result suggests that the penalties imposed under the Basel Accord are not sufficiently severe to discourage banks from using sub-optimal models.
Finally, the Diebold and Mariano (1995) test was adapted to test whether the computed daily capital charges were, in fact, statistically different from each other. The results of the Diebold and Mariano test suggested that almost all pairs of models led to statistically different daily capital charges. As capital charges represent a significant cost to ADIs, these empirical results show that ADIs should exercise great care in selecting an optimal portfolio of VaR models.
Chapter Four

4  PS-GARCH: Do Spillovers Matter?

4.1 Introduction

Accurate modelling of volatility (or risk) is of paramount importance in finance. As risk is unobservable, several modelling procedures have been developed to measure and forecast risk. The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model of Engle (1982) and Bollerslev (1986) has led subsequently to a family of autoregressive conditional volatility models. The success of GARCH models can be attributed largely to their ability to capture several stylised facts of financial returns, such as time-varying volatility, persistence and clustering of volatility, and asymmetric reactions to positive and negative shocks of equal magnitude. This has also contributed to the modelling and forecasting of Value-at-Risk (VaR) thresholds.

As financial applications typically deal with a portfolio of assets and risks, there are several multivariate GARCH models which specify the risk of one asset as depending dynamically on its own past risk as well as on the past risk of other assets (see McAleer (2005) for a discussion of a variety of univariate and multivariate, conditional and stochastic, volatility models). A volatility spillover is defined as the impact of any
previous volatility of asset \( i \) on the current volatility of asset \( j \), \( i=j=1,\ldots,m \) assets, and for any \( i \neq j \). A similar definition applies for returns spillovers. da Veiga and McAleer (2005) showed that the multivariate VARMA-GARCH model of Ling and McAleer (2003) and VARMA-Asymmetric GARCH (or VARMA-AGARCH) model of Hoti et al. (2003) provided superior volatility and VaR threshold forecasts than their nested univariate counterparts, namely the GARCH model of Bollerslev (1986) and the GJR model of Glosten, Jagannathan and Runkle (1992), respectively.

Multivariate extensions have great intuitive and empirical appeal as they enable modelling of the relationship between subsets of the portfolio and allow for scenario and sensitivity analyses (see Chapter 3 for further details). Moreover, their structural and asymptotic properties have been well established, especially for multivariate GARCH models (for further details, see Ling and McAleer (2003) and Hoti et al. (2003), which extend the results for a range of univariate GARCH models in Ling and McAleer (2002a, b)). However, the practical usefulness of this result can be affected by the computational difficulties in estimating the VARMA-GARCH and VARMA-AGARCH models for a large number of assets, as the number of parameters to be estimated can increase dramatically with the number of assets, and hence spillover effects.

Several parsimonious multivariate models have been proposed to deal with the over-parameterization problem. The CCC model of Bollerslev (1990), the Dynamic Conditional Correlation (DCC) model of Engle (2002), and the Varying Conditional Correlation (VCC) model of Tse and Tsui (2002) use a two-step estimation procedure to
facilitate estimation. McAleer et al. (2005) extended these conditional correlation models by specifying the shocks to returns as being time dependent, and established the structural and asymptotic properties of the more general model. The Orthogonal GARCH (O-GARCH) model of Alexander (2001) uses principal component analysis to reduce the number of parameters to be estimated.

The need to develop volatility models to estimate accurately large covariance matrices has become especially relevant following the 1995 amendment to the Basel Accord, whereby banks were permitted to use internal models to calculate their VaR thresholds. This amendment was a reaction to widespread criticism that the ‘Standardized’ approach, which banks were originally required to use in calculating their VaR thresholds, led to excessively conservative forecasts. Excessive conservatism has a negative impact on the profitability of banks as higher capital charges are subsequently required. While the amendment was designed to reward institutions with superior risk management systems, a backtesting procedure, whereby the realized returns are compared with the VaR forecasts, was introduced to assess the quality of the internal models. Banks using models that lead to a greater number of violations than can reasonably be expected, given the confidence level, are required to hold higher levels of capital. If a bank’s VaR forecasts are violated more than 9 times in a financial year, the bank may be required to adopt the ‘Standardized’ approach. The imposition of such a penalty is severe as it has an impact on the profitability of the bank directly through higher capital charges, may damage the bank’s reputation, and may also lead to the imposition of a more stringent external model to forecast the VaR thresholds.
In this chapter we investigate the importance of including spillover effects when modelling and forecasting financial volatility. We compare the forecasted conditional variances produced by the VARMA-GARCH model of Ling and McAleer (2003), in which the conditional variance of asset \( i \) is specified to depend dynamically on past squared unconditional shocks and past conditional variances of each asset in the portfolio, with the forecasted conditional variances produced by the CCC model of Bollerslev (1990), where the conditional variance of asset \( i \) is specified to depend only on the squared unconditional shocks and past conditional variances of asset \( i \). We also develop a new Portfolio Spillover GARCH (PS-GARCH) model, which allows spillover effects to be included in a more parsimonious manner. The parsimonious nature of the PS-GARCH model is of critical importance to practitioners as the model can be estimated for any number of assets, while several other multivariate models can be estimated only for a reasonably small number of assets. This parsimonious nature avoids the so-called “curse of dimensionality” that can render many multivariate models impractical in empirical applications. This parsimonious model is found to yield volatility and VaR threshold forecasts that are very similar to those of the VARMA-GARCH model. Using the taxonomy proposed in Bauwens et al. (2005), both the PS-GARCH and VARMA-GARCH models are nonlinear multivariate extensions of the standard univariate GARCH model.

The plan of the chapter is as follows. Section 4.2 presents the new PS-GARCH model, discusses alternative multivariate GARCH models with and without spillover effects, and
presents a simple two-step estimation method for PS-GARCH. The data for four international stock market indices are discussed in Section 4.3, the volatility and conditional correlation forecasts produced by alternative multivariate GARCH models are examined in Section 4.4, the economic significance of the VaR threshold forecasts arising from the alternative multivariate GARCH models is analysed in Section 4.5, and some concluding remarks are given in Section 4.6.

### 4.2 Models

This section proposes a parsimonious and computationally convenient PS-GARCH model which captures aggregate portfolio spillover effects, and discusses the structural and statistical properties of the model. The new model is compared with two constant conditional correlation models, one of which models spillover effects from each of the other assets in the portfolio and another which has no spillover effects.

It must be stressed that strictly speaking the PS-GARCH model is intended as an approximation only because if the variance structure of the portfolio follows a GARCH process as in (4.8) then the variance structure of the individual assets can not follow a GARCH process as in (4.9). However, the PS-GARCH is developed as an approximate way of capturing spillover effects parsimoniously. By way of comparison, Engle’s (2002) DCC model is not consistent with any existing static univariate or multivariate GARCH models. The DCC model is an approximation to capture dynamic effects in conditional correlations, which are ratios of conditional covariances to the square roots of the
products of the conditional variances. A more theoretically correct formulation, which does not have the parsimonious property of the PS-GARCH model and hence is not useful in practice, is presented in section 4.8.

### 4.2.1 PS-GARCH

Let the vector of returns on \( m \ (\geq 2) \) financial assets be given by

\[
Y_t = E(Y_t \mid F_{t-1}) + \varepsilon_t \tag{4.1}
\]

where the conditional mean of the returns follows a VARMA process:

\[
\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t. \tag{4.2}
\]

The return on the portfolio consisting of the \( m \) assets is denoted as:

\[
Y_{p,t} = E(\sum_{i=1}^{m} x_{i,t} y_{i,t} \mid F_{t-1}) + \varepsilon_{p,t} \tag{4.3}
\]
where \( y_{i,t} \) denotes the return on asset \( i=1,\ldots,m \), at time \( t \) and \( x_{i,t} \) denotes the portfolio weight of asset \( i \) at time \( t \), such that:

\[
\sum_{i=1}^{m} x_{i,t} = 1 \quad \forall \ t .
\] (4.4)

The portfolio spillover GARCH (PS-GARCH) model assumes that the returns on the portfolio follow an ARMA process, and that the conditional volatility of the portfolio can be approximated by a GARCH process, as follows:

\[
\Phi(L)(Y_{p,t} - \mu_p) = \Psi(L)\varepsilon_{p,t} ,
\] (4.5)

\[
\varepsilon_t = D_t \eta_t ,
\] (4.6)

\[
\varepsilon_{p,t} = h_{p,t}^{1/2} \eta_{p,t} ,
\] (4.7)

\[
h_{p,t} = \omega_p + \sum_{k=1}^{r} \alpha_{p,k} \varepsilon_{p,t-k}^2 + \sum_{j=1}^{s} \beta_{p,j} h_{p,t-j} ,
\] (4.8)
\[ H_t = \omega + \sum_{k=1}^r A_k \hat{\varepsilon}_{t-k} + \sum_{k=1}^r C_k I(\eta_{t-k}) \hat{\varepsilon}_{t-k} + \sum_{l=1}^s B_l H_{t-l} + \sum_{k=1}^r G_k \hat{\varepsilon}_{p,t-k}^2 + \sum_{l=1}^s I H_{p,t-l}, \quad (4.9) \]

where \( H_t = (h_{1t}, ..., h_{mt})', \ \omega = (\omega_1, ..., \omega_m)', \ D_t = \text{diag}(h_{it}^{1/2}), \ \eta_t = (\eta_{i1}, ..., \eta_{im})', \ \hat{\varepsilon}_t = (\varepsilon_{i1}^2, ..., \varepsilon_{im}^2) \), and \( \hat{\varepsilon}_{p,t-k}^2 \) and \( \hat{H}_{p,t-l} \) are the fitted values from (4.5) and (4.8), respectively. The \( m \times m \) matrices \( A_k, B_l, \) and \( C_k \) are diagonal, with typical elements \( \alpha_{ii}, \beta_{ii} \) and \( \gamma_{ii} \), respectively, \( G_k = (g_{1i}, ..., g_{mi})', \ K_l = (k_{i1}, ..., k_{mi})', \ I(\eta_t) = \text{diag}(I(\eta_{it})) \) is an \( m \times m \) diagonal matrix, \( \Phi(L) = I_m - \Phi_1 L - ... - \Phi_r L^r \) and \( \Psi(L) = I_m - \Psi_1 L - ... - \Psi_q L^q \) are polynomials in \( L \), the lag operator, \( F_t \) is the past information available to time \( t \), \( I_m \) is the \( m \times m \) identity matrix, and \( I(\eta_{it}) \) is an indicator function, given as:

\[
I(\eta_t) = \begin{cases} 1, & \varepsilon_{it} \leq 0 \\ 0, & \varepsilon_{it} > 0. \end{cases} \quad (4.10)
\]

The indicator function distinguishes between the effects of positive and negative shocks of equal magnitude on conditional volatility. Portfolio spillovers arise when \( G_k \) and \( K_l \) are not null matrices.

Using (4.6), the conditional covariance matrix for the PS-GARCH model is given by \( Q_t = D_t \Gamma D_t \), for which the matrix of conditional correlations is given by \( E(\eta_t \eta_t') = \Gamma \).
The matrix $\Gamma$ is the constant conditional correlation matrix of the unconditional shocks which is, by definition, equivalent to the constant conditional correlation matrix of the conditional shocks.

### 4.2.2 VARMA-GARCH

The VARMA-GARCH model of Ling and McAleer (2003), which assumes symmetry in the effects of positive and negative shocks on conditional volatility, is given by:

$$Y_t = E(Y_t | F_{t-1}) + \varepsilon_t,$$  \hspace{1cm} (4.11)

$$\Phi(L)(Y_t - \mu) = \Psi(L)\varepsilon_t,$$  \hspace{1cm} (4.12)

$$\varepsilon_t = D_t\eta_t,$$  \hspace{1cm} (4.13)

$$H_t = \omega + \sum_{k=1}^{r} A_k \tilde{\varepsilon}_{t-k} + \sum_{l=1}^{s} B_l H_{t-l},$$  \hspace{1cm} (4.14)
where \( H_t = (h_{t-1}, \ldots, h_m)' \), \( \omega = (\omega_1, \ldots, \omega_m)' \), \( D_t = \text{diag}(h_{t-1}^{1/2}) \), \( \eta_t = (\eta_{t-1}, \ldots, \eta_m)' \), \( \bar{e}_t = (\bar{e}_{t-1}, \ldots, \bar{e}_m)' \), \( A_k \) and \( B_l \) are \( m \times m \) matrices with typical elements \( \alpha_{ij} \) and \( \beta_{ij} \), respectively, for \( i, j = 1, \ldots, m \), \( I(\eta_t) = \text{diag}(I(\eta)) \) is an \( m \times m \) matrix, \( \Phi(L) = I_m - \Phi_1 L - \ldots - \Phi_p L^p \) and \( \Psi(L) = I_m - \Psi_1 L - \ldots - \Psi_q L^q \) are polynomials in \( L \), the lag operator, and \( F_t \) is the past information available to time \( t \). Spillover effects are given in the conditional volatility for each asset in the portfolio, specifically where \( A_k \) and \( B_l \) are not diagonal matrices. Based on equation (4.13), the VARMA-GARCH model also assumes that the matrix of conditional correlations is given by \( E(\eta_t, \eta_t') = \Gamma \).

An extension of the VARMA-GARCH model is the VARMA-AGARCH model of Hoti et al. (2002), which captures the asymmetric spillover effects from each of the other assets in the portfolio. The VARMA-AGARCH model is also a multivariate extension of the univariate GJR model.

### 4.2.3 CCC

The VARMA-GARCH, VARMA-AGARCH and PS-GARCH models have several popular constant conditional correlation univariate and multivariate models as special cases. If the model given by equation (4.14) is restricted so that \( A_k \) and \( B_l \) are diagonal matrices, the VARMA-GARCH model reduces to:

---

91
which is the constant conditional correlation (CCC) model of Bollerslev (1990). The CCC model also assumes that the matrix of conditional correlations is given by $E(\eta, \eta') = \Gamma$. As given in equation (4.15), the CCC model does not have volatility spillover effects across different financial assets, and hence is intrinsically univariate in nature. Moreover, CCC also does not capture the asymmetric effects of positive and negative shocks on conditional volatility.

4.3 Estimation

The parameters in models (4.9), (4.14), (4.15) can be obtained by maximum likelihood estimation (MLE) using a joint normal density, namely:

$$\hat{\theta} = \arg\min_\theta \frac{1}{2} \sum_{t=1}^n \left( \log |Q_t| + \varepsilon_t^\top Q_t^{-1} \varepsilon_t \right),$$  \hspace{1cm} (4.16)

where $\theta$ denotes the vector of parameters to be estimated in the conditional log-likelihood function, and $|Q_t|$ denotes the determinant of $Q_t$, the conditional covariance.
matrix. When $\eta_t$ does not follow a joint multivariate normal distribution, equation (4.16) is defined as the Quasi-MLE (QMLE).

The models described above can also be estimated using the following simple two-step estimation procedure:

1. For each financial index return series, the univariate GARCH (1,1) model with an AR(1) conditional mean specification is estimated, and the unconditional shocks and standardized residuals of all $m$ returns are saved.

2. For the portfolio returns, as defined by equation (4.3), the univariate GARCH (1,1) model with VARMA(1,1) conditional mean specification is estimated, and the unconditional shocks and standardized residuals are saved.

3. For each financial returns series, the univariate VARMA(1,1)-GARCH(1,1) model is estimated, including the lagged squared unconditional shocks and the lagged conditional variances of the remaining $m-1$ assets. The standardized residuals of the $m-1$ financial returns are saved.

4. For each financial returns series, the VARMA(1,1)-PS-GARCH(1,1) model is estimated, including the lagged squared unconditional shocks and the lagged conditional variances from step (2). The standardized residuals of all $m$ financial returns are saved.

5. For each returns series, the constant conditional correlation matrices of the VARMA(1,1)-GARCH(1,1) model are estimated by direct computation using the standardized residuals from step (3). Bollerslev's (1990) CCC matrix is estimated
directly using the standardized residuals from step (1). Finally, the constant conditional correlation matrix of the PS-GARCH model is estimated using the standardized residuals from step (4).

The tests of spillover and asymmetric effects are valid under the null hypothesis of independent (that is, no spillovers) and symmetric effects, so that steps (3) and (4) are valid under the joint null hypothesis. The primary purpose of the structural and asymptotic theory derived in Ling and McAleer (2003) is to demonstrate that such testing is statistically valid.

Using extensions of the structural and asymptotic properties derived in Ling and McAleer (2003), Hoti et al. (2002) and McAleer et al. (2005), it can be shown that the QMLE of the parameters in the PS-GARCH model are consistent and asymptotically normal in the absence of normality in the standardized shocks $\eta_{p,t}$ in (4.7) (the proof is available on request).

The VARMA-GARCH and VARMA-AGARCH models are available as pre-programmed options in, for example, the RATS 6 econometric software package. In this chapter, estimation is undertaken using the EViews 5.1 econometric software package, although the results were very similar using the RATS 6 econometric software package.
4.4 Data

The data used in the empirical application are daily prices measured at 16:00 Greenwich Mean Time (GMT) for four international stock market indices (henceforth referred to as synchronous data), namely S&P500 (USA), FTSE100 (UK), CAC40 (France), and SMI (Switzerland). New York and London are widely regarded as the two most important global markets, while Paris and Zurich are selected for purposes of examining spillovers using synchronous data. All prices are expressed in US dollars. The data were obtained from DataStream for the period 3 August 1990 to 5 November 2004, which yields 3720 observations. At the time the data were collected, this period was the longest for which data on all four variables were available. The rationale for employing daily synchronous data in modelling stock returns and volatility transmission is four-fold.

First, the Efficient Markets Hypothesis would suggest that information is quickly and efficiently incorporated into stock prices. While information generated yesterday may be significant in explaining stock price changes today, it is less likely that news generated last month would have any explanatory power today.

Second, it has been argued by Engle et al. (1990) that volatility is caused by the arrival of unexpected news and that volatility clustering is the result of investors reacting differently to news. The use of daily data may help in modelling the interaction between the heterogeneity of investor responses in different markets.
Third, studies that use close-to-close non-synchronous returns suffer from the non-synchronicity problem, as highlighted in Scholes and Williams (1977). In particular, these studies cannot distinguish a spillover from a contemporaneous correlation when markets with common trading hours are analysed. Kahya (1997) and Burns et al. (1998) also observe that, if cross market correlations are positive, the use of close-to-close returns for non-synchronous markets will underestimate the true correlations, and hence underestimate the true risk associated with a portfolio of such assets.

Finally, the use of synchronous data allows the system to be written in a simultaneous equations form, which can be estimated jointly. Such joint estimation of the parameters eliminates potential econometric problems associated with generated regressors, in which unobserved variables are obtained (or generated) through estimation of auxiliary regression models (see, for example, Pagan (1984) and Oxley and McAleer (1993, 1994)), improves efficiency in estimation, increases the power of the test for cross-market spillovers, and analyses market interactions simultaneously. This allows all the relationships to be tested jointly. Joint estimation is also consistent with the notion that spillovers are the impact of global news on each market.

The synchronous returns for each market $i$ at time $t$ ($R_{i,t}$) are defined as:

$$ R_{it} = \log\left( \frac{P_{i,t}}{P_{i,t-1}} \right), \quad (4.17) $$
where $P_{i,t}$ is the price in market $i$ at time $t$, as recorded at 16:00 GMT. Figure 4-1 to 4-4 plot the daily returns.
The descriptive statistics for the synchronous returns of the four indexes are given in Table 4-1. All series have similar means and medians at close to zero, minima which vary between -10.251 and -5.533, and maxima that range between 5.771 and 10.356. Although the four standard deviations vary slightly, the coefficients of variation (CoV) are quite different, ranging from 30.97 for S&P500 to 67.30 for CAC40. The skewness differs among all four series, but the kurtosis is reasonably similar for all series. The Jarque-Bera test strongly rejects the null hypothesis of normally distributed returns, which may be due to the presence of extreme observations. As each of the series displays a high degree of kurtosis, this would seem to indicate the existence of extreme observations. Each of the returns series exhibits clustering, which needs to be captured by an appropriate time series model.
Several definitions of volatility are available in the literature. This chapter adopts the measure of volatility proposed in Franses and van Dijk (2000), where the true volatility of returns is defined as:

\[ V_{t,t} = (R_{t,t} - E(R_{t,t} | F_{t-1}))^2, \]  

(4.18)

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

The plots of the volatilities of the synchronous returns are given in Figures 4-5 to 4-8. Each of the series exhibits clustering, which needs to be captured by an appropriate time series model. The volatility of all series appears to be high during the early 1990’s, followed by a quiet period from the end of 1992 to the beginning of 1997. Finally, the volatility of all series appears to increase dramatically around 1997, due in large part to the Asian economic and financial crises. This increase in volatility persists until the end of the period, and is likely to have been affected by the 11 September, 2001 terrorist attacks and the conflicts in Afghanistan and Iraq.
The descriptive statistics for the volatility of the synchronous returns of the four indexes, although not reported here, indicate that CAC40 displays the highest mean (median) volatility at 2.029 (0.665), while FTSE100 has the lowest mean (median) volatility at 1.357 (0.425). The maxima of the four volatility series differ substantially, with SMI displaying the highest maxima and S&P500 displaying the lowest. Although the four standard deviations vary, the coefficients of variation (CoV) are similar. All series are highly skewed. As each of the series displays a high degree of kurtosis, this would seem to indicate the existence of extreme observations.
4.5 Forecasts

The purpose of this section is to compare the volatility and conditional correlation forecasts produced by the CCC model of Bollerslev (1990), the VARMA-GARCH model of Ling and McAleer (2003), and the new PS-GARCH model proposed in this chapter. A rolling window approach is used to forecast the 1-day ahead conditional correlations and conditional variances. The sample ranges from 3 August 1990 to 5 November 2004. In order to strike a balance between efficiency in estimation and a viable number of rolling regressions, the rolling window size is set at 2000 for all four data sets, which leads to a forecasting period from 6 April 1998 to 5 November 2004.

Figure 4-9: Portfolio Conditional Variance Forecasts
Figure 4-9 plots the forecasted conditional variances using the three models for an equally weighted portfolio containing S&P500, FTSE100, CAC40 and SMI. Table 4-2 shows the correlations between the three sets of forecasts. The volatility forecasts produced by all models are remarkably similar, with correlation coefficients of the volatility forecasts ranging from 0.987 to 0.993.

<table>
<thead>
<tr>
<th></th>
<th>CCC</th>
<th>VARMA-GARCH</th>
<th>PS-GARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCC</td>
<td>1</td>
<td>0.987</td>
<td>0.993</td>
</tr>
<tr>
<td>VARMA-GARCH</td>
<td>1</td>
<td>0.991</td>
<td></td>
</tr>
<tr>
<td>PS-GARCH</td>
<td>0.993</td>
<td>0.991</td>
<td>1</td>
</tr>
</tbody>
</table>

The forecasted conditional correlations and the correlation of the conditional correlation forecasts are given in Figures 4-10 to 4-15 and Table 4-3, respectively. The conditional correlation forecasts are virtually identical for all three models, with correlation coefficients ranging from 0.996 to 0.999. This result suggests that for applications where the required inputs are the forecasts of the conditional variances and/or the conditional correlation matrix, all three models considered above yield very similar results.
Table 4-3: Correlations of Rolling Conditional Correlation Forecasts Between Pairs of Indexes

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P500 and FTSE100</th>
<th></th>
<th>S&amp;P500 and CAC40</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CCC</td>
<td>VARMA-GARCH</td>
<td>PS-GARCH</td>
<td>CCC</td>
</tr>
<tr>
<td>1</td>
<td>0.996</td>
<td>0.999</td>
<td>1</td>
<td>0.996</td>
</tr>
<tr>
<td>1</td>
<td>0.997</td>
<td></td>
<td>1</td>
<td>0.997</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>S&amp;P500 and SMI</td>
<td></td>
<td>FTSE100 and CAC40</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.995</td>
<td>0.999</td>
<td>1</td>
<td>0.992</td>
</tr>
<tr>
<td>1</td>
<td>0.996</td>
<td></td>
<td>1</td>
<td>0.996</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>FTSE100 and SMI</td>
<td></td>
<td>CAC40 and SMI</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.984</td>
<td>0.995</td>
<td>1</td>
<td>0.998</td>
</tr>
<tr>
<td>1</td>
<td>0.992</td>
<td></td>
<td>1</td>
<td>0.996</td>
</tr>
<tr>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
</tbody>
</table>
4.6 Economic Significance

The 1988 Basel Capital Accord, which was originally concluded between the central banks from the Group of Ten (G10) countries, and has since been adopted by over 100 countries, sets minimum capital requirements which must be met by banks to guard against credit and market risks. The market risk capital requirements are a function of the forecasted VaR thresholds (see Chapter 3). The Basel Accord stipulates that the daily capital charge must be set at the higher of the previous day’s VaR or the average VaR over the last 60 business days multiplied by a factor $k$. The multiplicative factor $k$ is set by the local regulators, but must not be lower than 3.

