Essays on Value at Risk and Asset Price Bubbles

by

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Declaration

I confirm that the contents of this thesis are my original research work and have not been presented or accepted in any previous application for a degree. The word length is within the prescribed limit as advised by my school and all sources are fully referenced and acknowledged.

Kwong Wai Man, Raymond

Abstract

This thesis describes a series of investigations into the reliability of different financial risk models for measuring downside risks during financial crises caused by the bursting of asset price bubbles. It also provides further insight into modelling asset price series with periodically collapsing asset price bubbles.

We start by reviewing the volatility models that are commonly used for quantifying downside financial risks in Chapter 2. The characteristics of several important univariate and multivariate autoregressive conditional heteroscedasticity family volatility models are reviewed. In Chapter 3, we apply the volatility models to identify the direction of volatility spillover effects among stock markets. The financial markets considered in this study include Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil. Findings from both the dynamic conditional correlation (DCC) and asymmetric DCC models show that the asymmetric volatility spillover effect is highly significant among financial markets, while the asymmetric correlation spillover effect is not. Financial contagion will be reflected in price volatility, but not in correlations.

Subsequently we move to testing different Value-at-Risk (VaR) approaches using market data. We define 1 June 2008 to 1 June 2009 as the financial crisis period. We study nine hypothetical single-stock portfolios and nine hypothetical multiple-asset portfolios in the nine countries considered. Both the univariate and multivariate VaR approaches are tested and the results show that the long memory RiskMetrics2006 model outperforms all other univariate methods, while the Glosten-Jagannathan-Runkle DCC model performs well among the multivariate VaR models. Next, in Chapter 5 we use simulations to explore the characteristics of financial asset price bubbles. Evans (1991) proposed a model for investigating asset price

movements with periodically collapsing explosive bubbles. We modify and extend this model to make it more realistic; as a result the modified model better controls the growth and collapse of bubbles, while exhibiting volatility clustering. In the simulation tests, the RiskMetrics VaR model performs well during financial turmoil.

Finally, we discuss the sup-augmented Dickey-Fuller test (SADF) and the generalized SADF test for identifying and date-stamping asset price bubbles in financial time series. Unlike in Chapter 4 (where we use personal judgement to define financial bubble periods), pre- and post-burst periods are defined here based on the identification results of the asset price bubbles' origination and termination dates from the backward SADF test. Our empirical results show that the criticism that VaR models fail in crisis periods is statistically invalid.

Dedication

To my parents, wife and son

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First and foremost, I would like to take this opportunity to express my greatest and most sincere gratitude to my supervisor, Prof. Robert Sollis, for allowing me the freedom to pursue my own research interests. Without his great patience, invaluable guidance, constructive criticism and continuous encouragement throughout these years, this thesis would not have come into existence. It has been my great honour to work with him.

This thesis is dedicated to my parents, Kwong Hung and Yuen Ha Tsui; my wife, Christine; and my son, Kris, for their undoubtable support, limitless understanding, unfailing encouragement, and unconditional love.

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Chapter 1. Introduction

Financial markets have experienced several crises over the last two decades. The Asian financial crisis in 1997, the bursting of the dot-com bubble in 2001, the sub-prime mortgage crisis in 2008, and the European sovereign debt crisis in 2009 have all spurred financial institutions to use better measures for managing downside risk. The losses caused by these financial crises were tremendous. Luttrell *et al.* (2013) estimated that the 2008 sub-prime mortgage crisis cost the U.S. economy up to $14 trillion, which is equivalent to the average annual output of the entire U.S. economy. At the same time, the world has become more integrated than ever and cross-border financial flows have steadily increased; given that the contagion effect means no single market can stand alone, the effects of financial crisis have become further complicated.

Financial crisis disrupts the normal functioning of financial market. The dot-com bubble occurred in late 1990s, the equity values of internet-based companies consecutively soared a recorded high and companies were grossly overvalued at that moment. During that period, companies could obtain capital easily from the public by simply using an Internet concept, their stock price can be tripled or quadrupled in one day after the initial public offerings. The bubble was eventually collapse around 2001 while many companies failed to meet the investors expectations. In 2004 to 2007, the U.S. experienced a fast expansion in household debt, while most of the debts were financed by mortgage-backed security (MBS) and collateralized debt obligations (CDO). In 2008, the real-estate price bubble burst followed by a large decline in housing price, which leaded to a massive default from low credit borrowers. In Sept 2008, Lehman Brothers collapsed due to its high exposure in CDO and MBS. The news shocked the market and triggered a financial turmoil.

Most financial crises are caused by the burst of asset price bubbles. Asset price bubbles are formed when the asset's price deviates from its fundamental value. During the bubble booming period, the asset price grows at an explosive rate. Blanchard and Watson (1982) suggested that no bubble will last forever, as the market will eventually awake and make corrections. Such a correction is usually associated with a large selling force that makes the stock price plunge and is commonly referred as a bubble burst. Nonetheless, it is difficult to identify the presence of bubbles and to date-stamp the bursts.

The losses incurred during financial crises are tremendous, and practitioners and regulators are keen to look for risk models that measure downside risks. In the past decade, value at risk (VaR) has become one of the most popular techniques for measuring downside risks. The VaR method measures a financial investment's downside risk, defined as a minimum portfolio value loss for a particular time period with a certain percentage of probability. After the 2008 sub-prime mortgage crisis, many financial institutions suffered unexpected losses that far exceeded the values described in risk models, and people started to question the reliability of the volatility models that were being used to quantify risks (see Oanea and Anghelache, 2015). However, empirical study of VaR performance in the crisis period has been limited. In this thesis, we studied the VaR performance in nine countries that across three trading zones of Asian market, European market, and North and South American market. Based on the market capitalization, we selected three equity markets in each zone to perform a series of robustness tests, the selected equity markets included: Tokyo Stock Exchange, Shanghai Stock Exchange, Hong Kong Stock Exchange, Deutsche Borse, London Stock Exchange and BME Spanish Exchange, New York Exchange, Toronto Stock Exchange, and BM&F Boverspa. The market capitalizations of each market are USD4.49 trillion, USD3.99 trillion, USD3.32 trillion, USD1.76 trillion, USD6.10 trillion, USD 0.94 trillion, USD19.22 trillion, USD1.94 trillion, and USD0.82 trillion, respectively.

1.1 Motivations and Objectives of the Thesis

This thesis studies the reliability of different financial risk models in periods with and without asset price bubbles, particularly in the periods before and after the bubbles burst.

International stock markets have been interacting more than ever before. The international financial contagion effect makes risk models fail, as most of the volatility models employed do not consider volatility spillover effects among different countries. With the large volume of cash flow created by hedge funds and the cross-regional operations of financial institutions, traditional macroeconomic theories fail to explain the spillover effect. At the same time, in the last two decades China has experienced rapid growth in global financial markets. Such rapid growth has attracted many to study the country's influential power on the rest of the world. This motivates us to examine the magnitude and the nature of the change in volatility spillover in the United States, China, and seven other developed and emerging markets in Chapter 3.

Chapter 4 extensively reviews on different VaR models and compares the reliability of them in the 2008-2009 global financial crisis period. The crisis period is defined as the sub-mortgage crisis period of 1 June 2008 to 1 June 2009, while the non-crisis period is defined as 1 June 2009 to 31 December 2012. The VaR approaches are tested by constructing hypothetical single- and multiple-asset portfolios. We studied the markets of Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil and formed nine single-stock portfolios and nine three-stock portfolios to explore the effectiveness of the univariate and multivariate VaR approaches in both the crisis and non-crisis periods.

Chapter 5 studies the performance of different VaR models in the periods with and without asset price bubbles using simulated data. We modified Evans (1991) bubbles model to simulate asset prices with periodically collapsing bubbles and accordingly examines the reliability of different VaR approaches. As the bubble generation process is controlled within our simulations, the bubble boom and burst dates are known in advance for studying the reliability of different VaR models in both pre- and post-burst periods.

The crisis and non-crisis periods defined in Chapter 4 are based on subjective judgement but researchers prefer to use statistical procedures to identify asset price bubbles. Early studies on asset price bubble identification included Shiller (1981) variance bound tests and Diba and Grossman (1988b) co-integration based test. As suggested by Evans (1991), both approaches fail to detect periodically collapsing bubbles. Phillips *et al.* (2011) proposed using a forward recursive sup-augmented Dickey-Fuller (SADF) test to detect periodically collapsing bubbles and demonstrated that the SADF test outperforms other traditional tests. However, Phillips *et al.* (2015) found that the SADF test may fail if multiple bubbles are present during the testing period. They proposed a generalized version of the sup-ADF (GSADF) test that allows the starting point of the testing window change to address this problem. We use the GSADF test to identify asset price bubbles and date-stamp their origination and termination dates in real market data.

1.2 Thesis Contributions

In this dissertation, we found that the International financial markets have been interacting more than ever before. We showed the importance of financial contagion effects on equity prices and volatility. As financial shocks propagate across markets, investors should pay attentions on asymmetric impacts on volatility from bad news. One interesting finding in Chapter 3 is that the asymmetric impacts of financial news will intensify the volatilities in different stock markets; however; finance turbulences have no significant effect on intensify correlations among the markets. One implication drawn from our results is that the international diversification effect still stands during the financial crisis, and they should benefit in a mean-variance manner. This idea is supported by Robert (2011) which empirically investigated international equity foreign portfolios during the financial crisis that across 42 countries. The results show that international stock market diversification provides large gains during the financial crisis. The reduction of home bias in equity holdings allows investors to reap the benefits of international diversification, especially during financial turmoil.

Next, we extensively reviewed the effectiveness of different VaR models during financial crises. Our results show that the criticism of VaR models fail to reveal the underlying risk is statistically invalid, the Longerstaey and Spencer (1996) RiskMetrics2006 approach performs well in both non-crisis and crisis period. Our results suggest financial institutions may consider to adopt the long-memory RiskMetrics2006 model as the internal VaR models for measuring the downside market risk, rather than using the traditional short-memory RiskMetrics model.

The thesis also propose a new method for simulating stock price series with periodically collapsing explosive bubbles has been proposed. Seminal work from Evans (1991) provided a model for simulating rational asset price bubbles with periodically collapsing explosive bubbles, which provides a more realistic results than the traditional random walk theory by geometric Brownian motion that simulates no financial crisis. Evan's work is particular useful in managing downside risk. However, as Evan's model suggests that the asset price bubble will collapse in one single observation, it may be adequate in simulating monthly data series but not in daily data series. We extended Evan's model by allowing the asset price bubble multiple collapse and introduced a mechanism to incorporate the asymmetric volatility clustering feature in the asset price series. Our model is more realistic and portfolio managers can apply it to perform Monte Carlo Simulation (MCS) for quantifying financial risks and to have a better financial budgets allocation.

1.3 Thesis Layout

The layout of this thesis is as follows. Chapter 2 reviews the volatility models that are used throughout this study. Chapter 3 studies the magnitude and nature of change in volatility spillover within international stock markets. Chapter 4 explores the performance of different VaR models in the last decade's sub-prime mortgage crisis, the period of which is specified as 1 June 2008 to 1 June 2009. Chapter 5 uses simulations to study the characteristics of asset price bubbles and proposed a new equity price simulation model. Chapter 6 studies the asset price bubbles and different VaR approaches by using the GSADF test using real stock data. The origination and termination dates of the bubbles are identified through the GSADF test, rather than through personal judgement.

Chapter 2. The Challenges of Volatility Modelling and a Review of Time Series Models

Modelling volatility is of fundamental importance to asset and derivatives pricing. Good volatility models enable financial institutions to price assets and derivatives in a more accurate way, reducing the probability of significant losses. The Black-Scholes-Merton (BMS) option pricing model is one of the famous option pricing models in the last few decades. However, it is unrealistic because it assumes that volatility is constant and known. From the collapse of the famous Long-Term Capital Management (LTCM) fund to the most recent sub-prime mortgage collapse in the United States, many events have disrupted the traditional derivative valuations process and raised interest in finding a better way to incorporate market uncertainty into this process.

In addition, better volatility models enable companies to greatly improve their effectiveness in controlling financial risks. In the past two decades, the VaR method has been one of the most popular methods for measuring the downside risks of financial assets. Nevertheless, after the sub-mortgage crisis in 2008 practitioners and regulators started to criticize the VaR model for managing risk based on just one number, which may be insufficient. In reality, VaR can be calculated in various ways based on different assumptions and volatility models. Financial institutions tend to use simple approaches that are susceptible to a large amount of model risk, which leads the VaR model to fail.

In this chapter, characteristics of several important time series models are discussed and reviewed, including the autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models. Furthermore, the autoregressive conditional heteroskedasticity (ARCH) family volatility models, including the ARCH, generalized ARCH

(GARCH), Glosten-Jagannathan-Runkle GARCH (GJR-GARCH), constant conditional correlation (CCC), dynamic conditional correlation (DCC), and GJR-CCC models are also reviewed. The volatility models described in this chapter are used in the different VaR approaches that are discussed in Chapters 3 and 5.

2.1 AR Models

Autoregressive models are linear prediction models that forecast output based on previous output. For an output variable Y_t, AR models take previous output variables $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-n}$ as the independent variables in the linear regression. The simplest way to model the dependency between the current variable Y_t and the past variable Y_{t-1} is the first-order AR, or AR(1), process.

$$Y_t = \delta + \theta Y_{t-1} + \varepsilon_t \tag{2.1}$$

where ε_t is a random component and considered as a white noise process with a mean of zero and constant variance, since $\varepsilon_t \sim N(0, \sigma^2)$, ε_t is homoskedastic and exhibits no autocorrelation (i.e. $\rho_k = \frac{cov\{\varepsilon_t, \varepsilon_{t-k}\}}{V\{\varepsilon_t\}} = 0$).

In the AR(1) process, the current value Y_t equals a constant δ plus θ times the previous value Y_{t-1} plus the random component ε_t.

2.1.1 Stationarity of AR models

A time series model is called stationary if its statistical properties do not change over time. The probability distribution of Y_1 should be the same as that of any other Y_t. In many cases, only the means, variances, and covariances of the series are of concern, and it is common to assume that these moments are independent of time. The second-order or covariance stationarity is then tested.

A process $\{Y_t\}$ is covariance stationary if it satisfies the following three conditions for all t:

a) $E\{Y_t\} = \mu$

b) $V\{Y_t\} = \gamma_0$

c) $cov\{Y_t, Y_{t-k}\} = \gamma_k, k = 1, 2, 3, \cdots$

The expected value of series $\{Y_t\}$ in the AR(1) model is:

$$E\{Y_t\} = \delta + \theta E\{Y_{t-1}\}$$

$$E\{Y_t\} = \delta + \theta(\delta + \theta E\{Y_{t-2}\}) = \delta + \theta\delta + \theta^2 E\{Y_{t-2}\}$$

$$E\{Y_t\} = \delta + \theta(\delta + \theta(\delta + \theta E\{Y_{t-3}\})) = \delta + \theta\delta + \theta^2\delta + \theta^3 E\{Y_{t-3}\}$$

in which it is covariance stationary if and only if $|\theta| < 1$, the expected value μ can be written as:

$$E\{Y_t\} = \mu = \frac{\delta}{1-\theta} \tag{2.2}$$

The variance of $\{Y_t\}$ in the AR(1) model is:

$$V\{Y_t\} = V\{\theta Y_{t-1}\} + V\{\varepsilon_t\} = \theta^2 V\{Y_{t-1}\} + \theta^2$$

where $V\{Y_t\} = V\{Y_{t-1}\}$ and $|\theta| < 1$,

$$V\{Y_t\} = \frac{\sigma^2}{1-\theta^2} \qquad (2.3)$$

Defining $y_t = Y_t - \mu$, equation (2.1) can be written as:

$$Y_t - \mu = \delta + \theta Y_{t-1} + \varepsilon_t - \mu$$

$$y_t = \theta Y_{t-1} + \frac{\theta\delta}{1-\theta} + \varepsilon_t$$

$$y_t = \theta y_{t-1} + \varepsilon_t \qquad (2.4)$$

The covariance of series $\{Y_t\}$ in the AR(1) model is:

$$cov\{Y_t, Y_{t-1}\} = E\{y_t y_{t-1}\} = E\{(\theta y_{t-1} + \varepsilon_t) y_{t-1}\} = \theta V\{y_{t-1}\} = \theta \frac{\sigma^2}{1-\theta^2}$$

for any $k = 1, 2, 3, \cdots$

$$cov\{Y_t, Y_{t-k}\} = \theta^k \frac{\sigma^2}{1-\theta^2} \qquad (2.5)$$

For any non-zero θ, the correlation of any two observations Y_t is non-zero and the dependence will be smaller while the observation distance k is larger.

Since the means, variances, and covariances in equations (2.2), (2.3), and (2.5) are all independent of time t and finite, the AR(1) process is covariance stationary.

2.2 MA models

Moving average models are linear prediction models that forecast output based on previous input. For a variable Y_t, an MA model takes previous input variables $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-n}$ as the independent variables in the linear regression. The simplest MA model is the first-order MA, or MA(1), process.

$$Y_t = \mu + \varepsilon_t + \alpha\varepsilon_{t-1} \tag{2.6}$$

In the MA(1) process, the current value Y_t is equal to the mean μ plus a weighted average of ε_t and ε_{t-1}, which are the current and past random components.

2.2.1 Stationarity of the MA process

To test the stationarity of the MA process, the expected value, variance, and covariance of the series $\{Y_t\}$ are examined.

The expected value of series $\{Y_t\}$ in the MA(1) model is:

$$E\{Y_t\} = \mu \tag{2.7}$$

The variance of series $\{Y_t\}$ in the MA(1) model is:

$$V\{Y_t\} = V\{\varepsilon_t\} + V\{\alpha\varepsilon_{t-1}\}$$

$$V\{Y_t\} = \sigma^2 + \alpha^2\sigma^2 = (1+\alpha^2)\sigma^2 \tag{2.8}$$

The covariance of series $\{Y_t\}$ in MA(1) model is:

$$cov\{Y_t, Y_{t-1}\} = E\{(\varepsilon_t + \alpha\varepsilon_{t-1})(\varepsilon_{t-1} + \alpha\varepsilon_{t-2})\} = \alpha E\{\varepsilon_{t-1}^2\} = \alpha\sigma^2$$

$$cov\{Y_t, Y_{t-2}\} = E\{(\varepsilon_t + \alpha\varepsilon_{t-1})(\varepsilon_{t-2} + \alpha\varepsilon_{t-3})\} = 0$$

In general,

$$cov\{Y_t, Y_{t-k}\} = \begin{cases} \alpha\sigma^2 & \text{for} \quad k = 1 \\ 0 & \text{for} \quad k \geqq 2 \end{cases} \tag{2.9}$$

Since the means, variances, and covariances in equations (2.7), (2.8), and (2.9) are all independent of time t and finite, the MA(1) process is covariance stationary.

2.3 The Lag Operator in Time Series Models

Time series models usually refer to past data. In order to simplify representation of the model, the lag (or backshift) operator denoted by L is commonly be used in literatures and which defined as follows:

$$\begin{array}{rcl} LY_t & = & Y_{t-1} \\ L^2Y_t & = & Y_{t-2} \\ \vdots & \vdots & \vdots \\ L^nY_t & = & Y_{t-n} \end{array} \tag{2.10}$$

The AR(1) process can be written as:

$$y_t = \theta L y_t + \varepsilon_t$$

In general, the AR(p) process can be written as:

$$\theta(L) y_t = \varepsilon_t \tag{2.11}$$

where $\theta(L)$ is the lag polynomial given by:

$$\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_p L^p \tag{2.12}$$

The lag polynomial $\theta(L)$ can be interpreted as a filter, which is considered as equation (2.11). After the filter is applied to the AR series $\{y_t\}$, the white noise ε_t in time t will be returned as output. The inverse of $\theta(L)$ is $\theta^{-1}(L)$, and it exists if and only if $|\theta| < 1$.

With the lag polynomial, the $AR(1)$ series can be written as the $MA(\infty)$ series and $MA(1)$ series can be written as the $AR(\infty)$ series.

$$
\begin{aligned}
AR(1): \quad y_t &= \theta L y_t + \varepsilon_t \\
(1-\theta L)y_t &= \varepsilon_t \\
(1-\theta L)^{-1}(1-\theta L)y_t &= (1-\theta L)^{-1}\varepsilon \\
y_t &= \sum_{j=0}^{\infty}\theta^j L^j \varepsilon_t \\
y_t &= \sum_{j=0}^{\infty}\theta^j \varepsilon_{t-j}
\end{aligned}
$$

$$
\begin{aligned}
MA(1): \quad Y_t &= \mu + \varepsilon_t + \alpha\varepsilon_{t-1} \\
y_t &= \varepsilon_t + \alpha L \varepsilon_t \\
(1+\alpha L)^{-1} y_t &= \varepsilon_t \\
\varepsilon_t &= \sum_{j=0}^{\infty}(-\alpha)^j y_{t-j}
\end{aligned}
$$

$$
MA(1): y_t = \alpha\sum_{j=0}^{\infty}(-\alpha^j)y_{t-j-1} + \varepsilon_t = AR(\infty)
$$

For the $MA(q)$ process, the lag polynomial is:

$$
\alpha(L) = 1 + \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q \tag{2.13}
$$

2.4 ARMA Models

Autoregressive MA processes are a combination of AR and MA models, which are considered as a combination of the AR(p) and MA(q) processes.

$$
\begin{aligned}
AR(p): &\quad y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t \\
MA(q): &\quad y_t = \varepsilon_t + \alpha_1\varepsilon_{t-1} + \alpha_2\varepsilon_{t-2} + \cdots + \alpha_q\varepsilon_{t-q}
\end{aligned}
$$

The ARMA(p, q) model is obtained by combining the AR(p) and MA(q) models.

$$ARMA(p,q): y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t + \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \cdots + \alpha_q \varepsilon_{t-q} \quad (2.14)$$

Using lag polynomials (2.12) and (2.13), the $ARMA(p,q)$ model can be written as:

$$\theta(L) y_t = \alpha(L) \varepsilon_t \quad (2.15)$$

Given that lag polynomials (2.12) and (2.13) are revertible, the ARMA model can be written as either the $MA(\infty)$ or the $AR(\infty)$ model.

$$y_t = \theta^{-1}(L) \alpha(L) \varepsilon_t$$

$$\alpha^{-1}(L) \theta(L) y_t = \varepsilon_t$$

As any invertible ARMA model can be approximated by AR or MA models and the estimation of MA and ARMA models is more complex than AR models, the AR model is the most commonly used of the three time series models. However, the three models do behave differently in different situations, and there are no economic reasons for choosing a particular model.

2.5 Univariate ARCH Family Models

2.5.1 The ARCH model

The AR, MA, and ARMA models assume that the condition variance of y_t does not change. Furthermore, when these models are used to forecast asset returns, it is assumed that asset returns are an independently and identically distributed (i.i.d.) random process with a zero mean and constant variance. In reality, however, the uncertainty or randomness are observed to vary widely over time and tend to cluster together. The assumptions of normality, independence, and homoskedasticity do not always hold with real data. Engle (1982) proposed the ARCH model with the volatility clustering effect accounted for in the modelling process.

Consider the distribution of y_t is normal with a mean equal to $x_t\beta$ plus a random component h_t. From equation (2.16) to (2.19), the distribution of y_t in the information set ψ_{t-1} is a linear combination of the vector and a coefficient vector $\beta = (\beta_1, \beta_2, \cdots, \beta_n)'$.

$$y_t \mid \psi_{t-1} \sim N(x_t\beta, h_t) \tag{2.16}$$

$$h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \cdots, \varepsilon_{t-p}, \alpha) \tag{2.17}$$

$$\varepsilon_t = z_t\sqrt{h_t} \tag{2.18}$$

$$y_t = x_t\beta + \varepsilon_t \tag{2.19}$$

where $z_t \sim N(0,1)$.

The ARCH model states that the variance of the error term h_t depends on the squared error terms from previous periods.

$$h_t = E\{\varepsilon_t^2 \mid \psi_{t-1}\} = \omega + \alpha(L)\varepsilon_t^2 \tag{2.20}$$

Defining a surprise term υ_t as $\upsilon_t = \varepsilon_t^2 - h_t$, the $ARCH(p)$ process can be written as:

$$\varepsilon_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \upsilon_t$$

where $\alpha(L)$ is the lag polynomial defined in equation (2.13). As υ_t is a surprise term not correlated over time, the ε_t is conditionally heteroskedastic, not with respect to x_t but with respect to ε_{t-n}. The ARCH model exhibits heteroskedasticity.

In general, to ensure the conditional variance h_t is positive, ω and the coefficients in the lag polynomial $\alpha(L)$ should be positive. Since the conditional variance h_t in the $ARCH(p)$ process depends on coefficients *p*, any old shock prior to *p* periods will not affect current volatility.

2.5.2 The GARCH model

In many empirical applications of the $ARCH(p)$ model, a long lag of the variance (a relative large number of *p*) is used. Bollerslev (1986) proposed the GARCH model to circumvent this problem.

In general, the $GARCH(p,q)$ model can be written as:

$$h_t = \omega + \alpha(L)\varepsilon_{t-1}^2 + \beta(L)h_{t-1} \tag{2.21}$$

where $\alpha(L)$ and $\beta(L)$ are the lag polynomials. Similar to the ARMA model, the $GARCH(p,q)$ model can also be written as an $ARCH(\infty)$ model with geometrically declining coefficients:

$$h_t = \omega(1+\beta+\beta^2+\cdots)+\alpha(\varepsilon_{t-1}^2+\beta\varepsilon_{t-2}^2+\cdots)$$

$$h_t = \frac{\omega}{1-\beta}+\alpha\sum_{j=1}^{\infty}\beta^{j-1}\varepsilon_{t-j}^2 \tag{2.22}$$

The GARCH model states that current volatility depends more heavily on recent than older volatility shocks, as the coefficients are geometrically declining.

If a surprise term is defined as υ_t as $\upsilon_t = \varepsilon_t^2 - h_t$, the $GARCH(1,1)$ process can be written as:

$$\varepsilon_t^2 = \omega+(\alpha+\beta)\varepsilon_{t-1}^2+\upsilon_t-\beta\upsilon_{t-1} \tag{2.23}$$

The equation (2.23) follows an ARMA(1,1) process. For stationarity, the value of the AR component $\alpha+\beta$ is required to be below 1. Under stationarity, $E\{\varepsilon_{t-1}^2\} = E\{h_{t-1}^2\} = h$, the unconditional variance of ε can be written as:

$$h = \frac{\omega}{1-\alpha-\beta}$$

In many applications, the unconditional variance h is considered as long-term variance, and we can rewrite the equation (2.22) to a higher order of ARCH process:

$$h_t - h = \alpha \sum_{j=1}^{\infty} \beta^{j-1} (\varepsilon_{t-j}^2 - h)$$

Since the GARCH model is a symmetric model, the results of negative and positive impacts will be the same. Its ability to model asset price movement is questioned.

2.5.3 The asymmetric GJR-GARCH model

As suggested by Engle and Ng (1993), Glosten *et al.* (1993) GJR-GARCH(1,1) model is the best ARCH family model for capturing the asymmetric impact of bad or good news information on return volatility. The conditional variance functions of symmetric and asymmetric models are specified in the GARCH(1,1) model by equations (2.24) and (2.25) and in the GJR-GARCH(1,1) model by equations (2.24) and (2.26).

$$r_t = \mu + \epsilon_t \tag{2.24}$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \epsilon_{t-1}^2 \tag{2.25}$$

$$h_t = \alpha_0 + \alpha_1 h_{t-1} + \alpha_2 \epsilon_{t-1}^2 + \alpha_3 s^- \epsilon_{t-1}^2 \tag{2.26}$$

$$\epsilon_t \mid I_{t-1} \sim N(0, h_t)$$

where if $\epsilon_{t-1} < 0$, $s^- = 1$, else $s^- = 0$.