In 1995, the 1988 Basel Accord was amended to allow banks to use internal models to determine their VaR. However, banks wishing to use internal models must demonstrate that the models are sound. Furthermore, the Basel Accord imposes penalties in the form of a higher multiplicative factor $k$ on banks which use models that lead to a greater number of violations than would reasonably be expected given the specified confidence level of 1%.

In certain cases, where the number of violations is deemed to be excessively large, regulators may penalize banks even further by requiring that their internal models be reviewed. In circumstances where the internal models are found to be inadequate, banks can be required to adopt the standardized method originally proposed in 1993 by the Basel Accord. The standardized method suffers from several drawbacks, the most noticeable of which is its systematic overestimation of risk, which stems from the
assumption of perfect correlation across different risk factors. Overestimating risk leads to higher capital charges which negatively impact both the profitability and reputation of the bank.

The economic significance of the various models proposed above is highlighted by forecasting VaR thresholds using the PS-GARCH, VARMA-GARCH and CCC models (see Jorion (2000) for a detailed discussion of VaR). In order to simplify the analysis, it is assumed that the portfolio returns are normally distributed, with equal and constant weights. We control for exchange rate risk by converting all prices to a common currency, namely the US Dollar. We use the forecasted variances and correlations from Section 4 to produce VaR forecasts for the period 6 May 1998 to 5 November 2004. The backtesting procedure is used to test the soundness of the models by comparing the realised and forecasted losses (see Basel Committee (1988, 1995, 1996) for further details).

Figures 4-16 to 4-18 show the VaR forecasts and realized returns for each empirical model considered. Both the CCC and PS-GARCH VaR forecasts violate the thresholds 7 times from 1720 forecasts, while the VARMA-GARCH model leads to 6 violations from 1720 forecasts.
Figure 4-16: Realized Returns and CCC VaR Forecasts.

Figure 4-17: Realized Returns and VARMA-GARCH VaR Forecasts.
Table 4-4 shows that the mean daily capital charge, which is a function of both the penalty and the forecasted VaR, implied by PS-GARCH is the largest at 9.180%, followed by VARMA-GARCH at 9.051% and CCC at 9.009%. A high capital charge is undesirable, other things equal, as it reduces profitability. Table 4-4 also shows that CCC leads to violations that are approximately 10% greater in terms of mean absolute deviations, at 0.498, than the VARMA-GARCH and PS-GARCH models, at 0.454 and 0.442, respectively. This is particularly important because large violations, on average, may lead to bank failures, as the capital requirements implied by the VaR threshold forecasts may be insufficient to cover the realized losses. Finally, CCC also leads to the largest maximum violation.
<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Violations</th>
<th>Mean Daily Capital Charge</th>
<th>AD of Violations</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCC</td>
<td>7</td>
<td>9.009</td>
<td>2.125</td>
</tr>
<tr>
<td>VARMA-GARCH</td>
<td>6</td>
<td>9.760</td>
<td>1.974</td>
</tr>
<tr>
<td>PS-GARCH</td>
<td>7</td>
<td>9.180</td>
<td>1.902</td>
</tr>
</tbody>
</table>

(1) The daily capital charge is given as the negative of the higher of the previous day’s VaR or the average VaR over the last 60 business days times (3+k), where k is the penalty.

### 4.7 Conclusions

Accurate modelling of volatility (or risk) is important in finance, particularly as it relates to the modelling and forecasting of Value-at-Risk (VaR) thresholds. As financial applications typically deal with a portfolio of assets and risks, there are several multivariate GARCH models which specify the risk of one asset as depending dynamically on its own past, as well as the past of other assets. These models are typically computationally demanding, due to the large number of parameters to be estimated, and can be impossible to estimate for a large number of assets.

The need to create volatility models that can be used to estimate large covariance matrices has become especially relevant following the 1995 amendment to the Basel Accord, whereby banks are permitted to use internal models to calculate their VaR.
thresholds. While the amendment was designed to reward institutions with superior risk management systems, a backtesting procedure in which the realized returns are compared with the VaR forecasts, was introduced to assess the quality of the internal models. Banks using models that lead to a greater number of violations than can reasonably be expected, given the confidence level, are penalized by having to hold higher levels of capital. The imposition of penalties is severe as it has an impact on the profitability of the bank directly through higher capital charges, may damage the bank's reputation, and may also lead to the imposition of a more stringent external model to forecast the VaR thresholds.

This chapter examined various conditional volatility models for purposes of forecasting financial volatility and VaR thresholds. Two constant conditional correlation models for estimating the conditional variances and covariances are the CCC model of Bollerslev (1990) and the VARMA-GARCH model of Ling and McAleer (2003). Although the VARMA-GARCH model accommodates spillover effects from the returns shocks of all assets in the portfolio, which are typically estimated to be significantly different from zero, the forecasts of the conditional volatility and VaR thresholds produced by the VARMA-GARCH model are very similar to those produced by the CCC model.

Finally, the chapter also developed a new parsimonious and computationally convenient Portfolio Spillover GARCH (PS-GARCH) model, which allowed spillover effects to be included parsimoniously. The PS-GARCH model was found to yield volatility and VaR threshold forecasts that were very similar to those of the CCC and VARMA-GARCH models. Therefore, although the empirical results suggest that spillover effects are
statistically significant, the VaR threshold forecasts are generally found to be insensitive to the inclusion of spillover effects in the multivariate models considered.

The following sections expands the discussion of parsimony in the context of multivariate conditional volatility models and formally develop a parsimonious conditional volatility model and a parsimonious stochastic volatility models, both with constant correlations, that can be used to forecast VaR thresholds for a large number of assets.

4.8 Appendix 1: Portfolio Single Index

This Section introduces the structure of parsimonious Portfolio Single Index (PSI) multivariate conditional and stochastic constant correlation volatility models, and methods for estimation of the underlying parameters. These multivariate estimates of volatility can be used for purposes of more accurate portfolio and risk management, to enable efficient forecasting of Value-at-Risk (VaR) thresholds, and to determine optimal Basel Accord capital charges (a comprehensive discussion of alternative univariate and multivariate, conditional and stochastic, financial volatility models for calculating VaR is given in McAleer (2005)).

The plan of the Section is as follows. Section 4.8.1 presents the portfolio single index approach to model the conditional and stochastic covariance matrices of a portfolio
of assets parsimoniously. Estimation methods for the conditional and stochastic volatility models are discussed in Section 4.9.

### 4.8.1 Portfolio Model

Let the returns on $m \geq 2$ financial assets be given by

$$y_{it} = \mu_{it} + \varepsilon_{it}, \quad i = 1, \ldots, m, \quad t = 1, \ldots, T,$$

or

$$y_t = \mu_t + \varepsilon_t, \quad \text{(4.17)}$$

where $y_t$, $\mu_t$, and $\varepsilon_t$ are $m$ dimensional column vectors, $\mu_t = E(y_t | F_{t-1})$, and $F_t$ is the past information available at time $t$. The return of the portfolio consisting of $m$ assets is denoted as

$$y_{p,t} = w'y_t = w'\mu_t + w'\varepsilon_t, \quad \text{(4.18)}$$
where \( w = (w_1, \ldots, w_m)' \) denotes the portfolio weights, such that \( \sum_{i=1}^{m} w_i = 1 \). For the returns to the portfolio, the conditional mean vector and disturbance of the portfolio are defined by

\[
\mu_p,t = E(y_{p,t} | F_{t-1}) = w' \mu_t
\]

and

\[
\epsilon_{p,t} = y_{p,t} - \mu_{p,t},
\]

respectively. In order to consider the volatility of the portfolio, it is necessary to model the conditional and stochastic covariance matrices \( Q_t \) and \( \Sigma_t \), respectively.

### 4.8.2 Conditional Volatility

Consider the conditional covariance matrix of \( y_t \), which is given as:

\[
f_t(\alpha_{p,t+1|t}) = \lambda_t \alpha_{p,t-1} \quad Q = V(y_t | F_{t-1}) = E(\epsilon_t \epsilon'_{t+1} | F_{t-1}) \tag{4.19}
\]

and the conditional volatility of the portfolio, which is given by

\[
h_{p,t} = V(y_{p,t} | F_{t-1}) = w' Q_t w.
\]
In the framework of multivariate GARCH models, the constant conditional correlation (CCC) model of Bollerslev (1990) abandons significant information as each component of $y_t$ follows a univariate GARCH(1,1) process, and hence does not capture the effects of the remaining $m-1$ assets. On the other hand, more general specifications, such as the VARMA-GARCH model of Ling and McAleer (2003) and the BEKK (Baba, Engle, Kraft and Kroner) model of Engle and Kroner (1995) suffer from the fact that the number of parameters increases significantly as the number of variables increases. This can cause serious problems for convergence of the appropriate estimators, especially for a portfolio with a large number of assets.

As an illustration, consider the VARMA-AGARCH model of Hoti, Chan and McAleer (2002). This model is an asymmetric extension of the VARMA-GARCH model of Ling and McAleer (2003), and is given by

$$
\varepsilon_i = D_i \eta_i, \quad \eta \sim iid(0, \Gamma), \quad (4.20)
$$

$$
Q_i = D_i \Gamma D_i, \quad (4.21)
$$

$$
H_i = \omega + \sum_{k=1}^{q} \left[ A_k + C_k \text{diag}\left\{ d_{t-k} \right\} \right] \left( \varepsilon_{t-k} \circ \varepsilon_{t-k} \right) + \sum_{l=1}^{q} B_l H_{i-l}, \quad (4.22)
$$
where \( D_t = \text{diag}\{h_t\} \), \( H_t = (h_{t1}, \ldots, h_{tn})' \), \( \text{diag}\{x\} \) for any vector \( x \) denotes a diagonal matrix with \( x \) along the diagonal, and ‘\( \odot \)’ denotes the Hadamard product of two identically-sized matrices or vectors, which is computed simply by element-by-element multiplication. The vector \( d_t^- = (d_{t1}^-, \ldots, d_{tn}^-)' \) denotes a set of indicator variables, where \( d_{it}^- \) takes the value one if \( \varepsilon_{it}^- \) is negative, and zero otherwise. For estimation of the parameters, \( \Gamma \) is the positive definite correlation matrix of \( \eta_t \), that is, \( E(\eta_t \eta_t') = \Gamma \), \( \omega = (\omega_1, \ldots, \omega_m)' \), and \( A_k \), \( B_l \), and \( C_k \) are \( m \times m \) matrices, with typical elements \( \alpha_{ij,k} \), \( \beta_{ij,l} \) and \( \gamma_{ij,k} \), respectively.

The model of Ling and McAleer (2003) assumes \( C_k = O \) for all \( k \) in equation (4.22). Thus, when \( p = q = 1 \), \( m = 4 \) implies that the number of parameters to be estimated in equation (4.22) is 52. The regularity conditions and asymptotic properties of the estimators for the various models given above are developed in Ling and McAleer (2003) and Hoti et al. (2002). These regularity conditions are extensions of the univariate results given in Ling and McAleer (2002a, b).

There are other approaches for modelling \( Q_t \), such as the dynamic conditional correlation (DCC) model suggested by Engle (2002). However, this does not affect the ways in which a portfolio can be transformed to a single index using the methods described above.
As an intermediate approach, namely one that incorporates volatility spillover effects parsimoniously, this Section proposes the portfolio single index model, which is given as follows:

\[ H_t = \omega + \sum_{k=1}^{q} (\alpha_k + \gamma_k \circ d_{r-k} \circ (\varepsilon_{r-k} \circ \varepsilon_{r-k})) + \sum_{l=1}^{p} \beta_l \circ H_{t-l} \circ \sum_{s=1}^{r} (\delta_s \varepsilon_{p,s}^2 + \lambda_s h_{p,s}) \]  \hspace{1cm} (4.23)

where \( \alpha_k = (\alpha_{1,k}, \ldots, \alpha_{m,k})' \), \( \beta_l = (\beta_{1,l}, \ldots, \beta_{m,l})' \), \( \gamma_k = (\gamma_{1,k}, \ldots, \gamma_{m,k})' \), \( \delta_s = (\delta_{1,s}, \ldots, \delta_{m,s})' \) and \( \lambda_s = (\lambda_{1,s}, \ldots, \lambda_{m,s})' \). It should be noted that, for the portfolio returns, \( \varepsilon_{p,t} = w' \varepsilon_t \) and \( h_{p,t} = w' Q_t w \). The model in equations (4.17)-(4.21) and (4.23) will be called the Portfolio Single Index GARCH (PSI-GARCH or, equivalently, Ψ-GARCH) model. In the Ψ-GARCH model, the conditional volatility for each \( y_{it} \) may be considered as a combination of the GJR model and the portfolio spillover effects. When \( \gamma_k \), \( \delta_s \) and \( \lambda_s \) are all equal to zero, the model reduces to CCC. The asymmetry arises when \( \gamma_k \) is not a null vector, while non-zero \( \delta_s \) and \( \lambda_s \) capture the portfolio spillover effects. When \( p = q = r = 1 \) and \( m = 4 \), the number of parameters to be estimated in equation (4.23) is 24. Compared with equation (4.22), this is a significant reduction in the number of parameters, while retaining spillover effects.

Based on the concept of weak and strong GARCH processes, as defined in Drost and Nijman (1993), Nijman and Sentana (1996) show that a linear combination of variables
generated by a multivariate GARCH process is also a weak GARCH process. Thus, the
Ψ-GARCH model developed in this Section is a weak GARCH process.

4.8.3 Stochastic Volatility

Now we turn to the stochastic covariance matrix given by $\Sigma_t$. For purposes of
convenience and parsimony, we assume the presence of constant correlations in the
model, such that:

$$\Sigma_t = D_t \Gamma D_t,$$  \hfill (4.24)

where $D_t = \text{diag} \{0.5 \exp(\alpha_t)\}$, $\alpha_t = (\alpha_{t1}, \ldots, \alpha_{tm})'$, and ‘exp’ denotes the operator for
vectors which performs element-by-element exponentiation. In the model, $\exp(\alpha_{it})$
denotes the stochastic volatility for $y_{it}$, while the volatility for the portfolio is defined as

$$\sigma_{p,t}^2 = \exp(\alpha_{p,t}),$$  \hfill (4.25)

where

$$\alpha_{p,t} = \log|w'D_t \Gamma D_t w|$$
$$= \log|ww'| + \log|\Gamma| + \log|D_t^2|,$$  \hfill (4.26)
$$= \log|w'w| + \log|\Gamma| + \sum_{i=1}^{m} \alpha_{it}.$$
Hence, the log-volatility of the portfolio is defined as a constant term plus the sum of the log-volatility of each asset in the portfolio.

Before developing the new stochastic volatility model, consider the VAR(p)-ASV model, as follows:

\[ \varepsilon_t = D_t \eta_t, \quad \eta_t \sim N(0, \Gamma), \quad (4.27) \]

\[ \alpha_{t+1} = \omega + \sum_{l=1}^{p} \Phi_l \alpha_{t+1-l} + \xi_t, \quad \xi_t \sim N(0, \Sigma), \quad (4.28) \]

\[ E(\xi_t \eta_t) = \text{diag} \left\{ \rho_{1} \sigma_{\xi 1,1}^{1/2}, \ldots, \rho_{m} \sigma_{\xi m,m}^{1/2} \right\}, \quad (4.29) \]

where \( \Sigma = \left\{ \sigma_{\xi ij} \right\} \). For convenience, normality is assumed for the VAR(p)-ASV model.

A multivariate \( t \) distribution is also assumed for \( \eta_t \), as in Harvey, Ruiz and Shephard (1994). Non-zero values of \( \rho_1, \ldots, \rho_m \) refer to the existence of leverage in the volatility of each asset. In the VAR(p)-ASV model, each log-volatility is affected by the past log-volatilities of the other \( m-1 \) assets through \( \Phi_l \), and also has a contemporaneous effect between the log-volatilities via \( \Sigma \). Assuming \( p = 1, \ \rho_1 = \cdots = \rho_m = 0 \), and \( \Phi_1 \) is the
diagonal matrix, we have the model proposed by Harvey et al. (1994). Based on the MSV model of Harvey et al. (1994), Asai and McAleer (2005b) considered non-zero values of $\rho_1, \ldots, \rho_m$, as in equation (4.29), and proposed the MCL estimation procedure for an asymmetric multivariate stochastic volatility model with a constant correlation structure.

As a closed form expression for the likelihood function of SV models does not exist, estimation of the parameters in SV models is undertaken using numerical methods by evaluating the likelihood (through numerical integration) or by simulation methods. The Monte Carlo Likelihood (MCL) methods proposed by Durbin and Koopman (1997) and Sandmann and Koopman (1998) are based on importance sampling. Although the econometrics and statistics literature has tended to focus on the Bayesian Markov Chain Monte Carlo (MCMC) method, the MCL method has the advantage in being computationally fast (in comparison with most other simulation methods) and relatively easy to implement.

A similar discussion about conditional volatility can be applied to equation (4.28). If we set all the off-diagonal elements of $\Phi_i$ and $\Sigma_\xi$ to zero, then each $y_{it}$ collapses to the simple ASV model of Harvey and Shephard (1996). On the other hand, the above VAR($p$)-ASV model has many parameters to be estimated. When $p=1$, $m=4$ implies that the number of parameters in equation (4.28) is 30.
For the Portfolio Single Index MSV (PSI-MSV or, equivalently, Ψ-MSV) model, the log-volatility is defined as follows:

\[
\alpha_{t+1} = \omega + \sum_{l=1}^{p} \phi_l \alpha_{t+1-l} + \sum_{s=1}^{r} f \left( e_{P,t+1-s}, \alpha_{P,t+1-s} \right) + \xi_t, \\
\xi_t \sim N(0, \text{diag} \{\sigma_{\xi,11}, \ldots, \sigma_{\xi,mm}\})
\]  

(4.30)

where \( \phi_l = (\phi_{l,1}, \ldots, \phi_{l,m})' \) and \( f \left( y_{P,t}, \alpha_{P,t} \right) \) is a function of the information contained in the portfolio. Neglecting \( e_{P,t} \), if we assume that

\[
\alpha_{t+1} = \sum_{s=1}^{r} \lambda_s \alpha_{P,t-s}
\]

(4.32)

and \( p = r \), where \( \lambda_s = (\lambda_{s,1}, \ldots, \lambda_{s,m})' \), then we can obtain the off-diagonal elements of \( \Phi_t \) under appropriate restrictions, since the log-volatility of the portfolio is defined as equation (4.26). If we assume that

\[
f_2 \left( e_{P,t+1-s} \right) = \delta_{1,s} e_{P,t-s} + \delta_{2,s} |e_{P,t-s}|,
\]

(4.33)

where \( \delta_{1,s} = (\delta_{1,1,s}, \ldots, \delta_{1,m,s})' \), \( \delta_{2,s} = (\delta_{2,1,s}, \ldots, \delta_{2,m,s})' \), then we can capture the asymmetric effects from shocks in the portfolio. Asai and McAleer (2005a) developed and discussed this type of asymmetry in detail. Other specifications, including a combination of (4.32)
and (4.33), can be considered. However, returning to the purpose of the PSI approach, we concentrate on equation (4.33). In this case, the number of parameters in equations (4.30) and (4.33) reduces dramatically to 20 when \( p = r = 1 \) and \( m = 4 \).

Next, consider the model that \( \varepsilon_{p,t} \) in (4.33) is replaced by the returns of the market portfolio, say \( y_{M,t} \). For this model, each element of volatility is determined by using the information of the market portfolio instead of the portfolio discussed in the Section. Although this idea has intuitive appeal, we will consider them separately.

It should be stressed that the \( \Psi \)-MSV model in (4.27), (4.29), (4.30) and (4.33) has been developed as an intermediate approach for incorporating the information from the other assets in the portfolio. It is a separate matter altogether whether to use the information from market returns to supplement the information that is contained in the portfolio.

### 4.9 Estimation

#### 4.9.1 Conditional Volatility Model

Under the assumption of normality of the conditional distribution of the standardized residuals, we can obtain the parameters by maximum likelihood (ML) estimation, as follows:
\[ \hat{\theta} = \arg \max \sum_{t=1}^{T} l_t, \]

where

\[ l_t = -\frac{1}{2} \log h_{p,t} - \frac{\hat{\varepsilon}_{p,t}^2}{2h_{p,t}} \]  \hspace{1cm} (4.34)

and \( \theta \) denotes the vector of parameters to be estimated in the conditional log-likelihood function. If the assumption of normality does not hold for the standardized residuals, equation (4.34) is defined as the Quasi-maximum likelihood estimator (QMLE).

### 4.9.2 Stochastic Volatility Model

We focus on the \( \Psi \)-MSV model in (4.27), (4.29), (4.30) and (4.33). Estimation of the parameters in MSV models is computationally demanding, even for \( m = 2 \). As the PSI approach presented in the Section concentrates information contained in the other assets into a single index, it enables the use of a computationally efficient method, as described below. Importantly, given the structure of the model, we can estimate the parameters for each asset, namely \( \omega_i, \phi_{i,i}, \sigma_{i,i}, \rho_i, \delta_{i,i,i}, \delta_{2,i,i} \) and the parameters for \( \mu_i \), neglecting the remaining assets. There are numerous ways in which MSV models can be estimated,
such as Monte Carlo Likelihood (MCL) method, or the Bayesian Markov Chain Monte Carlo (MCMC) method proposed by Jacquier, Polson and Rossi (1994). On the basis of Monte Carlo experiments, Sandmann and Koopman (1998) showed that the finite sample properties of the two estimators were very similar. McAleer (2005) discusses these and other methods for estimating univariate and multivariate SV models.

The recommended two step estimation method is as follows:

1. For each financial asset, \( y_u \), obtain a consistent estimate of \( \epsilon_u, \hat{\epsilon}_u \), to calculate the portfolio shocks, \( \hat{\epsilon}_{p,t} \);

2. For each financial asset, estimate the parameters for each volatility by using \( \hat{\epsilon}_{p,t} \) to calculate an estimate of \( \alpha_u, \hat{\alpha}_u \);

3. The standardized residuals, \( \hat{\eta}_t = \hat{\epsilon}_t \exp(-0.5\hat{\alpha}_t) \), can be used to obtain an estimate of the correlation matrix, \( \Gamma \).

After obtaining the two step estimates using the approach given above, we can obtain the estimate of \( \alpha_{p,t} \) based on equation (4.26).
5  *VaR Forecasts Based on Constant and Dynamic Conditional Correlations.*

5.1  *Introduction*

The aim of this chapter is to compare the VaR forecasts produced by models that assume constant conditional correlations with forecasts that allow for time varying conditional correlations. In order to study this issue, we use Chinese A and B share price index data which, due to some recent regulatory changes, are found to display significantly time-varying correlations.

An important feature of the shares issued by the typical state-owned enterprises in the People’s Republic of China (PRC) is that they are divided into negotiable and non-negotiable blocks of scrip. The non-negotiable block is typically larger, accounting for 60-70% of issued equity, and is controlled by the PRC. The negotiable portion of issued equity can be traded in three forms, namely A, B or H shares: H shares are listed in exchanges outside mainland China while A and B shares can be listed in either the Shanghai or Shenzen exchange, with dual listing not permitted. Furthermore, companies listed in the Shanghai stock exchanges have typically greater market capitalization than
those listed in the Shenzen stock exchange. Prior to 28 February 2001, ownership of A shares was restricted to residents of the PRC, while ownership of B shares was restricted to foreign investors. However, starting from 28 February 2001, Chinese residents were allowed to open foreign exchange accounts to trade in B shares.

As both classes of shares represent identical ownership in the same company, the Efficient Market Hypothesis (EMH) would suggest that both classes of shares should trade at the same price. Yet prior to the deregulation, B shares tended to trade at a significant discount to their A share counterparts. Various studies have documented this observed market segmentation, including Bailey (1994) and Ma (1996). Subsequent papers analysed the volatility in the Chinese stock markets. For example, Su and Fleisher (1999) analysed daily data for a matched sample of 24 firms issuing both A and B shares, and found that both types of shares exhibited time varying-volatility and that A shares tended to be more volatile. Poon and Fung (2000) used threshold GARCH models to investigate the asymmetric response of A and B share volatility to positive and negative shocks, and found that A and B shares reacted asymmetrically to good and bad news. Brooks and Raganathan (2003) analysed the information transmission between A and B shares prior to the B share market reform, and found evidence of returns spillovers but not volatility spillovers. More recently, Chiu et al. (2005) used the Autoregressive Conditional Jump Intensity model of Chan and Maheu (2002) to investigate the impact of the B share market reform on the volatility dynamics between A and B shares. Their results suggested that deregulation led to an increase in jump intensity and frequency and that the volatility transmission had accelerated.
All the studies mentioned above suggest that the B share market reform had a significant impact on the covariance matrix between A and B shares. The covariance matrix of a portfolio of assets is one of the most important inputs in virtually all financial applications, from risk management, asset and option pricing to portfolio construction and management, to mention but a few. Chiu et al. (2005) calculated the historical sample correlations between A and B shares for the pre- and post-deregulation periods and concluded that all pairs of correlations increased substantially following the B share market reform.

The use of historical correlations is limited, however, as it does not allow an investigation of the time-varying structure of the dynamic correlations. Furthermore, the results presented in Chiu et al. (2005) suffer from the disadvantage that the pre-deregulation sample is roughly ten times greater than the post-deregulation sample.

As B shares are typically traded at a significant discount to their A share counterparts, the B share market reform has created substantial arbitrage opportunities for Chinese investors. These arbitrage opportunities suggest that many Chinese investors would have expanded their portfolios to include B shares. An important consideration for such investors is the degree to which A and B shares are correlated, because the strength of the correlation between the A and B shares will determine the potential benefits of diversifying across both types of shares. Furthermore, many modern risk management
practices and strategies require estimates of the variance of the portfolio as well as an understanding of the co-movements between different components of the portfolio.

The aim of this chapter is to examine the impact of the recent B share market reform on the correlation dynamics between A and B shares issued in the same market, by estimating Engle’s (2002) Dynamic Conditional Correlation (DCC) model. The DCC model is chosen because it models correlations and being time-varying, as opposed to the Constant Conditional Correlation (CCC) model of Bollerslev (1990), which models the conditional correlations as being constant. Two alternative conditional volatility models with time-varying conditional correlations and covariances are available, namely the Varying Conditional Correlation model of Tse and Tsui (2002) and BEKK models of Engle and Kroner (1995). However, BEKK models the conditional covariances, and hence models the conditional correlations only indirectly (see McAleer (2005) for a comprehensive discussion of univariate and multivariate, conditional and stochastic volatility models). These models are not considered in this chapter as they are difficult to estimate when the number of assets is large and hence, not useful in modern portfolio management where risk measures for a very large number of assets are required. To the best of our knowledge this chapter represents that first attempt to model the dynamic nature of the correlations between A and B market shares.

The results of the chapter suggest that the correlations between A and B shares increased substantially over the sample period, and that this increase began well before the B share market reform. One plausible explanation would be that Chinese investors had access to
B share by establishing joint venture with foreign investors. This chapter also examines the importance of accommodating time-varying correlations when forecasting VaR thresholds by using both CCC and the DCC models to forecast 1000 VaR thresholds for three theoretical portfolios containing A and B shares. The empirical results suggest that accommodating time-varying correlations improves the VaR forecasts.

The plan of the chapter is as follows. Section 5.2, describes the data used. The Section 5.3 discusses the models used. The empirical results are discussed in Section 5.4. The forecasts are evaluated in Section 5.5. Some concluding remarks are given in Section 5.6.

5.2 Data

The data used in this chapter are daily returns for the Shanghai A share index (SHA), Shanghai B share index (SHB), Shenzen A share index (SZA) and Shenzen B share index (SZB) for the period 6 October 1992 to 10 August 2005, and are obtained from Bloomberg. At the time of data collection, this was the longest sample for which data were available for all series. All data was gathered from Datastream and converted to a single currency, namely the US dollar. Figures 5-1 to 5-4 plot the respective indices rebased to 100 as at 6 October 1992. Table 5-1 gives the sample correlations. SHA and SZA indices display the greatest sample correlation at 0.952, followed by the SHB and SZB at 0.833. SHB and SZA have the lowest sample correlation at 0.338, followed by SHA and SZB at 0.352.
Figures 5-5 to 5-8 the daily returns for the respective indices. The correlation between the various index returns are given in Table 5-2. These results suggest that SHA and SZA index returns display the greatest sample correlation at 0.782, followed by SHB and SZB at 0.692. SHA and SZB have the lowest sample correlation at 0.288, followed by SZA and SHB at 0.319. Of particular interest is that the results show the correlation between the same class of share across different exchanges is typically much higher than for different classes of shares within the same exchange. This is somewhat surprising as cross listing is not permitted, so the SHA (SHB) and SZA (SZB) indices are mutually exclusive.
Table 5-1: Sample Correlations Between Indices

<table>
<thead>
<tr>
<th>SHA</th>
<th>SHB</th>
<th>SZA</th>
<th>SZB</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.375</td>
<td>0.952</td>
<td>0.352</td>
<td></td>
</tr>
<tr>
<td>0.338</td>
<td>0.833</td>
<td></td>
<td>0.317</td>
</tr>
</tbody>
</table>

Figure 5-5: Shanghai A Share Index Returns.

Figure 5-6: Shanghai B Share Index Returns.

Figure 5-7: Shenzen A Share Index Returns.

Figure 5-8: Shenzen B Share Index Returns.

Table 5-2: Sample Correlations Between Index Returns

<table>
<thead>
<tr>
<th>SHA</th>
<th>SHB</th>
<th>SZA</th>
<th>SZB</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.298</td>
<td>0.782</td>
<td>0.288</td>
<td></td>
</tr>
<tr>
<td>0.319</td>
<td>0.692</td>
<td></td>
<td>0.341</td>
</tr>
</tbody>
</table>
Table 5-3 gives the descriptive statistics for the daily returns. All series display similar means and median, which are close to zero. The A shares consistently display a greater range than their B share counterparts, with significantly higher maxima and lower minima. Moreover, all series display excess kurtosis, with the distribution of A shares displaying significantly thicker tails than B shares. Furthermore, the SHA, SHB and SZB return series are positively skewed, while the SZA return series are negatively skewed. Finally, all series are found to be highly non-normal according to the Jarque-Bera Lagrange multiplier test statistic.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>SHA</th>
<th>SHB</th>
<th>SZA</th>
<th>SZB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.005</td>
<td>0.001</td>
<td>-0.011</td>
<td>0.015</td>
</tr>
<tr>
<td>Median</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Maximum</td>
<td>30.886</td>
<td>12.184</td>
<td>29.608</td>
<td>13.597</td>
</tr>
<tr>
<td>SD</td>
<td>2.670</td>
<td>2.142</td>
<td>2.456</td>
<td>2.188</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.628</td>
<td>0.427</td>
<td>-0.470</td>
<td>0.369</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>37.649</td>
<td>8.307</td>
<td>40.055</td>
<td>10.917</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>167898</td>
<td>4037</td>
<td>191897</td>
<td>8830</td>
</tr>
</tbody>
</table>

5.3 Model Specifications

Before discussing the various conditional volatility (or variance) models used in this chapter, it is useful to present Engle’s (1982) conditional volatility approach in which a random process may be expressed as:
\[ y_t = E(y_t | F_{t-1}) + \varepsilon_t \] 

(5.1)

where \( y_t = (y_{1t}, \ldots, y_{mt})' \) and \( E(y_t | F_{t-1}) \) denotes the conditional expectation of \( y_t \), given the information set \( F_{t-1} \) which contains all the information to \( t-1 \). The vector \( \varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{mt})' \) is the unconditional error of \( y_t \), which can be decomposed as:

\[ \varepsilon_t = D_t^{1/2} \eta_t, \] 

(5.2)

where \( \eta_t = (\eta_{1t}, \ldots, \eta_{mt})' \) is a sequence of independently and identically distributed (iid) random vectors. \( D_t = \text{diag}(h_{1t}, \ldots, h_{mt}) \), which is a diagonal matrix with the conditional variances of each asset on the diagonal.

The dynamic conditional covariance and correlation can be written as:

\[ E(\varepsilon_t \varepsilon_t' | F_{t-1}) = Q_t = D_t^{1/2} E(\eta_t \eta_t' | F_{t-1}) D_t^{1/2} = D_t^{1/2} \Gamma_t D_t^{1/2} \] 

(5.3)

\[ \Gamma_t = \{ \rho_{ij} \}, \ i, j = 1, \ldots, m, \]

in which \( Q_t \) is the conditional covariance matrix and \( \Gamma_t \) is the conditional correlation matrix.
A problem which was encountered in the early development of multivariate models was that they were computationally difficult due to the large number of parameters to be estimated. This issue was discussed in more detail by McAleer and da Veiga (2005) and Asai et al. (2005). In particular these papers show that models, to be discussed below, are attempts to reduce the so-called “curse of dimensionality”. In this chapter the Constant Conditional Correlation Model of Bollerslev (1990) and the Dynamic Conditional Correlation Model of Engle (2002) are used. The DCC and CCC models are discussed in detail in Chapters 3 and 4. Unless otherwise stated all estimates are obtained using EViews 5.1.

### 5.4 Empirical Results

In order to analyse the correlation dynamics between A and B shares in the Shanghai and Shenzen markets the Dynamic Conditional Correlation Model is estimated for the entire sample period. Structural dummies are included in the conditional variance and conditional correlation equations to capture the effect of the B share market reform. The augmented conditional variance and conditional correlation equations can be found as follows:

\[
H_i = W + \sum_{k=1}^{\infty} A_k \bar{e}_{i-k} + \sum_{l=1}^{\infty} B_l H_{i-l} + CV\text{-DUM}_i,
\]
\[ Q_t = (ii' - \theta_1 - \theta_2) \circ Q + \theta_1 \circ \eta_{t-1}, \eta_{t-1}' + \theta_2 \circ Q_{t-1} + \theta_3 \circ C\text{-DUM}, \]

where V-DUM and C-DUM are the two dummy variables, such that

\[
V\text{-DUM} = \begin{cases} 
0, & t < 28/2/2001 \\
1, & t \geq 28/2/2001 
\end{cases}
\]

and

\[
C\text{-DUM} = \begin{cases} 
0, & t < 28/2/2001 \\
1, & t \geq 28/2/2001.
\end{cases}
\]

Moreover, \( C \) is a \( m \times m \) diagonal matrix with typical elements \( c_{ii} \) for \( i = 1, \ldots, m \) and \( \theta_3 \) is a \( m \times m \) matrix. Therefore, the impact of the market reform can be investigated by examining the statistical significance of the estimated elements in \( \theta_2 \) and \( \theta_3 \).

Table 5-4: Conditional Mean and Variance Equations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>SHA</th>
<th>SHB</th>
<th>SZA</th>
<th>SZB</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Conditional Mean</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>0.013</td>
<td>-0.012</td>
<td>0.011</td>
<td>0.098</td>
</tr>
<tr>
<td></td>
<td>(1.253)</td>
<td>(-1.765)</td>
<td>(2.876)</td>
<td>(1.087)</td>
</tr>
<tr>
<td>AR</td>
<td>0.541</td>
<td>0.368</td>
<td>0.582</td>
<td>0.556</td>
</tr>
<tr>
<td></td>
<td>(2.441)</td>
<td>(2.015)</td>
<td>(1.138)</td>
<td>(5.330)</td>
</tr>
<tr>
<td>MA</td>
<td>-0.537</td>
<td>-0.217</td>
<td>-0.549</td>
<td>-0.424</td>
</tr>
<tr>
<td></td>
<td>(-2.403)</td>
<td>(-2.015)</td>
<td>(-1.027)</td>
<td>(-3.791)</td>
</tr>
<tr>
<td><strong>Conditional Variance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \omega_i )</td>
<td>0.079</td>
<td>0.200</td>
<td>0.305</td>
<td>0.464</td>
</tr>
<tr>
<td></td>
<td>(3.150)</td>
<td>(3.812)</td>
<td>(4.120)</td>
<td>(4.409)</td>
</tr>
<tr>
<td>( \alpha_i )</td>
<td>0.093</td>
<td>0.189</td>
<td>0.150</td>
<td>0.270</td>
</tr>
<tr>
<td></td>
<td>(4.329)</td>
<td>(5.265)</td>
<td>(5.414)</td>
<td>(6.178)</td>
</tr>
<tr>
<td>( \beta_i )</td>
<td>0.914</td>
<td>0.780</td>
<td>0.839</td>
<td>0.636</td>
</tr>
<tr>
<td></td>
<td>(55.354)</td>
<td>(20.000)</td>
<td>(29.548)</td>
<td>(14.900)</td>
</tr>
<tr>
<td>V-Dum</td>
<td>-0.033</td>
<td>-0.012</td>
<td>-0.244</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>(-2.236)</td>
<td>(-0.263)</td>
<td>(-3.292)</td>
<td>(0.680)</td>
</tr>
<tr>
<td>Log Moment</td>
<td>-0.017</td>
<td>-0.093</td>
<td>-0.103</td>
<td>-0.214</td>
</tr>
</tbody>
</table>

Note: The two entries for each parameter correspond to the parameter estimate and Bollerslev and Wooldridge robust t-ratios.
The estimated parameters for the conditional mean and conditional variance equations are reported in Table 5-4. It is important to note that as the specification of the conditional mean and conditional variance equations are the same for both the CCC and DCC models, the parameter estimates reported in Table 5-4 apply to both models considered. The Bollerslev and Wooldridge (1992) robust t-ratios are reported in order to accommodate non-normality of the error terms and the possible existence of outliers.

All series, except for SZA display AR(1) and MA(1) coefficients. In the conditional variance equation, all series display significant ARCH ($\alpha$) and GARCH ($\beta$) effects, suggesting that all series display time-varying volatility and are affected by both the short and long run persistence. An interesting finding is that A shares tend to exhibit greater long run persistence of shocks, while B shares tend to exhibit greater short run persistence of shocks. As the log-moment conditions are satisfied, the parameter estimates in the conditional variance equation are consistent and asymptotically normal. Finally, the structural dummy in the conditional variance equation is negative and significant for both the SHA and SZA series, indicating that the B share market reform led to a fall in the volatility of A shares.

The parameter estimates for the conditional correlation equation are given in Table 5-5. It is interesting to note that the structural dummies are not significant in the conditional correlation equation, indicating that the B share market reform may not have had a significant impact on the conditional correlation between A and B shares.
Figures 5-9 and 5-10 plot the fitted dynamic conditional correlations between the A and B share indices in the Shanghai and Shenzen stock markets. As can be seen, both pairs of indices display significant variability in the fitted conditional correlations, with the dynamic correlation coefficients ranging from 0 to over 0.8. More importantly, the correlation between A and B share indices appears to have increased dramatically over the sample period and this increase began well before the B share market reform. The conditional correlations measure the correlations in risk-adjusted returns. Therefore, as the conditional correlations approach 1, portfolio managers should not be diversifying across both A and B shares but should be specializing and selecting the shares that are expected to yield the greatest returns.

Table 5-5: Conditional Correlation Equation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>SHASHB</th>
<th>SZASZB</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_i$</td>
<td>0.075</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(1.987)</td>
<td>(1.067)</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>0.001</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(23.842)</td>
<td>(12.729)</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>0.999</td>
<td>0.993</td>
</tr>
<tr>
<td></td>
<td>(63.402)</td>
<td>(24.797)</td>
</tr>
<tr>
<td>C_Dum</td>
<td>0.093</td>
<td>0.262</td>
</tr>
<tr>
<td></td>
<td>(0.601)</td>
<td>(1.265)</td>
</tr>
</tbody>
</table>

Note: The two entries for each parameter correspond to the parameter estimate and Bollerslev and Wooldridge robust t-ratios.

5.5 Economic Significance

In this chapter a VaR example is used to demonstrate the economic significance of accommodating the dynamic nature of the conditional correlations between A and B market shares. Three portfolios are considered: the first comprises equal percentages of the Shanghai A and B share indices (SHAB), the comprises equal percentages of the
Shenzen A and B share indices (SZAB), and the third comprises equal percentages of the Shanghai and Shenzen A and B share indices. All portfolios are assumed to be rebalanced daily, so that all weights are kept equal and constant. Both the CCC and DCC models discussed above are used to forecast the conditional variance, $h_i$, of the portfolio, which replaces $\sigma_i$ in equation (2.3), to calculate the VaR thresholds for the period 11 October 2002 to 10 August 2005, which corresponds to 1000 forecasts. In order to eliminate exchange rate risk, all returns are converted to US Dollars.

Figure 5-9: Fitted DCC between SHA and SHB
5.6 Forecast Evaluation

The VaR threshold Forecasts are compared using the Unconditional Coverage (UC), Serial Independence (Ind), Conditional Coverage (CC) and Time Until First Failure (TUFF) tests described in Chapter 4. In addition to the statistical tests described above, the forecasting performance of the two models considered are also evaluated by the following four metrics: 1) the number of violations, which gives an indication that the model is providing the correct coverage; 2) the proportion of time spent out of the green zone, which gives an indication of the likely additional regulatory constrains that may be imposed upon the bank; 3) the mean daily capital charge, which captures the opportunity cost of using each model; 4) the absolute deviation of actual returns versus forecasted VaR thresholds. As VaR is a technique designed to manage risk, the magnitude of a
violation is of paramount importance as large violations are of much greater concern than small violations.

Figures 5-11 to 5-16 give the forecasted conditional variances for the three portfolios using both the CCC and DCC models. The conditional variance forecasts produced by the CCC and DCC models are highly correlated, with a correlation coefficient of 0.988 for the variance forecasts of the Shanghai A and B share portfolio, 0.986 for the variance forecasts of the Shenzen A and B share portfolio and 0.971 for the variance forecasts of the Shanghai and Shenzen A and B share portfolio. Figure 5-17 to 5-22 plot the portfolio returns and VaR threshold forecasts, the VaR forecasts are also highly correlated.
The empirical results are reported in Tables 5-6 and 5-7. All models perform well according Ind, CC and TUFF. However, the CCC model fails the UC test, as it leads to excessive violations, for both Shanghai A and B share portfolio and the Shenzen A and B share portfolio. Based on the number of violations and proportion of time spent out of the Green zone, the DCC model always dominates CCC as it always leads to a smaller number of violations and substantially less time in the yellow zone. Figures 5-23 to 5-28 plot the rolling backtest results for all model and portfolio combinations, while Figures 5-29 to 5-34 plot the rolling capital charges. As can be seen the DCC model always leads to
the same or fewer cumulative violations than does the CCC model. These results suggest that the DCC model leads to superior VaR forecasts.

Figure 5-23: CCC Rolling Backtest for Shanghai A and B Share Portfolio

Figure 5-24: DCC Rolling Backtest for Shanghai A and B Share Portfolio

Figure 5-25: CCC Rolling Backtest for Shenzen A and B Share Portfolio

Figure 5-26: DCC Rolling Backtest for Shenzen A and B Share Portfolio

Figure 5-27: CCC Rolling Backtest for Shanghai and Shenzen A and B Share Portfolio

Figure 5-28: DCC Rolling Backtest for Shanghai and Shenzen A and B Share Portfolio
Figure 5-29: CCC Rolling Capital Charges for Shanghai A and B Share Portfolio

Figure 5-30: DCC Rolling Capital Charges for Shanghai A and B Share Portfolio

Figure 5-31: CCC Rolling Capital Charges for Shenzen A and B Share Portfolio

Figure 5-32: DCC Rolling Capital Charges for Shenzen A and B Share Portfolio

Figure 5-33: CCC Rolling Capital Charges for Shanghai and Shenzen A and B Share Portfolio

Figure 5-34: DCC Rolling Capital Charges for Shanghai and Shenzen A and B Share Portfolio
Table 5-6: Unconditional Coverage (UC), Serial Independence (SI), Conditional Coverage (CC) and Time Until First Failure (TUFF) Tests

<table>
<thead>
<tr>
<th>Model</th>
<th>UC</th>
<th>SI</th>
<th>CC</th>
<th>TUFF</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Shanghai A and B Share Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC</td>
<td>4.091</td>
<td>0.299</td>
<td>4.39</td>
<td>0.005</td>
</tr>
<tr>
<td>DCC</td>
<td>3.077</td>
<td>0.264</td>
<td>3.341</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>Shenzen A and B Share Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC</td>
<td>5.225</td>
<td>0.336</td>
<td>5.561</td>
<td>0.853</td>
</tr>
<tr>
<td>DCC</td>
<td>3.077</td>
<td>0.264</td>
<td>3.341</td>
<td>1.016</td>
</tr>
<tr>
<td><strong>Shanghai and Shenzen A and B Share Portfolio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC</td>
<td>3.077</td>
<td>0.264</td>
<td>3.341</td>
<td>1.016</td>
</tr>
<tr>
<td>DCC</td>
<td>0.099</td>
<td>0.124</td>
<td>0.223</td>
<td>0.121</td>
</tr>
</tbody>
</table>

(1) The Unconditional Coverage (UC) and Time Until First Failure (TUFF) tests are asymptotically distributed as $\chi^2(1)$.
(2) The Serial Independence (Ind) and Conditional Coverage tests are asymptotically distributed as $\chi^2(2)$.
(3) Entries in **bold** denote significance at the 5% level and * denotes significance at the 1% level.

On the other hand, based on the mean and maximum absolute deviation of violations, the CCC model dominates DCC as it always leads to a lower maximum and mean absolute deviation of violations. Finally, according to the mean daily capital charge, the CCC model gives lower average daily capital charges for the Shanghai A and B share index portfolio and for both the Shanghai and Shenzen A and B share portfolio. However, the DCC model leads to lower mean daily capital charges for the Shenzen A and B share index portfolio.
Table 5-7: Mean Daily Capital Charges and AD of Violations

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Violations</th>
<th>Proportion of Time out of the Green Zone</th>
<th>Daily Capital Charge</th>
<th>AD of Violations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Diebold &amp; Mariano</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Maximum</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td></td>
</tr>
<tr>
<td>Shanghai A and B Share Portfolio</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC</td>
<td>17</td>
<td>37%</td>
<td>9.361%</td>
<td>86.56%</td>
</tr>
<tr>
<td>DCC</td>
<td>16</td>
<td>23%</td>
<td>9.405%</td>
<td>82.85%</td>
</tr>
<tr>
<td>Shanghai A and B Share Portfolio</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC</td>
<td>18</td>
<td>30%</td>
<td>10.055%</td>
<td>82.13%</td>
</tr>
<tr>
<td>DCC</td>
<td>16</td>
<td>11%</td>
<td>9.977%</td>
<td>83.39%</td>
</tr>
<tr>
<td>Shanghai and Shenzen A and B Share Portfolio</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCC</td>
<td>16</td>
<td>17%</td>
<td>9.072%</td>
<td>67.39%</td>
</tr>
<tr>
<td>DCC</td>
<td>11</td>
<td>0%</td>
<td>9.227%</td>
<td>63.39%</td>
</tr>
</tbody>
</table>

(1) The daily capital charge is given as the negative of the higher of the previous day’s VaR or the average VaR over the last 60 business days times \((3+k)\), where \(k\) is the penalty. The capital charge represents the proportion of the portfolio that must be kept in reserves.

(2) All portfolios are equally weighted.

(3) AD denotes absolute deviation which is computed as (actual return minus the forecasted VaR) divided by the forecasted VaR.

(4) The Diebold and Mariano statistic evaluates the null hypothesis of no difference between the two forecasted capital charges for each portfolio. This statistic is asymptotically distributed as t-distribution with \(n-1\) degrees of freedom.

(5) Entries in bold are significant at the 5% level and * denotes significance at the 1% level.

(6) As there are 1000 days in the forecasting period, the expected number of violations at the 1% level of significance is 10.