2.6 Multivariate ARCH Family Models

The multivariate GARCH models are represented as:

$$r_t = \epsilon_t,$$

$$\epsilon_t \mid I_{t-1} \sim N(0, H_t), \tag{2.27}$$

$$H_t = g(H_{t-1}, H_{t-2}, \cdots, \epsilon_{t-1}, \epsilon_{t-2}),$$

where r_t is a $(n \times 1)$ vector of asset returns at time t, H_t is the covariance matrix of the n asset returns at time t. The function $g(.)$ is a function of the lagged conditional covariance matrices and the covariance matrices can be modelled in a variety of ways. The BEKK model proposed by Engle and Kroner (1995) is one of the most widely used multivariate GARCH specifications. This model allows interactions among variances, but as it requires $(n(n+1)/2) + n^2(q+p)$ parameters to be estimated, the optimization process becomes extremely complex and unstable when the dimensions of the model increase.

2.6.1 The CCC model

Bollerslev (1990) suggested that the CCC model restricts the correlation coefficients to being constant while letting the conditional variances vary. The CCC model is calculated as:

$$H_t = \Sigma_t^{1/2} C \Sigma_t^{1/2} \tag{2.28}$$

where $\Sigma_t^{1/2} = diag(h_{(1,1),t}, \cdots, h_{(n,n),t})$ is a diagonal matrix with the diagonal element h_t in GARCH(p,q) specifications, and $C = [\rho_{i,j}]$ is a symmetric positive definite matrix with the diagonal element equals to one, $\rho_{i,i} = 1$, for $i = 1, \cdots, n$.

To better illustrate this, the specifications of the CCC(1,1) model in Test 1 are:

$$H_t = \begin{bmatrix} \sqrt{h_{(1,1),t}} & 0 & 0 \\ 0 & \sqrt{h_{(2,2),t}} & 0 \\ 0 & 0 & \sqrt{h_{(3,3),t}} \end{bmatrix} \begin{bmatrix} 1 & c_{1,2} & c_{1,3} \\ c_{1,2} & 1 & c_{2,3} \\ c_{1,3} & c_{2,3} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{(1,1),t}} & 0 & 0 \\ 0 & \sqrt{h_{(2,2),t}} & 0 \\ 0 & 0 & \sqrt{h_{(3,3),t}} \end{bmatrix}$$

where the conditional variance $h_{(i,i),t}$ is obtained from the univariate GARCH(p,q) model.

$$h_{(i,i),t} = \alpha_{i,0} + \sum_{j=1}^{q} \alpha_{i,j} \epsilon_{(i,i),t-j}^2 + \sum_{k=1}^{p} \beta_{i,k} h_{(i,i),t-k}$$

and the covariance is obtained by assuming that a constant correlation $\rho_{i,j}$ exists:

$$h_{(i,j),t} = \rho_{i,j} (h_{(i,i),t} h_{(j,j),t})^{1/2}$$

The number of parameters under estimation is relatively small in the CCC model, namely $(n(n-1)/2) + n(p+q+1)$.

2.6.2 The DCC model

Engle (2002) proposed the DCC model to generalize the CCC model, relaxing the constant correlation constraint that allows the correlation to vary over time. The DCC model represents a two-step estimation model. It first estimates a series of univariate GARCH models, which yields GARCH parameters and residuals; it then uses these residuals (rather than the covariance, as the CCC model does) to estimate the conditional correlation. Engle's DCC (DCC-E) model is as follows:

$$H_t = \Sigma_t^{1/2} C_t \Sigma_t^{1/2} \tag{2.29}$$

$$\Sigma_t^{1/2} = diag(h_{(1,1),t}, \cdots, h_{(n,n),t})$$

where the conditional variance $h_{(i,i),t}$ is obtained from the univariate GARCH(p,q) model, and the standardized residuals are represented as $s_{i,t} = \frac{\hat{\epsilon}_{i,t}}{\sqrt{\hat{h}_{(i,i),t}}}$.

$$h_{(i,i),t} = \alpha_{i,0} + \sum_{j=1}^{q} \alpha_{i,j} \epsilon_{(i,i),t-j}^2 + \sum_{k=1}^{p} \beta_{i,k} h_{(i,i),t-k} \tag{2.30}$$

The term C_t in equation (2.29) is time varying, which is different from term C in equation (2.28); the time-varying correlation matrix is in the form of:

$$C_t = Q_t^{*-1/2} Q_t Q_t^{*-1/2}$$

The correlation matrix Q_t is estimated by smoothing the standardized residuals as suggested by Engle:

$$Q_t = (1-\sum_{m=1}^{q*} a_m - \sum_{c=1}^{p*} b_c)\bar{Q} + \sum_{m=1}^{q*} a_m (s_{t-m}s'_{t-m}) + \sum_{c=1}^{p*} b_c Q_{t-c} \qquad (2.31)$$

where $s_t = (s_{1,t}, s_{2,t}, \cdots, s_{n,t})'$, $Q_t^{*-1/2} = diag(q_{(1,1),t}^{-1/2}), diag(q_{(2,2),t}^{-1/2}), \cdots, diag(q_{(n,n),t}^{-1/2})$, $\bar{Q}$ is unconditional covariance of the standardized residuals $E[s_{t'}s'_t]$ and $\sum_{m=1}^{q*} a_m + \sum_{c=1}^{p*} b_c < 1$.

To simplify the estimation process, we set $q* = p* = 1$ and the number of parameters under estimation is $n(p+q+1)+2$, excluding the unconditional covariance $\bar{Q}$.

2.6.3 The asymmetric generalized DCC model

Variance asymmetry is modelled by adding the GJR terms in equation (2.30) to become the GJR-DCC model. The number of parameters under estimation becomes $n(p+q+2)+2$.

Cappiello *et al.* (2006) generalized the DCC model by introducing the asymmetric generalized DCC (AGDCC) model that modified the correlation matrix Q_t in equation (2.31) to:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G) + A's_{t-1}s'_{t-1}A + G'n_{t-1}n'_{t-1}G + B'Q_{t-1}B \qquad (2.32)$$

where A, B, and G are $k \times k$ parameters matrix, n_t is the zero-threshold standardized error $n_t = I[s_t < 0] \odot s_t$, $I[*]$ is $k \times 1$ indicator function, and $\bar{N}$ is the unconditional covariance of the zero-threshold standardized errors $E[n_{t'}n'_t]$.

Correlation asymmetry is modelled by the asymmetric DCC (ADCC) model, which is a generalized version of the AGDCC model that sets the matrices G, A, and B in equation (2.32) as scalars: $G = \sqrt{g}$, $A = \sqrt{a}$, and $B = \sqrt{b}$.

Chapter 3. Volatility Spillover Effects and Interdependence Among Stock Markets

The stock market in China has experienced rapid growth and provided impressive returns in the last decade; it has received much attention from the world and started to play an important role in the international stock market. Interdependence and spillover effects among the United States and emerging markets (including China) attracted great attention from researchers, particularly in relation to the extreme market conditions of the 1997 Asian stock market crisis and the 2008 financial tsunami. During 2000 to 2015, China accounted for nearly one-third of the global growth (see Arslanalp *et al.* 2016). Chinese market has a gradually increasing influence on the global market and becomes more integrated with the rest of the world. As suggested by Li et al., 2012; Das, 2014; Arslanalp et al., 2016, the growing influences are mainly driven by trade-related and financial activity, and the financial spillovers from China to regional markets are on the rise. At the same time, the role of financial linkages in driving spillovers is found to be growing in importance. In this chapter, we examine how information spillover affects stock markets and the degree to which the influence of China's stock market has changed in the last decade.

In the literature, Eun and Shim (1989) used vector-AR developed by Sims (1980) to capture interdependence between the world's nine largest stock markets in terms of capitalization value in the year 1985, which included Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the United Kingdom, and the United States. Eun and Shim (1989) found that a substantial amount of interdependence exists among different national stock markets; most importantly, they also found that the U.S. stock market is the most influential market and that others are followers. Hamao *et al.* (1990) and Koutmos and Booth (1995) found similar results using Bollerslev (1986) GARCH process. Allen *et al.* (2013) used a tri-variate

GARCH model to study the volatility spillover among the U.S., Australian, and Chinese (proxied by the Hang Seng Index) markets and found strong evidence of changing correlations among these markets during financial crisis periods.

With the rapid growth of the China's stock market, international stock markets have been experiencing greater interaction than ever before. We study the magnitude and the nature of the change in information spillover among the United States and developed and emerging markets (including China). Unlike previous studies that identify the directions of dependency using Granger causality and a vector-AR model, we model the information spillover direction by considering the exchanges' trading hours and classifying them into three time zones. Our model suggests that information spills over different time zones in a cyclical manner, which provides more economic meaning when the empirical results are analysed. The empirical results from different multivariate GARCH models enable us to identify the spillover effects in terms of both volatility and correlation among different markets in different trading time zones.

3.1 The Data

The data used in this study consist of daily stock prices that are represented by market indices at closing time, in terms of local currency units. To study how the information spills over among the United States and developed and emerging markets (including China), nine countries (as represented by nine market indices) are used: Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil. These nine markets were selected based on their market capitalization and trading hours. Since the spillover effect is mainly driven by trade-related and financial activity (see Li et al., 2012; Das, 2014; Arslanalp et al., 2016), indices that represent the largest and the most influential companies to a country were selected. For China, we select Shanghai Stock Exchange (SHSE) instead of Shenzhen Stock Exchange (SZSE) as the companies listed in SHSE are large and more established companies, which is a better reflection from the trade-related activity among different countries. Similarly, instead of S&P500 and Nasdaq, we selected Dow Jone Index (DJI) that represents the largest and most influential companies in the U.S. We further divided the nine markets into three time zones according to their trading hours, as shown in Table 3.1 and Figure 3.1.

Zone	*m*	Country	Exchange Name	Index used	Market Capitalization (USD millions)
A	1	Japan	Tokyo Stock Exchange	NIKKEI 225 STOCK AVERAGE	4,485,449.8
	2	China	Shanghai Stock Exchange	SHANGHAI SE Composite	3,986,011.9
	3	Hong Kong	Hong Kong Stock Exchange	HANG SENG	3,324,641.4
B	4	Germany	Deutsche Börse	DAX 30 PERFORMANCE	1,761,712.8
	5	United Kingdom	London Stock Exchange	FTSE100	6,100,083.0
	6	Spain	BME Spanish Exchanges	IBEX 35	942,036.0
C	7	United States	New York Stock Exchange	DOW JONES INDUSTRIALS	19,222.875.6
	8	Canada	Toronto Stock Exchange	S&P/TSX COMPOSITE INDEX	1,938,630.3
	9	Brazil	BM&F Bovespa	IBOVESPA	823,902.7

*The data of Market Capitalization are obtained from World Federation of Exchange (WFE), Jan 2015.
#Obtained from London Stock Exchange Main Market Factsheet, Jan 2015.

Table 3.1 – Exchanges and the Respective Indices Used

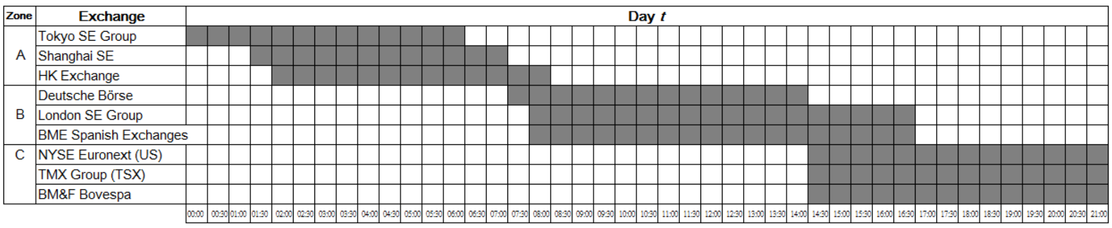


Figure 3.1 – Exchange Trading Hours in GMT

The data covers the period 1 January 2000 to 31 December 2012, excluding non-trading days in each market, a total of 3,391 observations are obtained from DataStream for each price series. All of the data are transformed in logarithmic scale and all nine series are non-stationary, as shown in Figure 3.2. We further transform the market indices to daily returns busing the formula $r_{m,t} = ln(P_{m,t} / P_{m,t-1})$, where $r_{m,t}$ denotes the return for index m at time t and $P_{m,t}$ denotes the index m value at time t. There are $n = 3,390$ observations for the nine indices' returns, as shown in Figure 3.3. The graph indicates that the returns are stationary.

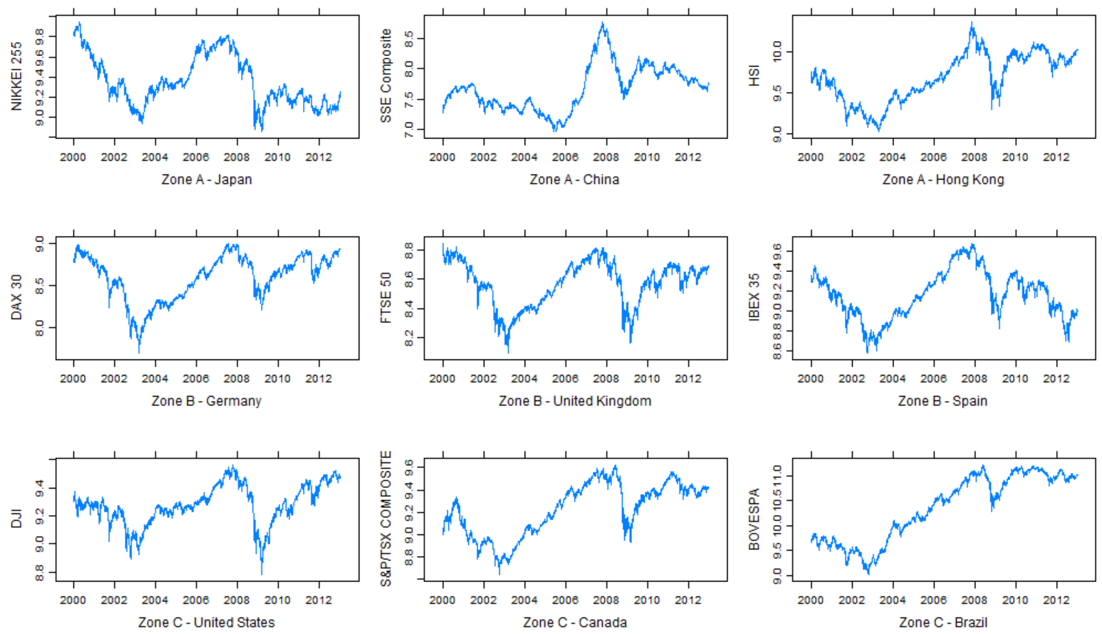


Figure 3.2 – Indices Transformed in Logarithmic Scale

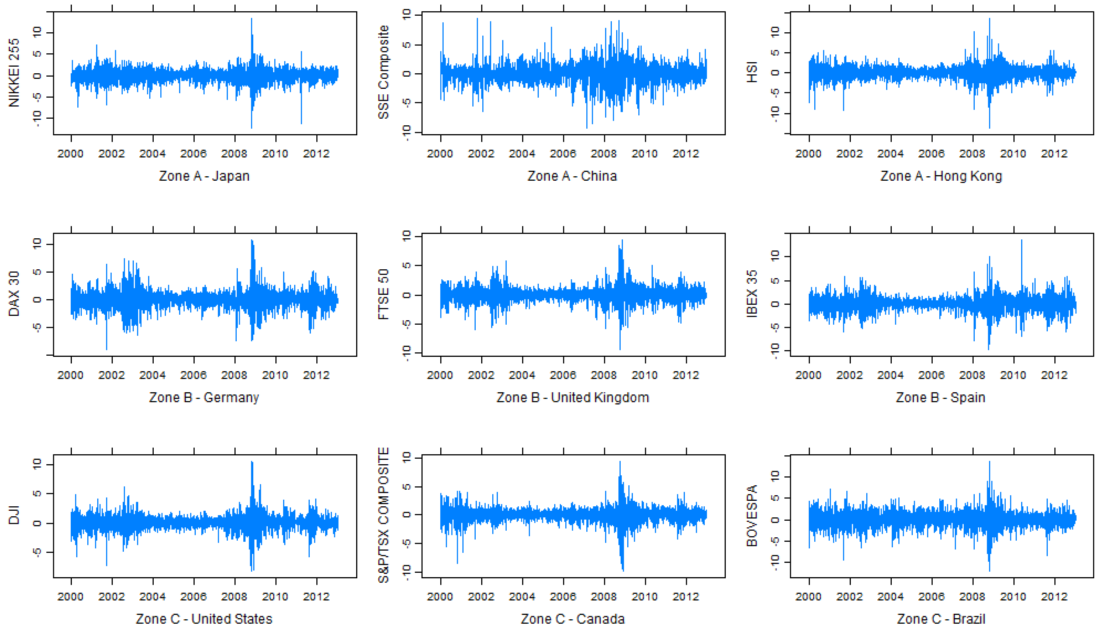


Figure 3.3 – Stock Markets Returns for Countries in Zones A, B, and C

Table 3.2 shows the descriptive statistics for the returns. The mean returns of the nine markets show no great difference, with a range from -0.0177% (Japan) to 0.0378% (Brazil), which is close to zero. Furthermore, the standard deviations of the returns are also not significantly different; the range is from 1.2067% (Canada) to 1.8588% (Brazil). Nevertheless, if we consider the variances together with the maximum and minimum returns values, the stock markets in Japan, Hong Kong, and Brazil are apparently more volatile than those in the other six countries. The minimum returns of these three stock markets are -12.1110% (Japan), -13.5820% (Hong Kong), and -12.0961% (Brazil), while their maximum returns are 13.2346% (Japan), 13.4068% (Hong Kong), and 13.6794% (Brazil). The higher levels of volatility can be explained by investor behaviour in the relevant countries, which reflects a phenomenon of individuals being highly influenced by the market atmosphere.

Ljung-Box (LB) tests run for the nine returns series reveal that no potential serial correlations exist in the first lag level (except for in U.S. and UK markets), but the LB tests for the squared returns indicate a strong and significant level of serial correlation. As a result, ARCH family volatility models are used.

	Zone A			Zone B			Zone C		
	Japan	China	Hong Kong	Germany	United Kingdom	Spain	United States	Canada	Brazil
Mean	-0.0177%	0.0145%	0.0078%	0.0035%	-0.0048%	-0.0104	0.0042%	0.0115%	0.0378%
Median	0.0000%	0.0000%	0.0000%	0.0364%	0.0000%	0.0205%	0.0112%	0.0299%	0.0000%
Maximum	13.2346%	9.3998%	13.4068%	10.7975%	9.3843%	13.4836%	10.5083%	9.3703%	13.6794%
Minimum	-12.1110%	-9.2608%	-13.5820%	-8.8747%	-9.2656%	-9.5859%	-8.2005%	-9.7880%	-12.0961%
Std. Dev.	1.5195%	1.5733%	1.5835%	1.6016%	1.2780%	1.5493%	1.2379%	1.2067%	1.8588%
Skewness	-0.4104	-0.0811	-0.0665	0.0047	-0.1434	0.1223	-0.0455	-0.6418	-0.1183
Kurtosis	7.2870	4.6610	8.0090	4.2481	5.9933	5.0783	7.7121	8.7096	4.1450
LB(1)	0.3581	0.0050	1.3339	1.2619	7.5175	0.0012	22.4274	1.2316	0.0006
	(0.5496)	(0.9437)	(0.2481)	(0.2613)	(0.0061)	(0.9720)	(0.0000)	(0.2671)	(0.9803)
LB(5)	8.6349	12.6994	3.2650	18.9197	67.9514	22.3707	35.8997	37.4697	8.3270
	(0.1245)	(0.0264)	(0.6592)	(0.0020)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.1391)
LB(10)	12.0605	19.4925	17.6809	22.8755	83.6961	31.0759	49.3298	51.3487	16.5715
	(0.2810)	(0.0344)	(0.0606)	(0.0112)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0844)
LB(20)	17.8182	45.3738	42.2095	37.4391	102.9141	50.6066	77.6954	65.7252	60.5450
	(0.5994)	(0.0010)	(0.0026)	(0.0104)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
$LB^2(1)$	99.2789	62.2146	392.9535	97.4088	182.8441	107.9072	102.5691	300.1172	74.4446
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LB^2(5)$	1629.8394	228.8236	1382.1450	959.5099	1468.4803	706.0515	1176.5448	1214.7329	972.7194
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

$LB^2(10)$	2836.1986	414.5513	2062.0492	1751.6265	2376.9488	1172.9548	2305.1072	2683.8647	1912.4325
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LB^2(20)$	3779.4337	633.2438	3047.4543	2981.8039	3750.7619	1791.7683	4082.4519	4584.1648	3154.4209
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

*Numbers in parentheses in LB(n) statistics are at a significant level to reject the null hypothesis of no autocorrelation existing in n lag.

Table 3.2 – Summary Statistic for Stock Market Daily Returns

3.2 Testing for Structural Breaks

The assumption of stationarity implies that the parameters in the statistics model are constant over time, while structural change indicates that at least one of the parameters in the model changed at some date (i.e. break date) in the sample period. As any structural break in our sample data may lead to incorrect results in the volatility spillover test, we may consider dividing the samples into different subsamples if strong evidence of potential structure breaks are found.

The model used in the structural break test for the nine stock markets is as follows:

$$r_{m,t} = \mu_m + \epsilon_{m,t}, \quad \epsilon_{m,t} \sim i.i.d(0, \sigma_{m,t}^2) \tag{3.1}$$

where $r_{m,t}$ is the stocks return for market m at time t, and μ_m is the mean return of stocks in the market m in the whole sample period. The idea of the structural break test is based on difference between the pre- and post-break date mean stock returns if a break present. If equation (3.1) is rewritten to include a dummy variable $D_{m,t}$, it becomes:

$$r_{m,t} = \mu_m + \mu_m^{+} D_{m,t} + \epsilon_{m,t} \tag{3.2}$$

$$D_{m,t} = 0 \text{ for } t < t_{break}; D_{m,t} = 1 \text{ for } t >= t_{break}$$

where t_{break} is the structural break date. Equation (3.2) states the mean return in market m is μ_m before the structural break date, while it is $\mu_m + \mu_m^{+}$ after. If the structural break dates are known prior to the test, we can split the sample into two sets, estimate the two sets of parameters, and test their equality using the classical Chow (1960) test. The problem is that we never know when the market has experienced structural change; the structural break test for unknown timing is preferred in this study. Andrews (1993) and Andrews and Ploberger (1994) extended Quandt (1960) idea and proposed a solution for unknown break dates that entailed aggregating a series of *F* statistics into test statistics. In doing so they provided tables of critical values for asymptotic distributions. Equations (3.3), (3.4), and (3.5) are the test statistics suggested by Andrews. Hansen (1995) examined Andrews' work and provided a method to calculate the *p*-values. As suggested in the Quandt-Andrews test, we based our work on the *supF* statistic and trimmed both the first and last 15% of observations for the structural break test. The *F* statistics F_i for observations between $\underline{i} = floor(0.15n)$ and $\bar{i} = ceil(0.85n)$ are computed. The Andrews 5% critical value is 8.85, as there is only one parameter to test in equation (3.1). Results of the structural break tests are shown in Table 3.3 and Figure 3.4. We failed to reject the null hypothesis of no structural break in the returns of the sample period. Together with a desire for simplicity, this led us to not dividing our data into different subsamples in the remaining tests.

$$supF = \sup_{\underline{i} \le i \le \bar{i}} F_i \tag{3.3}$$

$$aveF = \frac{1}{\bar{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} F_i \tag{3.4}$$

$$expF = log\left(\frac{1}{\bar{i} + \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} exp(0.5F_i) \right) \tag{3.5}$$

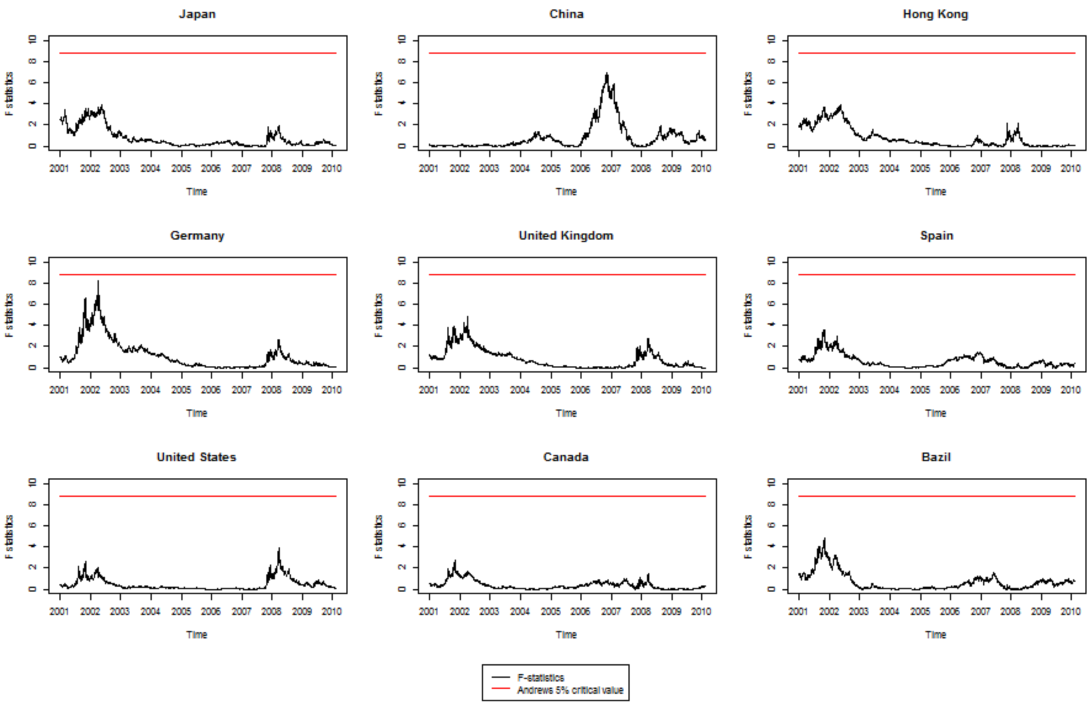


Figure 3.4 – Quandt-Andrews Structural Break Test (supF) for the Nine Stock Markets' Returns

Zone	*m*	Country	*supF*	*aveF*	*expF*
A	1	Japan	3.8737 (0.3943)	0.7457 (0.4702)	0.5098 (0.4332)
	2	China	7.0111 (0.1030)	0.8453 (0.4144)	0.8097 (0.2627)
	3	Hong Kong	3.9004 (0.3901)	0.7821 (0.4488)	0.5356 (0.4138)
B	4	Germany	8.2203 (0.0597)	1.1502 (0.2850)	0.9697 (0.2057)
	5	United Kingdom	4.8712 (0.2613)	0.8036 (0.4368)	0.5342 (0.4149)
	6	Spain	3.5867 (0.4421)	0.6118 (0.5587)	0.3680 (0.5629)
C	7	United States	3.9491 (0.3825)	0.4543 (0.6854)	0.2776 (0.6736)
	8	Canada	2.7099 (0.6167)	0.3818 (0.7525)	0.2163 (0.7673)
	9	Brazil	4.8642 (0.2621)	0.6984 (0.4996)	0.4810 (0.4561)

*Numbers in parentheses are the p-values of 5% significant level to reject the null hypothesis of no structural break in the sample period.

Table 3.3 – Quandt-Andrews Structural Break Test

3.3 Univariate Models

In Table 3.2, stock returns show significant nonlinear serial dependencies in volatility levels, which we captured by using both symmetric and asymmetric GARCH models. As suggested by Engle and Ng (1993), the Glosten *et al.* (1993) GJR-GARCH(1,1) model is the best ARCH family model for capturing the asymmetric impacts of bad or good news information on return volatility. The conditional variance functions of symmetric and asymmetric models are specified in the GARCH(1,1) model by equations (3.6) and (3.7) and in the GJR-GARCH(1,1) model by equations (3.6) and (3.8).

$$r_{m,t} = \mu_m + \epsilon_{m,t} \tag{3.6}$$

$$h_{m,t} = \alpha_{m,0} + \alpha_{m,1}\epsilon^2_{m,t-1} + \beta_{m,1}h_{m,t-1} \tag{3.7}$$

$$h_{m,t} = \alpha_{m,0} + \alpha_{m,1}\epsilon^2_{m,t-1} + \beta_{m,1}h_{m,t-1} + \gamma_{m,1}s^-_m\epsilon^2_{m,t-1} \tag{3.8}$$

$$\epsilon_{m,t} \mid I_{m,t-1} \sim N(0, h_{m,t})$$

where if $\epsilon_{m,t-1} < 0$, $s^-_m = 1$, else $s^-_m = 0$. Table 3.4 shows the results of the tests that used the GARCH(1,1) and GJR-GARCH(1,1) models. The mean returns of all nine markets are not significantly different statistically from zero in any of the asymmetric models. Nevertheless, even if some of the coefficients μ are statistically significant in symmetric model, the magnitudes are too small to be considered deviational from zero.

The conditional variances h_t for the nine markets follow stationary processes with the coefficients $\alpha_1 + \beta_1 < 1$ in symmetric models and $\alpha_1 + \beta_1 + \frac{\gamma_1}{2} < 1$ in asymmetric models.

In relation to the asymmetric impact of bad news on return volatility, the coefficients γ_1 are all significantly positive, which implies that bad news contributes to a further increase in return volatility. Among the nine markets, those in Zones B and C (namely Germany, the United Kingdom, Spain, the United States, Canada, and Brazil) strongly indicate that only bad news contributes to volatility (with a highly significant coefficient γ_1), while the coefficient α_1 is not statistically different from zero.

To compare whether asymmetric models are better for describing stock market volatility, we perform several likelihood-ratio (LR) tests.

3.4 LR Tests

In LR tests, the asymmetric model is considered the unrestricted model while the symmetric model is considered the restricted model. The result *LR* in the equation (3.9) follows the χ^2 -distribution with k degrees of freedom (DF), where k is the number of restrictions in the restricted model and can be calculated by subtracting the number of DF in the unrestricted model from the number of DF in the restricted model. If the null hypothesis is rejected, we reject the hypothesis that the restricted model is preferable to the unrestricted model.

$$LR = -2 * ln(\frac{L_0}{L_1}) = -2(lnL_0 - lnL_1) \tag{3.9}$$

L_0 : Value of the likelihood function of the restricted model
L_1 : Value of the likelihood function of the unrestricted model

Table 3.5 shows the results of the LR tests. The rejection of the null hypothesis implies that the symmetric models are not good simplifications of the asymmetric models. Asymmetric models are thus better to use for explaining volatility movement in different stock markets: bad news yesterday will induce intense reactions from investors.

	Japan		China		Hong Kong		Germany		United Kingdom		Spain		United States		Canada		Brazil	
Model	S	A	S	A	S	A	S	A	S	A	S	A	S	A	S	A	S	A
μ	0.0364	0.0031	0.0163	0.0020	**0.0488**	0.0225	**0.0703**	0.0190	**0.0365**	-0.0027	**0.0587**	0.0132	**0.0436**	0.0055	**0.0497**	0.0242	**0.0771**	0.0328
	(1.7749)	(0.0222)	(0.7233)	(0.1470)	**(2.5710)****	(0.7235)	**(3.7764)***	(1.2399)	**(2.4859)****	-(0.1839)	**(3.2114)***	(0.1511)	**(3.1160)***	(0.3928)	**(3.4536)***	(1.7710)	**(2.8822)***	(1.4205)
α_0	**0.0369**	**0.0471**	**0.0262**	**0.0273**	**0.0129**	**0.0199**	**0.0224**	**0.0253**	**0.0124**	**0.0155**	**0.0191**	**0.0184**	**0.0133**	**0.0135**	**0.0093**	**0.0135**	**0.0634**	**0.0743**
	(4.2608)*	**(11.8668)***	**(4.4435)***	**(4.5584)***	**(3.4026)***	**(4.8891)***	**(4.2884)***	**(5.8082)***	**(3.8068)***	**(5.5089)***	**(4.3701)***	**(5.2816)***	**(5.1144)***	**(6.0206)***	**(3.6927)***	**(5.4519)***	**(4.1181)***	**(4.5756)***
α_1	**0.0945**	**0.0266**	**0.0600**	**0.0430**	**0.0630**	**0.0184**	**0.0951**	0.0000	**0.1056**	0.0000	**0.0996**	0.0000	**0.0841**	0.0000	**0.0721**	0.0045	**0.0678**	0.0069
	(9.9618) *	**(4.9771)***	**(8.8460)***	**(6.1712)***	**(9.4528)***	**(3.0469)***	**(10.1175)***	(0.0000)	**(9.8096)***	(0.0000)	**(9.8784)***	(0.0000)	**(10.4798)***	(0.0000)	**(9.0142)***	(0.5263)	**(7.9351)***	(0.8996)
β_1	**0.8908**	**0.8918**	**0.9302**	**0.9306**	**0.9315**	**0.9318**	**0.8968**	**0.9103**	**0.8889**	**0.9098**	**0.8955**	**0.9218**	**0.9069**	**0.9175**	**0.9207**	**0.9275**	**0.9124**	**0.9174**
	(85.4826) *	**(95.1606)***	**(124.6769)***	**(127.4501)***	**(133.7461)***	**(135.9343)***	**(94.2699)***	**(96.0056)***	**(83.7733)***	**(71.0185)***	**(90.6319)***	**(43.8363)***	**(111.7689)***	**(98.0821)***	**(108.0168)***	**(106.3564)***	**(81.0248)***	**(76.1072)***
γ_1		**0.1155**		**0.0314**		**0.0766**		**0.1528**		**0.1543**		**0.1362**		**0.1428**		**0.1027**		**0.1010**
		(11.5774)*		**(3.6016)***		**(6.8457)***		**(9.5281)***		**(9.4772)***		**(8.2222)***		**(9.7527)***		**(7.3416)***		**(6.6291)***
$\alpha_1 + \beta_1$	0.9853		0.9902		0.9945		0.9919		0.9945		0.9951		0.9909		0.9928		0.9801	
$\alpha_1 + \beta_1 + \frac{\gamma_1}{2}$		(0.9762)		(0.9892)		(0.9885)		(0.9867)		(0.9869)		(0.9899)		(0.9888)		(0.9833)		(0.9748)
Log likelihood	-5784.0024	-5749.9375	-5988.4510	-5981.7557	-5722.3690	-5693.4175	-5761.6230	-5689.5072	-4913.8293	-4846.3870	-5699.7665	-5628.7805	-4797.4739	-4722.0744	-4677.6119	-4645.4326	-6585.3604	-6547.9959
AIC	3.4148	3.3952	3.5354	3.5320	3.3784	3.3619	3.4015	3.3596	2.9014	2.8622	3.3651	3.3238	2.8327	2.7888	2.7620	2.7436	3.8875	3.8661
BIC	3.4220	3.4043	3.5426	3.5410	3.3856	3.3709	3.4088	3.3686	2.9086	2.8712	3.3723	3.3328	2.8400	2.7979	2.7692	2.7527	3.8948	3.8751
SIC	3.4147	3.3952	3.5354	3.5320	3.3784	3.3619	3.4015	3.3596	2.9014	2.8622	3.3651	3.3238	2.8327	2.7888	2.7620	2.7436	3.8875	3.8661
HQIC	3.4173	3.3985	3.5380	3.5352	3.3810	3.3651	3.4041	3.3628	2.9040	2.8654	3.3676	3.3270	2.8353	2.7921	2.7646	2.7468	3.8901	3.8693
LB(1)	0.9533	0.7515	9.8470	10.3294	4.1060	5.7063	7.7960	8.2723	12.5940	12.9652	4.1583	3.9597	9.1543	8.1339	9.6381	8.4672	2.3469	3.2669
	[0.9662]	[0.9800]	[0.0797]	[0.0664]	[0.5343]	[0.3359]	[0.1678]	[0.1419]	[0.0275]	[0.0237]	[0.5269]	[0.5552]	[0.1031]	[0.1490]	[0.0862]	[0.1323]	[0.7994]	[0.6589]
LB(5)	4.9480	5.2785	27.6614	28.5904	11.3767	12.3164	10.2615	11.4942	13.1821	13.9661	9.2959	8.1496	11.7045	10.8035	13.2334	13.0430	10.2601	11.1554

	[0.8946]	[0.8718]	[0.0020]	[0.0015]	[0.3289]	[0.2644]	[0.4179]	[0.3203]	[0.2137]	[0.1745]	[0.5043]	[0.6142]	[0.3053]	[0.3730]	[0.2109]	[0.2213]	[0.4180]	[0.3455]
LB(10)	9.0059	10.7020	47.5215	49.2868	32.1198	31.4548	17.6271	21.1896	28.2254	30.3163	22.0061	21.6968	27.5763	26.4281	17.9838	18.0265	31.4926	32.0595
	[0.9828]	[0.9536]	[0.0005]	[0.0003]	[0.0420]	[0.0495]	[0.6120]	[0.3860]	[0.1042]	[0.0649]	[0.3402]	[0.3572]	[0.1198]	[0.1521]	[0.5885]	[0.5857]	[0.0490]	[0.0427]
LB(20)	0.0716	5.6130	0.0917	0.0509	4.2815	9.8910	6.0064	20.8006	1.8237	7.9681	2.7055	4.3549	6.9273	10.7592	1.3684	3.9886	1.5076	7.9614
	[0.7891]	[0.0178]	[0.7620]	[0.8215]	[0.0385]	[0.0017]	[0.0143]	[0.0000]	[0.1769]	[0.0048]	[0.1000]	[0.0369]	[0.0085]	[0.0010]	[0.2421]	[0.0458]	[0.2195]	[0.0048]
LB^2(1)	2.4718	6.1498	0.9204	0.6629	10.7384	17.5153	14.7679	20.9425	7.1794	8.3220	35.7877	21.4669	9.0650	12.9528	3.7111	4.3603	13.8931	13.1244
	[0.7807]	[0.2919]	[0.9687]	[0.9849]	[0.0568]	[0.0036]	[0.0114]	[0.0008]	[0.2076]	[0.1394]	[0.0000]	[0.0007]	[0.1065]	[0.0238]	[0.5917]	[0.4988]	[0.0163]	[0.0222]
LB^2(5)	6.5394	10.7231	2.0136	2.1186	15.6641	27.1129	15.4591	22.4371	10.1866	11.8375	37.4361	24.2435	17.3704	19.0893	9.5859	8.8521	20.9713	24.5172
	[0.7681]	[0.3795]	[0.9962]	[0.9953]	[0.1097]	[0.0025]	[0.1162]	[0.0130]	[0.4243]	[0.2961]	[0.0000]	[0.0070]	[0.0666]	[0.0391]	[0.4775]	[0.5462]	[0.0213]	[0.0063]
LB^2(10)	16.0039	19.3773	11.0291	9.1322	24.8382	37.0480	31.0076	36.7496	31.5829	31.9697	54.2906	45.0684	21.0435	25.2022	18.0694	14.9630	27.9450	29.9877
	[0.7164]	[0.4974]	[0.9455]	[0.9813]	[0.2077]	[0.0115]	[0.0551]	[0.0125]	[0.0480]	[0.0436]	[0.0001]	[0.0011]	[0.3946]	[0.1938]	[0.5828]	[0.7785]	[0.1107]	[0.0701]
LB^2(20)	14.6003	18.8467	12.5942	10.6848	25.3504	37.6047	32.0645	37.6463	31.8796	31.3572	51.4003	40.2149	20.9247	23.8836	18.3399	15.2931	24.6212	25.2561
	[0.7476]	[0.4667]	[0.8587]	[0.9340]	[0.1493]	[0.0067]	[0.0307]	[0.0066]	[0.0322]	[0.0369]	[0.0001]	[0.0031]	[0.3410]	[0.2007]	[0.4998]	[0.7038]	[0.1734]	[0.1523]

* Significance at 1% level, ** Significance at 5% level

Numbers in parentheses are *t*-statistics, numbers in square brackets of LB(*n*) tests are significant level to reject the null hypothesis of autocorrelation not exists in *n* lag.

Model S: GARCH(1,1)

Model A: GJR-GARCH(1,1)

Table 3.4 – GARCH(1,1) and GJR-GARCH(1,1) Model Results

	Test statistic D	χ^2 p-value
Japan	68.1298	0.0000%
China	13.3907	0.0025%
Hong Kong	57.9031	0.0000%
Germany	144.2317	0.0000%
United Kingdom	134.8846	0.0000%
Spain	141.9720	0.0000%
United States	150.7990	0.0000%
Canada	64.3586	0.0000%
Brazil	74.7291	0.0000%

Table 3.5 – LR Tests Results of the Unrestricted Model (Asymmetric Model) and Restricted Model (Symmetric Model)

3.5 Testing the Spillover Effect

Table 3.6 shows the unconditional correlations among the nine stock markets' returns. These results indicate that the unconditional correlations between different markets are relatively higher within each zone, especially in European markets (i.e. Zone B). One possible explanation is that exchanges within the same zone exhibit some degrees of interdependence as the markets trade at the same time. Surprisingly, China's market, which has drawn much attention from the world in the last decade, shows a weak correlation with the countries outside its zone. Similar results are also seen in relation to the Japanese market. Intuitively, the poor results are due to the negligent trading hour differences, which are shown in Figure 3.1. Furthermore, the information spillover directions are not being considered. To address these issues, we modelled and incorporated the following cyclical spillover directions among different time zones (depicted in Figure 3.5): Zone A to Zone B, Zone B to Zone C, and Zone C to Zone A.

Zone		A			B			C		
		Japan	China	HK	Germany	UK	Spain	US	Canada	Brazil
A	Japan	100.00%								
	China	20.53%	100.00%							
	HK	58.06%	34.38%	100.00%						
B	Germany	25.46%	8.67%	33.02%	100.00%					
	UK	29.20%	9.42%	36.88%	81.16%	100.00%				
	Spain	26.08%	8.12%	33.02%	79.27%	79.19%	100.00%			
C	US	12.07%	3.98%	18.62%	59.84%	52.25%	50.05%	100.00%		
	Canada	21.24%	8.44%	26.79%	53.71%	53.32%	48.42%	65.87%	100.00%	
	Brazil	15.87%	11.57%	26.76%	48.87%	47.78%	44.72%	58.52%	58.34%	100.00%

Table 3.6 – Unconditional Correlation Among the Nine Stocks Markets' Returns

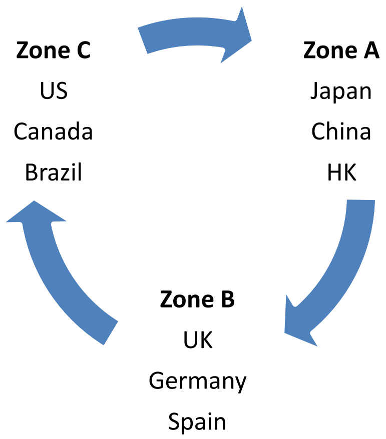


Figure 3.5 – Information Spillover Among Different Markets by Time Zone

In order to test the potential information spillover effects, we carry out nine volatility and correlation spillover tests using different multivariate GARCH models, as shown in Table 3.7.

	From			To			Dimensions of the Multivariate Model
Test	Zone	Trading Day	Countries	Zone	Trading Day	Country	
AB1	A	t	Japan, China, and HK	B	t	Germany	n = 4
AB2		t			t	UK	
AB3		t			t	Spain	
BC1	B	t	Germany, UK, and Spain	C	t	US	n = 4
BC2		t			t	Canada	
BC3		t			t	Brazil	
CA1	C	t	US, Canada, and Brazil	A	t+1	Japan	n = 4
CA2		t			t+1	China	
CA3		t			t+1	Hong Kong	

Table 3.7 – The Nine Tests for Information Spillover Effects Among Different Time Zones

3.6 Multivariate Models

The multivariate GARCH models used in this study are represented as:

$$r_t = \epsilon_t,$$

$$\epsilon_t \mid I_{t-1} \sim N(0, H_t), \tag{3.10}$$

$$H_t = g(H_{t-1}, H_{t-2}, \cdots, \epsilon_{t-1}, \epsilon_{t-2}),$$

where r_t is a $(n \times 1)$ vector of the returns of the night markets $r_t = [r_{1,t}, r_{2,t}, \cdots, r_{9,t}]'$ at time t. The function $g(.)$ is a function of the lagged conditional covariance matrices. Covariance matrices can be modelled in a variety of ways. Engle and Kroner (1995) proposed the BEKK model, which allows for interactions among the variances in the multivariate model and is capable of modelling volatility spillover among different returns series. However, its major weaknesses are that the $(n(n+1)/2)+n^2(q+p)$ parameters must be estimated and that the optimization process is extremely complex and unstable when the model's dimensions increase. If the BEKK(1,1) model were to be used in this study (n = 4), 42 parameters would need to be estimated. Parsimonious multivariate GARCH models such as Bollerslev (1990) CCC model, Engle (2002) DCC model, and Cappiello *et al.* (2006) ADCC are thus used in this study instead.

3.7 Comparison of Different Multivariate Models that Incorporate the Information Spillover Effect

The multivariate GARCH models described in the previous section are used to test the potential information spillover effect. Evidence of information spillover will be provided if we discover (1) volatility spillover in the cyclical direction that we have shown in Figure 3.5 and (2) significant correlation among the nine stock markets. To ascertain volatility spillover, we compare the results from different models.

Table 3.8 shows the estimated results of the multivariate models. The models we test are CCC(1,1), GARCH(1,1)-DCC(1,1), GARCH(1,1)-DCC(2,2), GARCH(2,2)-DCC(1,1), GARCH(2,2)-DCC(2,2), GJR-GARCH(1,1)-DCC(1,1), GJR-GARCH(1,1)-DCC(2,2), GJR-GARCH(2,2)-DCC(1,1), GJR-GARCH(2,2)-DCC(2,2), GARCH(1,1)-ADCC(1,1), GARCH(1,1)-ADCC(2,2), GARCH(2,2)-ADCC(1,1), GARCH(2,2)-ADCC(2,2), GJR-GARCH(1,1)-ADCC(1,1), GJR-GARCH(1,1)-ADCC(2,2), GJR-GARCH(2,2)-ADCC (1,1), and GJR-GARCH(2,2)-ADCC(2,2). Among the models, Table 3.8 shows the CCC model has the highest information criterion, which is the least preferred.Table 3.8(a) shows all the AIC value of the CCC model in the nine tests are are the highest among all models. In the tests AB1, AB2, AB3, BC1, BC2, BC3, CA1, CA2, and CA3, CCC model has the highest AIC values of 13.1616, 12.6458, 13.1394, 9.8578, 9.8198, 11.0480, 11.6603, 11.9994, and 11.6138 respectively. Similarly, CCC model has the highest BIC, SIC, and HQIC among all the models in all the tests, the CCC model is least preferred. In contrast, GJR-GARCH(1,1)-DCC(1,1) has the lowest BIC values among all the volatility models in all the nine tests, with the value of 13.0967, 12.5833, 13.0698, 9.5993, 9.6238, 10.8496, 11.5146, 11.8852, and 11.4891 in the test AB1, AB2, AB3, BC1, BC2, BC3, CA1, CA2, and CA3 respectively. Meanwhile, the SIC and HQIC show preference on GJR-GARCH(1,1)-DCC(1,1) and GJR-GARCH(1,1)-DCC(2,2) model, Table 3.8(d) shows GJR-GARCH(1,1)-DCC(2,2) model has the lowest SIC in the tests of AB1, BC2, BC3, CA1, CA2, and CA3, while its AIC, BIC, and HQIC value are only slightly higher the others. In summary, the AIC, BIC, SIC, and HQIC show preference on asymmetric volatility models; the GJR-GARCH(1,1)-DCC(1,1) and GJR-GARCH(1,1)-DCC(2,2) models are the most preferred. The results lead us to posit the following: (1) Correlations among different stock markets are time-varying, as the CCC model (which assumes that the correlations are constant over time) is not preferred; (2) volatility spills over different stock markets, and DCC models that allow interaction between volatilities are preferred over the CCC model; (3) asymmetric impacts on volatility from bad or good news are significant, as the results favour asymmetric volatility models; and (4) asymmetric impacts on correlation are not significant in stock markets: a drop in one stock market does not increase the correlations among other markets (which may be due to stock markets consistently exhibiting positive correlation over time). To confirm these intuitions, the LR tests in Table 3.9 are performed to determine whether they are statistically significant.

Test A in Table 3.9 compares the CCC and DCC models. It rejects the CCC model as a simplified version of the DCC model in all of the markets that are in different time zones. This test suggests that the assumption that stock returns among different markets are constantly correlated is not suitable when modelling the interaction among different markets.

Furthermore, it reveals volatility spillovers among different stock markets in the cyclical direction that we showed in Figure 3.5.

Evidence that bad and good news delivers asymmetric impacts on volatility can be found in the results of tests B and C in Table 3.9. These tests compare the symmetric and asymmetric volatility versions of the DCC and ADCC models by adding the GJR term in the volatility equations. The hypothesis that symmetric restricted models are better than unrestricted asymmetric models was strongly rejected. The volatility asymmetry should be considered when modelling the interactions between international stock markets. Both bad and good news shock the stock markets to different extents, and the volatility level is higher when the market is in a downswing. This is commonly explained by factors related to leveraging and the psychological behaviour of investors.

In addition to the characteristic of volatility asymmetry in international stock markets, we also study asymmetric correlations concerning how the correlations vary according to the good or bad news. Correlations between different markets are expected to be higher when stock returns are negative, especially during crisis periods (when the correlations converge to one). The heightened interaction between different markets may be induced by the liquidity needs and psychological behaviour of investors. Tests D and E in Table 3.9, which are LR tests, examine the asymmetric impacts on international markets correlations. The results of test D suggest that adding an asymmetric component when modelling the correlation provides no benefit. However, when we consider asymmetric correlation together with asymmetric volatility in test E, some asymmetric terms in conditional correlation become significant. We cannot draw any conclusion about the asymmetric correlation effect in the likelihood tests. Strong evidence that a drop in stock markets will intensify correlations among different markets does not exist.

The LR tests (namely F-I, J-M, N-Q, and R-U) compare multivariate models with lower order terms to those with higher order terms. Almost all of the models prefer the lower order terms, with the exception of the GJR-GARCH-ADCC model; furthermore, groups 4, 5, 6, and 7 in test S reject the lower order terms models at a 5% significance level.

Aggregating the results from the LR tests in Table 3.9, we preliminarily select the GJR-GARCH(1,1)-DCC(1,1) model for tests AB1, AB2, and AB3; the GJR-GARCH(1,1)-ADCC(2,2) model for tests BC1, BC2, BC3, and CA1; and the GJR-GARCH(1,1)-ADCC(1,1) model for tests CA2 and CA3. Table 3.10 shows the estimated results of the different models.

The estimated parameters of the different models that are suggested by the LR tests are not promising. In Table 3.10, the parameters dcc_{a1}, dcc_{b1}, and dcc_{b2} and all of the asymmetric correlation parameters dcc_{g1} are insignificant. The higher order DCC model (DCC(2,2) model) and the ADCC model are both inadequate for describing the interactions among different stock markets. Instead of using the higher order DCC model, we thus exanimate the parsimony GJR-GARCH(1,1)-DCC(1,1) model. In contrast to the results in Table 3.10, the estimated DCC parameters in Table 3.11 are all highly significant. The LB tests reject that autocorrelation exists in the standardized residuals, and the GJR-GARCH(1,1)-DCC(1,1) model is found to be adequate for describing the interaction between different markets. As a result, we adopt the GJR-GARCH(1,1)-DCC(1,1) model.

	Test Details	CCC(1,1)						GARCH(1,1)-DCC(1,1)						GARCH(2,2)-DCC(1,1)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22290.8502	18	13.1616	13.1941	13.1615	13.1732	-22218.8924	20	13.1203	13.1564	13.1202	13.1332	-22199.6600	28	13.1137	13.1643	13.1135	13.1318
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21416.6362	18	12.6458	12.6783	12.6457	12.6574	-21342.7739	20	12.6034	12.6396	12.6033	12.6163	-21333.1146	28	12.6024	12.6530	12.6023	12.6205
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22253.3626	18	13.1394	13.1720	13.1394	13.1511	-22177.6692	20	13.0960	13.1321	13.0959	13.1089	-22166.8135	28	13.0943	13.1449	13.0942	13.1124
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16690.9832	18	9.8578	9.8903	9.8578	9.8694	-16373.0399	20	9.6714	9.7076	9.6713	9.6843	-16403.8985	28	9.6943	9.7450	9.6942	9.7124
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16626.6229	18	9.8198	9.8524	9.8198	9.8315	-16340.4353	20	9.6522	9.6883	9.6521	9.6651	-16372.6170	28	9.6759	9.7265	9.6757	9.6940
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18708.2936	18	11.0480	11.0805	11.0479	11.0596	-18429.0875	20	10.8844	10.9206	10.8843	10.8973	-18459.2537	28	10.9069	10.9576	10.9068	10.9250
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19746.1925	18	11.6603	11.6928	11.6602	11.6719	-19565.9351	20	11.5585	11.5947	11.5585	11.5715	-19570.8172	28	11.5661	11.6168	11.5660	11.5842
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20321.0572	18	11.9994	12.0320	11.9994	12.0111	-20166.5786	20	11.9130	11.9492	11.9129	11.9259	-20166.1125	28	11.9174	11.9681	11.9173	11.9355
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19667.4162	18	11.6138	11.6464	11.6138	11.6254	-19514.7412	20	11.5283	11.5645	11.5283	11.5413	-19514.0849	28	11.5327	11.5833	11.5325	11.5508

Table 3.8 (a) – Comparison of the CCC(1,1), GARCH(1,1)-DCC(1,1), and GARCH(2,2)-DCC(1,1) Models

	Test Details	GARCH(1,1)-DCC(2,2)						GARCH(2,2)-DCC(2,2)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22216.4441	22	13.1200	13.1598	13.1199	13.1342	-22197.7184	30	13.1137	13.1679	13.1135	13.1331
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21341.5544	22	12.6039	12.6436	12.6038	12.6181	-21332.2488	30	12.6031	12.6573	12.6029	12.6225
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22177.2803	22	13.0969	13.1367	13.0968	13.1111	-22166.6193	30	13.0954	13.1496	13.0952	13.1147
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16368.6856	22	9.6700	9.7098	9.6699	9.6842	-16403.7065	30	9.6954	9.7496	9.6952	9.7148
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16333.6381	22	9.6493	9.6891	9.6493	9.6636	-16370.6629	30	9.6759	9.7301	9.6758	9.6953
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18422.3533	22	10.8816	10.9214	10.8815	10.8958	-18458.1240	30	10.9074	10.9617	10.9073	10.9268
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19561.5598	22	11.5571	11.5969	11.5570	11.5714	-19569.5366	30	11.5666	11.6208	11.5664	11.5860
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20164.5571	22	11.9130	11.9528	11.9129	11.9272	-20165.5916	30	11.9183	11.9726	11.9182	11.9377
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19512.8895	22	11.5284	11.5682	11.5283	11.5426	-19514.1552	30	11.5339	11.5881	11.5337	11.5533

Table 3.8 (b) – Comparison of the GARCH(1,1)-DCC(2,2) and GARCH(2,2)-DCC(2,2) Models

	Test Details	GJR-GARCH(1,1)-DCC(1,1)						GJR-GARCH(2,2)-DCC(1,1)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22101.3184	24	13.0533	13.0967	13.0532	13.0688	-22083.9914	36	13.0501	13.1152	13.0499	13.0734
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21231.2138	24	12.5399	12.5833	12.5398	12.5555	-21214.0946	36	12.5369	12.6020	12.5367	12.5602
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22055.8152	24	13.0264	13.0698	13.0263	13.0419	-22039.0726	36	13.0236	13.0887	13.0234	13.0469
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16173.2874	24	9.5559	9.5993	9.5558	9.5714	-16178.7891	36	9.5662	9.6313	9.5660	9.5895
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16214.8553	24	9.5804	9.6238	9.5803	9.5960	-16218.1994	36	9.5895	9.6546	9.5893	9.6128
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18292.5504	24	10.8062	10.8496	10.8061	10.8217	-18292.4476	36	10.8132	10.8783	10.8130	10.8365
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19413.9689	24	11.4712	11.5146	11.4711	11.4867	-19405.8923	36	11.4735	11.5386	11.4733	11.4968
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20041.9452	24	11.8418	11.8852	11.8417	11.8573	-20035.8925	36	11.8453	11.9104	11.8451	11.8686
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19370.7957	24	11.4457	11.4891	11.4456	11.4612	-19363.1773	36	11.4483	11.5134	11.4481	11.4716