The adjusted Diebold and Mariano test described in Chapter 4 is also used to determine whether the calculated daily capital charges are statistically different from each other. The results of the adjusted Diebold and Mariano test, reported in Table 5-7, suggest that the daily capital charges produced by each model are statistically different from each other. These results suggest that the choice of model can have serious implications for the calculated capital charges, and ADIs should exercise great care in choosing between alternative models.
The results presented in this chapter have interesting implications for risk managers as they suggest that, while the DCC model leads to fewer violations and hence less time spent out of the Green zone than the CCC model, the capital charges given by the CCC model tend to be higher. Therefore, the penalty structure imposed under the Basel Accord may not be severe enough to discourage ADIs from adopting VaR models that lead to excessive violations.

5.7 Conclusions

The aim of this chapter was to model the dynamic conditional correlations between Chinese A and B share returns for the period 6 October 1992 to 10 August 2005. Prior to 28 February 2001, ownership of A shares was restricted to residents of the PRC, while ownership of B shares was restricted to foreign investors. However, starting from 28 February 2001, Chinese residents were allowed to open foreign exchange accounts to trade in B shares. A shares typically traded at a significant discount to their B share counterparts, which represented a violation of the Efficient Markets Hypothesis as both types of shares represented identical ownership in the same company. The deregulation of the B share market created substantial arbitrage opportunities, as the price of A and B shares converged, and many Chinese investors found themselves owning portfolios containing both A and B shares.
An important question for Chinese investors is the degree to which A and B shares are correlated as this will affect the portfolio construction process. The DCC model of Engle (2002) was used to estimate the dynamic conditional correlations. It was found that the correlations between Chinese A and B share returns increased substantially over the sample period, and that this increase began well before the B share market reform. The results presented in this chapter are important because, as the correlation between Chinese A and B shares approaches 1, the benefits of diversifying across both types of shares diminishes and investors should focus on the class of shares that will yield the greatest expected returns.

Given that many financial institutions are likely to hold portfolios of both Chinese A and B shares, it is necessary to analyse the importance of accommodating time-varying conditional correlations on the Value-at-Risk (VaR) threshold forecasts. To study this important issue the VaR thresholds were forecasted using both the CCC model of Bollerslev (1990) (which imposes the restriction of Constant Conditional Correlations) and the DCC model. The forecasting performance of the models was evaluated using a variety of popular statistical tests, including the UC, SI and CC tests of Christoffersen (1998) and the TUFF test of Kupiec (1995). Both models performed well according to the SI, CC and TUFF tests, while the DCC model appeared to dominate the CCC model according to the UC tests as it generally yielded a greater number of violations.

Three other measures were also considered to reflect the concerns of both ADI’s and regulators. The first measure is the proportion of time that each model leads to
‘backtesting’ results that fall outside the Green zone, reflecting the likely extra regulatory burden that an ADI would face given the use of each model. According to this measure, the DCC model dominates CCC as it is always found to lead to a lower proportion of time spent out of the Green zone. The second measure used in this chapter is the size of the average and maximum absolute deviation of violations. As VaR is a procedure designed for managing risk, by allowing ADIs to hold sufficient capital in reserves to cover extraordinary losses, the size of the violation is of extreme importance. In almost all cases, the DCC model was found to lead to lower average and maximum absolute deviations.

Finally, we compare the daily capital charges given by each model. As capital charges represent an opportunity cost, ADIs effectively face a constrained optimization problem whereby they would like to minimise capital charges subject to not violating any regulatory constraints (see da Veiga, Chan and McAleer (2005) for further details). According to this measure the CCC model is found to lead to lower capital charges, on average. The Diebold and Mariano (1995) test showed that the daily capital charges produced by each model were statistically different from each other. This result is consistent with the results reported in da Veiga, Chan, Medeiros and McAleer (2005), who found that the current Basel Accord penalty structure is not sufficiently severe and leads to lower capital charges for models with excessive violations than for models with the correct number of violations.
da Veiga et al. (2005b) formulate the maximization problem faced by ADI’s as follows: Let

\[
VaR_i = \bar{r}_{i,t} - \tilde{z}_{i,t} \bar{\sigma}_{i,t},
\]

(6.1)

where \( \bar{r}_{i,t} \) is the forecasted return from model \( i \) at time \( t \), \( \tilde{z}_{i,t} \) is the forecasted critical value from model \( i \) at time \( t \), and \( \bar{\sigma}_{i,t} \) is the forecasted standard deviation from model \( i \) at time \( t \),

\[
Vio_i = \begin{cases} 
1 & r_i < VaR_i \\
0 & r_i \geq VaR_i
\end{cases},
\]

(6.2)

\[
Vio_i^{250} = \sum_{\tau=1}^{250} Vio_{i,\tau},
\]

(6.3)

and
Let

\[ CC_t^* = \left[ \sum_{\tau=1}^{60} \frac{VaR_{t-\tau}}{60} \right] [3 + k], \]  

(6.5)

\[ \Omega_t = \begin{cases} 
0 & VaR_{t-1} \leq VaR_{t-1}^p \\
1 & VaR_{t-1} > VaR_{t-1}^p 
\end{cases} \]  

(6.6)

Therefore, the Basel Accord Capital Charges are given by:

\[ CC_t = (1 - \Omega_t) VaR_{t-1} + \Omega_t CC_{t-1}^*. \]  

(6.7)

Therefore ADIs must solve the following problem:

\[ \text{Min} \quad CC_t = (1 - \Omega_t) VaR_{t-1} + \Omega_t CC_{t-1}^* \]  

over choice of model and distributional assumption

(6.8)
subject to

$$\text{Vio}_i^{250} \leq \mathcal{G},$$

(6.9)

where \( \mathcal{G} \) is the upper bound allowed by regulators. Alternative constraints could be included to take into account other concerns of regulators and ADIs.

A common trend throughout this thesis is that models that lead to an excessive number of violations also tend to yield lower capital charges, compared with models that lead to the correct number of violations. This suggests that ADIs are likely to have an incentive to choose poor models that understate their true market risk exposure, as capital charges represent a cost to ADIs. This finding suggests that the penalty structure associated with the Basel Accord backtesting procedure is not severe enough. Lucas (2001) first presented this finding and showed, that under the current penalty structure, ADIs are likely to underreport risk by 25%. This finding is consistent with Berkowitz and O’Brien (2002), where it was found that commercial banks tend to underestimate risk and lead to excessive, and serially correlated, violations.

The aim of this chapter is to investigate this issue further and to develop backtesting procedures that will better align the interests of regulators and ADIs. Section 6.2 presents an empirical exercise that compares the capital charges produced by various models and
shows that under the current penalty structure ADIs have an incentive to underpredict risk.

### 6.1 Empirical Exercise

In this section the VaR thresholds for a long series of the S&P500 index are forecasted. The data range from 14 January 1986 to 28 March 2005. In order to remain consistent with the Basel Accord, a 10 day holding period return is used, as plotted in Figure 6-1. The returns display significant clustering, which needs to be modelled using an appropriate conditional volatility model. Figure 6-2 gives the histogram and descriptive statistics for the S&P500 returns. The series has mean and median close to zero and standard deviation of 3.2%. The returns range from 14.3% to -37.7%, which corresponds to the 87 crash. Furthermore, the returns series are negatively skewed, are found to display excess kurtosis, and are highly non-normal according to the Jarque-Bera test statistic.
The VaR thresholds are forecasted using the Riskmetrics™, ARCH, GARCH, GJR and EGARCH models and a rolling window of 2000 observations, as described in Chapter 3. This yields 3010 forecasts, as there are 5010 observations in the sample period. Furthermore, the VaR thresholds are calculated under three distributional assumptions as in Chapter 4. In addition, the critical values are also obtained through bootstrapping.
Figures 6-3 to 6-6 plot the estimated critical values used in this section. The t distribution generally gives the widest confidence intervals, while the normal distribution gives the narrowest. In order to remain consistent with the Basel Accord, a 99% level of confidence is used.

The results of the forecasting exercise are given in Table 6-1, ranked by the number of violations. A general trend is that the VaR thresholds obtained under the assumption of normality generally lead to the highest number of violations, the greatest amount of time spent out of the Green zone, and the lowest Basel Accord capital charges. A t distribution leads to the least number of violations, the least amount of time spent out of the Green zone, and the highest Basel Accord capital charges. Results obtained using the GED and bootstrapped critical values are very similar, lying between those obtained for a t and normal distributions. It's interesting to note that using a t distribution often leads to results that fail the UC test due to insufficient violations, suggesting that the VaR thresholds obtained are excessively conservative.
Table 6-1: VaR Threshold Forecast Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Violations</th>
<th>Capital Charges</th>
<th>Statistical Tests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Basel Accord</td>
<td>New Penalty</td>
</tr>
<tr>
<td>ARCH N</td>
<td>80</td>
<td>8.993</td>
<td>9.901</td>
</tr>
<tr>
<td>GARCH N</td>
<td>47</td>
<td>7.928</td>
<td>9.200</td>
</tr>
<tr>
<td>GJR N</td>
<td>45</td>
<td>7.656</td>
<td>8.635</td>
</tr>
<tr>
<td>ARCH GED</td>
<td>43</td>
<td>8.542</td>
<td>9.931</td>
</tr>
<tr>
<td>ARCH BS</td>
<td>42</td>
<td>8.448</td>
<td>9.821</td>
</tr>
<tr>
<td>EGARCH N</td>
<td>42</td>
<td>7.536</td>
<td>8.516</td>
</tr>
<tr>
<td>RiskMetrics™ GED</td>
<td>35</td>
<td>8.271</td>
<td>8.768</td>
</tr>
<tr>
<td>RiskMetrics™ BS</td>
<td>31</td>
<td>8.483</td>
<td>8.737</td>
</tr>
<tr>
<td>GJR GED</td>
<td>30</td>
<td>8.307</td>
<td>8.974</td>
</tr>
<tr>
<td>EGARCH GED</td>
<td>28</td>
<td>8.123</td>
<td>8.591</td>
</tr>
<tr>
<td>GJR BS</td>
<td>27</td>
<td>8.509</td>
<td>8.989</td>
</tr>
<tr>
<td>EGARCH BS</td>
<td>25</td>
<td>8.301</td>
<td>8.18</td>
</tr>
<tr>
<td>GARCH GED</td>
<td>22</td>
<td>8.308</td>
<td>8.536</td>
</tr>
<tr>
<td>GARCH BS</td>
<td>21</td>
<td>8.591</td>
<td>8.778</td>
</tr>
<tr>
<td>EGARCH t dist</td>
<td>15</td>
<td>9.710</td>
<td>9.710</td>
</tr>
<tr>
<td>RiskMetrics™ t dist</td>
<td>14</td>
<td>10.095</td>
<td>10.095</td>
</tr>
<tr>
<td>GARCH t dist</td>
<td>13</td>
<td>10.353</td>
<td>10.353</td>
</tr>
<tr>
<td>GJR t dist</td>
<td>13</td>
<td>10.095</td>
<td>10.095</td>
</tr>
<tr>
<td>ARCH t dist</td>
<td>11</td>
<td>11.542</td>
<td>11.555</td>
</tr>
</tbody>
</table>

(1) The Unconditional Coverage (UC) test is asymptotically distributed as $\chi^2(1)$.
(2) The Serial Independence (Ind) and Conditional Coverage tests are asymptotically distributed as $\chi^2(2)$.
(3) Entries in **bold** denote significance at the 5% level and * denotes significance at the 1% level.
(4) As there are 3010 days in our forecasting period, the expected number of violations at the 1% level is 30.
The results reported in Table 6-1 clearly show that the current penalty structure proposed by the Basel Accord rewards ADIs that use models that underreport risk and lead to excessive violations. Therefore, the current penalty structure does not align the interests of regulators with that of ADIs. In order to relieve this problem, we suggest that the penalty structure should be much more severe. In this chapter we modify the Basel Accord capital charges to be given by:

\[ CC_t = (1 - \Omega_t)VaR_R + \Omega_tCC^*_t, \]  

where

\[ CC^*_t = \left[ \sum_{z=1}^{60} \frac{VaR_{t-z}}{60} \right] \left[ 3 + \nu I(k)e^k \right], \]  

\[ I(k) = \begin{cases} 0 & k = 0 \\ 1 & k \neq 0 \end{cases} \]  

where \( \nu \) is a scaling factor chosen by regulators. In this chapter, \( \nu \) has been set equal to one, two and three. The capital charges given by the new penalty structures are also given in Table 6-1. Under the Basel Accord penalty structure, the minimum capital charge, at 7.54%, is given by the EGARCH model estimated under the assumption of normality, which leads to backtesting results that fall outside the Green zone 35% of the time. The new penalty structures, which are substantially more severe than the existing one, do a much better job of aligning the interests of ADIs and regulators. Using the new penalty
structure, the minimum capital charges are given by the EGARCH model using bootstrapped critical values, which leads to backtesting results that fall outside the Green zone only 8% of the time.

More importantly, under the existing penalty structure, models that lead to excessive violations, such as the Riskmetrics™ and ARCH models under the assumption of normality, lead to some of the lowest capital charges, while leading to backtesting results that fall outside the green zone 57% and 67% of the time, respectively. The new penalty structures reverse this trend and give substantially higher capital charges for models that lead to excessive violations than models that lead to the correct coverage.

Figure 6-7 plots the relationship between the number of violations and capital charges given by each model under the current Basel Accord penalty structure. As previously stated, the minimum point corresponds to the EGARCH model estimated under the assumption of normality, which leads to an average capital charge of 7.54%. Figure 6-7 also fits a second order polynomial to the data, with the values given in parentheses being the t ratios corresponding to the parameter estimates. Using elementary calculus on the estimated equation, the capital charges are minimised under the current penalty structure when violations occur approximately 1.86% of the time, which is nearly twice the correct number of violations.

The relationship between the number of violations and capital charges given by each model under the new penalty structures are given in Figure 6-8 for $\nu = 1$, Figure 6-9 for
\( \nu = 2 \), and Figure 6-10 for \( \nu = 3 \). The minimum capital charges, according to the estimated equations, occur when violations occur approximately 1.36\% of the time for \( \nu = 1 \), when violations occur approximately 0.80\% of the time for \( \nu = 2 \), and when violations occur approximately 0.30\% of the time for \( \nu = 3 \). Based on the above analysis, it appears that the penalty structure using \( \nu = 2 \) is superior to the others as it would lead ADIs to choose models that lead to violations approximately 0.8\% of the time, which is closest to the target level of violations at the 1\% level of significance.

Figure 6-7: Relationship Between Number of Violations and Capital Charges for the Basel Accord Penalty Structure

\[
y = 0.0014x^2 - 0.1572x + 11.903
\]

\[
(4.849) (-6.322) (26.273)
\]

\( R^2 = 0.7796 \)
Figure 6-8: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 1$)

![Graph showing the relationship between number of violations and capital charges for $\nu = 1$. The equation is $y = 0.0015x^2 - 0.1222x + 11.373$ with coefficients (3.913, -3.888, 19.851) and $R^2 = 0.4773$.](image)

Figure 6-9: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 2$)

![Graph showing the relationship between number of violations and capital charges for $\nu = 2$. The equation is $y = 0.0015x^2 - 0.0729x + 10.658$ with coefficients (3.216, -1.803, 14.470) and $R^2 = 0.6565$.](image)
6.2 Simulation Exercise

Careful analysis of the results presented in Table 6-1 show that the difference between different types of models, under the same distributional assumption, is much smaller than the difference between the same model under different distributional assumptions. This result suggests that within the class of conditional volatility models, the most important consideration for ADIs is what distribution the critical values should be based on. In this section we used simulated data to analyse the importance of choosing the correct critical value. The returns used here are simulated using a GARCH model and a t distribution with 10 degrees of freedom, so that a total of 20,000 returns are simulated. Figure 6-11 plots the simulated returns.
In order to analyse the Current Basel Accord penalty structure, the industry standard Riskmetrics™ model is used to forecast the conditional variance for the simulated returns series. As the Riskmetrics™ model is a simple formula and does not require estimation, ADIs must choose what critical value to use. In this chapter we analyse the importance of choosing the correct critical value by estimating VaR threshold and calculating average capital charges for a range of critical values. The critical values chosen range, with increments of 0.01, from 1 to 7. As the correct critical value for returns that follow a t distribution with 10 degrees of freedom is 2.764, it is expected that critical values lower (higher) than 2.764 will lead to a greater (lower) number of violations than expected at the 1% level.
Figure 6-12: Relationship Between Number of Violations and Capital Charges for the Basel Accord Penalty Structure

Correct Critical Value Leads to an Average Capital Charge of 6.95%

Figure 6-13: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 1$)

Correct Critical Value Leads to an Average Capital Charge of 7.47%
Figure 6-14: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 2$)

Figure 6-15: Relationship Between Number of Violations and Capital Charges for the New Penalty Structure ($\nu = 3$)

Figure 6-12 gives the relationship between the number of violations and the Basel Accord Capital Charges. Each point on this graph corresponds to the results obtained for one critical value used. These results suggest that the Basel Accord capital charges are a decreasing function of the number of violations, such that banks are likely to have an
incentive to choose models that will lead to the maximum number of violations permitted by regulators.

Figures 6-13 to 6-15 give the relationship between the number of violations and the capital charges obtained under the new penalty structure, which produces a local minimum between 0 and 4% of violations. If it is assumed that regulators will place an upper bound on the maximum number of violations allowed before a model is deemed to be inadequate, then the new penalty structure is superior to the existing one as it would lead ADIs to choose models that provide much more conservative VaR forecasts.

6.3 Conclusion

This chapter investigated the ability of the current penalty structure proposed in the Basel Accord to align the interests of regulators with those of ADIs. In accordance with the findings of Lucas (2001), the current Basel Accord penalty structure was found to be highly inadequate. In particular, the results suggest that the Basel Accord penalty structure provided an incentive for ADIs to underreport risk, thereby lowering the required capital charges.

In order to demonstrate that more severe penalties were needed, this chapter presented a simple new penalty structure. The results showed that this new penalty structure was substantially more effective in aligning the interests of ADIs with that of regulators by giving ADIs an incentive to choose more conservative VaR models. Through a simulation exercise, it was shown that the new penalty structure creates a relationship
between the capital charges and the number of violations where a local minimum arises. This suggests that if regulators place an upper bound on the permitted number of violations before an ADI is required to change models, the new penalty structure is much better in aligning the interests of ADIs and regulators.
7 Application to VaR to Country Risk Ratings

7.1 Introduction

Hoti and McAleer (2004, 2005a) argue that country risk ratings, that is country creditworthiness, have a direct impact on the cost of borrowing as they reflect the probability of debt default by a country. Therefore, changes in country risk ratings are conceptually the same as financial returns. An improvement in country risk ratings will lower a country’s cost of borrowing and debt servicing obligations, and vice-versa.

In this context, it is useful to analyse country risk ratings data, much like financial data, in terms of the time series patterns, since such an analysis would provide policy makers and the industry stakeholders with more accurate methods to forecast future changes in the risks and returns of country risk ratings. Empirical research in this area consists of in-sample univariate and multivariate analysis of the dynamics in the conditional volatility associated with country risk ratings and risk returns in order to demonstrate how such modelling can be applied to country risk ratings.

Specifically, Hoti et al. (2002) presented a constant conditional correlation asymmetric VARMA-GARCH model with its underlying structure, including convenient sufficient
conditions for the existence of moments for empirical analysis. These conditions permitted an empirical evaluation of the usefulness of the models for analysing country risk ratings and risk returns, and their associated volatility for four countries. Similarly, Hoti (2005a) provided an analysis of economic, financial, political and composite risk ratings using univariate and multivariate volatility models for nine Eastern European countries. The empirical results enabled a comparative assessment of the conditional means and volatilities associated with country risk returns, defined as the rate of change in country risk ratings, across countries. Moreover the estimated constant conditional correlation coefficients provided useful information as to whether these countries are similar in terms of shocks to the four risk returns.

Hoti and McAleer (2005a) used various univariate and multivariate conditional volatility models to analyse the dynamics of the conditional volatility associated with country risk returns for 120 countries across eight geographical regions. This extensive analysis classified the countries according to the persistence of shocks to risk returns and the correlation coefficients of the conditional shocks to risk returns.

Hoti and McAleer (2005b) estimated and tested the constant conditional correlation asymmetric VARMA-GARCH (or VARMA-AGARCH) models for four countries. The paper analysed the conditional means and volatilities of economic, financial, political and composite risk returns and evaluated the multivariate spillover effects of the four risk returns for specific countries. Indeed, significant multivariate spillover effects were found in the rate of change of country risk ratings (or risk returns) across economic, financial,
political and composite risk returns. Moreover, Hoti (2005b) was the first to model spillover effects for risk returns across different countries. The paper provided a novel analysis of four risk returns using multivariate conditional volatility models for six countries situated in the Balkan peninsula. The empirical results showed that these models are able to capture the existence of country spillover effects in country risk returns.

This chapter represents the first attempt to introduce modern risk management techniques to the analysis of country risk ratings. In particular, the popular Value-at-Risk (VaR) approach is adapted, and it is demonstrated how this approach can be used not only by the countries wishing to borrow money (or attract foreign investment), but also by parties considering making such a loan (or investment).

The plan of the chapter is as follows. Section 7.2 describes Country Risk. Section 7.3 describes Country Risk Ratings. Section 7.4 extends the traditional VaR framework and provides and describes a new risk measure called Country Risk Bounds that is more useful in analysing country risk ratings. The models used are given in Section 7.5 while the data are described in Section 7.6. Section 7.7 describes the forecasting exercise and discusses policy implications. Finally, some concluding remarks are given in Section 7.8.
7.2 Country Risk

Numerous events in the last two decades have alerted international investors to the fact that trade globalisation and open capital markets are risky elements that can cause financial crises with rapid contagion effects, which threaten the stability of the international financial sector (Hayes, 1998). Following the Third World debt crisis in the early 1980s, political changes after the end of the Cold War, the implementation of market-oriented economic and financial reforms in Eastern Europe, the East Asian and Latin American crises since 1997, and the aftermath of 11 September 2001, the uncertainty associated with engaging in international businesses has increased substantially. Owing to the increased uncertainty, the associated risks have become more difficult to analyse and predict for decision makers in the economic, financial and political sectors (for further details, see Howell (2001) and Hoti and McAleer (2004, 2005a)).

Given the above, the need for a detailed assessment of country risk and its impact on international business operations is crucial. Country risk refers broadly to the likelihood that a sovereign state or borrower from a particular country may be unable and/or unwilling to fulfil their obligations towards one or more foreign lenders and/or investors (Krayenbuehl, 1985). Country risk assessment evaluates economic, financial, and political factors, and their interactions in determining the risks associated with a particular country. As such, the primary function of country risk assessment is to anticipate the possibility of debt repudiation, default or delays in payment by sovereign borrowers (Burton and Inoue, 1985). Perceptions of the determinants of country risk are
important because they affect both the supply and cost of international capital flows (Brewer and Rivoli, 1990).

The country risk literature distinguishes between the risk associated with a borrowing sovereign government and the risk associated with lending/investing in country as a whole, including individual borrowers residing in the country. While the latter type of risk refers to country risk, the former is known as sovereign risk, which is the risk exposure vis-à-vis a sovereign government. Moreover, the country risk literature holds that economic, financial and political risks affect each other. As argued by Overholt (1982), international business scenarios are generally political-economic as businesses and individuals are interested in the economic consequences of political decisions.

According to Ghose (1988), sovereign risk emerges when a sovereign government repudiates its overseas obligations, and when a sovereign government prevents its subject corporations and/or individuals from fulfilling such obligations. In particular, sovereign risk refers to the situations when repudiation occurs even if the country is in a financial position to meet its obligations. However, sovereign risk also emerges where countries are experiencing genuine difficulties in meeting their obligations. In an attempt to extract concessions from their lenders and to improve rescheduling terms, negotiators sometimes threaten to repudiate their “borrowings” (Bourke, 1990).