Table 3.8 (c) – Comparison of the GJR-GARCH(1,1)-DCC(1,1) and GJR-GARCH(2,2)-DCC(1,1) Models

	Test Details	GJR-GARCH(1,1)-DCC(2,2)						GJR-GARCH(2,2)-DCC(2,2)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22098.9771	26	13.0531	13.1001	13.0530	13.0699	-22081.6640	38	13.0499	13.1186	13.0497	13.0745
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21230.0467	26	12.5404	12.5874	12.5403	12.5572	-21212.9747	38	12.5374	12.6061	12.5372	12.5620
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22055.3976	26	13.0274	13.0744	13.0273	13.0442	-22038.6542	38	13.0246	13.0933	13.0243	13.0491
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16168.0781	26	9.5540	9.6010	9.5539	9.5708	-16175.7830	38	9.5657	9.6344	9.5654	9.5902
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16207.7608	26	9.5774	9.6244	9.5773	9.5942	-16212.9612	38	9.5876	9.6563	9.5873	9.6121
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18287.2564	26	10.8043	10.8513	10.8042	10.8211	-18289.1975	38	10.8125	10.8812	10.8123	10.8371
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19409.9114	26	11.4700	11.5170	11.4699	11.4868	-19403.3513	38	11.4732	11.5419	11.4730	11.4978
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20039.3536	26	11.8415	11.8885	11.8413	11.8583	-20034.3437	38	11.8456	11.9143	11.8453	11.8701
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19368.5778	26	11.4456	11.4926	11.4455	11.4624	-19362.1633	38	11.4489	11.5176	11.4487	11.4735

Table 3.8 (d) – Comparison of the GJR-GARCH(1,1)-DCC(2,2) and GJR-GARCH(2,2)-DCC(2,2) Models

	Test Details	GARCH(1,1)-ADCC(1,1)						GARCH(2,2)-ADCC(1,1)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22218.7618	21	13.1208	13.1588	13.1207	13.1344	-22199.5499	29	13.1142	13.1666	13.1140	13.1329
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21342.6044	21	12.6039	12.6419	12.6038	12.6175	-21332.9568	29	12.6029	12.6554	12.6028	12.6217
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22177.6489	21	13.0965	13.1345	13.0965	13.1101	-22166.7930	29	13.0949	13.1473	13.0947	13.1136
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16373.0399	21	9.6720	9.7100	9.6719	9.6856	-16403.8986	29	9.6949	9.7474	9.6948	9.7137
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16340.1737	21	9.6526	9.6906	9.6525	9.6662	-16372.4079	29	9.6763	9.7288	9.6762	9.6951
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18428.8611	21	10.8849	10.9228	10.8848	10.8984	-18459.0430	29	10.9074	10.9598	10.9073	10.9261
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19565.8351	21	11.5591	11.5970	11.5590	11.5726	-19570.7208	29	11.5667	11.6191	11.5665	11.5854
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20165.9695	21	11.9132	11.9512	11.9132	11.9268	-20165.5188	29	11.9177	11.9701	11.9175	11.9364
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19514.7292	21	11.5289	11.5669	11.5288	11.5425	-19514.0618	29	11.5332	11.5857	11.5331	11.5520

Table 3.8 (e) – Comparison of the GARCH(1,1)-ADCC(1,1) and GARCH(2,2)-ADCC(1,1) Models

	Test Details	GARCH(1,1)-ADCC(2,2)						GARCH(2,2)-ADCC(2,2)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22216.3604	24	13.1212	13.1645	13.1211	13.1367	-22197.6044	32	13.1148	13.1727	13.1146	13.1355
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21341.4052	24	12.6050	12.6483	12.6049	12.6205	-21332.0826	32	12.6042	12.6620	12.6040	12.6249
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22177.2492	24	13.0981	13.1415	13.0980	13.1136	-22166.7747	32	13.0966	13.1545	13.0964	13.1173
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16368.6856	24	9.6712	9.7146	9.6711	9.6867	-16403.7065	32	9.6966	9.7544	9.6964	9.7173
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16332.9365	24	9.6501	9.6935	9.6500	9.6656	-16369.4094	32	9.6763	9.7342	9.6762	9.6970
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18421.9619	24	10.8826	10.9260	10.8825	10.8981	-18457.1492	32	10.9081	10.9659	10.9079	10.9287
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19561.4078	24	11.5582	11.6016	11.5581	11.5737	-19569.4065	32	11.5677	11.6255	11.5675	11.5883
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20164.3393	24	11.9140	11.9574	11.9139	11.9296	-20165.0837	32	11.9192	11.9771	11.9190	11.9399
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19512.8799	24	11.5296	11.5730	11.5295	11.5451	-19513.6008	32	11.5347	11.5926	11.5346	11.5554

Table 3.8 (f) – Comparison of the GARCH(1,1)-ADCC(2,2) and GARCH(2,2)-ADCC(2,2) Models

	Test Details	GJR-GARCH(1,1)-ADCC(1,1)						GJR-GARCH(2,2)-ADCC(1,1)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22100.9478	25	13.0537	13.0989	13.0535	13.0698	-22083.6574	37	13.0505	13.1174	13.0503	13.0744
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21230.7992	25	12.5403	12.5855	12.5402	12.5565	-21213.7156	37	12.5373	12.6042	12.5371	12.5612
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22055.6580	25	13.0269	13.0721	13.0268	13.0431	-22038.9277	37	13.0241	13.0910	13.0239	13.0481
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16171.3938	25	9.5554	9.6006	9.5553	9.5716	-16176.9292	37	9.5657	9.6326	9.5655	9.5897
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16208.9795	25	9.5776	9.6228	9.5775	9.5937	-16212.6377	37	9.5868	9.6537	9.5866	9.6107
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18285.1097	25	10.8024	10.8476	10.8023	10.8186	-18285.4891	37	10.8097	10.8766	10.8095	10.8336
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19412.2578	25	11.4708	11.5160	11.4707	11.4870	-19404.2305	37	11.4731	11.5400	11.4729	11.4971
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20039.1841	25	11.8408	11.8860	11.8407	11.8569	-20033.2540	37	11.8444	11.9113	11.8441	11.8683
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19369.0257	25	11.4453	11.4905	11.4452	11.4614	-19361.6789	37	11.4480	11.5149	11.4478	11.4719

Table 3.8 (g) – Comparison of the GJR-GARCH(1,1)-ADCC(1,1) and GJR-GARCH(2,2)-ADCC(1,1) Models

	Test Details	GJR-GARCH(1,1)-ADCC(2,2)						GJR-GARCH(2,2)-ADCC(2,2)					
		$lnL(\theta)$	Number of parameters	Information Criteria				$lnL(\theta)$	Number of parameters	Information Criteria			
				AIC	BIC	SIC	HQIC			AIC	BIC	SIC	HQIC
Test AB1	Zone A: Japan, China , HK Zone B: Germany	-22098.6956	28	13.0541	13.1047	13.0540	13.0722	-22081.4098	40	13.0510	13.1233	13.0507	13.0768
Test AB2	Zone A: Japan, China , HK Zone B: UK	-21229.6776	28	12.5414	12.5920	12.5413	12.5595	-21212.6414	40	12.5384	12.6107	12.5382	12.5643
Test AB3	Zone A: Japan, China , HK Zone B: Spain	-22055.2339	28	13.0285	13.0791	13.0283	13.0466	-22038.5033	40	13.0257	13.0980	13.0254	13.0515
Test BC1	Zone B: Germany, UK, Spain Zone C: US	-16165.4881	28	9.5537	9.6043	9.5535	9.5718	-16172.3086	40	9.5648	9.6371	9.5645	9.5906
Test BC2	Zone B: Germany, UK, Spain Zone C: Canada	-16201.6992	28	9.5750	9.6257	9.5749	9.5931	-16206.2479	40	9.5848	9.6571	9.5845	9.6107
Test BC3	Zone B: Germany, UK, Spain Zone C: Brazil	-18279.6997	28	10.8010	10.8516	10.8009	10.8191	-18281.5210	40	10.8092	10.8815	10.8089	10.8350
Test CA1	Zone C: US, Canada, Brazil Zone A: Japan	-19407.8130	28	11.4699	11.5206	11.4698	11.4880	-19401.5788	40	11.4733	11.5457	11.4731	11.4992
Test CA2	Zone C: US, Canada, Brazil Zone A: China	-20036.2219	28	11.8408	11.8914	11.8407	11.8589	-20031.3273	40	11.8450	11.9173	11.8447	11.8708
Test CA3	Zone C: US, Canada, Brazil Zone A: HK	-19365.8465	28	11.4452	11.4958	11.4450	11.4633	-19359.4374	40	11.4485	11.5208	11.4482	11.4743

Table 3.8 (h) – Comparison of the GJR-GARCH(1,1)-ADCC(2,2) and GJR-GARCH(2,2)-ADCC(2,2) Models

				Zone A to Zone B						Zone B to Zone C						Zone C to Zone A					
				Test AB1		Test AB2		Test AB3		Test BC1		Test BC2		Test BC3		Test CA1		Test CA2		Test CA3	
Likelihood Ratio Test	Restricted	Unrestricted	DF	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
A	CCC(1,1)	GARCH(1,1)-DCC(1,1)	2	143.9156	0.0000	147.7245	0.0000	151.3868	0.0000	635.8865	0.0000	572.3751	0.0000	558.4122	0.0000	360.5148	0.0000	308.9572	0.0000	305.3500	0.0000
B	GARCH(1,1)-DCC(1,1)	GJR-GARCH(1,1)-DCC(1,1)	4	235.1479	0.0000	223.1201	0.0000	243.7080	0.0000	399.5050	0.0000	251.1601	0.0000	273.0742	0.0000	303.9324	0.0000	249.2669	0.0000	287.8909	0.0000
C	GARCH(1,1)-ADCC(1,1)	GJR-GARCH(1,1)-ADCC(1,1)	4	235.6280	0.0000	223.6104	0.0000	243.9819	0.0000	403.2923	0.0000	262.3883	0.0000	287.5029	0.0000	307.1545	0.0000	253.5706	0.0000	291.4070	0.0000
D	GARCH(1,1)-DCC(1,1)	GARCH(1,1)-ADCC(1,1)	1	0.2612	0.6093	0.3389	0.5605	0.0407	0.8401	0.0000	1.0000	0.5233	0.4694	0.4527	0.5010	0.2001	0.6546	1.2183	0.2697	0.0240	0.8770
E	GJR-GARCH(1,1)-DCC(1,1)	GJR-GARCH(1,1)-ADCC(1,1)	1	0.7412	0.3893	0.8292	0.3625	0.3145	0.5749	3.7873	0.0516	11.7515	0.0006	14.8814	0.0001	3.4222	0.0643	5.5220	0.0188	3.5401	0.0599
F	GARCH(1,1)-DCC(1,1)	GARCH(2,2)-DCC(1,1)	8	38.4649	0.0000	19.3186	0.0132	21.7115	0.0055	-61.7173	1.0000	-64.3633	1.0000	-60.3324	1.0000	-9.7641	1.0000	0.9323	0.9986	1.3126	0.9954
G	GARCH(1,1)-DCC(1,1)	GARCH(1,1)-DCC(2,2)	2	4.8966	0.0864	2.4390	0.2954	0.7779	0.6778	8.7087	0.0129	13.5945	0.0011	13.4683	0.0012	8.7507	0.0126	4.0431	0.1325	3.7034	0.1570
H	GARCH(2,2)-DCC(1,1)	GARCH(2,2)-DCC(2,2)	2	3.8831	0.1435	1.7316	0.4207	0.3885	0.8235	0.3841	0.8253	3.9082	0.1417	2.2593	0.3232	2.5612	0.2779	1.0418	0.5940	-0.1408	1.0000
I	GARCH(1,1)-DCC(2,2)	GARCH(2,2)-DCC(2,2)	8	37.4514	0.0000	18.6112	0.0171	21.3220	0.0063	-70.0419	1.0000	-74.0495	1.0000	-71.5414	1.0000	-15.9536	1.0000	-2.0690	1.0000	-2.5316	1.0000
J	GJR-GARCH(1,1)-DCC(1,1)	GJR-GARCH(2,2,)-DCC(1,1)	12	34.6540	0.0005	34.2385	0.0006	33.4852	0.0008	-11.0033	1.0000	-6.6882	1.0000	0.2056	1.0000	16.1532	0.1843	12.1054	0.4373	15.2368	0.2287
K	GJR-GARCH(1,1)-DCC(1,1)	GJR-GARCH(1,1)-DCC(2,2)	2	4.6827	0.0962	2.3343	0.3112	0.8352	0.6586	10.4186	0.0055	14.1890	0.0008	10.5880	0.0050	8.1151	0.0173	5.1831	0.0749	4.4359	0.1088
L	GJR-GARCH(2,2)-DCC(1,1)	GJR-GARCH(2,2)-DCC(2,2)	2	4.6548	0.0975	2.2398	0.3263	0.8368	0.6581	6.0122	0.0495	10.4765	0.0053	6.5001	0.0388	5.0819	0.0788	3.0976	0.2125	2.0280	0.3628
M	GJR-GARCH(1,1)-DCC(2,2)	GJR-GARCH(2,2)-DCC(2,2)	12	34.6261	0.0005	34.1440	0.0006	33.4868	0.0008	-15.4097	1.0000	-10.4007	1.0000	-3.8823	1.0000	13.1201	0.3604	10.0200	0.6142	12.8289	0.3816
N	GARCH(1,1)-ADCC(1,1)	GARCH(2,2,)-ADCC(1,1)	8	38.4237	0.0000	19.2953	0.0134	21.7117	0.0055	-61.7173	1.0000	-64.4683	1.0000	-60.3638	1.0000	-9.7715	1.0000	0.9014	0.9988	1.3347	0.9951
O	GARCH(1,1)-ADCC(1,1)	GARCH(1,1)-ADCC(2,2)	3	4.8027	0.1868	2.3984	0.4939	0.7993	0.8496	8.7087	0.0334	14.4745	0.0023	13.7984	0.0032	8.8545	0.0313	3.2602	0.3532	3.6985	0.2959
P	GARCH(2,2)-ADCC(1,1)	GARCH(2,2)-ADCC(2,2)	3	3.8910	0.2735	1.7483	0.6263	0.0366	0.9982	0.3841	0.9435	5.9970	0.1118	3.7877	0.2853	2.6287	0.4525	0.8702	0.8326	0.9221	0.8201
Q	GARCH(1,1)-ADCC(2,2)	GARCH(2,2)-ADCC(2,2)	8	37.5120	0.0000	18.6452	0.0169	20.9491	0.0073	-70.0419	1.0000	-72.9458	1.0000	-70.3745	1.0000	-15.9973	1.0000	-1.4887	1.0000	-1.4417	1.0000
R	GJR-GARCH(1,1)-ADCC(1,1)	GJR-GARCH(2,2,)-ADCC(1,1)	12	34.5808	0.0005	34.1672	0.0006	33.4606	0.0008	-11.0708	1.0000	-7.3164	1.0000	-0.7589	1.0000	16.0547	0.1887	11.8604	0.4570	14.6936	0.2586
S	GJR-GARCH(1,1)-ADCC(1,1)	GJR-GARCH(1,1)-ADCC(2,2)	3	4.5044	0.2119	2.2432	0.5235	0.8482	0.8379	11.8112	0.0081	14.5607	0.0022	10.8200	0.0127	8.8897	0.0308	5.9245	0.1153	6.3585	0.0954
T	GJR-GARCH(2,2)-ADCC(1,1)	GJR-GARCH(2,2)-ADCC(2,2)	3	4.4953	0.2127	2.1484	0.5422	0.8487	0.8378	9.2411	0.0263	12.7797	0.0051	7.9363	0.0473	5.3033	0.1509	3.8533	0.2778	4.4829	0.2138
U	GJR-GARCH(1,1)-ADCC(2,2)	GJR-GARCH(2,2)-ADCC(2,2)	12	34.5717	0.0005	34.0724	0.0007	33.4612	0.0008	-13.6409	1.0000	-9.0974	1.0000	-3.6426	1.0000	12.4683	0.4088	9.7891	0.6345	12.8180	0.3824

Table 3.9 – Comparison of the Multivariate Models by LR Tests

Test	AB1	AB2	AB3	BC1	BC2	BC3	CA1	CA2	CA3
From	Zone A (Japan$_{(i=1)}$, China$_{(i=2)}$, HK$_{(i=3)}$)			Zone B (Germany$_{(i=1)}$, UK$_{(i=2)}$, Spain$_{(i=3)}$)			Zone C (US$_{(i=1)}$, Canada$_{(i=2)}$, Brazil$_{(i=3)}$)		
To	Germany$_{(i=4)}$	UK$_{(i=4)}$	Spain$_{(i=4)}$	Germany$_{(i=4)}$	UK$_{(i=4)}$	Spain$_{(i=4)}$	Germany$_{(i=4)}$	UK$_{(i=4)}$	Spain$_{(i=4)}$
Model^	A	A	A	B	B	B	B	C	C
$\alpha_{1,0}$	0.0484	0.0484	0.0484	0.0260	0.0260	0.0260	0.0135	0.0135	0.0135
	[4.4287]***	[4.4285]***	[4.4282]***	[4.4367]***	[4.4502]***	[4.4392]***	[3.9765]***	[3.9686]***	[3.9712]***
$\alpha_{1,1}$	0.0260	0.0260	0.0260	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	[2.6304]***	[2.6304]***	[2.6303]***	[0.0023]	[0.0023]	[0.0023]	[0.002]	[0.002]	[0.002]
$\beta_{1,1}$	0.8917	0.8917	0.8917	0.9103	0.9103	0.9103	0.9176	0.9176	0.9176
	[71.3522]***	[71.3657]***	[71.3533]***	[86.3697]***	[87.4025]***	[87.1937]***	[101.646]***	[101.4546]***	[101.6045]***
$\gamma_{1,1}$	0.1180	0.1180	0.1180	0.1545	0.1545	0.1545	0.1427	0.1427	0.1427
	[5.3023]***	[5.3035]***	[5.3037]***	[7.5462]***	[7.6777]***	[7.6742]***	[8.2503]***	[8.2067]***	[8.2322]***
$\alpha_{2,0}$	0.0271	0.0271	0.0271	0.0156	0.0156	0.0156	0.0139	0.0139	0.0139
	[2.4027]**	[2.4027]**	[2.4025]**	[4.3291]***	[4.3324]***	[4.3378]***	[4.0481]***	[4.0501]***	[4.0535]***
$\alpha_{2,1}$	0.0432	0.0432	0.0432	0.0000	0.0000	0.0000	0.0041	0.0041	0.0041
	[3.9965]***	[3.9967]***	[3.9953]***	[0.011]	[0.011]	[0.011]	[0.4689]	[0.4687]	[0.4702]
$\beta_{2,1}$	0.9307	0.9307	0.9307	0.9097	0.9097	0.9097	0.9274	0.9274	0.9274
	[58.9393]***	[58.9436]***	[58.9245]***	[79.0426]***	[79.348]***	[79.6458]***	[74.4747]***	[74.4829]***	[74.4895]***
$\gamma_{2,1}$	0.0305	0.0305	0.0305	0.1547	0.1547	0.1547	0.1048	0.1048	0.1048
	[2.0808]**	[2.0808]**	[2.0805]**	[7.3184]***	[7.3909]***	[7.4142]***	[5.6354]***	[5.6615]***	[5.6743]***
$\alpha_{3,0}$	0.0203	0.0203	0.0203	0.0194	0.0194	0.0194	0.0744	0.0744	0.0744
	[3.8419]***	[3.844]***	[3.8412]***	[4.088]***	[4.0983]***	[4.0991]***	[2.9558]***	[2.9506]***	[2.9577]***
$\alpha_{3,1}$	0.0181	0.0181	0.0181	0.0000	0.0000	0.0000	0.0069	0.0069	0.0069
	[2.9552]***	[2.9539]***	[2.9541]***	[0.007]	[0.007]	[0.007]	[0.9228]	[0.9214]	[0.9203]
$\beta_{3,1}$	0.9319	0.9319	0.9319	0.9218	0.9218	0.9218	0.9173	0.9173	0.9173
	[115.1506]***	[115.1869]***	[115.1275]***	[87.3198]***	[88.1437]***	[87.9002]***	[51.1924]***	[51.1035]***	[51.3604]***
$\gamma_{3,1}$	0.0778	0.0778	0.0778	0.1386	0.1386	0.1386	0.1007	0.1007	0.1007
	[4.9058]***	[4.906]***	[4.9028]***	[6.5916]***	[6.6636]***	[6.6646]***	[4.4042]***	[4.3872]***	[4.4311]***
$\alpha_{4,0}$	0.0260	0.0156	0.0194	0.0135	0.0139	0.0741	0.0485	0.0272	0.0202
	[4.4403]***	[4.3522]***	[4.1019]***	[3.9714]***	[4.032]***	[2.9621]***	[4.4214]***	[2.4011]**	[3.8488]***
$\alpha_{4,1}$	0.0000	0.0000	0.0000	0.0000	0.0038	0.0070	0.0261	0.0426	0.0182
	[0.0023]	[0.0111]	[0.004]	[0.001]	[0.4334]	[0.9316]	[2.6332]***	[3.8976]***	[2.9758]***
$\beta_{4,1}$	0.9103	0.9097	0.9218	0.9175	0.9276	0.9173	0.8916	0.9309	0.9322
	[87.0569]***	[80.6293]***	[88.0876]***	[101.038]***	[73.7571]***	[51.6051]***	[71.1197]***	[58.6389]***	[116.3826]***
$\gamma_{4,1}$	0.1545	0.1547	0.1386	0.1430	0.1049	0.1007	0.1181	0.0310	0.0770
	[7.6901]***	[7.5096]***	[6.7075]***	[8.1396]***	[5.6698]***	[4.4598]***	[5.2777]***	[2.1263]**	[4.9067]***

dcc_{a1}	0.0038	0.0040	0.0043	0.0410	0.0380	0.0335	0.0212	0.0138	0.0144
	[5.412]***	[5.1334]***	[5.1552]***	[2.023]**	[0.9552]	[2.1204]**	[3.7351]***	[4.1389]***	[4.552]***
dcc_{a2}				0.0000	0.0000	0.0000	0.0060		
				[0.0000]	[0.0000]	[0.0000]	[1.0094]		
dcc_{b1}	0.9955	0.9953	0.9949	0.4029	0.3344	0.3348	0.0992	0.9772	0.9757
	[1009.9169]***	[917.9752]***	[840.9948]***	[0.4927]	[0.2602]	[0.4998]	[1.6155]	[126.2782]***	[136.7429]***
dcc_{b2}				0.5266	0.5959	0.6018	0.8582		
				[0.6906]	[0.4945]	[0.9488]	[14.638]***		
dcc_{g1}				0.0000	0.0009	0.0102	0.0069	0.0042	0.0037
				[0.0000]	[0.0219]	[0.6572]	[0.7169]	[1.4947]	[1.4548]

*** Significance at 1% level, ** Significance at 5% level, * Significance at 10% level
Numbers in square brackets are *t*-statistics.

^Model A: GJR-GARCH(1,1)-DCC(1,1)
^Model B: GJR-GARCH(1,1)-ADCC(2,2)
^Model C: GJR-GARCH(1,1)-ADCC(1,1)

#Parameters specification of the multivariate GARCH models are shown in Section 2.6

Table 3.10 – Estimated Parameters Using the Models Suggested by the LR Tests

Test	AB1	AB2	AB3	BC1	BC2	BC3	CA1	CA2	CA3
From	Zone A (Japan, China, HK)			Zone B (Germany, UK, Spain)			Zone C (US, Canada, Brazil)		
To	Germany	UK	Spain	US	Canada	Brazil	Japan	China	HK
$\alpha_{1,0}$	0.0484	0.0484	0.0484	0.0260	0.0260	0.0260	0.0135	0.0135	0.0135
	[4.4287]***	[4.4285]***	[4.4282]***	[4.4356]***	[4.4482]***	[4.4421]***	[3.9751]***	[3.9672]***	[3.9708]***
$\alpha_{1,1}$	0.0260	0.0260	0.0260	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	[2.6304]***	[2.6304]***	[2.6303]***	[0.0023]	[0.0023]	[0.0023]	[0.0002]	[0.0002]	[0.0002]
$\beta_{1,1}$	0.8917	0.8917	0.8917	0.9103	0.9103	0.9103	0.9176	0.9176	0.9176
	[71.3522]***	[71.3657]***	[71.3533]***	[86.5197]***	[87.1636]***	[87.2173]***	[101.4255]***	[101.4035]***	[101.5193]***
$\gamma_{1,1}$	0.1180	0.1180	0.1180	0.1545	0.1545	0.1545	0.1427	0.1427	0.1427
	[5.3023]***	[5.3035]***	[5.3037]***	[7.6328]***	[7.6895]***	[7.705]***	[8.1915]***	[8.183]***	[8.1944]***
$\alpha_{2,0}$	0.0271	0.0271	0.0271	0.0156	0.0156	0.0156	0.0139	0.0139	0.0139
	[2.4027]**	[2.4027]**	[2.4025]**	[4.3313]***	[4.3336]***	[4.341]***	[4.0429]***	[4.0441]***	[4.0489]***
$\alpha_{2,1}$	0.0432	0.0432	0.0432	0.0000	0.0000	0.0000	0.0041	0.0041	0.0041
	[3.9965]***	[3.9967]***	[3.9953]***	[0.011]	[0.011]	[0.011]	[0.4696]	[0.4696]	[0.4702]
$\beta_{2,1}$	0.9307	0.9307	0.9307	0.9097	0.9097	0.9097	0.9274	0.9274	0.9274
	[58.9393]***	[58.9436]***	[58.9245]***	[79.5427]***	[79.5342]***	[80.0018]***	[74.3647]***	[74.3459]***	[74.4182]***
$\gamma_{2,1}$	0.0305	0.0305	0.0305	0.1547	0.1547	0.1547	0.1048	0.1048	0.1048
	[2.0808]**	[2.0808]**	[2.0805]**	[7.4059]***	[7.4252]***	[7.4613]***	[5.6461]***	[5.656]***	[5.6785]***
$\alpha_{3,0}$	0.0203	0.0203	0.0203	0.0194	0.0194	0.0194	0.0744	0.0744	0.0744
	[3.8419]***	[3.844]***	[3.8412]***	[4.0979]***	[4.0987]***	[4.098]***	[2.9593]***	[2.9556]***	[2.9577]***
$\alpha_{3,1}$	0.0181	0.0181	0.0181	0.0000	0.0000	0.0000	0.0069	0.0069	0.0069
	[2.9552]***	[2.9539]***	[2.9541]***	[0.0007]	[0.0007]	[0.0007]	[0.9239]	[0.9217]	[0.9205]
$\beta_{3,1}$	0.9319	0.9319	0.9319	0.9218	0.9218	0.9218	0.9173	0.9173	0.9173
	[115.1506]***	[115.1869]***	[115.1275]***	[87.923]***	[88.3328]***	[88.2225]***	[51.2264]***	[51.2027]***	[51.3407]***
$\gamma_{3,1}$	0.0778	0.0778	0.0778	0.1386	0.1386	0.1386	0.1007	0.1007	0.1007
	[4.9058]***	[4.906]***	[4.9028]***	[6.6737]***	[6.7101]***	[6.709]***	[4.4177]***	[4.4185]***	[4.432]***
$\alpha_{4,0}$	0.0260	0.0156	0.0194	0.0135	0.0139	0.0741	0.0485	0.0272	0.0202
	[4.4403]***	[4.3522]***	[4.1019]***	[3.9727]***	[4.0336]***	[2.9588]***	[4.4258]***	[2.4015]**	[3.8483]***
$\alpha_{4,1}$	0.0000	0.0000	0.0000	0.0000	0.0038	0.0070	0.0261	0.0426	0.0182
	[0.0023]	[0.0111]	[0.0007]	[0.0004]	[0.4377]	[0.9304]	[2.6332]***	[3.8963]***	[2.9759]***
$\beta_{4,1}$	0.9103	0.9097	0.9218	0.9175	0.9276	0.9173	0.8916	0.9309	0.9322
	[87.0569]***	[80.6293]***	[88.0876]***	[101.0668]***	[74.0256]***	[51.5335]***	[71.1665]***	[58.6496]***	[116.3643]***
$\gamma_{4,1}$	0.1545	0.1547	0.1386	0.1430	0.1049	0.1007	0.1181	0.0310	0.0770
	[7.6901]***	[7.5096]***	[6.7075]***	[8.1423]***	[5.6688]***	[4.4538]***	[5.2949]***	[2.1293]**	[4.9141]***
dcc_{a1}	0.0038	0.0040	0.0043	0.0311	0.0285	0.0261	0.0153	0.0148	0.0157

	[5.412]***	[5.1334]***	[5.1552]***	[7.4181]***	[6.5252]***	[6.545]***	[4.1041]***	[3.7456]***	[4.1445]***
dcc_{b1}	0.9955	0.9953	0.9949	0.9520	0.9566	0.9608	0.9786	0.9790	0.9765
	[1009.9169]***	[917.9752]***	[840.9948]***	[112.9003]***	[112.5974]***	[125.5924]***	[151.8833]***	[137.1135]***	[134.9192]***

*** Significance at 1% level, ** Significance at 5% level, * Significance at 10% level
Numbers in square brackets are *t*-statistics.

Table 3.11 – Estimated Parameters Using the GJR-GARCH(1,1)-DCC(1,1) Model

3.8 The Interaction and Spillover Effects

The GJR-GARCH(1,1)-DCC(1,1) model is found to be the most appropriate model for describing stock returns by incorporating the spillover effect into the volatility equations. In Table 3.11, the parameters dcc_{a1} and dcc_{b1} are highly significant at 1% level in all the tests. It indicates that the interdependencies among the different markets are strong. The estimated parameter dcc_{b1} in Tests AB1, AB2, and AB3 for testing the spillover effect from countries in Zone A to Zone B are highly significant and closed to one, it shows that high persistence of the spillover effect in volatility among the Asian to European countries. Furthermore, the coefficients $\alpha_{i,1}$ that represent conditionally heteroskedastic in volatility equations for countries i in Zones B and C are insignificant in all the tests, while the coefficients $\gamma_{i,1}$ that represent asymmetric impact of bad news on return volatility are all significantly positive, which implies that only bad news contributes to a further increase in return volatility in countries in Zones B and C.

According to stock exchange trading times, the spillover effect is cyclical in the direction from Zone A to Zone B, Zone B to Zone C, and Zone C to Zone A, as depicted in Figure 3.5. Figure 3.6 shows the conditional correlation in different time zones. Overall, the correlation series among the different markets significantly differ from zero with the exception of Chinese market. In tests AB1, AB2, and AB3, the conditional correlations between the Chinese market and the stock markets in Zone B (Germany, the United Kingdom, and Spain) fluctuate around zero from 2000 to 2006. After mid-2006, however, the correlation raises sharply and remains constantly above zero; it fluctuates at around 0.15 and has a tendency to further increase in the future. This may be due to the capital liberalization in China in recent years. Since 2001, China has experimented with policies that promotes overseas direct investment by Chinese companies. In the year of 2003 and 2006, China has introduced the Qualified Foreign Institutional Investor Scheme (QFII) and Qualified Domestic Institutional Investor Scheme (QDII), QFII regulates portfolios inflow while QDII regulates portfolio outflow. As the QFII and QDII scheme evolves, China's gradually relaxing the capital control on the currencies conversions and cross-border funds transfer. In 2007, People's Bank of China (PBC) made an important liberalization step of allowing a $50,000 ceiling on free two-way conversion between renminbi and foreign currency by Chinese individuals per person per year. The financial liberalization increased the interactions between the Chinese and foreign market participants. As the capitalization of the Chinese market has continued to increase in recent years, the market has become more integrated with the rest of the world and is now playing a more important role globally than ever before.

Tests AB1, AB2, and AB3 reveal that both Japan and Hong Kong exhibit a stable volatility spillover to Zone B's countries (Germany, the United Kingdom, and Spain), with a correlation around 0.3 to 0.4. However, the correlation becomes unstable after 2007, particularly during the sub-prime mortgage crisis period and the European debt crisis in late 2009. Tests BC1, BC2, and BC3 indicate that the volatility spillover from Zone B to Zone C is significant; the correlations between the markets in these zones are sustainability high, with an average above 0.5 that further increases to above 0.6 after 2008. The European markets do play a more important role after both the U.S. sub-prime mortgage crisis and the European debt crisis.

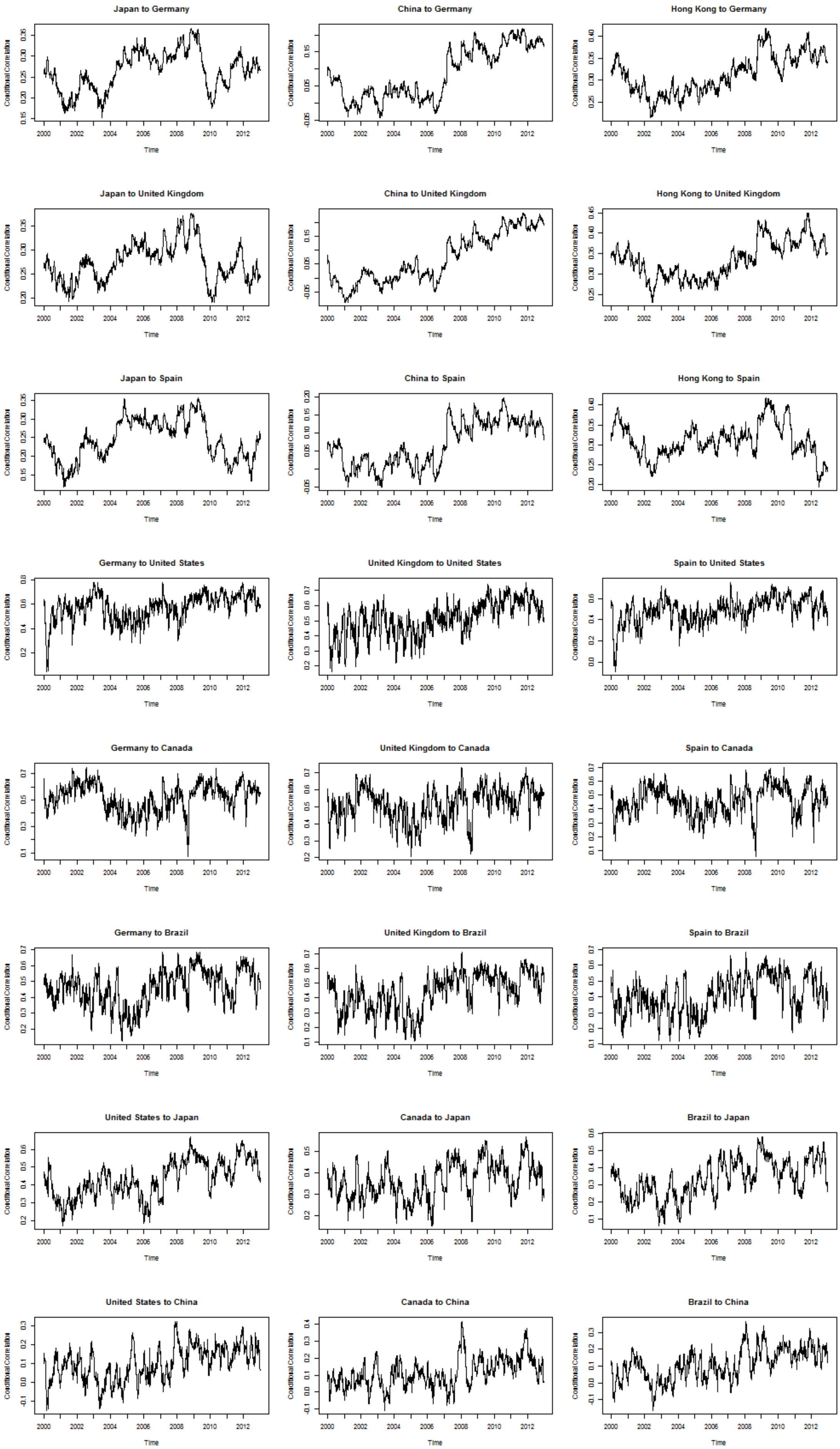
Tests of the correlations from Zone C and Zone A show an interesting phenomenon that the influential power of the U.S. market is not as strong as one may expect, particularly on the Chinese market. The conditional correlations between these two markets are low, fluctuating from around zero before 2006 and rising to around 0.2 after 2009. Similar findings are also found in relation to Canada and Brazil.

3.9 Conclusion

The empirical analysis has shown the volatility spillover among different stock markets: shocks in one market may indeed transmit to another market in the forthcoming trading period. In this paper, we selected nine stock markets in different trading time zones and studied how information is transmitted among them. The nine stock markets are Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil. Our study started by using traditional GARCH and GJR-GARCH models, which showed that all of the markets experienced significant asymmetric impacts from bad news on stocks volatility; stock markets became more volatile if there was a drop in the previous trading day. The volatility spillover effect was studied across three different time zones, which were defined based on the exchanges' trading hours in GMT. Multivariate GARCH models (including the CCC, GRACH-DCC, GJR-GARCH-DCC, GARCH-ADCC, and GJR-GARCH-ADCC models) were applied. As the DCC models are more preferred to the CCC models in all tests; we ascertained that volatility will indeed spillover among different markets. Furthermore, the asymmetric volatility spillover effect is highly significant while the asymmetric correlation spillover effect is not. Although the LR tests prefer asymmetric correlation models in some incidents, the estimated results were not at all significant. We concluded that the equity market tends to reflect bad news on volatility but not on correlations.

The result of no asymmetric correlation spillover among the stock market is important for investors. (Tesar and Werner, 1995) shows investors exhibit home bias in national investment portfolios despite of the potential benefits in international diversification. With the common belief of financial contagion effect, investors may think that international diversification is not necessary as the correlations among the different assets in different markets may largely increase. Investors tend to hold domestic portfolio and perform no international diversification that hurts their position much during financial crisis. Robert (2011) empirically investigated international equity foreign portfolios that across 42 countries during the financial crisis. The results show that international stock market diversification provides large gains during the financial crisis and investors should reduce the home bias in forming portfolios. Our result of no asymmetric correlation spillover among the stock market supports the effectiveness of international diversification on achieving a better risk-adjusted returns. Our results conform with Forbes and Rigobon (2002) findings that when markets experience increased volatility in the period of financial crisis, the correlation measure is biased upwards and leads to an incorrect conclusion of financial market contagion.

Correlation dynamics change significantly, and the GJR-GARCH(1,1)-DCC(1,1) model was found to be the best multivariate model for describing market behaviour. This model reflects the asymmetric volatility spillover effect among different markets and was adopted to study how conditional correlations vary over time. China's stock market, which has drawn much attention in recent decades, was found to have no significant influence on or from other stock markets before 2006. After 2006, however, the Chinese market began to have a gradually increasing influence on the global market and started to become more integrated with the rest of the world. Meanwhile, the European markets have played an important role in the world's financial market, and conditional correlations between the European and North America markets have been sustainably high.


Japan to Germany
China to Germany
Hong Kong to Germany
Japan to United Kingdom
China to United Kingdom
Hong Kong to United Kingdom
Japan to Spain
China to Spain
Hong Kong to Spain
Germany to United States
United Kingdom to United States
Spain to United States
Germany to Canada
United Kingdom to Canada
Spain to Canada
Germany to Brazil
United Kingdom to Brazil
Spain to Brazil
United States to Japan
Canada to Japan
Brazil to Japan
United States to China
Canada to China
Brazil to China
Conditional Correlation
Time

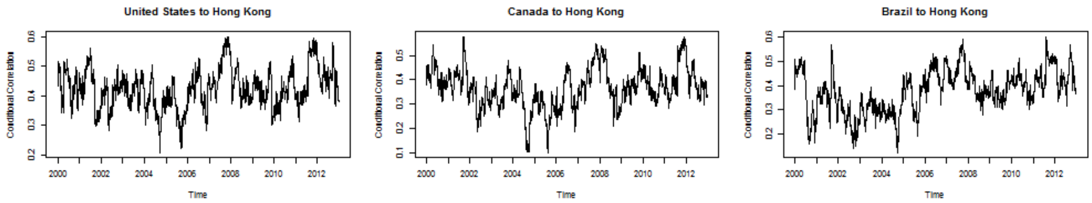


Figure 3.6 – Conditional Correlations in Different Time Zones from the GJR-GARCH(1,1)-DCC(1,1) Model

Chapter 4. The Performance of VaR in the Presence of Asset Price Bubbles: An Empirical Analysis

4.1 Introduction

In this chapter, we extensively review different VaR approaches and compare their reliability during the 2008-2009 global financial crisis using data from several stock markets. This financial crisis is thought to have been preceded by price bubbles in several different asset markets. It began with the collapse of the U.S. housing price bubble, which was quickly followed by the collapse of suspected bubbles in equity and commodity markets. VaR measures the downside risk of a financial investment, which defines the minimum loss of a portfolio value in a particular time period with a certain percentage of probability. If a portfolio has a 5% one-day VaR of $100,000, there is 5% chance that the portfolio will lose more than $100,000 in the next day; alternatively, the expected losses of the portfolio will not exceed $100,000 in the next day with a probability of 95%. The 5% one-day VaR is equivalent to a one-day VaR with 95% confidence level.

In general, VaR can be obtained using parametric and non-parametric approaches. Parametric approaches are based on estimating the statistical parameters of different risk factors, whereas non-parametric approaches are based on HS and MCS. Linsmeier and Pearson (1996) suggested that decisions concerning the type of approach to use should be based on the following criteria: (1) ability to capture the risk of options and option-like instruments, (2) ease of implementation, (3) ease of communication with senior management, (4) reliability of the results, and (5) flexibility in incorporating alternative assumptions. Furthermore, Christoffersen (2009) noted that univariate models in parametric VaR approaches are suitable for passive risk management, whereas the multivariate approaches in parametric VaR are useful for active risk management. There is no absolute advantage in using one method over the other. However, recent studies show that using VaR with GARCH family models to model volatility can adequately describe downside risks (see Kuester *et al.*, 2006; Drakos *et al.*, 2010). The effectiveness of incorporating GARCH volatility models in calculating VaR has not yet been explained.

The aim of this chapter is to provide a better understanding of the effectiveness of VaR during the crisis period. Szerszen (2014) found that bank VaR models were overly conservative in the pre-crisis period, although most banks use HS VaR. The author compared VaR performance between HS and GARCH, and the results show that GARCH performs better during the financial crisis period. However, Szerszen (2014) examine only the HS and GARCH VaR approaches and focused only on the banks of the U.S. Our study is more comprehensive. We examine VaR approaches by constructing hypothetical single- and multiple-asset portfolios across the markets of Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil. We then use these hypothetical single-asset and multiple-asset portfolios to explore the effectiveness of the univariate and multivariate VaR approaches in both crisis and non-crisis periods.

This chapter proceeds as follows. In Section 4.2, we introduce the hypothetical equity portfolios used in the study, which include both single- and multiple-asset portfolios. In Sections 4.3 and 4.4, we review parametric and non-parametric VaR approaches. The non-parametric approaches include HS and MCS; the univariate parametric approaches include MA, exponentially weighted moving average (EWMA or RiskMetrics), long memory EWMA (EWMA2006 or RiskMetrics2006), GARCH, GJR-GARCH, and fractionally integrated GARCH (FIGARCH); and the multivariate parametric approaches include DCC, GJR-DCC, ADCC, and GJR-ADCC. In Section 4.5 we review backtesting methods and in Section 4.6 we provide simulation results that show that the RiskMetrics2006 method outperforms other methods in passively managed portfolios, while the GJR-ADCC model can effectively estimating VaR multiple-asset portfolios with risk factors that have already been identified. Section 4.7 provides some concluding remarks.

4.2 The Portfolios

The empirical analysis uses nine stock markets that represent different characteristics of both developed and emerging markets, namely Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil. These countries are chosen based on their market capitalization and trading hours, as shown in Table 3.1 in Chapter 3. The empirical tests encompass VaR estimations for different hypothetical portfolios.

The data covers the period 1 June 2004 to 31 December 2012, with a total of 2,240 observations for each series that are obtained from DataStream. We test different VaR approaches by constructing hypothetical portfolios that contain single and multiple assets. The first set of tests contains nine single-stock portfolios, namely, S1 to S9. Table 4.1 shows that the constituent of the single-stock portfolios is the domestic market index, which simplified the risk factor mapping procedure in the parametric VCV model. The second set of tests involves nine three-stock portfolios, namely, M1 to M9. The three-stock portfolios are formed by including one asset in each of the three time zones, as show in Table 4.2. Details of the risk mapping procedure are discussed in Section 4.3.

Portfolio	Portfolio Asset (Stock Index)
S1	Japan
S2	China
S3	Hong Kong
S4	Germany
S5	United Kingdom
S6	Spain
S7	United States
S8	Canada
S9	Brazil

Table 4.1 – The Nine Single-asset Portfolios for Test Set 1

Portfolio	Portfolio Assets (Stock Index)
M1	Japan, Germany, United States
M2	Japan, United Kingdom, Canada
M3	Japan, Spain, Brazil
M4	China, Germany, United States
M5	China, United Kingdom, Canada
M6	China, Spain, Brazil
M7	Hong Kong, Germany, United States
M8	Hong Kong, United Kingdom, Canada
M9	Hong Kong, Spain, Brazil

Table 4.2 – The Nine Three-asset Portfolios for Test Set 2

4.3 Parametric and Non-parametric VaR Approaches

The calculation of VaR mainly fall into two categories: non-parametric (including the HS and MCS methods) and parametric (i.e., the VCV method).

4.3.1 Non-parametric approach: The HS approach

The HS method, which was introduced by Richardson *et al.* (1997) and Barone-Adesi *et al.* (1999), is the most widely used approach. It assumes that history will repeat itself and therefore uses series of historical risk factors to forecast the next period's VaR.

Using the HS method to calculate VaR is straightforward, and it requires relatively fewer assumptions than statistical parametric methods. It entails collecting historical data for a portfolio's return and rearranging the returns in ascending order (i.e., negative then positive returns), which enables the VaR value to be located at the appropriate percentile. The number of observations used to forecast risk is called the estimation window. An example is as follows: if the HS approach is used with 300 observations, the estimation window is 300 and the 1% one-day VaR of FTSE100 can be estimated by sorting the 300 returns in ascending order, where the third data point $(300 \times 1\%)$ is selected as the VaR. Figure 4.1 shows the results for the FTSE100 1% one-day VaR with the estimate windows of 250, 500, and 1,000 days for the period 1 January 2006 to 31 December 2012.

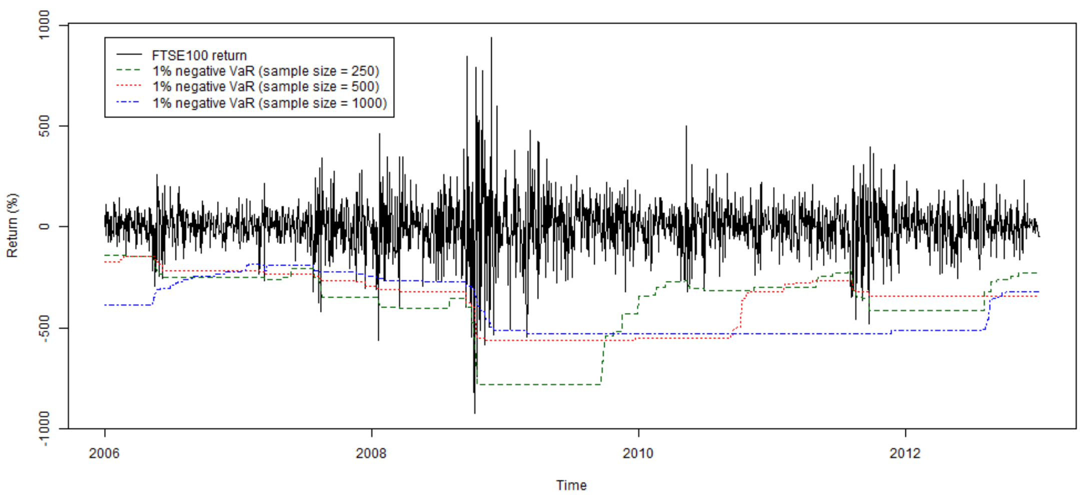


Figure 4.1 – FTSE100 1% One-day VaR by HS Approach (01 Jan 2006 to 31 Dec 2012)

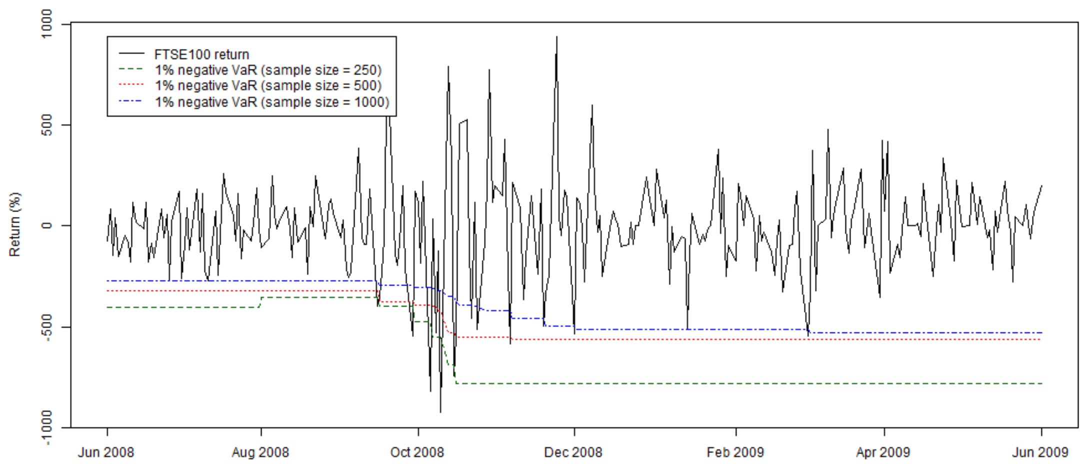


Figure 4.2 – FTSE100 1% One-day VaR by HS Approach (01 Jun 2008 to 01 Jun 2009)

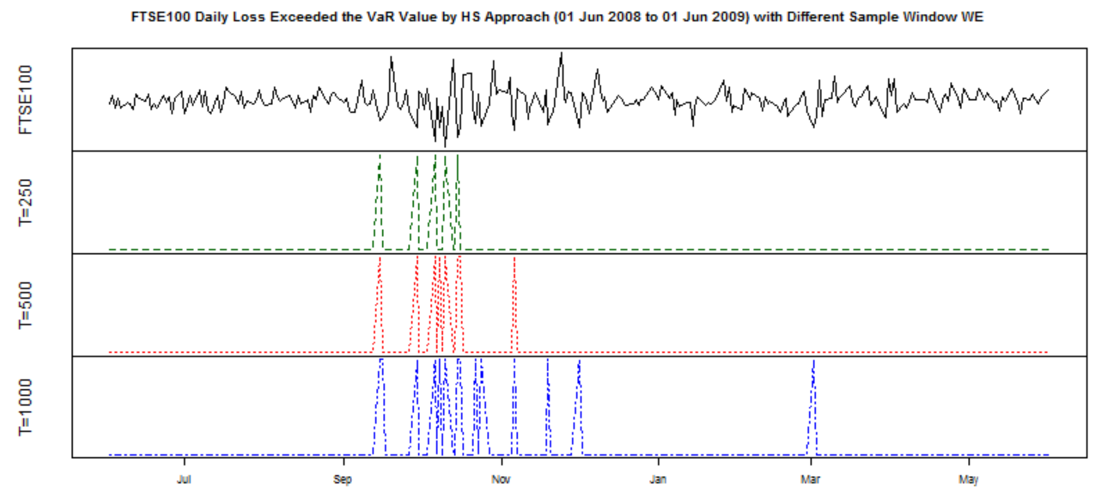


Figure 4.3 – FTSE100 Daily Loss Exceeded the 1% VaR by HS Approach with Different Estimation Window *WE* (01 Jun 2008 to 01 Jun 2009)

The HS method is clearly easy to both understand and implement. Unlike the parametric approaches, it does not require a particular probability distribution of an asset return be assumed; instead, it is based on the actual distribution of past asset returns. However, since the HS method uses the historical asset returns distribution, the choice of estimation window size becomes a critical factor, as the VaR results can be very different even there is a small different in the estimation window size. The HS method tends to underestimate risks when the estimation window covers a bull period with low volatility and to overestimate risks in inverse situations. Consider the results in Figures 4.2 and 4.3, for the period prior to the sub-prime mortgage crisis: the estimation window used for the HS method covers a low volatility bull period that caused a serious underestimation of risks when the crisis broke out in mid-September 2008. The VaR results from the HS method clearly failed in early October 2008, where risk was repeatedly underestimated. Nevertheless, the smaller estimation window in the HS approach tends to react faster to increasing volatility in potential financial crises, while its ex-post forecast simultaneously tends to be overestimated.

The VaR calculated using the HS method is highly sensitive to the chosen estimation window, and unfortunately, the choice is made according to subjective justifications, in practice. Consequently, the VaR calculated by this method can be intentionally manipulated. Having recognized the drawbacks of the HS method, regulators such as Basel II and, more recently, Basel III implemented a constraint that the method chosen must use an estimation window that is a minimum of one-year long. Nonetheless, the HS method remains seriously flawed given that the sampling problem persists.

4.3.2 Parametric approach: The VCV approach

In contrast to the HS approach, the VCV approach is based on parametric probability distribution assumptions of the risk factor returns. The most common assumption is that asset returns are i.i.d. random variables. The probability density function of the portfolio return x with mean μ and variance σ^2 is:

$$f(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

The respective cumulative distribution function $F(x)$ is:

$$F(x;\mu,\sigma) = P(X \le x) = \int_{\infty}^{x} f(y;\mu,\sigma)dy$$

Given that the standard normal cumulative distribution function $\Phi(x)$ in equation (4.1):

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{\infty}^{x} e^{\frac{y^2}{2}} dy \tag{4.1}$$

$$F(x;\mu,\sigma) = \Phi(\frac{x-\mu}{\sigma})$$

To calculate α percent one-day VaR, the mathematic equation we have to solve is:

$$\alpha = F(-VaR_{\alpha\%})$$

$$-VaR_{\alpha\%} = \mu + \Phi^{-1}(\alpha)\sigma$$

By the symmetry of the normal distribution function

$$\Phi^{-1}(\alpha) = -\Phi^{-1}(1-\alpha)$$

the α percent one-day VaR, expressed as a percentage of the asset return can be calculated by:

$$VaR_{\alpha\%} = \Phi^{-1}(1-\alpha)\sigma - \mu \tag{4.2}$$

The portfolio volatility of σ in the VCV approach can be estimated by both univariate and multivariate analyses. Univariate volatility models are used to estimate volatility at the portfolio level. One significant advantage is that the correlations between the assets in the portfolio do not need to be modelled. Meanwhile, the major drawback is that the variance is conditional on the portfolio weights: once the portfolio weights change, the risk model should be estimated. One major criticism of multivariate approaches is that estimated asset covariances will grow exponentially with the number of assets in the portfolio. As a detailed example, a portfolio with 100 assets will require one to estimate 5,050 VCV terms. Furthermore, if the number of return observations is smaller than the number of assets in the portfolio, the sample covariance matrix is singular and that complicated the optimization process. In this light, portfolio managers are recommended to perform risk mapping in order to compress the assets in the portfolio to a smaller set of base assets or risk factors that serve as the main risk drivers in the portfolio. Risk mapping is a procedure to map individual assets in a portfolio with a standardized market instrument (such as the prices of a market index, a future on the market index, foreign exchange rates, or a series of zero coupon bonds). The process of determining which factors to map depends on the assets in the portfolio. A portfolio is linear or non-linear depending on whether the price is a linear or a non-linear function of its risk factors (for example, a pure equity portfolio is a linear portfolio in which the price is a linear function of the risk factor systematic risk, whereas a bond portfolio or a portfolio that contains options is a non-linear function of the risk factor interest rate risk.).