According to Hoti (2005a), and Hoti and McAleer (2004, 2005a), country risk may be prompted by a number of country-specific and regional/external factors or events. There
are three major components of country risk, namely economic, financial and political risk. Political risk is generally viewed as a non-business risk introduced strictly by political forces. Banks and other multinational corporations have identified political risk as a factor that could seriously affect the profitability of their international ventures (Shanmugam, 1990). Ghose (1988) argues that political risk is analogous to sovereign risk and lies within the broader framework of country risk. Political risk emerges from events such as wars, internal and external conflicts, territorial disputes, revolutions leading to changes of government, and terrorist attacks around the world. Social factors include civil unrests due to ideological differences, unequal income distribution, and religious clashes. External factors represent a further political aspect of country risk (see Shanmugam (1990)). For instance, if the borrowing nation is situated alongside a country that is at war, the country risk level of the prospective borrower will be higher than if its neighbour were at peace. Although the borrowing nation may not be directly involved in the conflict, the chances of a spillover effects may exist. In practical terms, political risk relates to the possibility that the sovereign government may impose foreign exchange and capital controls, additional taxes, and asset freezes or expropriations. Delays in the transfer of funds can have serious consequences for investment returns, import payments and export receipts, all of which may lead to a removal of the forward cover (Juttner, 1995).

Economic and financial risks, the other two major components of country risk, include factors such as sudden deterioration in the country’s terms of trade, rapid increases in production costs and/or energy prices, unproductively invested foreign funds, and unwise
lending by foreign banks (Nagy, 1988). Changes in the economic and financial management of the country are also important factors. These risk factors interfere with the free flow of capital or arbitrarily alter the expected risk-return features for investment. Foreign direct investors are also concerned about disruptions to production, damage to installations, and threats to personnel (Juttner, 1995).

### 7.3 Country Risk Ratings

A primary function of country risk assessment is to anticipate payment problems by sovereign borrowers due to domestic and foreign economic, financial and political reasons. Country risk assessment evaluates economic, financial, and political factors, and their interactions in determining the risk associated with a particular country. The importance of country risk analysis is underscored by the existence of numerous prominent country risk rating agencies, such as Moody’s, Standard and Poor’s, Fitch IBCA, Euromoney, Institutional Investor, Economist Intelligence Unit, International Country Risk Guide, and Political Risk Services (for a critical review of the country risk rating systems, see Hoti (2005a) and Hoti and McAleer (2004, 2005a)).

Country risk ratings are crucial for countries seeking foreign investment and selling government bonds on the international financial market, and for lending and investment decisions by large corporations and international financial institutions. Rating agencies provide qualitative and quantitative country risk ratings, combining information about economic, financial and political risk ratings into a composite risk rating. This is
particularly important for developing countries, for which there is limited information available. Country risk ratings help developing countries to enter capital markets and provide economic, financial and political officials with essential tools to assess such risks.

Of the various risk rating agencies, the International Country Risk Guide (ICRG) has compiled quantitative economic, financial, political and composite risk ratings for 93 countries on a monthly basis since January 1984. As of December 2005, the four risk ratings were available for a total of 140 countries. As discussed in Hoti and McAleer (2005a), the ICRG rating system was adjusted in late-1997 to reflect the changing international climate created by the ending of the Cold War. Prior to this structural change, the financial risk ratings were highly subjective because of the lack of reliable statistics. By 1997, the risk assessments were made by the ICRG on the basis of independently generated data, such as from the IMF. The ICRG rating system comprises 22 variables representing three major components of country risk, namely economic, financial and political.

Both the economic and financial risk components are comprised of five variables, namely (GDP per capita, GDP growth, inflation rate, budget balance as a percentage of GDP, current account balance as a percentage of GDP), and (foreign debt as a percentage of GDP, foreign debt service as a percentage of export in goods and services, current account as a percentage of export in goods and services, net liquidity as months of import cover, exchange rate stability), respectively. The political risk component comprises the
following 12 variables, namely government stability, socio-economic conditions, investment profile, internal and external conflicts, corruption, military in politics, religious and ethic tensions, law and order, democratic accountability, and bureaucracy quality. Using each set of variables, a separate risk rating is created for the three components, on a scale of 0-100. The three component risk ratings are then combined to derive a composite risk rating as an overall measure of country risk, or country creditworthiness. Each of the five economic and financial components accounts for 25%, while the twelve political components account for 50% of the composite risk rating. The lower (higher) is a given risk rating (or creditworthiness), the higher (lower) is the associated risk.

Although the ICRG rating system does not take into account the interdependencies between economic, financial and political risk ratings, they are important in determining a composite country risk rating. Hoti and McAleer (2005b) found significant multivariate spillover effects in the rate of change of country risk ratings (or risk returns) across economic, financial, political and composite risk returns. Similarly, the ICRG rating system does not accommodate country spillover effects in economic, financial, political and composite risk returns. Hoti (2005b) was the first attempt to model such spillover effects for risk returns across different countries.

Agency risk ratings play a central role in integrated capital markets. As discussed by PRS Group (2005), country risk ratings as well as forecasts of country risk rating changes are very important for various parties in internationally oriented firms, lending institutions, insurance companies, and government offices. These parties include, the president, vice
president, business manager, project manager, project risk manager, director, strategic planner, finance officer, international officer, corporate security officer, economist, researcher, market analyst, and librarian. All of these officials employ country risk measures and forecasts in different ways to anticipate and plan for the political, economic, and financial risks involved in international business operations.

However, failure by the rating agencies to predict a number of major financial crises demands a thorough evaluation of agency rating systems. Rating systems have changed, especially after the South East Asian, Russian and South American crises of 1997-2002. These crises highlighted the need to accommodate factors such as contingent liabilities, adequacy of international reserves, relative likelihood of default on local currency against foreign currency sovereign debt, and assessment of individual debt instruments in selective default scenarios (Bhatia, 2002). Moreover, agency risk ratings may add to the instability of international financial markets. Amato and Furfine (2004) argue that when risk rating agencies evaluate a risk rating, they overreact relative to the present state of the aggregate economy.

In view of the above, accurate forecasts of future changes in country risk are crucial. This chapter is the first attempt in the country risk literature to adapt the popular Value-at-Risk approach in forecasting changes in country risk ratings. The chapter demonstrates how this approach can be used not only by the countries wishing to attract foreign investments (or borrowing money), but also by the parties considering making such investments (or loans).
7.4 Country Risk Bounds

The traditional VaR risk approach measures the extent of an extraordinary loss in an ordinary day. VaR is a technique that helps quantify the potential size of losses, given a certain confidence level, and it is widely used in the banking industry to determine appropriate capital requirements that can be set aside to protect banks from adverse movements in the value of their trading portfolios. However, for country risk ratings, both the potential maximum negative and positive returns are of interest. This is an important distinction from traditional VaR analysis.

From a lender’s point of view, it is easy to see why predicting the maximum negative change in country risk rating is important. The most obvious reason is that large negative changes in country risk ratings can indicate a substantial increase in the likelihood of default. Therefore, lenders can employ the VaR analysis developed in this chapter to help quantify the probability of default, which will aid lenders in deciding what rates to charge. Furthermore, debt covenants could be constructed in such a way as to take into account not only the current country risk rating but also the forecasted VaR threshold. Such covenants could, for example, stipulate higher interest rates if the forecasted VaR figure were to fall below a predetermined level.

However, from a lender’s point of view, the size of potential positive changes in country risk ratings is also important. For example, lenders typically hold a diversified portfolio of loans which will include a mixture of high and low risk loans. Substantial changes in the risk ratings of debtors will change the composition of the loan portfolio. Such change
in composition, if matched by appropriate changes in interest rates, may be of concern for lenders as they can adversely change the risk/return profile of the loan portfolio and may require costly rebalancing transactions.

From the point of view of a borrowing country the variables of interest are the likely terms and cost of future debt. A two-tailed (or twin-threshold) VaR analysis can help borrowers quantify the extent to which their credit rating is likely to change in the future. Understanding the size of such potential shifts will be important in determining future government expenditure, as substantial re-ratings can have a significant impact on the ability of a country to borrow money and service its debt. Therefore, for borrowing countries both the maximum expected positive and negative changes in country risk ratings are of interest as these will help predict the probability of substantial country risk ratings changes.

In order to accommodate the above discussion, we propose an extension of the VaR framework where both the upper and lower thresholds are considered. This measure will henceforth be referred to as Country Risk Bounds (CRBs). Formally, the upper CRB will be given by:

\[
CRB^+_i = E(Y_i | F_{i-1}) + z^+_i \sigma_i, \quad (7.1)
\]
while the lower CRB will be given by:

$$CRB_i^- = E(Y_i \mid F_{i-1}) - z_{t_i}^- \sigma_i,$$  \hspace{1cm} (7.2)

where $z_{t_i}^+$ is the upper tail critical value at time $t$ and $z_{t_i}^-$ is the lower tail critical value at time $t$. This formulation is general and allows the use of asymmetric and time-varying distributions.

### 7.5 Model Specifications

da Veiga et al. (2005) showed that the variance of a portfolio could be estimated through Single Index (SI) or Portfolio Methods (PM) (see Chapter 3 above). The SI approach treats the portfolio as a single index and models its variance directly using a univariate volatility model, while the PM approach models the variance of each individual asset in the portfolio as well as the covariance between different subsections of the portfolio using multivariate volatility models. These variance and covariance forecasts are then combined to produce a variance forecast for the entire portfolio.

The data used in this chapter are composite country risk ratings. These composite risk ratings are portfolios of political, economic and financial country risk ratings, where political risk rating carries a 50% weight and economic and financial risk ratings each carry a 25% weight. Hence, following the approach of da Veiga et al. (2005), the
conditional variance of the composite risk ratings can be forecasted using an SI or PM approach.

There are a multitude of univariate and multivariate volatility models that can be used to forecast the variance of the composite risk ratings returns (for a comprehensive survey, see McAleer (2005)). In this chapter both the SI and PM versions of the Exponentially Weighted Moving Average (EWMA) model are used as they do not have to estimated, and hence only requires a small number of observations to produce variance forecasts (see Chapter 3 for a detailed description of these models).

### 7.6 Data for Ten Selected Countries

The risk ratings and risk returns are discussed for ten developed and developing countries, namely Argentina, Australia, Brazil, China, France, Japan, Mexico, Switzerland, UK and the USA. These countries represent 4 geographical regions, namely South America (Argentina, Brazil), North and Central America (Mexico, USA), East Asia and the Pacific (Australia, China, Japan), and West Europe (France, Switzerland, UK). The ICRG country risk ratings for these countries are available from January 1984 to April 2005, the exception being China, for which data are available from December 1984. Of the ten countries, Argentina, Brazil, China and Mexico generally have a low risk rating for each of the four categories, which is consistent with low creditworthiness and high associated risk, while Switzerland, Australia and Japan generally have a high risk rating, which is consistent with high creditworthiness and low associated risk.
7.7 Descriptive Statistics for Risk Ratings

Five descriptive statistics, namely mean, standard deviation (SD), skewness, minimum and maximum, for the four risk ratings by country are given in Table 7-1. The mean risk ratings vary substantially across the ten countries and the four risk ratings. For the economic risk ratings, the mean ranges from 55.48 for Argentina to 86.53 for Switzerland. Three countries, namely Argentina, Brazil and Mexico, have mean risk ratings that are less than 60. Australia, China, France, UK and the USA have means of low to high 70s, while the means for Japan and Switzerland are higher than 82. The mean for the financial risk ratings ranges from 52.01 for Argentina to 96.87 for Switzerland. As for the economic risk ratings, the lowest means are observed for Argentina, Brazil and Mexico, all being less than 69. Australia and China have means of low to high 70s, while France, UK and the USA are in the mid to high 70s. Only Japan and Switzerland have means that are higher than 95. For the political risk ratings, the mean ranges from 65.24 for China to 90.20 for Switzerland. Only the mean for Switzerland is above 90. Of the remaining 9 countries, Argentina, Brazil, China and Mexico have means of mid to high 60s, France a mean of 79.53, and Australia, Japan, UK and the USA means in low 80s. Finally, the mean for the composite risk ratings ranges from 59.75 for Argentina to 90.88 for Switzerland. Of the remaining 8 countries, Brazil, China and Mexico have means of low to high 60s, while Australia, France, Japan, UK and the USA have means of low to high 80s.
### Table 7-1: Descriptive Statistics for Risk Ratings by Country

<table>
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<tr>
<th>Country</th>
<th>Risk Ratings</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
<th>Minimum</th>
<th>Maximum</th>
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</tr>
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<td>-0.11</td>
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<td></td>
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<td>35.75</td>
<td>76.25</td>
</tr>
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<td></td>
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<td>90.00</td>
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<td>-0.15</td>
<td>84.00</td>
<td>97.00</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>90.88</td>
<td>2.38</td>
<td>-0.03</td>
<td>86.00</td>
<td>95.75</td>
</tr>
<tr>
<td>UK</td>
<td>Economic</td>
<td>74.77</td>
<td>4.86</td>
<td>0.44</td>
<td>66.00</td>
<td>85.00</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>87.84</td>
<td>10.37</td>
<td>-0.47</td>
<td>65.00</td>
<td>100.00</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>83.56</td>
<td>4.85</td>
<td>-0.03</td>
<td>74.00</td>
<td>92.50</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>82.43</td>
<td>2.23</td>
<td>-0.06</td>
<td>77.25</td>
<td>87.75</td>
</tr>
<tr>
<td>USA</td>
<td>Economic</td>
<td>77.20</td>
<td>3.52</td>
<td>0.02</td>
<td>64.00</td>
<td>84.00</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>87.29</td>
<td>13.19</td>
<td>-0.72</td>
<td>56.00</td>
<td>98.00</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>83.40</td>
<td>4.37</td>
<td>0.31</td>
<td>74.00</td>
<td>95.00</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>82.82</td>
<td>3.24</td>
<td>-0.36</td>
<td>73.75</td>
<td>91.25</td>
</tr>
</tbody>
</table>
As discussed above, Argentina, Brazil and Mexico have the lowest mean risk ratings, while Switzerland has the highest mean risk ratings for all four risk categories. Moreover, there is a large difference between the minimum and maximum risk rating values for Argentina, Brazil, China and Mexico. Although SD varies substantially across the ten countries and four risk ratings, this primarily reflects differences in the mean risk ratings. In general, financial risk ratings have the highest SDs, followed by the economic, political, composite risk ratings. Apart from economic risk ratings for Australia, UK and the USA and financial risk ratings for the USA, the risk ratings for the selected countries are all negatively skewed.

7.8 Descriptive Statistics for Risk Returns

Risk returns are defined as the monthly percentage change in the respective risk rating. Three descriptive statistics, namely the mean, SD and skewness, for four risk returns by country are given in Table 8.2. The means of all four risk returns for the ten countries are close to zero, with standard deviations ranging from 1.36% (France) to 6.25% (Argentina) for economic risk returns, 1.22% (Japan) to 6.27% (Argentina) for financial risk returns, 0.75% (Switzerland) to 2.02% (Argentina) for political risk returns, and 0.60% (Switzerland) to 2.33% (Argentina) for composite risk returns. Of the ten countries, Argentina has the highest standard deviation for three of the four risk returns. There is no general pattern of skewness for the four risk returns for the ten countries, with all four risk returns being positively skewed for Switzerland. Apart from China and Switzerland, the financial risk ratings are negatively skewed. The political risk returns are
positively skewed only in the case of the USA, while the composite risk returns are positively skewed only for Australia and Switzerland.

7.9 Time Trends for Risk Ratings and Risk Returns

The four risk ratings and risk returns for the ten countries are given in Figures 7-1 to 7-40. For each country, the economic, financial, political and composite risk components are denoted ECO, FIN, POL, and COM, respectively. Significant differences are evident in the economic, financial and political risk ratings and risk returns for all ten countries. Moreover, the composite risk ratings and risk returns closely reflect the trends of the three component risk ratings and returns. A detailed analysis of the trends of the four risk ratings are given below. In all cases, there is a structural break for the financial risk rating in 1997 due to changes in the ICRG’s measurement procedure, as explained in Section 7.3. In general, after 1997, the financial risk ratings fall while the financial risk returns vary substantially.
<table>
<thead>
<tr>
<th>Country</th>
<th>Risk Returns</th>
<th>Mean</th>
<th>SD</th>
<th>Skewness</th>
</tr>
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<tr>
<td>Argentina</td>
<td>Economic</td>
<td>0.360%</td>
<td>6.250%</td>
<td>-0.2458</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>0.290%</td>
<td>6.270%</td>
<td>-1.7162</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>0.120%</td>
<td>2.020%</td>
<td>0.2753</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>0.210%</td>
<td>2.330%</td>
<td>-0.3154</td>
</tr>
<tr>
<td>Australia</td>
<td>Economic</td>
<td>0.040%</td>
<td>1.790%</td>
<td>-0.4757</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>-0.060%</td>
<td>1.970%</td>
<td>-2.6730</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>0.010%</td>
<td>1.040%</td>
<td>0.9130</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>0.000%</td>
<td>0.810%</td>
<td>0.0174</td>
</tr>
<tr>
<td>Brazil</td>
<td>Economic</td>
<td>0.330%</td>
<td>4.130%</td>
<td>0.3438</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>0.240%</td>
<td>4.280%</td>
<td>-0.0126</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>0.070%</td>
<td>1.780%</td>
<td>0.8949</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>0.170%</td>
<td>1.850%</td>
<td>-0.5868</td>
</tr>
<tr>
<td>China</td>
<td>Economic</td>
<td>0.030%</td>
<td>2.950%</td>
<td>-0.7672</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>0.100%</td>
<td>2.110%</td>
<td>3.3286</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>0.000%</td>
<td>1.670%</td>
<td>0.3432</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>0.030%</td>
<td>1.310%</td>
<td>-0.0487</td>
</tr>
<tr>
<td>France</td>
<td>Economic</td>
<td>0.000%</td>
<td>1.360%</td>
<td>0.5166</td>
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<td></td>
<td>Financial</td>
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<td></td>
<td>Political</td>
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<td>0.4294</td>
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<td></td>
<td>Composite</td>
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<td>0.950%</td>
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<tr>
<td>Japan</td>
<td>Economic</td>
<td>-0.040%</td>
<td>1.550%</td>
<td>-1.7142</td>
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<td>Financial</td>
<td>0.000%</td>
<td>1.220%</td>
<td>-0.2008</td>
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<tr>
<td></td>
<td>Political</td>
<td>-0.040%</td>
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<td>Composite</td>
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<td>0.780%</td>
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<tr>
<td>Mexico</td>
<td>Economic</td>
<td>0.190%</td>
<td>3.380%</td>
<td>0.7750</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>0.250%</td>
<td>3.000%</td>
<td>-1.3431</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>0.040%</td>
<td>1.530%</td>
<td>0.7350</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>0.120%</td>
<td>1.530%</td>
<td>-0.6609</td>
</tr>
<tr>
<td>Switzerland</td>
<td>Economic</td>
<td>-0.010%</td>
<td>1.750%</td>
<td>0.2988</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>0.000%</td>
<td>1.390%</td>
<td>0.5072</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>-0.030%</td>
<td>0.750%</td>
<td>0.5978</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
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<td>0.600%</td>
<td>0.5664</td>
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<td>UK</td>
<td>Economic</td>
<td>0.040%</td>
<td>1.740%</td>
<td>3.6134</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
<td>-0.050%</td>
<td>2.900%</td>
<td>-3.0709</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>-0.020%</td>
<td>1.400%</td>
<td>0.8330</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>-0.020%</td>
<td>1.050%</td>
<td>-0.8031</td>
</tr>
<tr>
<td>USA</td>
<td>Economic</td>
<td>-0.020%</td>
<td>1.970%</td>
<td>2.5212</td>
</tr>
<tr>
<td></td>
<td>Financial</td>
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<td>3.190%</td>
<td>-2.7680</td>
</tr>
<tr>
<td></td>
<td>Political</td>
<td>-0.060%</td>
<td>1.360%</td>
<td>-0.6046</td>
</tr>
<tr>
<td></td>
<td>Composite</td>
<td>-0.070%</td>
<td>1.070%</td>
<td>-0.6942</td>
</tr>
</tbody>
</table>
7.9.1 Argentina

The four risk ratings for Argentina are given in Figures 7-1 to 7-4. Argentina is rich in resources and has a well-educated workforce, but economic growth has generally not matched expectations. From 1880 to the 1930s, Argentina was one of the world’s ten wealthiest countries, owing to the rapid expansion of agriculture and foreign investment in infrastructure. However, over the past 25 years, Argentina has struggled with military dictatorship, the war with the UK over the Falkland Islands, and severe economic difficulties. There is a similar pattern, with a discernable clustering of volatility, in the economic and political risk ratings, starting at very low values and following a generally increasing trend until 1999, after which they have returned to their original values. Similarly, the financial risk rating increased to 1995 and then decreased, with an associated clustering of volatility. The low ratings in the 1980s were the result of protectionist and populist economic policies in the post-war era that led to economic stagnation and hyperinflation. When Carlos Menem was elected President in 1989, he abandoned the former policies in favour of market economics and liberalisation, resulting in a period of rapid growth. His failure to sustain the fiscal and structural reforms in his second term from 1995-1999 left the economy vulnerable to the 1994 Mexican “Tequila” crisis, the 1997 South East Asian crisis, the Russian default of 1998, and the Brazilian devaluation of 1999. These shocks led to a higher cost of foreign borrowing and less competitive exports. An IMF bailout package of nearly $40 billion in late 2000, involving tax rises and cuts in social welfare programs, resulted in a political crisis that caused the government to collapse amid violent protests. A new government was elected in January
2002, when Argentina abandoned the quasi-currency board system, which pegged the peso at parity to the US dollar for over 10 years. The subsequently floated peso increased a sense of expropriation for depositors, so that almost all dollar loans were converted to the peso at parity. Consequently, bank balance sheets and reputations were destroyed, and the number of banks and the scale of banking operations shrank significantly. The banking system, formerly one of the strongest in Latin America, has been decimated. Overall, the composite risk rating closely reflects the trends and volatility in the economic and political risk ratings.

7.9.2 Australia

The four risk ratings for Australia are presented in Figures 7-5 to 7-8. Australia is rich in natural resources, with a small domestic and developed market economy, dominant services sector, and agricultural and mining sectors significant for exports. Structural reforms in the 1980s transformed an inward-looking and import-substituting economy to an internationally competitive economy with an export orientation. Owing to these reforms, Australia was one of the fastest growing OECD economies throughout the 1990s. Ultimately, the aim is to become a competitive exporter of value-added manufactured products, services and technologies. The economic risk rating followed a generally increasing trend, with a clustering of volatility until 1998. After a period of fast growth, the risk rating followed a downward trend from 1998-1999 due to falling investments and rising debt. However, in 1999 the rating started to increase as the economy grew faster than both the US and EU economies. The rating fell again in late
2000, following a downturn caused by the implementation of the GST. After 2001 the Australian economy strengthened and the rating rose. There is a noticeable structural change in the financial risk rating in 1997 when the rating decreased by almost 20 points, prior to which there was some variation but no trend. Consequently, while there is substantial volatility in the rating after 1997, there is little volatility prior to 1997. With the introduction of the GST, the financial rating fell, after which it followed an increasing trend but remained relatively low. The political risk rating decreased until 1991, when Australia sent troops to assist US forces in the Gulf conflict, and then increased, with an associated clustering of volatilities. When John Howard became Prime Minister at the 1996 elections, this led to an increased risk rating until late 1997. The rating fell, but started to increase after Howard’s re-election in October 1998. The rating fell again in 1999 when Australia led an international coalition force to restore order in East Timor. Not surprisingly, the terrorist attacks of 11 September, 2001 had a negative impact on the rating for Australia. As a weighted sum of the three component risk ratings, the composite risk rating for Australia had an increasing trend in the middle of the sample, after which the rating decreased and then increased. There is comparable volatility in the composite risk rating relative to the economic and political risk ratings.