The VCV approach assumes that the underlying risk factors have a multivariate normal distribution, while the variance of the portfolio can be calculated using the VCV matrix:

$$\sigma_p^2 = \theta^T \Omega \theta$$

Where θ is a column vector that represents the risk factor sensitivities or asset weights and Ω is the VCV matrix of different risk factors or assets. In the univariate approach, both the column vector θ and the VCV matrix Ω become a scalar and the value of θ will become one if Ω represents the asset volatility.

4.3.3 Parametric approach: The MA approach

The MA method, which is the simplest method for estimating volatility, is based on obtaining the average deviation of the sample series of historical return $\{r_t\}$:

$$r_t = ln(\frac{P_t}{P_{t-1}})$$

Where r_t denotes the return of the asset at time t and P_t denotes the asset price at time t.

To simplify the calculation, the series $\{y_t\}$ is defined as the de-meaned series of returns.

$$y_t = r_t - \mu$$

With a sample size equal to N, the univariate volatility at time t can then be estimated by equation (4.3):

$$\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N} y_{t-i}^2 \qquad (4.3)$$

For modelling the volatility of a portfolio with n assets, the vector $Y_t = \{y_{1,t}, y_{2,t}, \cdots, y_{n,t}\}$ represents n asset returns at time t and the VCV matrix H can be calculated using equation (4.4):

$$H_t = \frac{1}{N}\sum_{1}^{N} Y_t^T Y_t \quad (4.4)$$

The MA method is seldom used in practice, as the forecasted volatility is unconditional, while the actual patterns of financial series volatility are clustered. The equally weighted calculation method fails to capture this clustering characteristic and causes the calculated VaR to be too low on average; risks are, therefore, usually understated. Furthermore, results of the MA method are highly sensitive to the chosen estimation window; as such this method suffers problems similar to those encountered with the HS approach.

Figures 4.4, 4.5, and 4.6 show the results of the FTSE100 1% one-day VaR with the estimation windows of 250, 500, and 1,000 days, using the MA method.

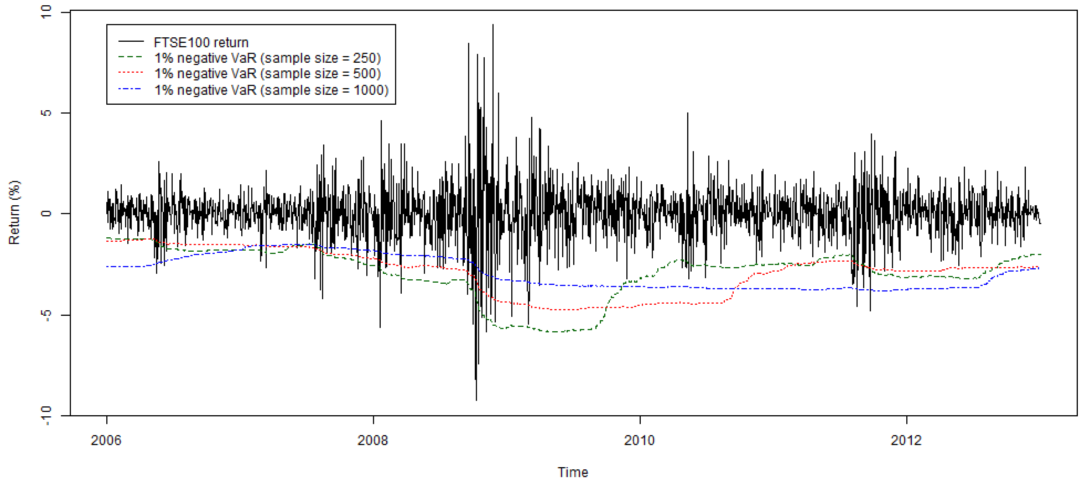


Figure 4.4 – FTSE100 1% One-day VaR by MA Method (01 Jan 2006 to 31 Dec 2012)

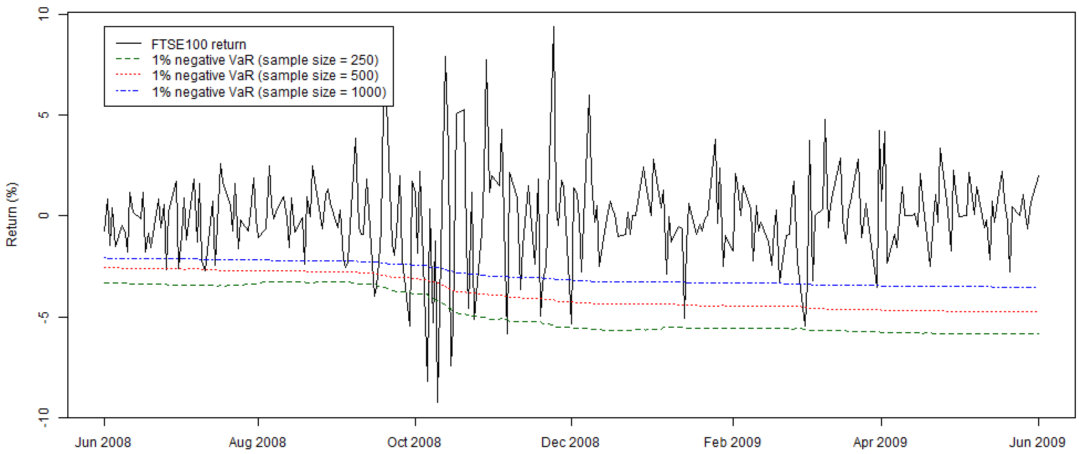


Figure 4.5 – FTSE100 1% One-day VaR by MA Method (01 Jun 2008 to 01 Jun 2009)

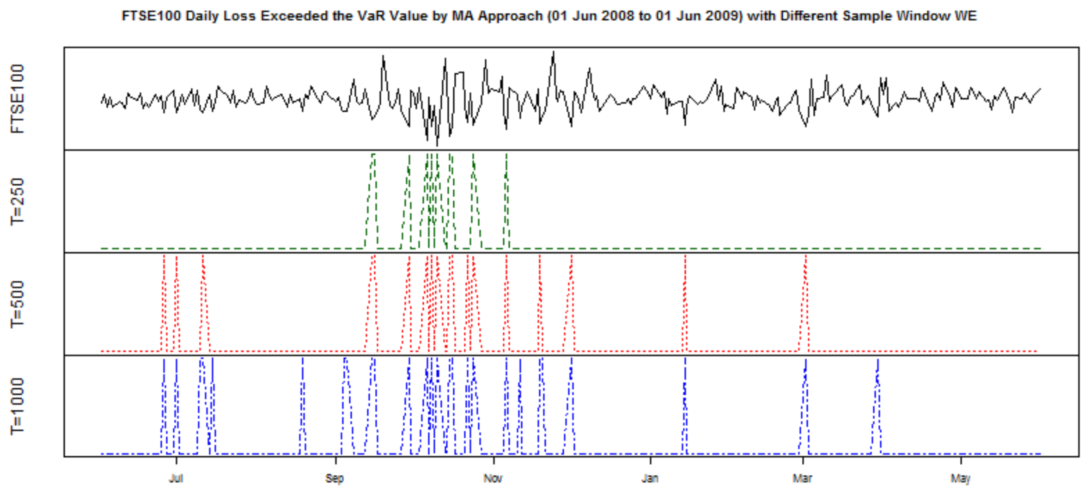


Figure 4.6 – FTSE100 Daily Loss Exceeded the 1% VaR by MA Approach with Different Estimation Window *WE* (01 Jun 2008 to 01 Jun 2009)

4.3.4 Parametric approach: The EWMA (or RiskMetrics) Approach

The EWMA method improves the MA method by assigning all of the previous observations an equal weights. It provides flexibility in allocating more weight to the most recent observations, which are more indicative of the existence of financial volatility clustering. The EWMA model was originally proposed by Longerstaey and Spencer (1996), who define a parameter λ as the decay factor of previous shocks. The next period volatility is estimated by considering both the previous volatility and return times the decay factor λ.

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)y_{t-1}^2 \tag{4.5}$$

Equations (4.5) and (4.6) show univariate and multivariate EWMA equations, respectively.

$$H_t = \lambda H_{t-1} + (1-\lambda)Y_{t-1}^T Y_{t-1} \tag{4.6}$$

The RiskMetrics approach suggests that when $\lambda = 0.94$, the forecasts of the daily variance rate will come closest to the realized variance rate.

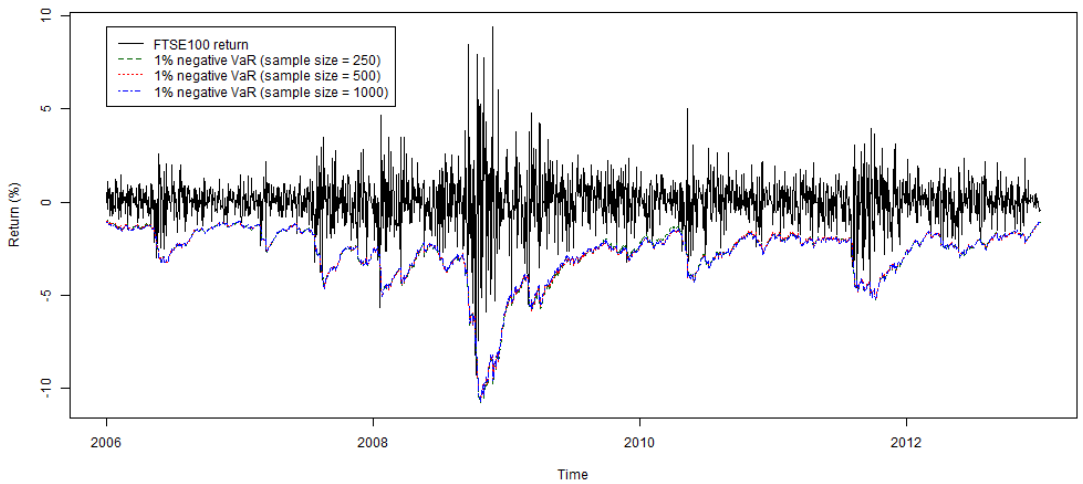


Figure 4.7 – FTSE100 1% One-day VaR by EWMA Method (01 Jan 2006 to 31 Dec 2012)

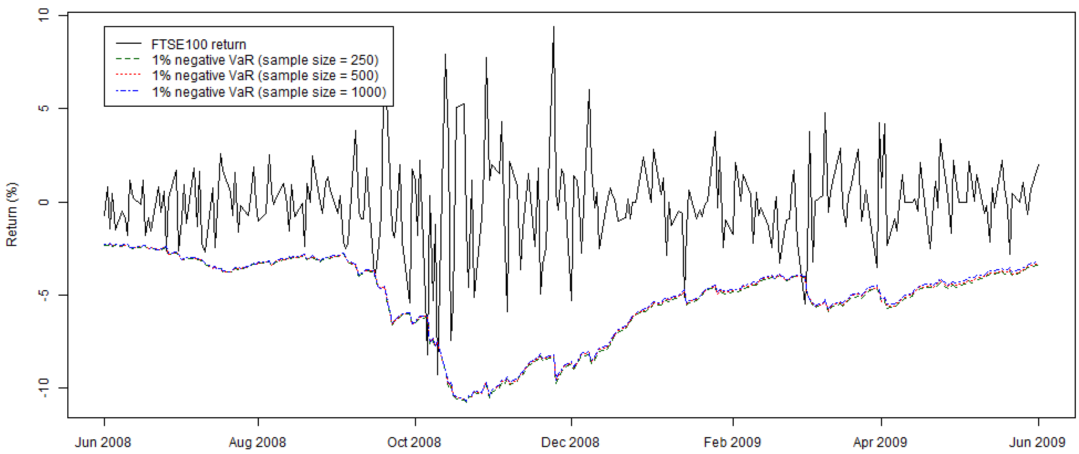


Figure 4.8 – FTSE100 1% One-day VaR by EWMA Method (01 Jun 2008 to 01 Jun 2009)

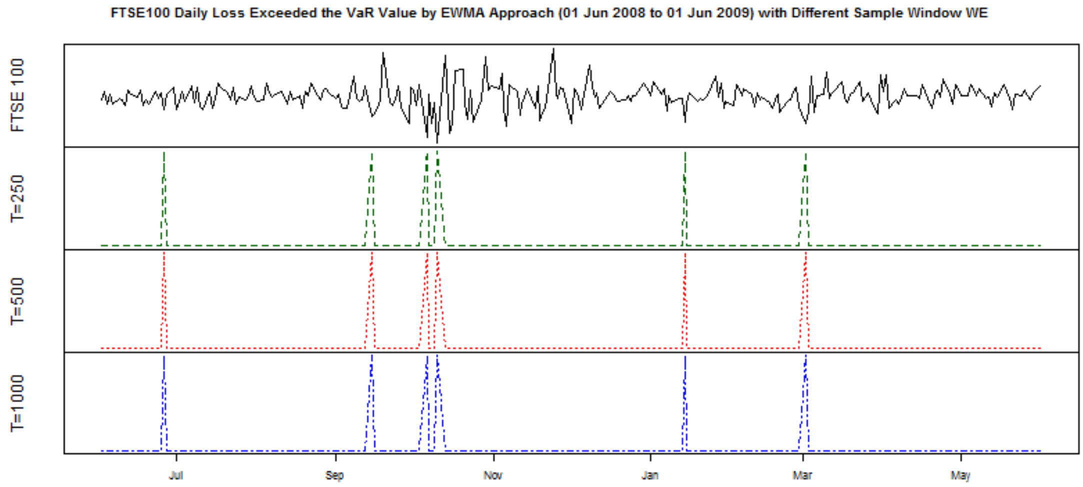


Figure 4.9 – FTSE100 Daily Loss Exceeded the VaR Value by EWMA Approach with Different Cut-off Estimation Window T (01 Jun 2008 to 01 Jun 2009)

Figures 4.7, 4.8, and 4.9 show the VaR estimated by the univariate EWMA method on FTSE100. Unlike the HS and MA methods, the EWMA method captures changes in volatility much more rapidly and captures the heteroskedasticity characteristic in general. Not surprisingly, the EWMA method is not sensitive to the chosen estimation window as the weights of previous observations decay exponentially to zero very quickly. With this method, the exponential decay factor should be adjusted for different risk horizons; if different decay factors are selected, the results given by the EWMA method can be quite differently. Figures

4.10, 4.11, and 4.12 show the results of using different decay factors under a cut-off estimation window equal to 250 days. The decay factors 0.94, 0.97, and 0.99 are arbitrarily picked and are for illustration purpose only (RiskMetrics suggests using $\lambda = 0.97$ for weekly data). The larger the value of λ chosen, the longer the previous volatility will persist (as the weights of the previous observation i is λ^i). When $\lambda = 1$, the EWMA method is thus yield the same results as the MA method. Since EWMA is not a statistical method, the choice of the decay factor cannot be obtained through computation or regression, which makes the model highly sensitive to the chosen decay factors. Because the weights of previous observations decay exponentially to zero very quickly, the EWMA method is a short memory model and has been mis-specified, as researchers such as Pafka and Kondor (2001) asserted. The EWMA model also cannot be an internal model to measure market risk in the Basel accords; thus, the "effective" observation period must be at least one year for weighting schemes that include historical observation periods to calculate VaR.

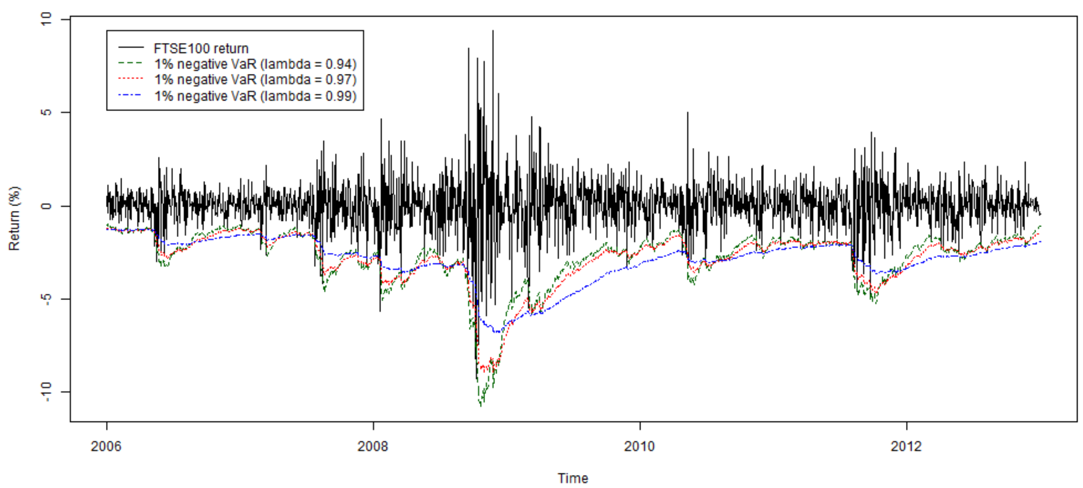


Figure 4.10 – FTSE100 1% One-day VaR by EWMA Method with Different λ
(01 Jan 2006 to 31 Dec 2012)

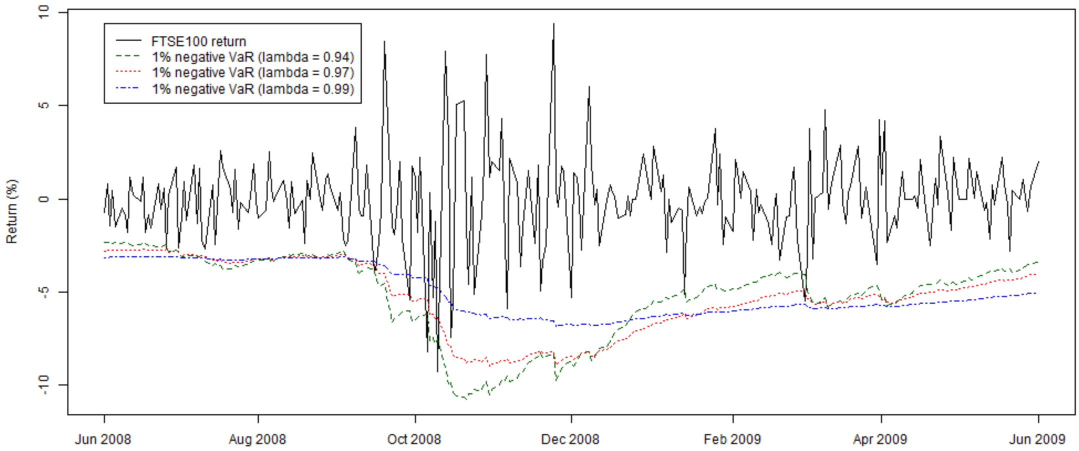


Figure 4.11 – FTSE100 1% One-day VaR by EWMA Method with Different λ (01 Jun 2008 to 01 Jun 2009)

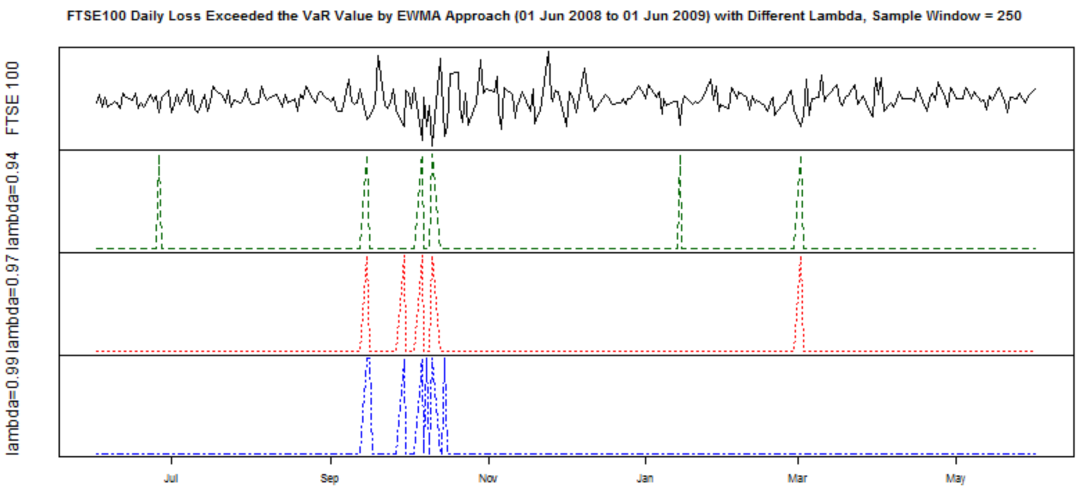


Figure 4.12 – FTSE100 Daily Loss Exceeded the VaR Value by EWMA Approach with Different λ (01 Jun 2008 to 01 Jun 2009)

4.3.5 Parametric approach: The long memory EWMA (EWMA2006 or RiskMetrics2006) model

Shocks in the equity market are unexpected but apparent in clusters with a long-lasting impact. The EWMA model fails to capture the "long memory" feature as the weights of past observations decay exponentially. In proposing a modified version of the EWMA method, Zumbach (2006) modified the EWMA's exponential decay rate to a hyperbolic decay in order to allow a long-lasting impact from any previous shock.

Unlike the original EWMA method, the RiskMetrics2006 method defines K historical volatilities at time t by using a decay factor μ_k that is based on the geometric time horizon τ_k:

$$\tau_k = \tau_1 \rho^{k-1}$$

$$\mu_k = exp(-\frac{1}{\tau_k})$$

$$H_{k,t} = \mu_k H_{k,t-1} + (1-\mu_k) Y_t^T Y_t \tag{4.7}$$

The RiskMetrics2006 method obtains the next period's conditional covariance matrix H_{t+1} as a sum of the K historical volatilities in equation (4.7), with logarithmic decay weights w_k:

$$H_{t+1} = \sum_{k=1}^{K} w_k H_{k,t} \tag{4.8}$$

where

$$w_k = \frac{1}{C}\left(1 - \frac{ln(\tau_k)}{ln(\tau_0)}\right)$$

$$C = K - \sum_{k=1}^{K} \frac{ln(\tau_k)}{ln(\tau_0)}$$

The purpose of the constant C is to make sure the sum of the weights is equal to one

($\sum w_k = 1$). The long memory RiskMetrics2006 model captures different scales of volatilities that are controlled by three parameters: τ_0 is the logarithmic decay factor, τ_1 is the low cut-off, and τ_k is the upper cut-off. As suggested by Zumbach (2007), the operationalized parameter ρ is set to $\sqrt{2}$, the optimal parameters value for τ_0 is 1,560 days, τ_1 is 4 days, and τ_k is 512 days; and K is set to 15.

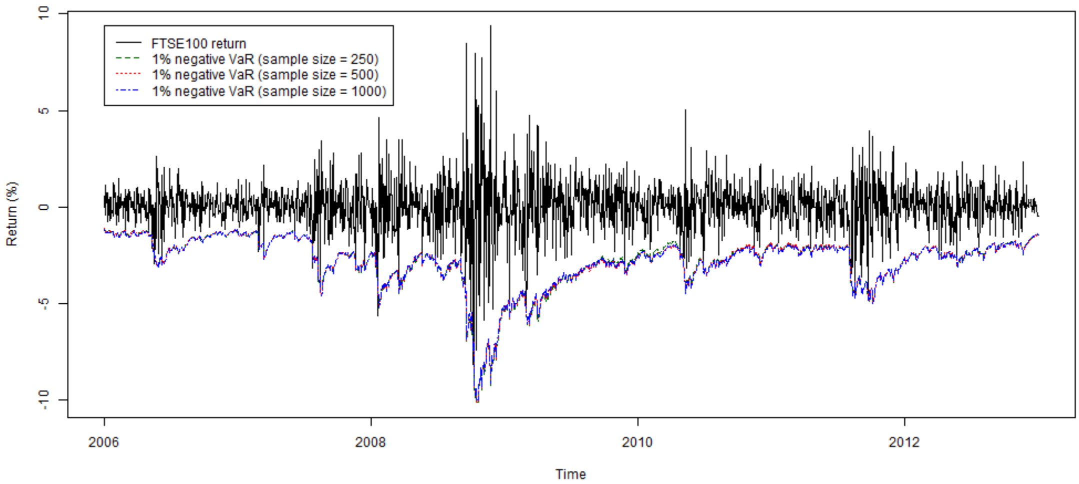


Figure 4.13 – FTSE100 1% One-day VaR by RiskMetrics2006 Method
(01 Jan 2006 to 31 Dec 2012)

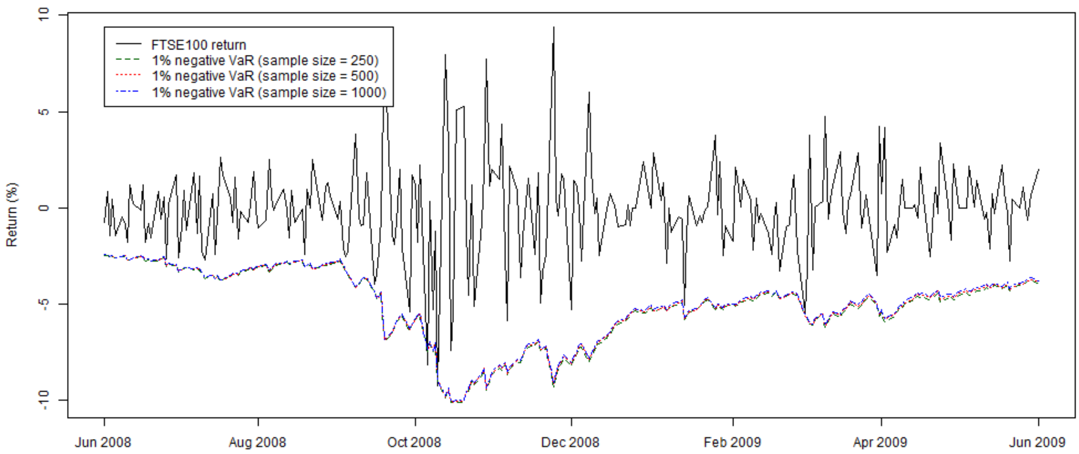


Figure 4.14 – FTSE100 1% One-day VaR by RiskMetrics2006 Method
(01 Jun 2008 to 01 Jun 2009)

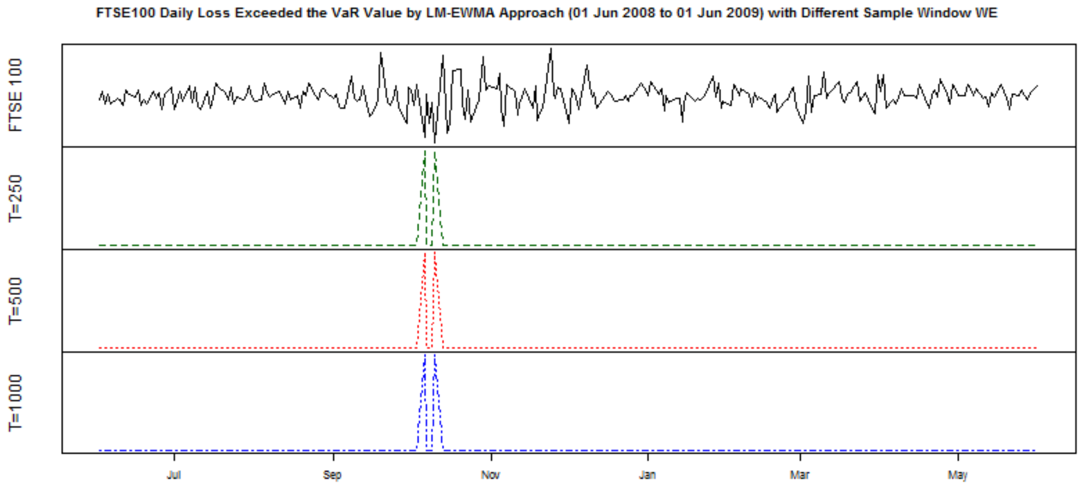


Figure 4.15 – FTSE100 Daily Loss Exceeded the VaR Value by RiskMetrics2006 Approach (01 Jun 2008 to 01 Jun 2009)

4.3.6 Parametric approach: The GARCH model

In traditional time-series analysis, AR, MA, and combined ARMA models are widely used to describe a time series that exhibits characteristics of a self-dependent, stationary process. However, when volatility is described in the financial market, randomness is observed to vary widely over time and tends to cluster together. The process is self-dependent and conditionally heteroskedastic. Engle (1982) introduced the ARCH model to capture the characteristics, and his student Bollerslev (1986) proposed the GARCH model by incorporating a moving average term to solve the high-order problem with the ARCH model.