7.9.3 Brazil

The four risk ratings for Brazil are given in Figures 7-9 to 7-12. Very rich in natural resources, its economy the based on import-substituting industrialization. The external position declined in the late 1970s, leading to hyperinflation, a collapse in investment,
and deterioration in income distribution. In 1982, Brazil defaulted on payment of one of the world’s largest foreign debts. Consequently, the economic risk rating was volatile to 1989, and varied in the low 40s. The volatile rating followed a generally increasing trend from 1990, reaching the low 70s by 2002. Under the radical economic reforms of 1990, rapid trade liberalization increased import penetration, though imports remained low, indicating a relatively closed economy. Despite the reforms, foreign debt payments were suspended and inflation reached a level of nearly 5000% in 1993. Economic risk fell after July 1994 as Brazil embarked on an economic stabilization program, the Plano Real. The rating rose, with one volatility peak in 1995, as the economy recovered and inflation fell to 2.5% by 1998. However, the rating fell again in 1998 due to high interest rates and the South-East Asian crisis, but followed an upward trend after 1999. Financial risk was high in 1984 after Brazil defaulted on its foreign debt payment. The rating surprisingly followed an upward trend, reaching a level of almost 80 by 1992, even though the country experienced deep economic and financial crises. From 1992-1997, the rating had no trend and varied around 70, with little or no volatility. Subsequently, the rating followed a slight decreasing trend with high volatility when the Real was unstable due to shocks, including a domestic energy crisis and the Argentine economic crisis. The political risk rating was low throughout the sample, with no trend but noticeable volatility. Brazil completed the transition from a military regime to an elected government in 1989. Brazilian politics are notable for the fragmented nature of parties, and government efforts to form and maintain workable coalitions. Social issues, including indigenous rights and land claims, and the development of the Amazon and the North East, remain unresolved. The composite risk rating had an upward trend through to
1998, followed by a downward trend, and was less volatile than the other three risk ratings.

### 7.9.4 China

Figures 7-13 to 7-16 give the four risk ratings for China, the world’s most populous country. In 1949, the Communist Party leader, Mao Zedong, founded the People’s Republic of China and led the country for three decades under strict economic and political controls. After gaining power in 1978, Mao’s successor, Deng Xiaoping, gradually introduced market reforms, decentralized economic decision-making, and consolidated his authority. China switched from collective agriculture to small-scale enterprises in services and manufacturing, opened the economy to foreign trade and investment, quadrupled GDP by 2000, and had become the world’s second largest economy by 2002. The economic risk rating was volatile and had a declining trend to late 1989 as the economy overheated and inflation rose. Economic activity expanded in the early 1990s, with the rating rising to 84 by late 1992, owing to a renewed drive for market reforms and the creation of a socialist market economy. Contractionary policies in 1993 led to an economic slowdown and a fall in the rating until early 1995. The rating rose until 1997 as inflation fell, after which it followed no trend around the 80s with lower volatility. With continued economic growth and liberalization, the income disparity rose between rural and urban areas. Reforms are needed in the obsolete state-owned industries and the financial sector. The strong economic performance has lowered financial risk in China, with the rating falling until 1992, a generally increasing trend
thereafter, greater volatility prior to 1992, and with one peak in 1997. A falling political risk rating until 1990 was followed by a rise to 1993, and then a decline, with a noticeable clustering of volatility in the sample. The risk rating fell in 1989, with a volatility peak, when the Tiananmen Square demonstrations by students, intellectuals and opponents from urban areas led to military intervention, untold casualties, and international outrage and sanctions. While legal reforms were a priority in the 1990s, human rights were often abused due to official intolerance of dissent and inadequate legal protection of human rights. WTO membership in 2001 renewed pressure on the hybrid system of strong political controls and a growing market system. Tibet remains a controversial issue, with China accused of systematic destruction of Tibetan Buddhist culture and persecution of monks loyal to the Dalai Lama, the exiled leader campaigning for autonomy within China. Overall, the composite risk rating reflects the trends and volatility in the three component risk ratings.

7.9.5 France

Figures 7-17 to 7-20 present the four risk ratings for France, the world’s fourth largest economy. The French economy is exceptionally diversified, with the services sector accounting for a large share of economic activity and responsible for almost all job creation in recent years. Until 1990, the economic risk rating had a downward trend associated with increasing volatility. The pattern changed in 1990 when the rating started an upward trend with a noticeable clustering of volatility. During this period, the government promoted investment and domestic growth in a stable fiscal and monetary
environment, with the double-digit unemployment rate successfully reduced in the late 1990s. Although the role of government has declined in the last 15 years following a wave of privatization, it continued to play a leading role in the provision of services. Financial risk rating in France was high, with no trend and little volatility prior to the 1997 structural change. After 1997, the rating fell and became more volatile with a noticeable peak in 2000, but displayed no trend. Political risk rating had no trend and was volatile throughout the sample period. The center-right victory in the 1986 led to a left-wing President, Francois Mitterrand, and a right-wing Prime Minister, Jacques Chirac. As a result, the political risk rating ended a downward trend, started to increase, and continued to rise when Mitterrand was re-elected president in 1988. Approval of the Maastricht Treaty in September 1992 led to a fall in the political rating until late 1994. When Chirac became President in May 1995 after a campaign against high unemployment rates, the rating increased in the first half of 1995 but decreased substantially in the second half, with an associated peak in volatility. France attracted international condemnation by conducting a series of nuclear tests in the Pacific. In late 1995, France experienced severe labour unrest and protests against government cutbacks. The political rating increased, with a volatility peak in early 1997 when Chirac called early elections. However, the rating fell in 1997 when Lionel Jospin, the Socialist Party leader, became Prime Minister. France remained politically volatile until 2002. As with the political risk rating, the composite risk rating had no trend and was highly volatile throughout the sample period.
7.9.6 Japan

The four risk ratings for Japan are given in Figures 7-21 to 7-24. Japan has long been the second largest economy in the world, with one of the highest economic growth rates during 1960-1980. Despite advanced technology, Japan is still a traditional society with strong social and employment hierarchies. The electronics and automotive industries dominate the manufacturing sector, and have successfully penetrated international markets. While deregulation and liberalisation are important structural reforms, the pace of change has been slow. A rapidly ageing population has large effects on the structure of the labour force, savings rate and government budget. The economy slowed dramatically in the early 1990s when the asset bubble collapsed, and entered a severe recession in 1997, which caused a sharp fall in the economic risk rating in 1997, prior to which it decreased and then increased. The risk rating continued to decrease until the end of the sample, with an associated increase in volatility, as Japan experienced its worst period of growth since the end of WWII. There was no trend in the financial risk rating with discernable volatility after 1997, prior to which there was no volatility, apart from 5 peaks. The political risk rating had a slightly decreasing trend until 1992, when bribery scandals and the recession led to the first loss of power for the Liberal Democratic Party since 1955. In 1993 the elections led to a seven-party coalition, which collapsed in 1994, when an administration supported by the LDP and Socialists gained power. During this period, the political risk rating increased and then decreased, after which it followed a generally increasing trend until 1997, when the economy entered a severe recession. In 1998, when Keizo Obuchi of the LDP became Prime Minister, the political risk rating
started to increase, which ended in 2001. Despite the current economic difficulties, Japan remains a major economic power. Foreign policy aims to promote peace and prosperity for Japan by working closely with the West and supporting the UN. While maintaining its strong relationship with the USA, Japan has diversified and expanded ties with other nations, especially its Asian neighbours. Overall, the composite risk rating for Japan reflects the trends in the three component risk ratings, but is less volatile than the political risk rating, in general, and the financial risk rating after 1997.

### 7.9.7 Mexico

The four risk ratings in Figures 7-25 to 7-28 are for Mexico, which two decades ago was closed to foreign investment and trade, with strong government participation. Now one of the world’s most trade-dependent countries, Mexico has Free Trade Agreements with the USA, Canada, EU, and other Countries. There is a large oil sector, which provides a third of government revenues, but is not enough for economic prosperity. However, the country is undergoing substantial change, as the 1997 elections resulted in a victory for the combined opposition, breaking the one-party system with a democratic façade. The 2000 presidential elections confirmed the development, as an opposition candidate, Vicente Fox, became President for the first time. Massive external debt default in 1982, the 1984 oil price crisis, and accession to GATT in 1986, are reflected in movements in the economic, financial and political risk ratings, which followed a declining trend to 1986. The upward trend after 1986 was due to economic reforms by the government,
including trade and investment liberalisation, privatisation, deregulation and fiscal consolidation. From 1988-1994, President Salinas began a process of restructuring the economy, which was continued by the Zedillo administration from 1994-2000. These reforms and growing ties with the USA led to a period of relatively strong growth and stability in the economy. The 1994-1995 peso crisis led to a fall in the financial rating, which rose and fell in 1997. However, the economy recorded a contraction in 2001, which affected the economic and political ratings, but not the financial rating. While the Argentine debt crisis had no significant effect on Mexico, the downturn was attributed to economic factors in the USA and the events of 11 September, 2001 that led to caution towards US border trade, in particular, and a significant reduction in tourism. The socio-political conflict in the southern province of Chiapas remains unresolved. In response to pressures for greater rights for indigenous people, President Fox has shown a willingness to deal with the demands of guerrillas. Traditionally, Mexico’s foreign policy has been based on non-intervention and self-determination. Overall, the composite risk rating reflects the trends and volatility in the economic, financial and political risk ratings.

7.9.8 Switzerland

Figures 7-29 to 7-32 present the four risk ratings for Switzerland, a small open economy with arguably the world’s highest per capita income and wages. With trade underlying economic prosperity, the country has liberal trade and investment policies, a conservative fiscal policy, and a very strong currency. Lacking natural resources, economic prosperity also depends on skilled labour, technological expertise in manufacturing, and services,
such as tourism, banking, engineering, and insurance. The Swiss economy stagnated from 1991-1997, becoming the weakest in Western Europe, with a zero average annual GDP growth rate. The economic risk rating varied around the 90s until 1987, with little volatility, decreased to 1992, with a volatility peak, increased with mild volatility until 1994, and had no trend to 1997, with greater volatility and a peak in 1996. A strong economic recovery after mid 1997 led to rising growth and a higher economic risk rating to 2000. However, as economic growth slowed due to contractions in the EU and USA, the rating decreased after 2000 with low associated volatility, improving slightly to the high 80s by the end of 2002. Given the strong protective investment policies and high standards in the banking and financial services sector, Switzerland was risk free until 1996, as the financial risk rating increased from 95 to 100 in 1984 until late 1996, after which it followed a decreasing trend to late 2000 and an upward trend until 2002, with high associated volatility. Switzerland has a diverse society, a stable democratic government, and minor domestic policy issues. The political risk rating decreased during 1984-1994, had no trend to 2000, and followed a generally increasing trend thereafter, with little volatility apart from some volatility peaks. Although the country was not involved in WWI or WWII, Swiss banks in the 1990s were pressured to return deposited funds to the relatives of Holocaust victims. The changing international climate has led to a revision in the defense, neutrality and immigration policies. In recent years the Swiss have broadened the scope of their activities without compromising their neutrality, and voted in favour of joining the UN in 2002. Unlike the other three risk ratings, the composite risk rating had greater volatility, with a decreasing trend to 1999 followed by an upward trend to 2002.
7.9.9 United Kingdom

The four risk ratings for the UK in Figures 7-33 to 7-36 reflect one of the world’s largest economies, and an important member of EU, UN and NATO. Britain’s imperial power declined after WWII and, given the continuing links with the former colonial territories, close ties with the USA, and a separate sense of identity, membership with the EU was delayed until 1973. Economic prosperity, formerly based on manufacturing, now depends on the services sector, particularly banking, insurance, and finance. Membership in the European Monetary Union (EMU) is still under debate, with a referendum proposed only if joining the EMU can be shown to improve investment, employment and growth. The UK experienced two deep recessions in the early 1980s and 1990s, and a severe crisis for the beef industry in 1996 with “mad cow” disease. The economic risk rating showed no trend and little volatility until 1997, when the newly elected Labour government, emphasizing the need for sound economic management, embarked on structural reforms. After 1997, the rating rose by almost 20 points to the low 80s, with greater volatility. Lower growth in 2001-2002 was due to the global downturn, high value of the Pound, lower manufacturing, and reduced exports, but the economy remained strong with low inflation, interest rates, and unemployment. There was no trend in the financial risk rating, ranging from the high 80s to 100 until 1997, when it fell by almost 20 points. It stayed in the low 70s until 2002, with little volatility throughout the sample, apart from a peak in 1997. The UK is a constitutional monarchy, governed by the Conservative Party until 1997 and Tony Blair’s Labour Party thereafter. The political risk rating followed a
decreasing trend until 1990, when Margaret Thatcher resigned as Prime Minister, and an increasing trend to 2002, with a discernable clustering of volatility. Elections in 1997 resulted in a substantial rise in the political risk rating, which was associated with a volatility peak. Significant constitutional reforms have been made in recent years, leading to the 1999 establishment of the Scottish Parliament, the National Assembly for Wales, and the Northern Ireland Assembly. As an overall measure of country risk, the composite risk rating reflects the trends and volatility in the economic and political risk ratings.

7.9.10 United States

Figures 7-37 to 7-40 present the four risk ratings for the USA, the world’s largest economic and pre-eminent military power. The USA was born in a revolution that led to a separation from the British Crown. Drafted in 1787, the constitution established a federal system with a division of powers, even at the central level, and has remained unchanged since its inception. There was a generally increasing trend in the economic risk rating, with a single sharp decrease in 1996 and a clear peak in the associated volatility. The strong economic performance from 1994 to 2000 ended in 2001, with the rating starting a declining trend. Economic imbalances that had built up during the preceding boom years, including a low propensity to save and large current account deficit, undermined economic stability. Inflationary pressures were controlled by structural and cyclical factors. Only a slight negative impact on the rating was discernible from the terrorist attacks of 11 September, 2001. Emergency measures to boost the economy and improve domestic security following the terrorist attacks pushed the federal
budget into deficit. However, a moderate increase in the rating occurred in late 2001 due to a slight improvement in the trade balance, after which the rating remained flat. There was virtually no change in the financial rating until a structural change in 1997, so that volatility was entirely flat before 1997, but mild thereafter. For the political risk rating, a downward trend until 1992 was followed by an upward trend until 2000, and volatility is observed to be tri-modal. The election of the Democratic Party candidate, Bill Clinton, as President in 1992 caused a change in the direction of the political risk rating trend. Perhaps coincidentally, the upward trend ended with the 2000 elections. After a series of legal challenges in January 2001, George W. Bush was elected President, thereby causing the political rating to rise. With the events of 11 September, 2001 and their aftermath, the rating fell and remained flat until the end of the sample. Overall, there was a downward trend in the composite risk rating, with greater volatility at the end of the sample. Surprisingly, the tragedy of 11 September, 2001 seems to have had only a small impact on the economic risk rating and no apparent impact on the financial risk rating, but substantial impacts on both the political and composite risk ratings.

Figure 7-1: Economic Risk Ratings and Returns: Argentina

Figure 7-2: Financial Risk Ratings and Returns: Argentina
7.10 Forecasting and Policy Implications

In this section we describe the forecasting exercise which will be used to demonstrate the practical application of the CRBs framework developed here, in the context of managing the risks associated with country risk ratings. As described in Section 7.6 the data used in this chapter are 10 country risk ratings and their associated returns. The sample period ranges from January 1984 to April 2005, corresponding to 256 monthly country risk ratings and 255 country risk ratings returns for each country.

A rolling window is used to forecast the 1-month ahead conditional variances and CRBs for the country risk ratings returns. In order to strike a balance between efficiency in calculation of conditional variances and a viable number of rolling regressions, the rolling window size is set at 55, which leads to a forecasting period from October 1988 to April 2005. A rolling window is a moving sub-sample within the entire sample data set. In the empirical example presented here, observations 1 to 55 of the data set, which corresponds to the January 1984 to September 1988, are used to calculate the conditional
variance and CRBs for October 1988. Then, observations 2 to 56, which corresponds to
the period February 1984 to October 1988, are used to calculate the conditional variance
and CRBs for November 1988, followed by observations 3 to 57, and so on until the last
rolling sample at the end of the total number of observations. This approach yields 200
out-of-sample forecasts.

The intention is to forecast the conditional variance and CRBs for the returns of
composite risk ratings. As described above, composite risk ratings are comprised of
political, financial and economic risk ratings, where political risk carries a weight of 50%,
while economic and financial risk carry a weight of 25% each. Hence, composite risk
ratings are effectively a portfolio of economic, financial and political risk ratings. In this
chapter, the EWMA model developed by Riskmetrics™ (1996) is used to forecast the 1-
month ahead conditional variance of country risk rating returns. Following da Veiga et al.
(2005), the variance of composite risk rating returns is forecasted using the SI approach
and PM approaches.
Figures 7-41 to 7-50 present the forecasted conditional variances for each country risk rating returns using both the SI and PM. Both models lead to very similar conditional variance forecasts, with the PM having a tendency to yield slight higher variance forecasts for all countries, except for the United States. Furthermore, Figure 7-51 to 7-90 plot the risk returns and CRBs for each country using a 90%, 95%, 98% and 99% level of confidence. As would be expected, the PM tends to give slightly wider bounds than the SI approach.
Figure 7-51: Risk Return and 90% CRBs: Argentina

Figure 7-52: Risk Return and 95% CRBs: Argentina

Figure 7-53: Risk Return and 98% CRBs: Argentina

Figure 7-54: Risk Return and 99% CRBs: Argentina

Figure 7-55: Risk Return and 90% CRBs: Australia

Figure 7-56: Risk Return and 95% CRBs: Australia
Table 7-3: Single Index CRBs Violations

<table>
<thead>
<tr>
<th>Country</th>
<th>99%</th>
<th>98%</th>
<th>95%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive Violations</td>
<td>Negative Violations</td>
<td>Positive Violations</td>
<td>Negative Violations</td>
</tr>
<tr>
<td>Argentina</td>
<td>3</td>
<td>5</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Australia</td>
<td>3</td>
<td>5</td>
<td>5</td>
<td>6</td>
</tr>
<tr>
<td>Brazil</td>
<td>4</td>
<td>1</td>
<td>5</td>
<td>6</td>
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<tr>
<td>China</td>
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<td>2</td>
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<tr>
<td>France</td>
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<td>1</td>
<td>7</td>
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<tr>
<td>Japan</td>
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<td>7</td>
<td>6</td>
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<tr>
<td>Mexico</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>6</td>
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<td>Switzerland</td>
<td>5</td>
<td>6</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>UK</td>
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<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>USA</td>
<td>6</td>
<td>2</td>
<td>6</td>
<td>2</td>
</tr>
</tbody>
</table>

Notes:
(1) Positive violations occur when the actual return is greater than the positive CRB threshold.
(2) Negative violations occur when the actual return is smaller than the negative CRB threshold.
(3) The level of confidence is given as a two-tailed level of confidence.
Table 7-4: Portfolio Method CRBs Violations

<table>
<thead>
<tr>
<th>Country</th>
<th>99% Positive Violations</th>
<th>99% Negative Violations</th>
<th>98% Positive Violations</th>
<th>98% Negative Violations</th>
<th>95% Positive Violations</th>
<th>95% Negative Violations</th>
<th>90% Positive Violations</th>
<th>90% Negative Violations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>7</td>
<td>7</td>
<td>8</td>
<td>12</td>
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<td>1</td>
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<td>1</td>
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<td>2</td>
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<td>2</td>
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<td>10</td>
<td>10</td>
</tr>
<tr>
<td>China</td>
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<td>2</td>
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<td>4</td>
<td>11</td>
<td>7</td>
</tr>
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<td>France</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>6</td>
<td>5</td>
<td>8</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>Japan</td>
<td>3</td>
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<td>5</td>
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<td>8</td>
<td>9</td>
<td>10</td>
</tr>
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<td>Mexico</td>
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<td>2</td>
<td>6</td>
<td>2</td>
<td>7</td>
<td>3</td>
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<td>Switzerland</td>
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<td>7</td>
<td>5</td>
<td>9</td>
<td>10</td>
<td>14</td>
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<tr>
<td>UK</td>
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<td>4</td>
<td>5</td>
<td>6</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>13</td>
</tr>
<tr>
<td>USA</td>
<td>3</td>
<td>8</td>
<td>6</td>
<td>9</td>
<td>7</td>
<td>10</td>
<td>8</td>
<td>12</td>
</tr>
</tbody>
</table>

Notes:
1. Positive violations occur when the actual return is greater than the positive CRB threshold.
2. Negative violations occur when the actual return is smaller than the negative CRB threshold.
3. The level of confidence is given as a two-tailed level of confidence.

The most basic test of model accuracy in the context of CRBs forecasts is conducted by comparing the number of observed violations, with the expected number of violations implied by the chosen level of significance. For example, CRB thresholds calculated assuming a 90% level of confidence should include 90% of the observations, leading to violations 10% of the time, on average. The probability of observing \( x \) violations in a sample of size \( T \), under the null hypothesis, is given by:

\[
\Pr(x) = C_T^x (\delta)^x (1-\delta)^{T-x},
\]  

(7.3)

where \( \delta \) is the desired level of violations, which is typically set at 1%.
Christoffersen (1998) referred to this test, as a test of Unconditional Coverage (UC). Therefore, the LR statistic for testing whether the number of observed violations, divided by \( T \), is equal to \( \delta \) is given by:

\[
LR_{UC} = 2[\log(\hat{\delta} (1-\hat{\delta})^{N-x}) - \log(\delta (1-\delta)^{N-x})],
\]

where \( \hat{\delta} = x/N \), \( x \) is the number of violations, and \( N \) is the number of forecasts. The LR statistic is asymptotically distributed as \( \chi^2(1) \) under the null hypothesis of correct UC.

### Table 7-5: Single Index Unconditional Coverage Test

<table>
<thead>
<tr>
<th>Country</th>
<th>99% Positive Violations</th>
<th>99% Negative Violations</th>
<th>98% Positive Violations</th>
<th>98% Negative Violations</th>
<th>95% Positive Violations</th>
<th>95% Negative Violations</th>
<th>90% Positive Violations</th>
<th>90% Negative Violations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>0.438</td>
<td>8.175*</td>
<td>3.209</td>
<td>5.265</td>
<td>0.193</td>
<td>1.566</td>
<td>0.000</td>
<td>0.102</td>
</tr>
<tr>
<td>Australia</td>
<td>0.438</td>
<td>8.175*</td>
<td>3.209</td>
<td>5.265</td>
<td>0.193</td>
<td>1.566</td>
<td>0.000</td>
<td>0.102</td>
</tr>
<tr>
<td>Brazil</td>
<td>1.565</td>
<td>0.000</td>
<td>3.209</td>
<td>5.265</td>
<td>0.731</td>
<td>2.663</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>China</td>
<td>0.619</td>
<td>0.000</td>
<td>0.000</td>
<td>0.619</td>
<td>3.992</td>
<td>0.220</td>
<td>0.000</td>
<td>0.102</td>
</tr>
<tr>
<td>France</td>
<td>3.209</td>
<td>0.000</td>
<td>7.666*</td>
<td>0.438</td>
<td>1.566</td>
<td>0.220</td>
<td>0.869</td>
<td>0.451</td>
</tr>
<tr>
<td>Japan</td>
<td>5.265</td>
<td>15.425*</td>
<td>5.265</td>
<td>10.364*</td>
<td>0.193</td>
<td>2.663</td>
<td>0.109</td>
<td>1.506</td>
</tr>
<tr>
<td>Mexico</td>
<td>1.565</td>
<td>8.175*</td>
<td>1.565</td>
<td>5.265</td>
<td>0.193</td>
<td>3.992</td>
<td>0.451</td>
<td>0.102</td>
</tr>
<tr>
<td>Switzerland</td>
<td>3.209</td>
<td>11.628*</td>
<td>10.364*</td>
<td>7.666*</td>
<td>3.992</td>
<td>2.663</td>
<td>2.297</td>
<td>0.397</td>
</tr>
<tr>
<td>UK</td>
<td>0.000</td>
<td>0.778</td>
<td>0.000</td>
<td>0.000</td>
<td>0.193</td>
<td>0.731</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>USA</td>
<td>5.265</td>
<td>0.778</td>
<td>5.265</td>
<td>0.000</td>
<td>0.193</td>
<td>2.381</td>
<td>0.109</td>
<td>1.054</td>
</tr>
</tbody>
</table>

Notes:

4. The Unconditional Coverage (UC) is asymptotically distributed as \( \chi^2(1) \).

5. Entries in **bold** denote significance at the 5% level, and * denotes significance at the 1% level.

6. The level of confidence is given as a two-tailed level of confidence.

Tables 7-5 and 7-6 give the results of the Unconditional Coverage tests for the SI and PM respectively. The results of the UC test are mixed, on average, with both the SI and PM approaches appearing to provide the correct unconditional coverage at the 95% and 90%
levels of confidence. However, at the 99% and 98% levels of confidence, both the SI and PM approaches appear to under-predict risk, and generally lead to excessive violations. This result is to be expected given that the CRBs are estimated under the assumption of normality, while all returns are found to be highly non-normal according to the Jarque-Bera test statistic.