In general, the conditional volatility of the $GARCH(p,q)$ model can be calculated as:

$$y_t = \epsilon_t \tag{4.9}$$

$$h_t^2 = \omega + \alpha(L)\epsilon_t^2 + \beta(L)h_t^2 \tag{4.10}$$

$$(1-\beta(L))h_t^2 = \omega + \alpha(L)\epsilon_t^2$$

$$h_t^2 = (1-\beta(L))^{-1}\omega + (1-\beta(L))^{-1}\alpha(L)\epsilon_t^2 \tag{4.11}$$

$$\epsilon_t \sim i.i.d(0, h_t)$$

Where L is the lag operator and $\alpha(L)$ and $\beta(L)$ are the lag polynomials in order p and q respectively.

$$\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \cdots + \alpha_q L^q$$

$$\beta(L) = \beta_1 L + \beta_2 L^2 + \cdots + \beta_p L^p$$

By defining the surprising term $\nu_t^2 = \epsilon_t^2 - h_t^2$, the equation (4.11) can be rewritten as:

$$(1-\beta(L)-\alpha(L))\epsilon_t^2 = \omega + (1-\beta(L))\nu_t \tag{4.12}$$

Many variations of ARCH family models exist. To model an asset return series, the auto-correlated property of a stock returns series can be captured by adding AR, integrated (I), or MA terms in equation (4.9), and these terms are then generalized as ARIMA(m,d,n) in equation (4.13):

$$(1-\Phi(L))(1-L)^d y_t = (1+\Theta(L))\sigma_t^2 \tag{4.13}$$

Where $\Phi(L)$ and $\Theta(L)$ are the lag equations:

$$\Phi(L) = \phi_1 L + \phi_2 L^2 + \cdots + \phi_m L^m$$

$$\Theta(L) = \theta_1 L + \theta_2 L^2 + \cdots + \theta_n L^n$$

4.3.7 Parametric approach: The GJR-GARCH model

Variations also exist among GARCH models regarding modelling volatility. As suggested by Engle and Ng (1993), Glosten *et al.* (1993) asymmetric GARCH models model stock return series better, as an asymmetric impact of bad or good news information on stock return volatility is reflected (see Christie (1982). According to Engle and Ng (1993), the GJR-GARCH model proposed by Glosten *et al.* (1993) is the best ARCH family model for capturing the asymmetric impact. It modifies the GARCH model in equation (4.10) by adding a threshold parameter N_t, which is a dummy variable that takes the value of 1 when ϵ_t is positive and 0 when ϵ_t is negative. The equation of GJR-GARCH(p,q) is:

$$h_t^2 = \omega + \alpha(L)\epsilon_t^2 + \gamma(L)N_t\epsilon_t + \beta(L)h_t^2$$

where

$$\gamma(L) = \gamma_1 L + \gamma_2 L^2 + \cdots + \gamma_q L^q$$

4.3.8 Parametric approach: The FIGARCH model

One problem with the GARCH models discussed so far is that they all fail to model the persistence characteristic of stock volatility and thus face the same problem as the original EWMA method. To allow long memory in the GARCH models, Baillie *et al.* (1996) proposed the FIGARCH model, which extends the integrated GARCH (IGARCH) model of Engle and Bollerslev (1986) by allowing the integration coefficient d to vary in a range from zero to one. As the coefficient d is allowed to be a fractional number in the FIGARCH model, unlike in the IGARCH model, a shock in the volatility process will not persist for an infinite prediction horizon; it will decay at a hyperbolic rate that represents the long memory characteristic of a volatility process.

The volatility process in the FIGARCH model is:

$$(1-\beta(L)-\alpha(L))(1-L)^d\epsilon_t^2 = \omega + (1-\beta(L))v_t \tag{4.14}$$

From equation (4.10), the conditional volatility of the GARCH model can be rewritten as:

$$h_t^2 = \omega + \beta(L)h_t^2 + (1-\beta(L)+\alpha(L)+\beta(L)-1)\epsilon_t^2$$

If $\alpha(L)+\beta(L)=1$, it is a unit root process by substituting $1-\alpha(L)-\beta(L)$ with $\phi(L)(1-L)^d$.

The FIGARCH model can also be represented as:

$$h_t^2 = \omega + \beta(L)h_t^2 + (1-\beta(L)-\phi(L)(1-L)^d)\epsilon_t^2 \qquad (4.15)$$

Using Taylor expansion, the polynomial $(1-L)^d$ can be written as:

$$\delta_d(L) = (1-L)^d = \sum_{i=0}^{\infty}\delta_{d,i}L^i \qquad (4.16)$$

$$\delta_{d,i} = \frac{\Gamma(i-d)}{\Gamma(i+1)\Gamma(-d)}$$

$$\delta_{d,i+1} = \frac{i-d}{i+1}\delta_{d,i}$$

The coefficients $\delta_{d,i}$ decay at a rate of i^{-d-1}, which is a long memory process.

The equation for the FIGARCH model can be further written as:

$$h_t^2 = \omega + \beta(L)h_t^2 + (1-\beta(L)-\phi(L)\delta_d(L))\epsilon_t^2 \qquad (4.17)$$

The FIGARCH(1,d,1) model is thus defined as:

$$h_t^2 = \omega + \beta_1 h_{t-1}^2 + (1-\beta_1 L-(1-\phi_1 L)\delta_d(L))\epsilon_t^2$$

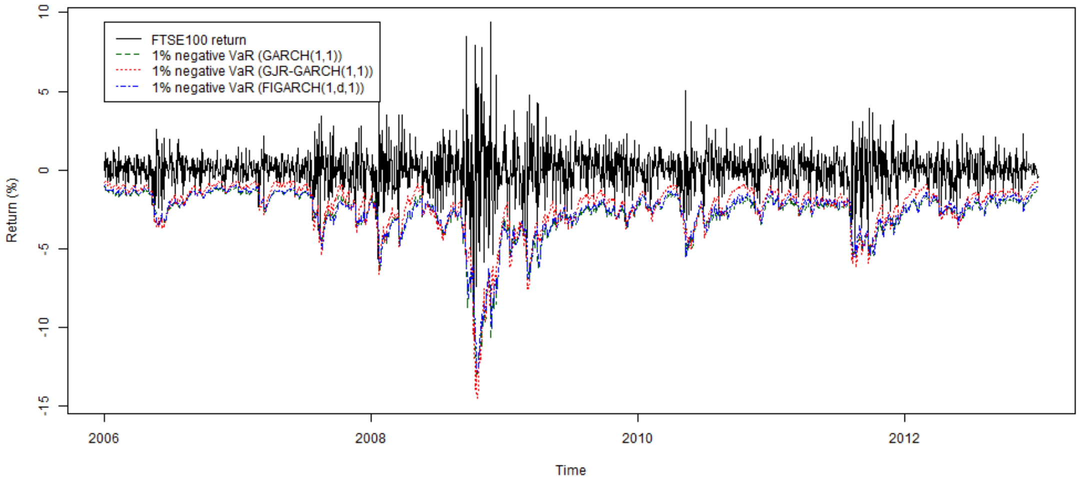


Figure 4.16 – FTSE100 1% One-day VaR by GARCH(1,1), GJR-GARCH(1,1) and FIGARCH(1,d,1) Methods
(01 Jan 2006 to 31 Mar 2012)

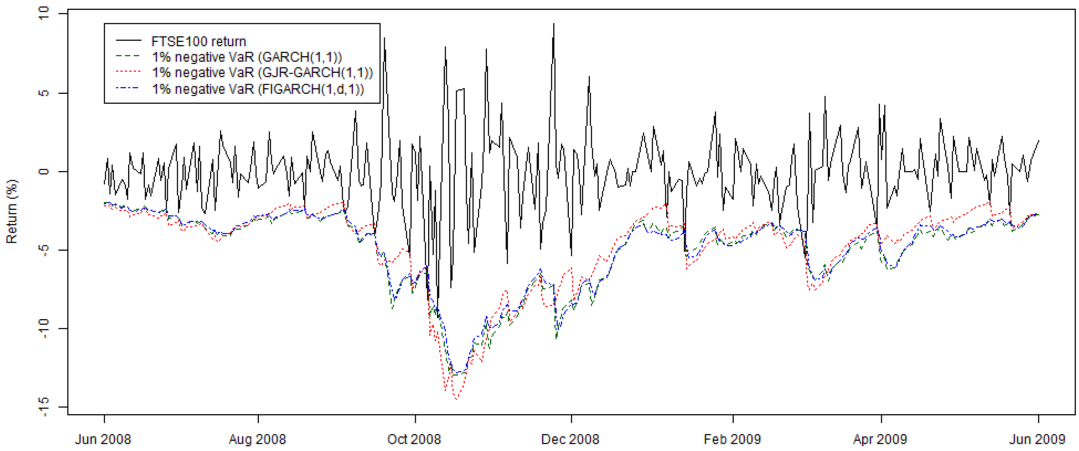


Figure 4.17 – FTSE100 1% 1-day VaR by GARCH(1,1), GJR-GARCH(1,1) and FIGARCH(1,d,1) Methods
(01 Jun 2008 to 01 Jun 2009)

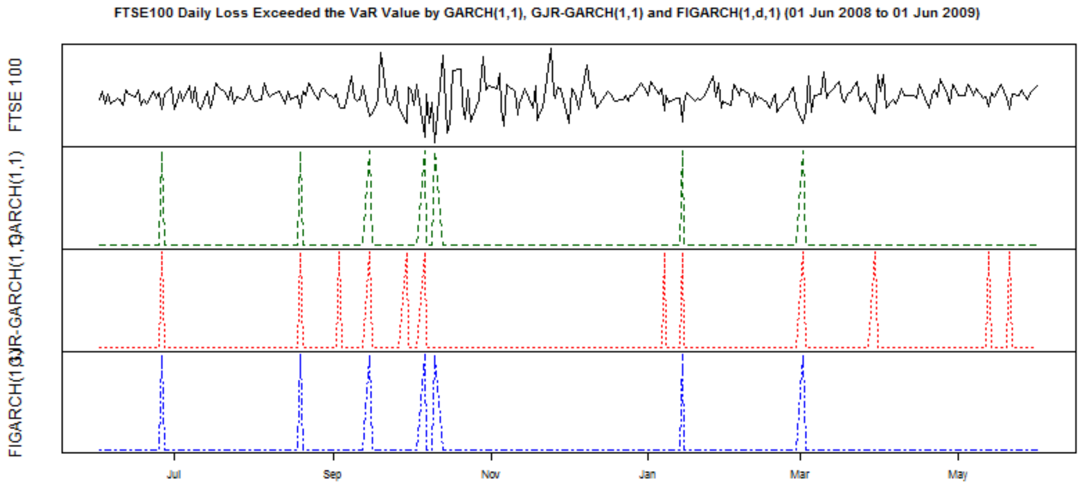


Figure 4.18 – FTSE100 Daily Loss Exceeded the VaR Value by GARCH(1,1), GJR-GARCH(1,1) and FIGARCH(1,d,1) Approaches (01 Jun 2008 to 01 Jun 2009)

Figure 4.16 shows the VaR results obtained using the GARCH(1,1), GJR-GARCH(1,1), and FIGARCH(1,d,1) models with an estimation window of $W_E = 1,000$. The results in Figures 4.16, 4.17, and 4.18 are intentionally for illustration purposes only; a comparison of the use of different GARCH models in VaR calculation is presented in the next section.

Using ARCH family volatility models to calculate single-asset portfolio VaR is straightforward but computational. As these models require statistical methods to estimate the parameters, the estimation windows that they use cannot be too small. The estimation window $W_E = 1,000$ is used in this study.

4.4 Multivariate Models

The multivariate GARCH models used in this study are represented as:

$$r_t = \epsilon_t,$$

$$\epsilon_t \mid I_{t-1} \sim N(0, H_t), \tag{4.18}$$

$$H_t = g(H_{t-1}, H_{t-2}, \cdots, \epsilon_{t-1}, \epsilon_{t-2}),$$

where r_t is a $(n \times 1)$ vector of the asset returns or risk factors $r_t = [r_{1,t}, r_{2,t}, \cdots, r_{n,t}]'$ at time t. The function $g(.)$ is a function of lagged conditional covariance matrices. There are variety ways to model covariance matrices. In this study, we apply Engle (2002) DCC model and Cappiello *et al.* (2006) ADCC model.

4.4.1 Volatility spillover in multivariate models

Eun and Shim (1989) applied Sims (1980) vector autoregression model to capture the interdependence between the world's nine largest stock markets, which including Australia, Canada, France, Germany, Hong Kong, Japan, Switzerland, the United Kingdom, and the United States, in terms of capitalization value in the year 1985. They found that a substantial amount of interdependence exists among different national stock markets; most importantly, they discovered that the U.S. stock was the most influential stock market and that the others were followers. Hamao *et al.* (1990) and Koutmos and Booth (1995) found similar results using the GARCH process of Bollerslev (1986). Bae *et al.* (2003) found that contagion is predictable and depends on regional interest, exchange rate changes, and conditional stock return volatility. Allen *et al.* (2013) used a tri-variate GARCH model to study volatility spillover among the U.S., Australian, and Chinese (proxied by the Hang Seng Index) markets and found strong evidence of changing correlations among the markets during financial crisis periods.

As mentioned in Section 4.2, the first set of tests contains nine single-stock portfolios, and the equity asset in each portfolio is the stock market index of each of the nine countries. After considering volatility spillover among the different stock markets, we incorporate other risk factors into the multivariate GARCH models, as shown in Table 4.3.

Portfolio	Portfolio Asset (Stock Index)	Factors (Stock Indices) in the Multivariate Models
S1	Japan	United States, Canada, Brazil
S2	China	United States, Canada, Brazil
S3	Hong Kong	United States, Canada, Brazil
S4	Germany	Japan, China, Hong Kong
S5	United Kingdom	Japan, China, Hong Kong
S6	Spain	Japan, China, Hong Kong
S7	United States	Germany, United Kingdom, Spain
S8	Canada	Germany, United Kingdom, Spain
S9	Brazil	Germany, United Kingdom, Spain

Table 4.3 – The Nine Single-asset Portfolios and Risk Factors in the Multivariate GARCH Models

4.5 Backtesting VaRs

The aim of backtesting is a statistical procedure to identify the weaknesses of a VaR model. A VaR violation is recorded for a particular date on which a portfolio of assets' losses exceeds the calculated VaR value. Backtesting identifies the significance of VaR violations in a given testing period.

We define T as the total number of observations in the data set, W_E as the size of the estimation windows, and W_T as the testing window for VaR violations. A VaR violation

($\kappa_t = 1$) is recorded if the loss on a particular trading day t exceeds the calculated VaR value. The total number of VaR violations v_1 in the testing period W_T is calculated by equation (4.19), while v_0 in equation (4.20) is the number of days without violations in the testing period.

$$W_E + W_T = T$$

$$\kappa_t = \begin{cases} 1, & \text{if } y_t \leq -VaR_t \\ 0, & \text{if } y_t > -VaR_t \end{cases}$$

$$v_1 = \sum \kappa_t \qquad (4.19)$$

$$v_0 = W_T - v_1 \qquad (4.20)$$

The number of violations and clustering of violations are two major issues of consider when evaluating the performance of different VaR models is evaluated. Unconditional coverage tests such the POF and TUFF test of Kupiec (1995) are commonly used to evaluate VaR models by testing the number of violations at a given confidence level. Conditional coverage tests such as the interval forecast test of Christoffersen (1998) and the mixed-Kupiec test capture violation clustering.

4.5.1 Unconditional coverage

In general, unconditional coverage tests are based on a binomial probability distribution. For a trading day with losses that exceed VaR estimates, a failure event (VaR violation) is recorded ($\kappa_t = 1$). With the failure rate p. defined as $p = \frac{v_1}{W_T}$ and successful rate $(1-p)$ defined as $(1-p) = \frac{v_0}{W_T}$, the sequence of failure events can be expressed as a Bernoulli trial process. The number of VaR violations v_1 follows a binomial probability distribution:

$$f(v_1) = \binom{W_T}{v_1} p^{v_1} (1-p)^{W_T - v_1} \tag{4.21}$$

The binomial distribution in equation (4.21) can be approximated through a normal distribution if the size of the testing window W_T increases.

4.5.2 Unconditional coverage: The POF test

Intuitively, if a number of VaR violations exceeds the selected confidence level, the VaR model may be underestimating the risk. In contrast, too few violations may indicate that the VaR model is overestimating the risk. Kupiec (1995) suggested a POF hypothesis test to determine whether the number of VaR violations is consistent with the selected confidence level.

The null hypothesis is:

$$H_0 : p = \hat{p} = \frac{v_1}{W_T}$$

The POF test aims to test whether the observed failure rate (i.e. the number of VaR violations) is significantly different from the selected failure rate p.

Under a true null hypothesis, LR is asymptotically χ^2 distributed with one degree of freedom. The LR test is defined as:

$$LR_{POF} = -2ln\left(\frac{(1-p)^{W_T - v_1} p^{v_1}}{(1-\hat{p})^{W_T - v_1} \hat{p}^{v_1}}\right) \tag{4.22}$$

The POF test is biased if the size of the testing window is small. In such a case, this test will not work well, even if the model does comply with the Basel accords, which require that the "effective" observation period must be at least one year (i.e., 250 trading days). Furthermore, the POF test does not provide any information about the "timing" of the violations, and it fails to reject a VaR model that produces clustered violations.

4.5.3 Unconditional coverage: The TUFF test

In addition to the POF test, Kupiec (1995) also introduced the TUFF test, which measures the first violation that occur. It assumes that the first violation occurs in $v = \frac{1}{p}$ days. For 99% VaR calculation, a violation is expected to occurs every 100 days.

The null hypothesis is:

$$H_0 : p = \hat{p} = \frac{1}{v}$$

Under a true null hypothesis, the LR is asymptotically χ^2 distributed with one degree of freedom. The LR test is defined as:

$$LR_{TUFF} = -2ln\left(\frac{p(1-p)^{v-1}}{(\frac{1}{v})(1-\frac{1}{v})^{v-1}}\right) \tag{4.23}$$

The major problem of the TUFF test is that it fails to identify a bad VaR model, with unacceptably high type II error (see Sinha and Chamu 2000). However, the TUFF test provides a useful framework for exploring independence using the Hass (2001) mixed-Kupiec test , which is discussed in the next section.

4.5.4 Conditional coverage

In theory, VaR violations should spread out over time, and they should not occur as a sequence of consecutive exceptions. An effective VaR model should be able to react to changing volatility and correlations. Unconditional coverage tests focus only on the number of exceptions while ignoring the timing of failure events. They also fail to account for volatility clustering. The conditional coverage tests aim to address these problems by testing both the frequency and timing of failures.

4.5.5 Conditional coverage: Christoffersen's interval forecast test

Christoffersen (1998) tested the independence of VaR violation by considering a binary first-order Markov chain with the transition probability matrix Π_1. Christoffersen (1998) defines an indicator variable I_t that returns a value of 0 or 1 when a VaR violation occurs:

$$I_t = \begin{cases} 0 & \text{if no VaR violation occurs} \\ 1 & \text{if VaR violation occurs} \end{cases}$$

$$\Pi_1 = \begin{pmatrix} (1-p_{01}) & p_{01} \\ (1-p_{11}) & p_{11} \end{pmatrix}$$

where $p_{ij} = Pr(I_t = j \mid I_{t-1} = i)$.

The likelihood function for the violation sequence is Bernoulli distributed following the first-order Markov chain:

$$L_R(\Pi_1; I_1, I_2, \cdots, I_t) = (1-p_{01})^{n_{00}} p_{01}^{n_{01}} (1-p_{11})^{n_{10}} p_{11}^{n_{11}}$$

where n_{ij} is the total number of observations that indicator variable $I_t = j$ follows by $I_{t-1} = i$.

The maximum likelihood (ML) estimates for the log-likelihood functions $L_R(\Pi_1)$ are simply ratios of the count of the respective cells.

$$\Pi_1 = \begin{pmatrix} \dfrac{n_{00}}{n_{00}+n_{01}} & \dfrac{n_{01}}{n_{00}+n_{01}} \\ \dfrac{n_{10}}{n_{10}+n_{11}} & \dfrac{n_{11}}{n_{10}+n_{11}} \end{pmatrix}$$

If VaR violations are independent, today's violation should be independent from yesterday's violation; the probability of p_{01} should be equal to p_{11}. The transition probability matrix under the null hypothesis is:

$$\Pi_0 = \begin{pmatrix} (1-p) & p \\ (1-p) & p \end{pmatrix}$$

The ML estimates for the log-likelihood function $L_U(\Pi_0)$ are:

$$\Pi_0 = \begin{pmatrix} (1-\hat{p}) & \hat{p} \\ (1-\hat{p}) & \hat{p} \end{pmatrix}$$

where

$$\hat{p} = \frac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}}$$

The unrestricted likelihood function is:

$$L_U(\Pi_1; I_1, I_2, \cdots, I_t) = (1-\hat{p})^{n_{00}+n_{10}}\,\hat{p}^{n_{01}+n_{11}}$$

The LR test for the independence:

$$LR_{ind} = 2(logL_U(\Pi_0) - logL_R(\Pi_1)) \sim \chi^2(1)$$

A joint test of coverage and independence can be undertaken by combining the LR_{ind} and LR_{POF} statistics as conditional coverage LR_{cc} statistics:

$$LR_{cc} = LR_{POF} + LR_{ind} \sim \chi^2(2)$$

4.5.6 Conditional coverage: The mixed-Kupiec test

The flaws of Christoffersen's interval forecast test are that it is based on a first-order Markov chain and considers only the dependence between two consecutive trading days. Hass (2001) combined the ideas of Christoffersen and Kupiec in proposing a mixed-Kupiec test use the LR test to consider both the occurrence of the first violation and the time of different occurrences:

$$LR_i = -2ln\left(\frac{p(1-p)^{v_i-1}}{(\frac{1}{v_i})(1-\frac{1}{v_i})^{v_i-1}}\right)$$

where v_i is the time between the VaR violations $i-1$ and i. With n exceptions in the testing period, the LR test equation is:

$$LR_{ind} = \sum_{i=1}^{n} -2ln\left(\frac{p(1-p)^{v_i-1}}{(\frac{1}{v_i})(1-\frac{1}{v_i})^{v_i-1}}\right)$$

Based on the idea of Christoffersen, the conditional coverage test is a mixed test for independence and coverage. It entails combining the new LR_{ind} statistic and the original Kupiec LR_{POF} statistic as conditional coverage LR_{mixed} statistics:

$$LR_{mixed} = LR_{POF} + LR_{ind} \sim \chi^2(n+1)$$

4.6 Backtesting Results

The entire data set contains 2,240 observations for the period from 1 June 2004 to 31 December 2012. Since the parametric ARCH family models require more data in the estimation window for optimization, we use the estimation window size $W_E = 1,000$ in our tests. The estimation window is subsequently rolled forward on observation. To determine how well different VaR models perform during crisis and non-crisis periods, we conduct the backtests in batches for two periods: the sub-prime mortgage crisis period from 1 June 2008 to 1 June 2009 and the non-crisis period from 1 June 2009 to 31 December 2012. The backtesting results are shown in Figures 4.20 to 4.37 and Tables 4.5 to 4.22.

4.6.1 Tests for single-asset portfolios

We calculate the 1% one-day VaR of the nine single-stock portfolios that are described in Section 4.2; the equity asset in each portfolio is solely the stock market index of each of the nine countries. We test the following VaR approaches: HS, MS, EWMA, long memory EWMA (RiskMetrics2006), GARCH, GJR-GARCH, FIGARCH, DCC, GJR-DCC, ADCC, and GJR-ADCC. The calculated VaR values are then backtested using coverage, independence, and joint tests.

Figures 4.20 to 4.29 and Tables 4.5 to 4.13 illustrate the nine portfolio's VaR violations using different VaR approaches. Surprisingly, none of the univariate or multivariate GARCH-type approaches work well in the crisis period. Table 4.5 shows the backtest results of single-asset portfolio S1, the GARCH, GJR-GARCH, DCC, and ADCC failed in the coverage tests, Independent tests and joint test at 5% significant level. GARCH, DCC, and ADCC model has a p-value of 2.38%, 0.61%, and 0.16% in the POF coverage tests, Chistoffersen Independence test and the mixed Kupiec joint test respectively. Among the univariate GARCH-type approaches, the GJR-GARCH(1,1) model performs the worst while the FIGARCH(1,1) model performs the best. The GJR-GARCH(1,1) model is insignificant in all the single-asset portfolios, it has a p-value of zero in the POF coverage tests, Chistoffersen independence test, Chistoffersen joint tests, and Mixed-Kupiec test. Similar findings are obtained in all other portfolios of S2 to S9. Despite the GJR-GARCH(1,1) model's poor performance, we find that many loss violations slightly exceed the calculated VaR; the absolute value of the model's forecasting errors is thus small. Nonetheless, as the estimation results are too close to the true value, leading VaR violations to occur frequently. The GJR-GARCH model is good for forecasting volatility but it may not suitable for calculating VaR to measure downside risk, as the minimum forecasting errors do not provide sufficient cushion in estimating losses. However, using multivariate GARCH models to calculate single-stock portfolio's VaR provides no advantage over using univariate GARCH models, as the VaR values obtained from the multivariate GARCH approaches do not differ from those obtained from the univariate GARCH approaches. The reason is that the multivariate GARCH models uses quasi-ML estimation in two steps: the model's joint log-likelihood is split into two and then maximized sequentially. If we do not include exogenous variables in the return series estimation process or in the volatility function, using multivariate GARCH models to calculate VaR for a single-stock portfolio with single-risk factors offers no benefit. The multivariate GARCH models nevertheless offer an advantage in estimating the interdependence between the model's assets or risk factors. A multi-asset portfolio can thus benefit from multivariate GARCH models in estimating the VCV matrix of risk factors. If a portfolio contains only a single-risk factor, however, multivariate GARCH models should not be used.

Among all of the approaches used to calculate VaR in a single-asset portfolio, the long memory RiskMetrics2006 method performed overwhelmingly well in all of the coverage, independence, and joint tests. In Table 4.5, RiskMetrics2006 is highly significant in the coverage, independence, and joint tests. The p-value of the POF, TUFF, Christoffersen independence test, Christoffersen joint test are 81.27%, 80.12%, 70.13%, and 93.88% respectively. Similar observations are found in other portfolios of S2 to S9 in Table 4.6 to 4.13. The VaR violations in different equity indices were recorded around late September 2008 and early October 2008, just a few days after the bankruptcy of Lehman Brothers Holdings Inc. on 15 September 2008.

4.6.2 Tests for multiple-assets portfolios

To test how well the different VaR approaches perform with multiple-asset portfolios, we perform tests on the nine three-asset portfolios shown in Table 4.2.