Table 7-6: Portfolio Method Unconditional Coverage Test

<table>
<thead>
<tr>
<th>Country</th>
<th>99% Positive Violations</th>
<th>99% Negative Violations</th>
<th>98% Positive Violations</th>
<th>98% Negative Violations</th>
<th>95% Positive Violations</th>
<th>95% Negative Violations</th>
<th>90% Positive Violations</th>
<th>90% Negative Violations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>8.175*</td>
<td>8.175*</td>
<td>3.209</td>
<td>7.666*</td>
<td>0.731</td>
<td>1.566</td>
<td>0.397</td>
<td>0.109</td>
</tr>
<tr>
<td>Australia</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>2.663</td>
<td>0.955</td>
<td>3.232</td>
<td>3.199</td>
</tr>
<tr>
<td>Brazil</td>
<td>0.778</td>
<td>0.778</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.193</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>China</td>
<td>11.628*</td>
<td>0.000</td>
<td>5.265*</td>
<td>0.000</td>
<td>0.193</td>
<td>0.220</td>
<td>0.102</td>
<td>1.054</td>
</tr>
<tr>
<td>France</td>
<td>2.612</td>
<td>8.175*</td>
<td>1.565</td>
<td>5.265</td>
<td>0.000</td>
<td>1.566</td>
<td>1.954</td>
<td>0.000</td>
</tr>
<tr>
<td>Japan</td>
<td>2.612</td>
<td>0.778</td>
<td>1.565</td>
<td>3.209</td>
<td>0.193</td>
<td>1.566</td>
<td>0.109</td>
<td>0.000</td>
</tr>
<tr>
<td>Mexico</td>
<td>8.175*</td>
<td>0.000</td>
<td>5.265</td>
<td>0.000</td>
<td>0.731</td>
<td>0.955</td>
<td>0.451</td>
<td>3.199</td>
</tr>
<tr>
<td>Switzerland</td>
<td>5.136</td>
<td>11.628*</td>
<td>3.209</td>
<td>7.666*</td>
<td>0.000</td>
<td>2.663</td>
<td>0.000</td>
<td>1.506</td>
</tr>
<tr>
<td>UK</td>
<td>2.612</td>
<td>5.136</td>
<td>3.209</td>
<td>5.265</td>
<td>0.193</td>
<td>0.731</td>
<td>0.451</td>
<td>0.869</td>
</tr>
<tr>
<td>USA</td>
<td>2.612</td>
<td>19.520*</td>
<td>5.265</td>
<td>13.324*</td>
<td>0.731</td>
<td>3.992</td>
<td>0.451</td>
<td>0.397</td>
</tr>
</tbody>
</table>

Notes:
(1) The Unconditional Coverage (UC) is asymptotically distributed as \( \chi^2(1) \).
(2) Entries in **bold** denote significance at the 5% level, and * denotes significance at the 1% level.
(3) The level of confidence is given as a two-tailed level of confidence.

The average CRB for each country and confidence level combination for the SI and PM approaches is given in Tables 7-7 and 7-8, respectively. As a symmetric distribution has been assumed in the calculation of the CRBs, only one figure is given in Tables 7-7 and 7-8, which corresponds to the absolute value of the average upper and lower bounds. An average CRB gives an indication of the likely range of risk returns. For example, Australia has an average CRB of 2.197% at the 99% level of confidence, which suggests...
that, on average, one can be 99% certain that Australian country risk returns will not vary by more than ±2.197% on a monthly basis.

**Table 7-7: Average CRBs Using the Single Index Approach**

<table>
<thead>
<tr>
<th>Country</th>
<th>99%</th>
<th>98%</th>
<th>95%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switzerland</td>
<td>1.528%</td>
<td>1.382%</td>
<td>1.163%</td>
<td>0.976%</td>
</tr>
<tr>
<td>Japan</td>
<td>1.985%</td>
<td>1.795%</td>
<td>1.510%</td>
<td>1.267%</td>
</tr>
<tr>
<td>Australia</td>
<td>2.116%</td>
<td>1.914%</td>
<td>1.610%</td>
<td>1.351%</td>
</tr>
<tr>
<td>France</td>
<td>2.353%</td>
<td>2.128%</td>
<td>1.790%</td>
<td>1.502%</td>
</tr>
<tr>
<td>UK</td>
<td>2.415%</td>
<td>2.185%</td>
<td>1.838%</td>
<td>1.542%</td>
</tr>
<tr>
<td>USA</td>
<td>2.669%</td>
<td>2.415%</td>
<td>2.031%</td>
<td>1.705%</td>
</tr>
<tr>
<td>China</td>
<td>3.105%</td>
<td>2.809%</td>
<td>2.363%</td>
<td>1.983%</td>
</tr>
<tr>
<td>Mexico</td>
<td>3.438%</td>
<td>3.110%</td>
<td>2.616%</td>
<td>2.196%</td>
</tr>
<tr>
<td>Brazil</td>
<td>4.485%</td>
<td>4.056%</td>
<td>3.412%</td>
<td>2.864%</td>
</tr>
<tr>
<td>Argentina</td>
<td>5.122%</td>
<td>4.633%</td>
<td>3.897%</td>
<td>3.271%</td>
</tr>
</tbody>
</table>

**Notes:**

1. The Average CRB measures the average confidence interval around the risk returns given each level of confidence.
2. The level of confidence is given as a two-tailed level of confidence.

**Table 7-8: Average CRBs Using the Portfolio Method**

<table>
<thead>
<tr>
<th>Country</th>
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<th>98%</th>
<th>95%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swiss</td>
<td>1.581%</td>
<td>1.430%</td>
<td>1.203%</td>
<td>1.010%</td>
</tr>
<tr>
<td>Japan</td>
<td>2.039%</td>
<td>1.844%</td>
<td>1.551%</td>
<td>1.302%</td>
</tr>
<tr>
<td>Australia</td>
<td>2.197%</td>
<td>1.987%</td>
<td>1.671%</td>
<td>1.403%</td>
</tr>
<tr>
<td>France</td>
<td>2.396%</td>
<td>2.167%</td>
<td>1.823%</td>
<td>1.530%</td>
</tr>
<tr>
<td>UK</td>
<td>2.454%</td>
<td>2.219%</td>
<td>1.867%</td>
<td>1.567%</td>
</tr>
<tr>
<td>USA</td>
<td>2.866%</td>
<td>2.592%</td>
<td>2.180%</td>
<td>1.830%</td>
</tr>
<tr>
<td>China</td>
<td>3.233%</td>
<td>2.924%</td>
<td>2.460%</td>
<td>2.065%</td>
</tr>
<tr>
<td>Mexico</td>
<td>3.505%</td>
<td>3.170%</td>
<td>2.667%</td>
<td>2.238%</td>
</tr>
<tr>
<td>Brazil</td>
<td>4.562%</td>
<td>4.126%</td>
<td>3.471%</td>
<td>2.913%</td>
</tr>
<tr>
<td>Argentina</td>
<td>5.693%</td>
<td>5.149%</td>
<td>4.331%</td>
<td>3.635%</td>
</tr>
</tbody>
</table>

**Notes:**

1. The Average CRB measures the average confidence interval around the risk returns given each level of confidence.
2. The level of confidence is given as a two-tailed level of confidence.
The countries in Table 7-7 and 7-8 are ranked from lowest to highest average CRBs. Switzerland, Japan and Australia have the lowest average CRB, while Argentina, Brazil and Mexico have the highest average CRB. It is worth noting that the relative rankings are invariant to the choice of model. These results suggest that the country risk ratings of Switzerland, Japan and Australia are much more likely to remain close to current levels than the country risk ratings of Argentina, Brazil and Mexico. This type of analysis would be useful to investors evaluating the attractiveness of investing in alternative countries.

7.11 Conclusion

The country risk literature argues that country risk ratings have a direct impact on the cost of borrowings as they reflect the probability of debt default by a country. An improvement in country risk ratings, or country creditworthiness, will lower a country’s cost of borrowing and debt servicing obligations, and vice-versa. In this context, it is useful to analyse country risk ratings data, much like financial data, in terms of the time series patterns, as such an analysis would provide policy makers and the industry stakeholders with a more accurate method of forecasting future changes in the risks and returns of country risk ratings. This chapter considered an extension of the Value-at-Risk (VaR) framework where both the upper and lower thresholds are considered. The purpose of the chapter was to forecast the conditional variance and Country Risk Bounds (CRBs) for the rate of change of risk ratings for ten representative countries.
The conditional variances of composite risk returns for the ten countries were forecasted using the Single Index (SI) and Portfolio Methods (PM) approaches of da Veiga et al (2005). Both models led to very similar conditional variance forecasts, with PM having a tendency to yield slightly higher variance forecasts for all countries, except the USA. The CRBs for each country were calculated using 90%, 95%, 98% and 99% levels of confidence. As would be expected, PM in general gave slightly wider bounds than the SI approach. An interesting result was that the number of violations in the upper and lower tails was often different, suggesting that the country risk returns may follow an asymmetric distribution. Therefore, future research might improve upon the accuracy of risk returns threshold forecasts by considering asymmetric distributions. The average CRB for each country and the confidence level combination for the SI and PM approaches showed that Switzerland, Japan and Australia have the lowest average CRB, while Argentina, Brazil and Mexico have the highest average CRB. Moreover, the relative rankings are invariant to the choice of model. The results suggested that the country risk ratings of Switzerland, Japan and Australia are much more likely to remain close to current levels than the country risk ratings of Argentina, Brazil and Mexico. This type of analysis would be useful to lenders/investors in evaluating the attractiveness of lending/investing in alternative countries.
8 Application of VaR to International Tourism

8.1 Introduction

International tourism is widely regarded as the principal economic activity in Small Island Tourism Economies (SITEs) (see Shareef (2004) for a comprehensive discussion). Historically, SITEs have been dependent on international tourism for economic development, employment, and foreign exchange, among other economic indicators. A unique SITE is the Maldives, an archipelago of 1190 islands in the Indian Ocean, of which 200 are inhabited by the indigenous population of 271,101, and 89 islands are designated for self-contained tourist resorts. The Maldivian economy depends substantially on tourism, and accounts directly for nearly 33% of real GDP. According to the Ministry of Planning and National Development (2005) of the Government of Maldives, transport and communications are the second largest economic sector, contributing 14%, while government administration accounts for 12% of the economy. Fisheries are still the largest primary industry, but its contribution to the economy has gradually declined to 6% in 2003. Employment in tourism accounts for 17% of the working population, while tourism accounts for 65% of gross foreign exchange earnings.
Any shock that would adversely affect international tourist arrivals to the Maldives would also affect earnings from tourism dramatically, and have disastrous ramifications for the entire economy. An excellent example is the impact of the 2004 Boxing Day Tsunami, which sustained extensive damage to the tourism-based economy of the Maldives and dramatically reduced the number of tourist arrivals in the post-tsunami period. Therefore, it is vital for the Government of the Maldives, multilateral development agencies such as the World Bank and the Asian Development Bank who are assisting Maldives in the Tsunami recovery effort, and the industry stakeholders, namely the resort owners and tour operators, to obtain accurate estimates of international tourist arrivals and their variability. Such accurate estimates would provide vital information for government policy formulation, international development aid, profitability and marketing.

A significant proportion of research in the literature on empirical tourism demand has been based on annual data (see Shareef (2004)), but such analyses are useful only for long-term development planning. An early attempt to improve the short-run analysis of tourism was undertaken by Shareef and McAleer (2005), who modelled the volatility (or predictable uncertainty) in monthly international tourist arrivals to the Maldives. Univariate and multivariate time series models of conditional volatility were estimated and tested. The conditional correlations were estimated and examined to determine whether there was specialisation, diversification or segmentation in the international tourism demand shocks from the major tourism source countries to the Maldives. In a similar vein, Chan, Lim and McAleer (2005) modelled the time-varying means, dynamic
conditional variances and constant conditional correlations of the logarithms of the monthly arrival rate for the four leading tourism source countries to Australia.

This chapter provides a template for the future analysis of earnings from international tourism, particularly tourism taxes for SITEs, discusses the direct and indirect monetary benefits from international tourism, highlights tourism taxes in the Maldives as a development financing phenomenon, and provides a framework for discussing the design and implementation of tourism taxes.

Daily international arrivals to Maldives and the number of tourists in residence are analysed for the period 1994-2003, using daily data obtained from the Ministry of Tourism of Maldives. In the international tourism demand literature to date, there does not seem to have been any empirical research using daily tourism arrivals data. One advantage of using daily data, as distinct from monthly and quarterly data, is that volatility clustering in the number of international tourist arrivals and their associated growth rates can be observed and analysed more clearly using standard financial econometric techniques. Therefore, it is useful to analyse daily tourism arrivals data, much like financial data, in terms of the time series patterns, as such an analysis would provide policy makers and industry stakeholders with accurate indicators associated with their short-term objectives.

In virtually all SITEs, and particularly the Maldives, tourist arrivals or growth in tourist arrivals translates directly into a financial asset. Each international tourist is required to
pay USD 10 for every tourist bed-night spent in the Maldives. This levy is called a ‘tourism tax’ and comprises over 30% of the current revenue of the government budget (Ministry of Planning and National Development, 2005). Hence, tourism tax revenue is a principal determinant of development expenditure. As a significant financial asset to the economy of SITEs, and particularly for Maldives, the volatility in tourist arrivals and their growth rate is conceptually identical to the volatility in financial returns, which is interpreted as financial risk.

This chapter models the volatility in the number of tourist arrivals, tourists in residence and their growth rates. The purpose of this analysis of volatility is to present a framework for managing the risks inherent in the variability of total tourist arrivals, tourists in residence, and hence government revenue, through the modelling and forecasting of Value-at-Risk (VaR) thresholds for the number of tourist arrivals, tourists in residence and their growth rates. Thus, the chapter provides the first application of the VaR portfolio approach to manage the risks associated with tourism revenues.

The structure of the chapter is as follows. The economy of Maldives is described in Section 8.2, followed by an assessment of the impact of the 2004 Boxing Day Tsunami on tourism in Maldives in Section 8.3. The concept of Value-at-Risk (VaR) is discussed in Section 8.4. The data are discussed in Section 8.5 and volatility models are presented in Section 8.6. The empirical results are examined in Section 8.7, forecasting is undertaken in Section 8.8, and some concluding remarks are given in Section 8.9.
8.2 The Tourism Economy of the Maldives

Maldives is an archipelago in the Indian Ocean, was formerly a British protectorate, and became independent in 1965. It stretches approximately 700 kilometres north to south, about 65 kilometres east to west, and is situated south-west of the Indian sub-continent. The Exclusive Economic Zone of Maldives is 859,000 square kilometres, and the aggregated land area is roughly 290 square kilometres.

With an average growth rate of 7% per annum over the last two decades, Maldives has shown an impressive economic growth record. This economic performance has been achieved through growth in international tourism demand. Furthermore, economic growth has enabled Maldivians to enjoy an estimated real per capita GDP of USD 2,261 in 2003, which is considerably above average for small island developing countries, with an average per capita GDP of USD 1,500. The engine of growth in the Maldives has been the tourism industry, accounting for 33% of real GDP, more than one-third of fiscal revenue, and two-thirds of gross foreign exchange earnings in recent years. The fisheries sector remains the largest sector in terms of employment, accounting for about one-quarter of the labour force, and is an important but declining source of foreign exchange earnings. Due to the high salinity content in the soil, agriculture continues to play a minor role. The government, which employs about 20% of the labour force, plays a dominant role in the economy, both in the production process and through its regulation of the economy.
Tourism in the Maldives has a direct impact on fiscal policy, which determines development expenditure. More than one-fifth of government revenue arises from tourism-related levies. The most important tourism-related revenues are the tourism tax, the resort lease rents, resort land rents, and royalties. Except for the tourism tax, the other sources of tourism-related revenues are based on contractual agreements with the Government of the Maldives. Tourism tax is levied on every occupied bed night from all tourist establishments, such as hotels, tourist resorts, guest houses and safari yachts. Initially, this tax was levied at USD 3 in 1981, and was then doubled to USD 6 in 1988. After 16 years with no change in the tax rate, the tax rate was increased to USD 10 on 1 November 2004. This tax is regressive as it does not take into account the profitability of the tourist establishments. Furthermore, it fails to take account of inflation, such that the tax yield has eroded over time.

Tourism tax is collected by tourist establishments and is deposited at the Inland Revenue Department at the end of every month. This tax revenue is used directly to finance the government budget on a monthly basis. As the tax is levied directly on the tourist, any uncertainty that surrounds international tourist arrivals will affect tourism tax receipts, and hence fiscal policy. Any adverse affect on international tourist arrivals may also result in the suspension of planned development expenditures.

The nature of tourist resorts in the Maldives is distinctive as they are built on islands that have been set aside for tourism development. Tourism development is the greatest challenge in the history of Maldives, and has led to the creation of distinctive resort
islands. Domroes (1985, 1989, 1993, 1999) asserts that these islands are deserted and uninhabited, but have been converted into ‘one-island-one-hotel’ schemes. The building of physical and social infrastructure of the resort islands has had to abide by strict standards to protect the flora, fauna and the marine environment of the islands, while basic facilities for sustainability of the resort have to be maintained. The architectural design of the resort islands in Maldives varies profoundly in their character and individuality. Only 20% of the land area of any given island is allowed to be developed, which is imposed to restrict the capacity of tourists. All tourist accommodation must face a beachfront area of five metres. In most island resorts, bungalows are built as single or double units. Recently, there has been extensive development of water bungalows on stilts along the reefs adjacent to the beaches. All tourist amenities are available on each island, and are provided by the onshore staff.

8.3 Impact of the 2004 Boxing Day Tsunami on Tourism in the Maldives

As the biggest ever national disaster in the history of Maldives, the 2004 Boxing Day Tsunami caused widespread damage to the infrastructure on almost all the islands. The World Bank, jointly with the Asian Development Bank (World Bank (2005a)), declared that the total damage of the Tsunami disaster was USD 420 million, which is 62% of the annual GDP. In the short run, the Maldives will need approximately USD 304 million to recover fully from the disaster to the pre-tsunami state.
A major part of the damage was to housing and tourism infrastructure, with the education and fisheries sectors also severely affected. Moreover, the World Bank damage assessment highlighted that significant losses were sustained in water supply and sanitation, power, transportation and communications. Apart from tourism, the largest damage was sustained by the housing sector, with losses close to USD 65 million. Approximately, 1,700 houses were destroyed, another 3,000 were partially damaged, 15,000 inhabitants were fully displaced, and 19 of the 200 inhabited islands were declared uninhabitable.

The World Bank also stated that the tourism industry would remain a major engine of the economy, and that the recovery of this sector would be vital for Maldives to return to higher rates of economic growth, full employment and stable government revenue. In the Asian Development Bank report, similar reactions were highlighted by stating that it would be vitally important to bring tourists back in full force, as tourism is the most significant contributor to GDP. In fact, tourism is of vital importance to the Maldivian economy.

In the initial macroeconomic impact assessment undertaken by the World Bank, the focus was only on 2005. The real GDP growth rate was revised downward from 7% to 1%, consumer prices were expected to rise by 7%, the current account balance was to double to 25% of GDP, and the fiscal deficit was to increase to 11% of GDP, which is unsustainable, unless the government were to implement prudent fiscal measures.
The 2004 Boxing Day Tsunami also caused widespread destruction and damage to countries such as Indonesia, India and Sri Lanka. Compared with the damage caused to the Maldives, the destruction which occurred in these other countries was substantially different in terms of its scale and nature. In India, widespread socioeconomic and environmental destruction was caused in the eastern coast, affecting the states of Andhra Pradesh, Kerala and Tamil Nadu, and the Union Territory (UT) of Pondicherry. The tsunami struck with 3 to 10-metre waves and penetrated as far as 3 kilometres inland, affecting 2,260 kilometres of coastline (World Bank (2005b)). Nearly 11,000 people died in India. The tsunami also adversely affected the earning capacity of some 645,000 people, whose principal economic activity is fisheries.

According to the damage assessment report published in World Bank (2005c), nearly 110,000 lives were lost in Indonesia, 700,000 people were displaced, and many children were orphaned. The total estimate of damages and losses from the catastrophe amounted to USD 4.45 billion, of which 66% constituted damages, while 34% constituted losses in terms of income flows to the economy. Furthermore, total damages and losses amounted to 97% of Aceh’s GDP. Although Aceh’s GDP derives primarily from oil and gas, which were not affected, and the livelihoods of most residents rely primarily on fisheries and agriculture, this was undeniably a catastrophe of unimaginable proportions.

In Sri Lanka, the human costs of the disaster were also phenomenal, with more than 31,000 people killed, nearly 100,000 homes destroyed, and 443,000 people remaining displaced. The economic cost amounted to USD 1.5 billion dollars, which is
approximately 7% of annual GDP (World Bank (2005d)). As in India, Indonesia and Maldives, the tsunami affected the poorest Sri Lankans, who work in the fisheries industry, and some 200,000 people lost their employment in the tourism industry.

Compared with all the tsunami-stricken countries, Maldives was affected entirely as a result of its geophysical nature. When the tsunami struck, the Maldives was momentarily wiped off the face of the earth.

8.4 Tourism and Value-at-Risk

As described in Chapter 2, Value-at-Risk (VaR) is a technique designed to quantify the size of possible losses, given a certain level of confidence. In the case of SITEs such as Maldives, where tourism revenue is a major source of income and foreign exchange reserves, it is important to understand the risks associated with this particular source of income, and to implement adequate risk management policies to ensure economic stability and sustained growth. Forecasted VaR thresholds can be used to estimate the level of reserves required to sustain desired long term government projects and foreign exchange reserves. Furthermore, an understanding of the variability of tourist arrivals, and hence tourism-related revenue, is critical for any investor planning to invest in or lend funds to SITEs.

McAleer et al. (2005) develop a Sustainable Tourism@Risk (or ST@R) model, which examines the impact of alternative estimates of volatility on the VaR of international
tourist arrivals. The ST@R model also adapts the traditional VaR approach to better reflect the needs of SITES.

8.5 Data Issues

The data used in this chapter are total daily international tourist arrivals from 1 January 1994 to 31 December 2003, and were obtained from the Ministry of Tourism of Maldives. There were over four million tourists during this ten-year period, with Italy being the largest tourist source country, followed by Germany, United Kingdom and Japan. The top four countries accounted for over 60% of tourist arrivals to Maldives. Furthermore, tourists from Western Europe accounted for more than 80% of tourists to Maldives, with Russia seen as the biggest emerging market.

A significant advantage of using daily data, as distinct from monthly and quarterly data, is that volatility clustering in the number of international tourist arrivals and their associated growth rates can be observed and analysed more clearly using standard financial econometric techniques.

There exists a direct relationship between the daily total number of tourists in residence and the daily tourism tax revenue. Modelling the variability of daily tourist arrivals (namely, the number of international tourists who arrive in the Maldives, predominantly by air) can be problematic as institutional factors, such as predetermined weekly flight schedules, lead to excessive variability and significant day-of-the-week effects. This
problem can be resolved in one of two ways. Weekly tourist arrivals could be examined, as this approach removes both the excess variability inherent in daily total arrivals and day-of-the-week effects. However, this approach is problematic as it leads to substantially fewer observations being available for estimation and forecasting.

An alternative solution, and one that is adopted in this chapter, is to calculate the daily tourists in residence, which is the total number of international tourists residing in Maldives on any given day. This daily total tourists in residence is of paramount importance to the Government of Maldives as it has a direct effect on the tourism tax revenues. The tourists in residence series are calculated as the seven-day rolling sum of the daily tourist arrivals series, which assumes that tourists stay in the Maldives for seven days, on average. This is a reasonable assumption as the typical tourist stays in the Maldives for approximately 7 days (Ministry of Planning and National Development (2005)).

The graphs for daily tourist arrivals, weekly tourist arrivals and tourists in residence are given in Figures 8-1 to 8-3, respectively. All three series display high degrees of variability and seasonality, which is typical of tourist arrivals data. As would be expected, the highest levels of tourism arrivals in the Maldives occur during the European winter, while the lowest levels occur during the European summer. The daily tourist arrivals series display the greatest variability, with a mean of 1,122 arrivals per day, a maximum of 4,118 arrivals per day, and a rather low minimum of 23 arrivals per day. Furthermore, the daily arrivals series have a coefficient of variation (CoV) of 0.559, which is nearly
twice the CoV of the other two series. The weekly arrivals and tourists in residence series are remarkably similar, with virtually identical CoV values of 0.3 and 0.298, respectively, and the normality assumption of both being strongly rejected.

Figure 8-1: Daily Tourist Arrivals
As the focus of this chapter is on managing the risks associated with the variability in tourist arrivals and tourist tax revenues, the modelling of growth rates, namely the returns in both total tourist arrivals and total tourists in residence is examined. The graphs for the returns in total daily tourist arrivals, total weekly tourist arrivals and total daily tourists in residence are given in Figures 8-4 to 8-6, respectively. Daily tourist arrivals display the greatest variability, with a standard deviation of 81.19%, a maximum of 368.23%, and a minimum of -412.57%. Based on the Jarque-Bera Lagrange Multiplier test statistic for normality, each of the series is found to be non-normal. Such non-normality can, in practice, change the critical values to obtain more precise VaR threshold forecasts (for further details, including a technical discussion of issues such as bootstrapping the distribution to obtain the dynamic critical values, see McAleer et al. (2005)).
8.6 Volatility Models

Risk evaluations are at the heart of research in financial markets, so much so that any assessment of the volatility of financial asset returns without such evaluations cannot be taken seriously. Engle (1982) developed the Autoregressive Conditional Heteroskedasticity (ARCH) model for undertaking risk evaluations by assuming that the conditional variance of the random error depends systematically on its past history. In this context, volatility clustering is taken to mean that large (small) shocks in the current period are followed by large (small) fluctuations in subsequent periods. There are two components of the ARCH specification, namely a model of asset returns and a model to explain how risk changes over time.

Subsequent developments led to the extension of ARCH by Bollerslev (1986) to the Generalised ARCH (GARCH) model. The main feature of GARCH is that there is a distinction made between the short and long run persistence of shocks to financial returns. A serious limitation of GARCH is the assumption that a positive shock (or “good news”) to daily tourist arrivals, tourists in residence, or their respective growth rates, has the same impact on their associated volatilities as does a negative shock (or “bad news”) of equal magnitude. It is well known that a negative shock to financial returns tends to have a greater impact on volatility than does a positive shock. This phenomenon was first explained by Black (1976), who argued that a negative shock increases financial leverage through the debt-equity ratio, by decreasing equity which, in turn, increases risk. Although there is not necessarily a comparable interpretation of leverage that applies to international tourist arrivals, there is nevertheless a significant difference in terms of
positive and negative shocks, which make a tourist destination more and less appealing, respectively. Therefore, positive and negative shocks would be expected to have differential impacts on volatility in daily tourist arrivals, tourists in residence, and in their respective growth rates.

In order to incorporate asymmetric behaviour, Glosten, Jagannathan and Runkle (1992) (GJR) extended the GARCH model by incorporating an indicator variable to capture the differential impacts of positive and negative shocks. Several alternative models of asymmetric conditional volatility are available in the literature (see McAleer (2005) for a comprehensive and critical review).

There have been only a few applications of GARCH models in the tourism research literature to date. Through estimation of ARCH and GARCH models, Raab and Schwer (2003) examine the short and long run impacts of the Asian financial crisis on Las Vegas gaming revenues. Shareef and McAleer (2005) model univariate and multivariate conditional volatility in monthly international tourist arrivals to the Maldives. Chan, Lim and McAleer (2005) investigate the conditional mean and variance in the GARCH framework for international tourist arrivals to Australia from the four main tourist source countries, namely Japan, New Zealand, UK and USA. Chan et al. (2005) show how the GARCH model can be used to measure the conditional volatility in monthly international tourist arrivals to three SITEs. Hoti et al. (2005) provide a comparison of country risk ratings, risk returns and their associated volatilities (or uncertainty) for six SITEs where monthly data compiled by the International Country Risk Guide are available (see Hoti
and McAleer (2004, 2005) for further details). Their results also show that the symmetric GARCH(1,1) and asymmetric GJR(1,1) models provide an accurate measure of the uncertainty associated with country risk returns for the six SITEs. Nicolau (2005) investigates the variations in the risk of a hotel chain’s performance derived from opening a new lodging establishment.

The primary inputs required for calculating a VaR threshold are the forecasted variance, which is typically obtained as a conditional volatility, and the critical value from an appropriate distribution for a given level of significance. Several models are available for measuring and forecasting the conditional volatility. In this chapter, two popular univariate models of conditional volatility will be used for estimating the volatilities and forecasting the corresponding VaR thresholds. These specifications are the symmetric GARCH model of Bollerslev (1986), which does not distinguish between the impact of positive and negative shocks to tourist arrivals (that is, increases and decreases in tourist arrivals), and the asymmetric GJR model of Glosten, Jagannathan and Runkle (1992), which does discriminate between the impact of positive and negative shocks to tourist arrivals on volatility.

The asymmetric GJR\((p,q)\) model is given as:

\[
Y_t = E(Y_t | F_{t-1}) + \varepsilon_t,
\]

\[
\varepsilon_t = h_t^{1/2} \eta_t,
\]
\[ h_t = \omega + \sum_{i=1}^{\eta} (\alpha_i \varepsilon_{t-i}^2 + \gamma \eta_{t-i} \varepsilon_{t-i}^2) + \sum_{i=1}^{\eta} \beta_i h_{t-i}, \]

\[ I(\eta_t) = \begin{cases} 1, & \varepsilon_t \leq 0 \\ 0, & \varepsilon_t > 0 \end{cases}, \]

where \( F_t \) is the information set available at time \( t \), and \( \eta_t \sim iid(0,1) \) The four equations in this asymmetric model of conditional volatility state the following:

(i) the growth in tourist arrivals depends on its own past values (namely, the conditional mean);

(ii) the shock to tourist arrivals, \( \varepsilon_t \), has a predictable conditional variance (or risk) component, \( h_t \), and an unpredictable component, \( \eta_t \);

(iii) the conditional variance depends on its own past values, \( h_{t-i} \), and previous shocks to the growth in the tourist arrivals series, \( \varepsilon_{t-i}^2 \); and

(iv) the conditional variance is affected differently by positive and negative shocks to the growth in tourist arrivals, as given by the indicator function, \( I(\eta_t) \).

In this chapter, \( E(Y_t \mid F_{t-i}) \) is modelled as a simple \( AR(1) \) process. For the case \( p = q = 1 \), \( \omega > 0, \alpha_i \geq 0, \alpha_i + \gamma \geq 0 \) and \( \beta_i \geq 0 \) are sufficient conditions to ensure a strictly positive conditional variance, \( h_t > 0 \). The ARCH (or \( \alpha_i + \frac{1}{2} \gamma \)) effect captures the short run persistence of shocks (namely, an indication of the strength of the shocks to international
tourist arrivals in the short run), and the GARCH (or $\beta_1$) effect indicates the contribution of shocks to long run persistence (or $\alpha_1 + \frac{1}{2} \gamma_1 + \beta_1$), namely, an indication of the strength of the shocks to international tourist arrivals in the long run. For the GJR(1,1) model, $\alpha_1 + \frac{1}{2} \gamma_1 + \beta_1 < 1$ is a sufficient condition for the existence of the second moment (that is, a finite variance), which is necessary for sensible empirical analysis. Restricting $\gamma_1 = 0$ in the GJR(1,1) model leads to the GARCH(1,1) model of Bollerslev (1986). For the GARCH(1,1) model, the second moment condition is given by $\alpha_1 + \beta_1 < 1$.

In the GJR and GARCH models, the parameters are typically estimated using the maximum likelihood estimation (MLE) method. In the absence of normality of the standardized residuals, $\eta_t$, the parameters are estimated by the Quasi-Maximum Likelihood Estimation (QMLE) method (for further details see, for example, Li, Ling and McAleer (2002) and McAleer (2005)). The second moment conditions are also sufficient for the consistency and asymptotic normality of the QMLE of the respective models, which enables standard statistical inference to be conducted.

8.7 Empirical Results

The variable of interest for the Maldivian Government is the number of tourists in residence on any given day as this figure is directly related to tourism revenue. As mentioned previously, every tourist is obliged to pay the tourism tax of USD 10 for every occupied bed night. In this section, the tourists in residence series are used to estimate the
GARCH(1,1) and GJR(1,1) models described above. Estimation is conducted using the EViews 5.1 econometric software package, although similar results can be obtained using the RATS 6 econometric software package. The QMLE of the parameters are obtained for the case $p=q=1$.

The estimated GARCH(1,1) equation for the tourists in residence series for the full sample is given as follows:

\[
\hat{Y}_t = 0.001 + 0.1561Y_{t-1},
\]

\[
h_t = 0.598 + 0.149\epsilon^2_{t-1} + 0.799h_{t-1},
\]

where the figures in parentheses are standard errors.

The estimated GJR(1,1) equation for the tourists in residence series for the full sample is given as follows:

\[
Y_t = 0.001 + 0.1561Y_{t-1},
\]

\[
h_t = 0.592 + 0.121\epsilon^2_{t-1} + 0.048I(\eta_{t-1})\epsilon^2_{t-1} + 0.803h_{t-1},
\]
All the parameters are estimated to be positive and significant, which indicates that both models provide adequate explanation of the data. As $\gamma_1$ is estimated to be positive and significant, volatility is affected asymmetrically by positive and negative shocks. In this sense, the asymmetric GJR model dominates its symmetric GARCH counterpart empirically. It is found that negative shocks (or a decrease in tourist arrivals) have a greater impact on volatility than do positive shocks (or an increase in tourist arrivals) of a similar magnitude. Furthermore, as the respective estimates of the second moment conditions, $\tilde{\alpha}_1 + \tilde{\beta}_1 = 0.948$ for GARCH(1,1) and $\tilde{\alpha}_1 + \frac{1}{2} \tilde{\gamma}_1 + \tilde{\beta}_1 = 0.948$ for GJR(1,1), are satisfied, the QMLE are consistent and asymptotically normal. This means that the estimates are statistically adequate and sensible for purposes of interpretation.

### 8.8 Forecasting

A rolling window is used to forecast the 1-day ahead conditional variances and VaR thresholds for the tourists in residence, with the sample ranging from 7 January 1994 to 31 December 2003. In order to strike a balance between efficiency in estimation and a viable number of rolling regressions, the rolling window size is set at 1,000, which leads to a forecasting period from 3 May 1997 to 31 December 2003. A rolling window is a moving sub-sample within the entire sample data set. In the empirical example presented here, estimation starts from observations 1 to 1000 of the data set, which corresponds to the period 7 January 1994 to 7 May 1997. Then, rolling the sample to observations 2 to 1001, which corresponds to the period 8 January 1994 to 8 May 1997, estimation is
undertaken again, followed by observations 3 to 1002, and so on until the last rolling sample is reached.

Using the notation developed in Chapter 2, the VaR threshold forecast for the growth rate of tourists in residence at any given time \( t \) is given by:

\[
VaR_t = E(Y_t | F_{t-1}) + z\sqrt{h_t},
\]

where \( E(Y_t | F_{t-1}) \) is the forecasted expected growth rate of total tourists in residence at time \( t \), \( h_t \) is the forecasted conditional variance of the growth rate in total tourist arrivals, and \( z = -2.33 \) is the negative critical value from the normal distribution at the one-sided 1% level of significance.

Figures 8-7 and 8-8 give the forecasted variances for both models. As can be seen from the figures, the forecasts are quite similar, with a correlation coefficient of 0.98. The forecasted VaR thresholds are given in Figures 8-9 and 8-10, respectively. As discussed above, the forecasted VaR threshold represents the maximum expected negative growth rate that could be expected given a specific confidence level. As is standard in the finance literature, where many of these techniques were developed and refined, this chapter uses a 1% level of significance to calculate the VaR thresholds. In other words, growth rates smaller than the forecasted VaR should only be observed in 1% of all forecasts, which is referred to as the correct “conditional coverage”.

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Figure 8-7: GARCH Conditional Variance Forecast for Tourist in Residence Returns

Figure 8-8: GJR Conditional Variance Forecast for Tourist in Residence Returns
Figure 8-9: Growth Rates for Tourists in Residence and GARCH VaR Thresholds

Figure 8-10: Growth Rates for Tourists in Residence and GJR VaR Thresholds
The empirical results show that, in using the GJR (GARCH) model, we observe 32 (30) instances where the actual daily growth rate is smaller than the forecasted VaR threshold. Based on a Likelihood Ratio test, both models display the correct conditional coverage. In addition, Figures 8-11 and 8-12 plot the second moment conditions for each rolling window of both models. As the condition is satisfied for every rolling window, this provides greater confidence in the statistical adequacy of the two estimated models. Finally, both models lead to the same average VaR at -6.59%, which means that the lowest expected daily growth rate in tourists in residence, and hence in tourist tax revenues, is -6.59%, given a 99% level of confidence. In other words, it can be stated with a 99% degree of confidence that the daily growth rate will exceed -6.59%.

Figure 8-11: Rolling Second Moment Condition for GARCH
8.9 Conclusions

In Maldives, tourist arrivals and the growth in tourist arrivals translate directly into a financial asset for the government, as each international tourist is required to pay USD 10 for every tourist bed-night. This levy is called a tourism tax and enters directly into government revenue. Thus, tourism tax revenue is a principal determinant of development expenditure. As a significant financial asset to the economies of SITEs, and particularly so in the case of Maldives, the volatility in tourist arrivals and in their growth rates are conceptually equivalent to the volatility in financial returns, which is widely interpreted as financial risk.
This chapter provided a template for the future analysis of earnings from international tourism, particularly tourism taxes for SITEs, discussed the direct and indirect monetary benefits from international tourism, highlighted tourism taxes in the Maldives as a development financing phenomenon, and provided a framework for the quantification of the risks associated with tourism tax receipts, which should facilitate the future design and implementation of tourism taxes in SITEs.

Daily international arrivals to Maldives and their associated growth rates were analysed for the period 1994-2003. This seems to be the first analysis of daily tourism arrivals and growth rates data in the tourism research literature. The primary purpose for analysing volatility was to model and forecast the Value-at-Risk (VaR) thresholds for the number of tourist arrivals and their growth rates. This would seem to be the first attempt in the tourism research literature to apply the VaR portfolio management approach to manage the risks associated with tourism revenues.

The empirical results based on two widely-used conditional volatility models showed that volatility was affected asymmetrically by positive and negative shocks, with negative shocks to the growth in tourist arrivals having a greater impact on volatility than previous positive shocks of a similar magnitude. The forecasted VaR threshold represented the maximum expected negative growth rate that could be expected given a specific confidence level. Both conditional volatility models led to the same average VaR at -6.59%, which meant that the lowest possible growth rate in daily tourists in residence, and hence in tourist tax revenues, was expected to be -6.59% at the 99% level of
confidence. This should be useful information for the Maldivian Government and private tourism service providers in the Maldives.

In the Maldives Tourism Act (Law No: 2/99), it is stated that the tourism tax is USD 10 and is to be paid in USD, which increases foreign exchange reserves directly. Tourist establishments also typically hold large quantities of USD, which encourages the general public to follow suit, and causes the economy to become highly ‘dollarized’. Such dollarization substantially changes the way in which a country conducts monetary policy. In the case of Maldives, in the event of a contraction of USD inflows, the authorities will have to change the way in which they conduct monetary policy. Therefore, understanding the extent to which tourism tax receipts, and hence foreign exchange reserves, can vary will aid the Maldivian Government in planning the conduct of future monetary policy operations.

Tourism taxes also have a significant influence on the Maldivian Government’s budget. There are three main components of government expenditure, namely: (1) direct government expenditure on public projects; (2) transfer payments; and (3) debt servicing. In turn, these have to be funded by: (i) tax receipts; (ii) government borrowing; or (iii) money creation. The analysis presented in this chapter shows that tax receipts in Maldives are highly variable. Therefore, if the Maldivian Government wishes to maintain a relatively constant level of government expenditure, it must compensate reductions in tax receipts with government borrowing or increases in the money supply. Hence, the analysis presented in this chapter should assist the Maldivian Government in quantifying
the extent to which they may have to borrow funds in the future. Such knowledge will be useful in aiding the Government in undertaking sustainable development projects that do not have to be interrupted, thereby improving the efficiency of government development projects.

This is precisely what has happened in the post-tsunami period. According to the Ministry of Tourism of the Government of Maldives, international tourist arrivals declined by 44% during the first 8 months of 2005 as compared with the same period in the preceding year. Furthermore, the average capacity utilization or occupancy rate was only 58% from January through to August 2005, as compared with the first eight months of 2004. The World Bank (2005e) has recently stated that there would be a budget shortfall of USD 96 million due to the decline in tourism, of which one-half would have to be raised locally, with the rest to be raised by international donors and development banks.

The analysis presented in this chapter also quantified the potential fall in daily government tax receipts, which affects the ability of the Maldivian Government to service its debt obligations. Hence, potential creditors can use the analysis presented here to decide what should be the appropriate interest rate on loans to the Maldivian Government. Furthermore, VaR thresholds for tourism tax receipts could be incorporated into loan covenants to provide a greater level of protection for financial institutions that might provide loans to the Maldivian Government.
The commercial stability of the tourist resorts owned by local and foreign investors depends significantly on the tourists in residence figures, which will also determine the capacity utilisation rate. Working capital, as obtained in the form of an overdraft facility, is required for the smooth operation of these facilities. An extremely large negative shock, such as the 2004 Indian Ocean Tsunami, would reduce the asset value of some resorts below the constant debt level, which is the total amount borrowed to finance the purchase of the asset. Following the 2004 Tsunami, 19 resorts in the Maldives were closed completely due to extensive damage. In order to recover their asset value, certain occupancy or capacity utilisation rates would have to be achieved.

The VaR analysis presented in this chapter could be used by resort operators in a ‘real options’ framework. Resort operators have the option to shut down, either wholly or in part, as this choice can help to minimise losses. Therefore, VaR thresholds have value and can be priced using identical principles as in the case of financial options. In pricing financial options, a crucial input is the volatility of the underlying asset which, in the case of tourist resorts, is the number of tourists in residence. Hence, modelling the conditional volatility of tourists in residence will aid resort operators in deciding whether to remain open, shut down a portion of the resort, or shut down operations in their entirety. Therefore, managing Value-at-Risk should assist significantly in achieving optimal risk management strategies.
Chapter Nine

9 Conclusion

9.1 Summary of Thesis

This thesis has examined the topic of dynamic modelling of volatility and Value-at-Risk (VaR) thresholds, both theoretically and for a variety of applications. VaR has emerged as one of the most widely used financial risk management tools of the late 20th and early 21st Centuries. The popularity of VaR methods stem partly from their conceptual simplicity and partly from the fact that the Basel Accord requires Autorised Deposit-taking Institutions (ADIs) to use VaR methods to calculate capital charges for exposures to market risk.

Although VaR is a widely researched and applied market tool, this thesis investigated several areas that had hitherto been unexplored. In addition, several novel ways in which VaR methods could be evaluated were developed based on measures that are meant to reflect the concerns of ADIs and regulators. Such measures represent a significant extension of the traditional literature that has tended to focus on statistical methods that only evaluated the statistical accuracy of VaR models, but have been unable to distinguish among statistically adequate models.
Chapter 3 investigated the performance of Single Index (SI) and Portfolio Methods (PM) in forecasting VaR thresholds. This is an important issue in modern risk management as risk managers are often required to calculate VaR thresholds for portfolios comprising a large number of assets, which can be cumbersome and sometimes impossible for certain types of models. Therefore, in order to analyse this important issue, several univariate and multivariate conditional volatility models were used to forecast the VaR thresholds for a portfolio comprising 56 stocks listed in the Australian Stock Exchange. The empirical results offered mixed evidence for the performance of PM versus SI models, with the choice of distributional assumption proving to be a much more important decision than the choice of model.

Chapter 4 compared the performance of modelling spillover effects. Recently developed multivariate conditional volatility models, such as the Vector Autoregressive Moving Average Generalised Autoregressive Conditional Heteroskedasticity (VARMA-GARCH) model of Ling and McAleer (2003), model the conditional volatility of an asset as depending dynamically on its own past as well as on the past volatility of other assets. Such models, while intuitively appealing, are often not useful in practice as they cannot be estimated for large numbers of assets. In contrast, the Constant Conditional Correlation (CCC) model of Bollerslev (1990) does not include any spillover effects and, therefore, can be used to model any number of assets.
In addition to comparing the forecasting performance of the VARMA-GARCH and CCC models, this chapter developed the Portfolio Spillover (PS) GARCH model. The PS-GARCH model was developed to model the spillover effects for any number of assets in a parsimonious manner. The empirical results suggested that, although the spillover effects in the VARMA-GARCH and PS-GARCH models are statistically significant, the forecasting performance of such models is essentially the same as the CCC model. Therefore, it was concluded that the inclusion of spillover effects was not an important consideration in forecasting VaR thresholds.

Chapter 5 analysed the importance of accommodating dynamic conditional correlations in the modelling and forecasting of VaR thresholds. In order to analyse this issue, Chinese A and B shares were used because these had been shown to have increased substantially in correlation since the B share market reform. The VaR threshold forecasts produced by the Dynamic Conditional Correlation (DCC) model of Engle (2002) was compared with the forecasts produced by the CCC model. The results suggested that forecasts based on the DCC model were superior, such that accommodating dynamic conditional correlations was important. In addition, the fitted conditional correlations between A and B shares were also shown to have increased substantially over the sample period, and that this increase began well before the B share market reform.

A common trend in the empirical results of Chapters 3 to 5 was that models that tended to under-predict risk, and hence led to excessive violations, also tended to have lower capital charges. Chapter 6 used a variety of SI conditional volatility models and four
distributional assumptions to forecast VaR thresholds for a long series of the S&P500 index. The results showed that the lowest capital charges were achieved by models that led to twice the target number of violations, suggesting that ADIs had an incentive to choose models that under-predict risk, and hence lead to excessive violations. The Basel Accord penalty structure was then modified to align more accurately the interests of regulators and ADIs. The results showed that the new penalty structure was significantly better at aligning the interest of ADIs and regulators by producing models that lead to the correct number of violations with minimum capital charges.

Although VaR has traditionally been used to manage the risk of financial returns, it can be used in a wide range of applications. Chapter 7 introduces VaR methods to the analysis of country risk ratings. Country risk ratings are important because they have a direct impact on the national cost of borrowing, and changes in country risk ratings lead to changes in the cost of borrowing. Therefore, country risk rating returns are analogous to financial returns. The concept of Country Risk Bounds (CRBs) was developed and used to quantify the likelihood of re-ratings. As would be expected, developing countries were found to have not only the lowest credit worthiness, as indicated by the lowest risk ratings, but also the greatest likelihood of experiencing a change in risk ratings. This type of analysis was shown to be useful for parties intending to engage with countries in lending or borrowing.

Finally, the VaR method was adapted to the tourism literature in Chapter 8 by applying it to international tourist demand to the Maldives. The Maldives was chosen because the
Maldivian government depends heavily on tourism receipts, with tourism accounting for over one-third of GDP. As each tourist is required to pay a tax of US$10, for each night spent in the Maldives, changes in tourism demand are analogous to financial returns as they translate directly to financial gains or losses. The empirical results suggested that the models used were well suited for forecasting VaR in tourism demand to the Maldives. The chapter also outlined several ways in which this information could be used by various parties to improve the decision making process.

9.2 Future Research

The research undertaken in this thesis could be extended and adapted in the following ways:

1) A wider range of distributional assumptions could be used, including asymmetric and time-varying distributions;

2) VaR thresholds could be obtained using a variety of non-parametric methods;

3) The portfolios could be constructed assuming different weight structures;

4) More advanced penalty structures could be developed to align the interests of regulators and ADIs;
5) The impact of different synchronisation procedures for returns to calculate VaR thresholds could be investigated;

6) VaR thresholds could be obtained using alternative univariate and multivariate stochastic volatility models;

7) The PS-GARCH and PSI conditional and stochastic volatility models developed in this thesis could be extended to accommodate dynamic correlations;

8) Application of the Country Risk Bounds (CRBs) developed in this thesis to the sovereign risk spread literature to obtain a better explanation of yield spreads.
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