For these tests, we use passive portfolios that implement a buy-and-hold strategy, are equally weighted and were purchased on 31 May 2004 (the portfolio return series starts on 1 June 2004). We form the portfolio by initially purchasing \$100,000 in each asset and holding them until the end of 31 December 2012. To simplify the situation, we ignore the exchange rate factor and assume that all index value is dominated in dollars. For example, the portfolio value of portfolio M1 on 31 May 2004 is \$300,000, and the number of units brought in the equity indices of Japan, Germany, and the United States are 8.8997, 25.5010, and 9.8150 respectively. Table 4.4 shows the details of the calculations.

	Japan	Germany	United States
Stock Index Value	$11,236.37	$3,921.41	$10,188.45
Number of Units Brought	$100,000/$11,236.37 = 8.8997	$100,000/$3,921.41 = 25.5010	$100,000/$10,188.45 = 9.8150
Market Value	$100,000	$100,000	$100,000

Table 4.4 – Market Value of Portfolio M1 on 1 Jun 2004

The calculation method used for univariate VaR models with multiple-asset portfolios is similar to the methods used with single-asset portfolios; we considers the portfolio as a whole, single asset. Unlike with univariate VaR models, the calculation of VaR with multivariate models requires continual adjustment to risk factor weights. Portfolio variances can be obtained using multivariate models to estimate the VCV matrix Ω of different risk factors, and then multiplying the risk factor sensitivities vector as shown in equation (4.24).

$$\sigma_p^2 = \theta^T \Omega \theta \tag{4.24}$$

where θ is a column vector representing the risk factor sensitivities or asset weights. As the market value of individual asset changes over time, so does the asset weights vector θ. The weights of asset i in time t can be calculated as:

$$\theta_{i,t} = \frac{MV_{i,t}}{MV_{p,t}}$$

where $MV_{i,t}$ is the market value of asset i and $MV_{p,t}$ is the portfolio market value at time t.

Figure 4.19 shows how the market value of the nine three-asset portfolios change over time. The VaR violations of the nine portfolios are shown in Figures 4.29 to 4.37.

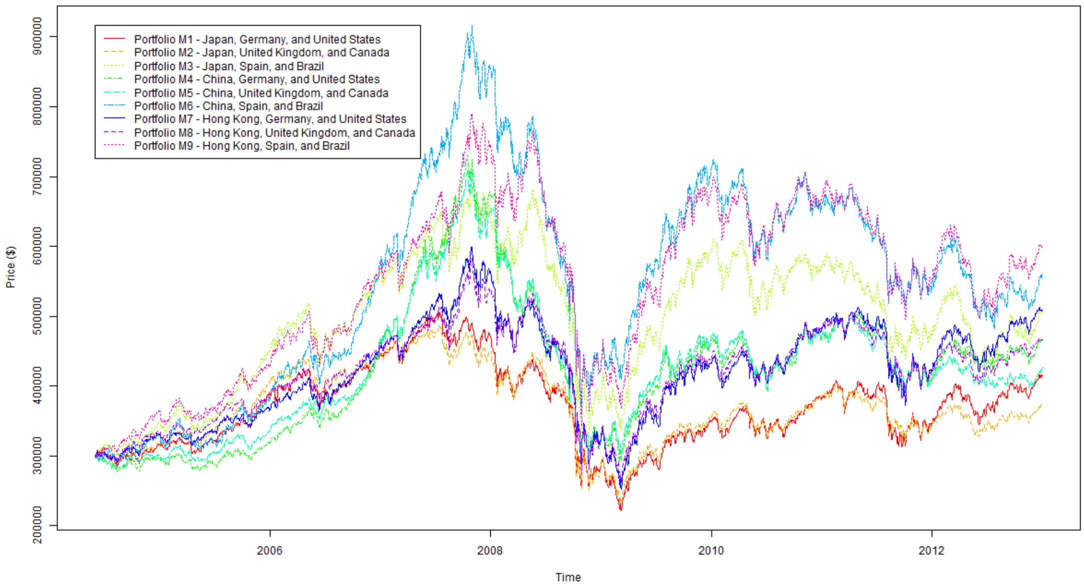


Figure 4.19 – Market Value of the Three-asset Portfolios M1 to M9

For multiple-asset portfolio with previously unknown risk factors, the univariate RiskMetrics2006 method would be the best choice among the VaR approaches. Tables 4.14 to 4.22 indeed show that the RiskMetrics2006 outperforms the other univariate methods in all the coverage, independence, and joint tests, in both the crisis and after-crisis periods. However, if the risk factors are identified in multiple-asset portfolios, one should calculate VaR with multivariate VaR models instead of univariate VaR models.

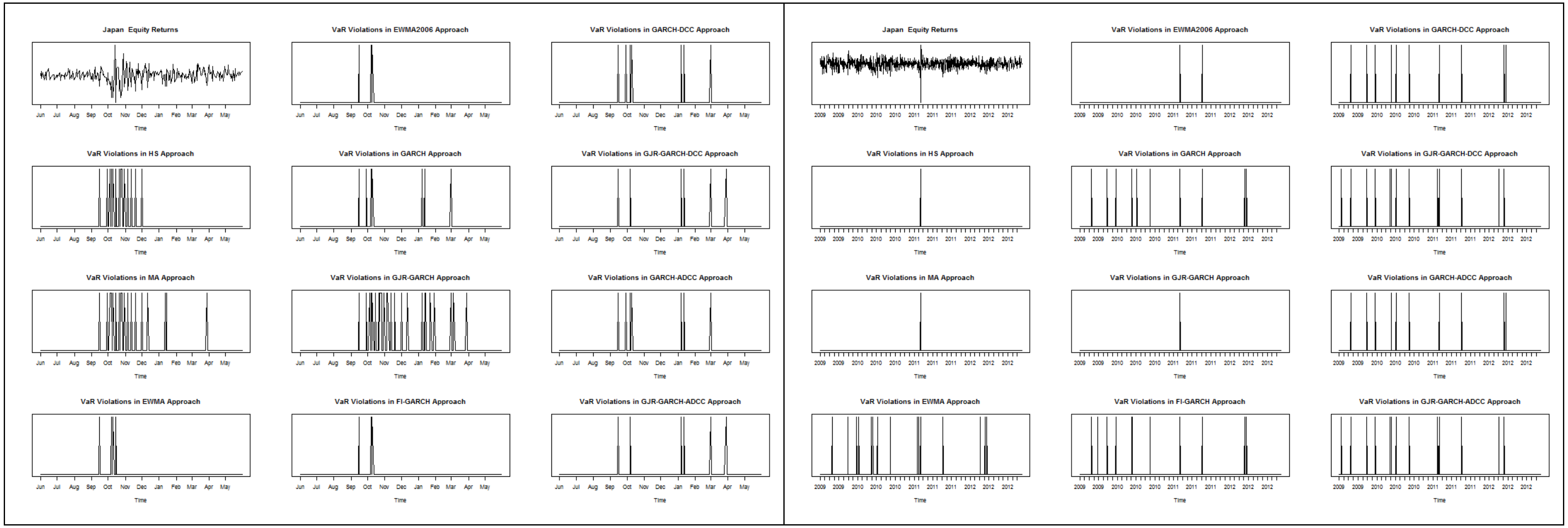
Unlike the results for the univariate models, the results for the multivariate RiskMetrics2006 model do not show that the model offers any advantage over the multivariate GARCH models. In general, multivariate VaR models work well in the both the crisis and after-crisis periods. Moreover, the multivariate GARCH models perform very well in the independence tests but not the coverage tests during the crisis period; however, they perform better in the coverage tests than in the independence tests during the after-crisis period. The DCC, GJR-DCC, ADCC, and GJR-ADCC models show little differences during the backtesting. Although the asymmetric GJR-ADCC model slightly outperforms the others in a few scenarios (Table 4.15b, 4.20b, and 4.21b), if these results are compared and reconciled with those obtained in Chapter 3, it may not be worthwhile to use asymmetric correlation to calculate VaR in multivariate models. The GJR-DCC model is adequate for calculating multivariate VaR; as suggested in Chapter 3, equity markets tend to reflect bad news on volatility but not on correlations.

4.7 Conclusion

This chapter reviewed the major approaches to calculating VaR. In total, 14 VaR approaches including non-parametric approaches (HS), univariate parametric approaches (MA, EWMA, RiskMetrics2006, GARCH, GJR-GARCH, and FIGARCH), and multivariate parametric approaches (MA, EWMA, RiskMetrics2006, DCC, GJR-DCC, ADCC, and GJR-ADCC), were examined in both the sub-prime mortgage crisis and after-crisis periods. Two sets of portfolios were formed to test the effectiveness of different the VaR approaches. Univariate approaches were used to consider a portfolio as a single asset, while multivariate approaches were used to map individual assets to the base risk factors.

The HS, MA, and GJR-GARCH approaches performed worse during the crisis period for both the single- and multiple-asset portfolios. They seriously understated risks during this period while overstating risks in the after-crisis period. The univariate RiskMetrics2006 method showed promising results, as it did not over- or understate risks in either period. It also performed well in all of the unconditional coverage, independence, and joint tests.

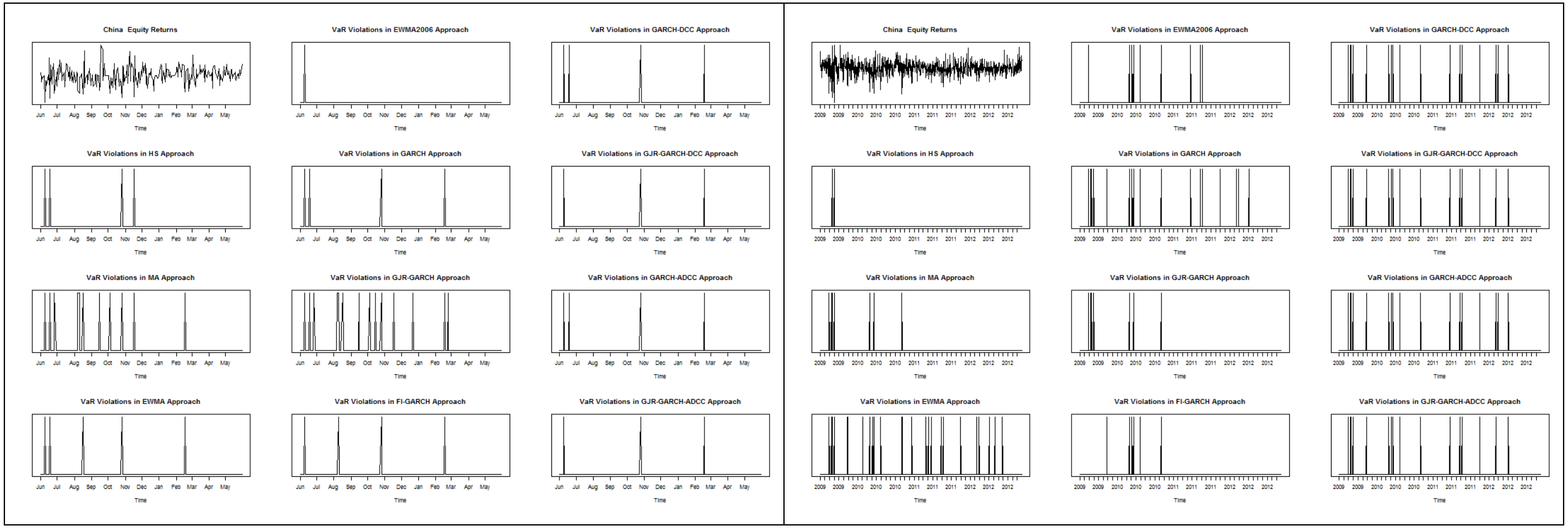
The findings in this chapter provides guidelines for portfolio managers to manage downside financial risks. For single-asset portfolios or multiple-asset portfolios without any risk factor being identified, it is suggested to use univariate RiskMetrics2006 method calculating the VaR. In contrast, for portfolios with identified risk factors, the portfolio manager should consider using multivariate GARCH models to estimate the conditional covariance matrix for a VCV approach. Adding asymmetric terms in modelling volatility will generally provide better results; however, there is no benefit from adding asymmetric terms in the modelling correlations. We recommend using the GJR-DCC model which incorporates the asymmetric volatility effect in the equity market for calculating VaR in multiple-asset portfolio.



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

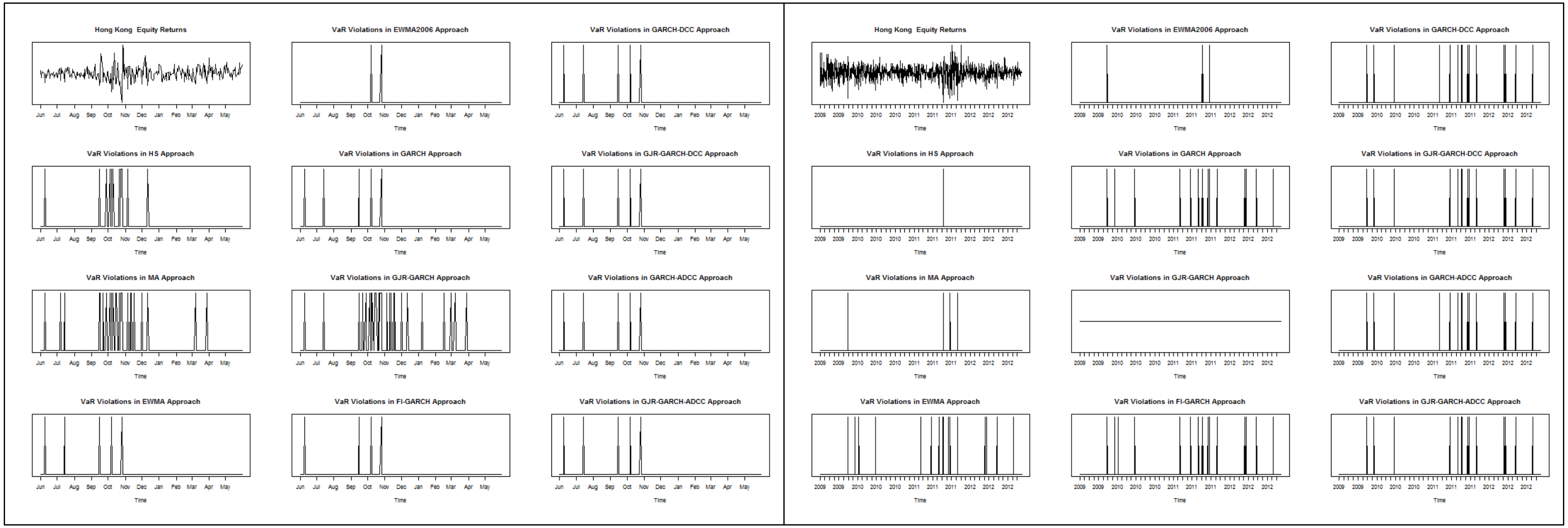
Figure 4.20 – Backtesting Results for Portfolio S1 - Japan



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

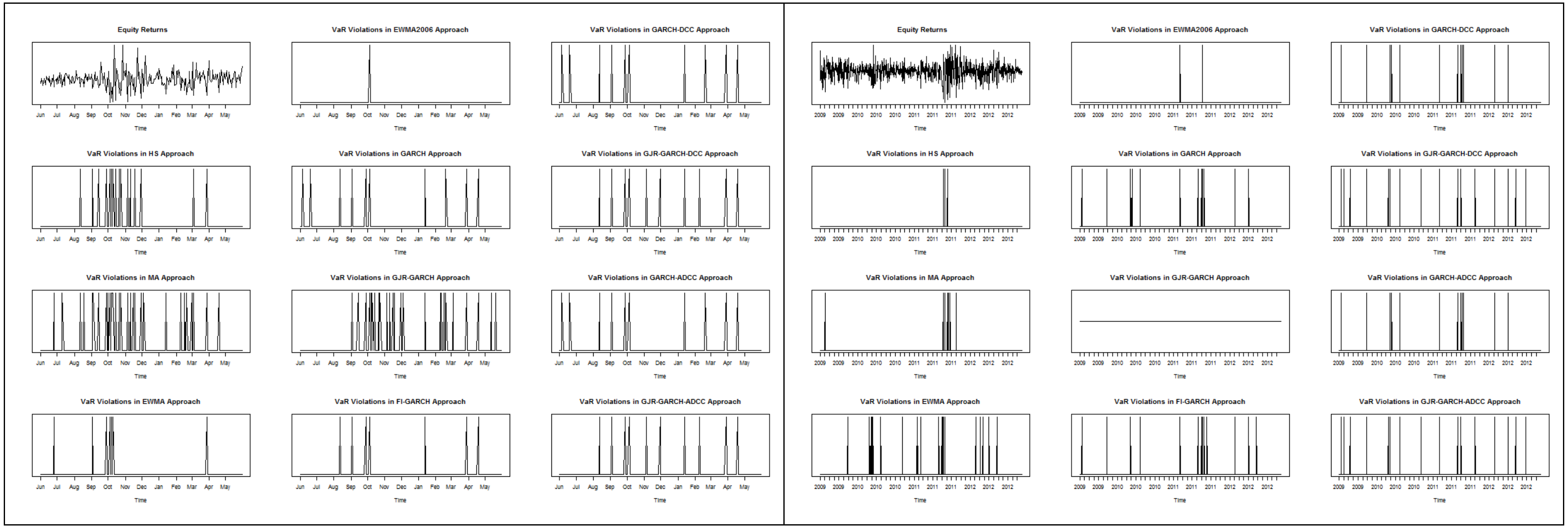
(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

Figure 4.21 – Backtesting Results for Portfolio S2 - China



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009 (b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

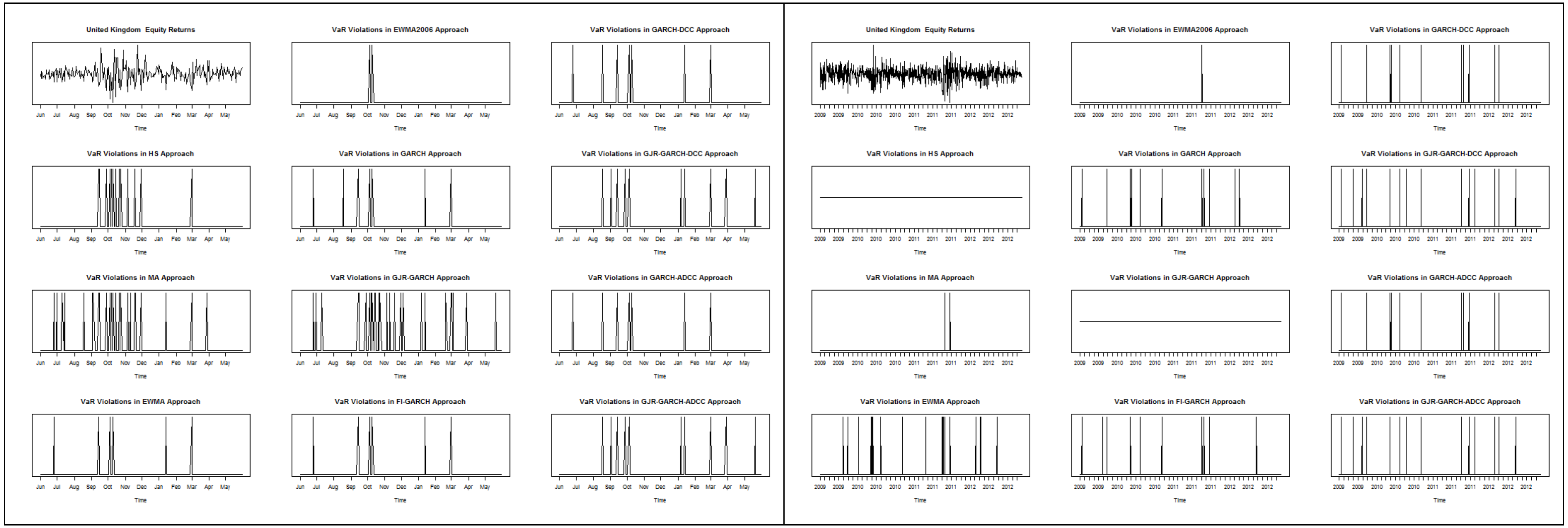
Figure 4.22 – Backtesting Results for Portfolio S3 - Hong Kong



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

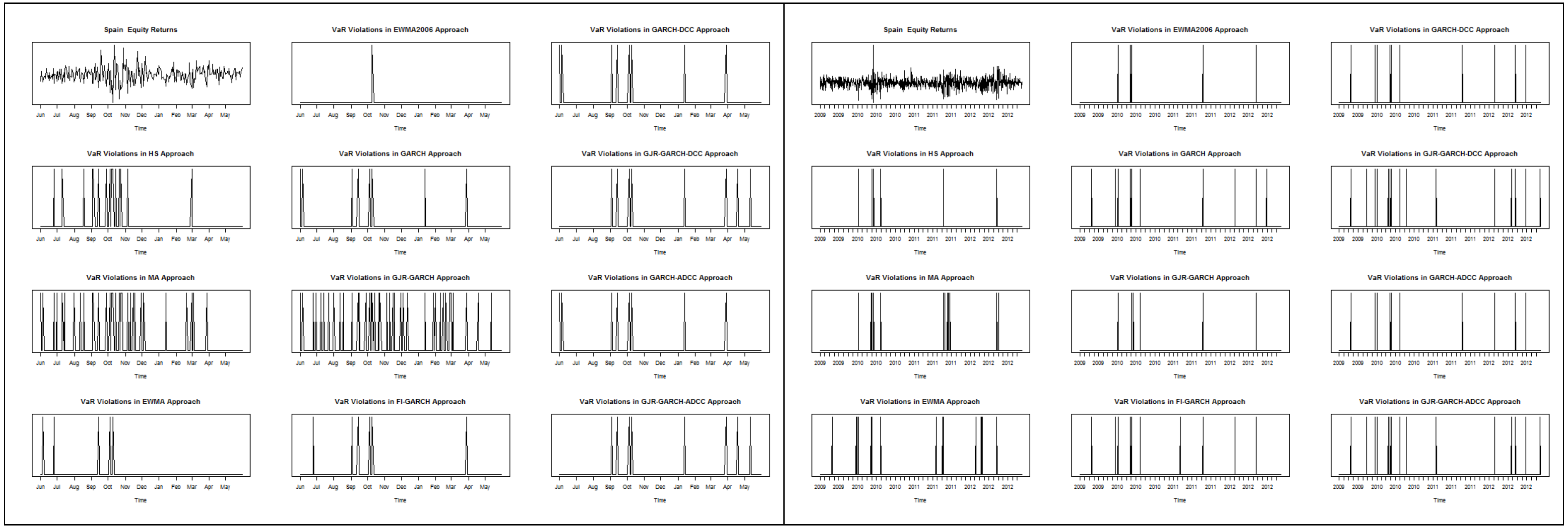
Figure 4.23 – Backtesting Results for Portfolio S4 - Germany



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

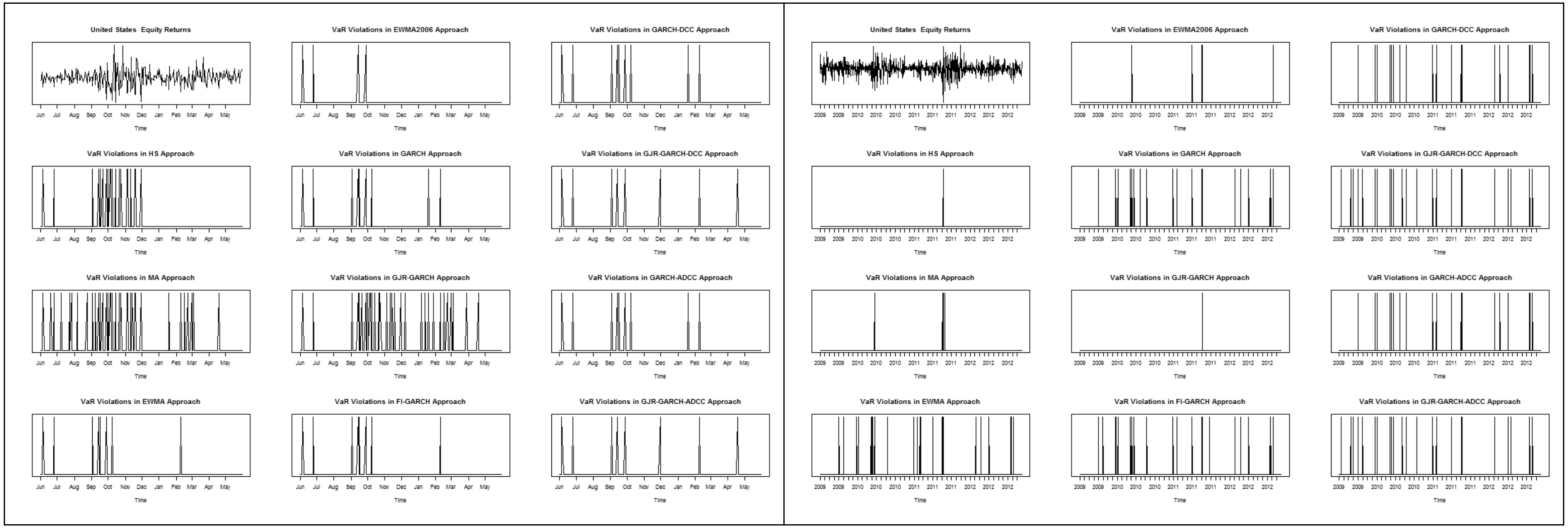
Figure 4.24 – Backtesting Results for Portfolio S5 - United Kingdom



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

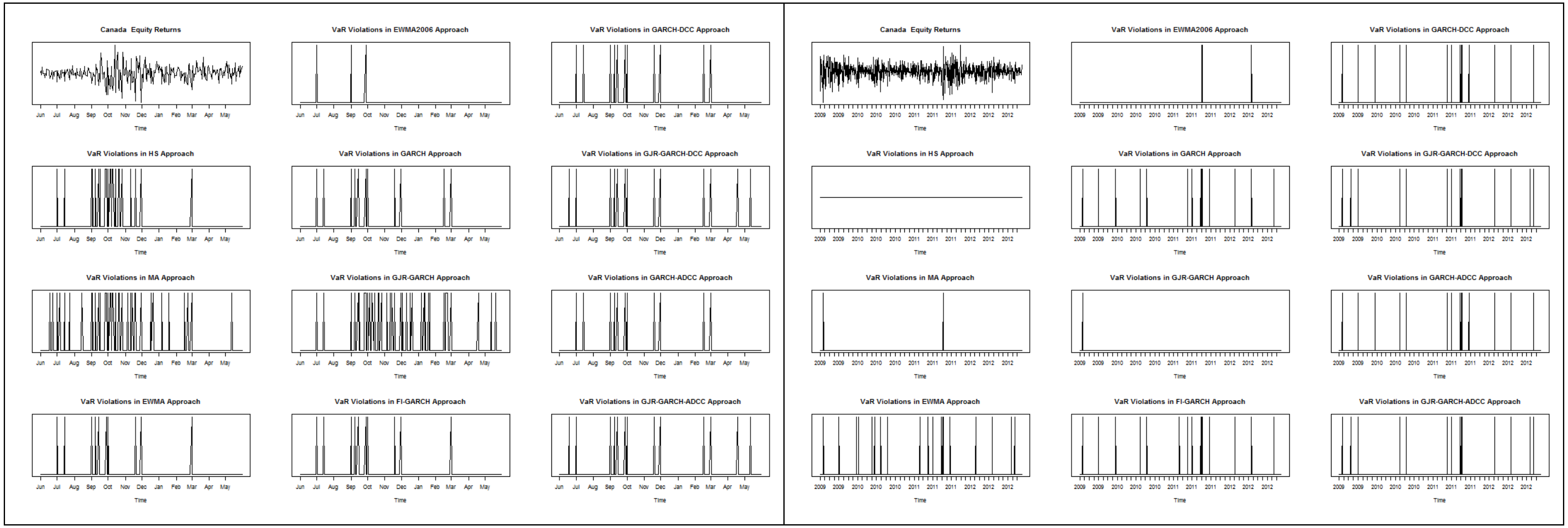
Figure 4.25 – Backtesting Results for Portfolio S6 - Spain



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

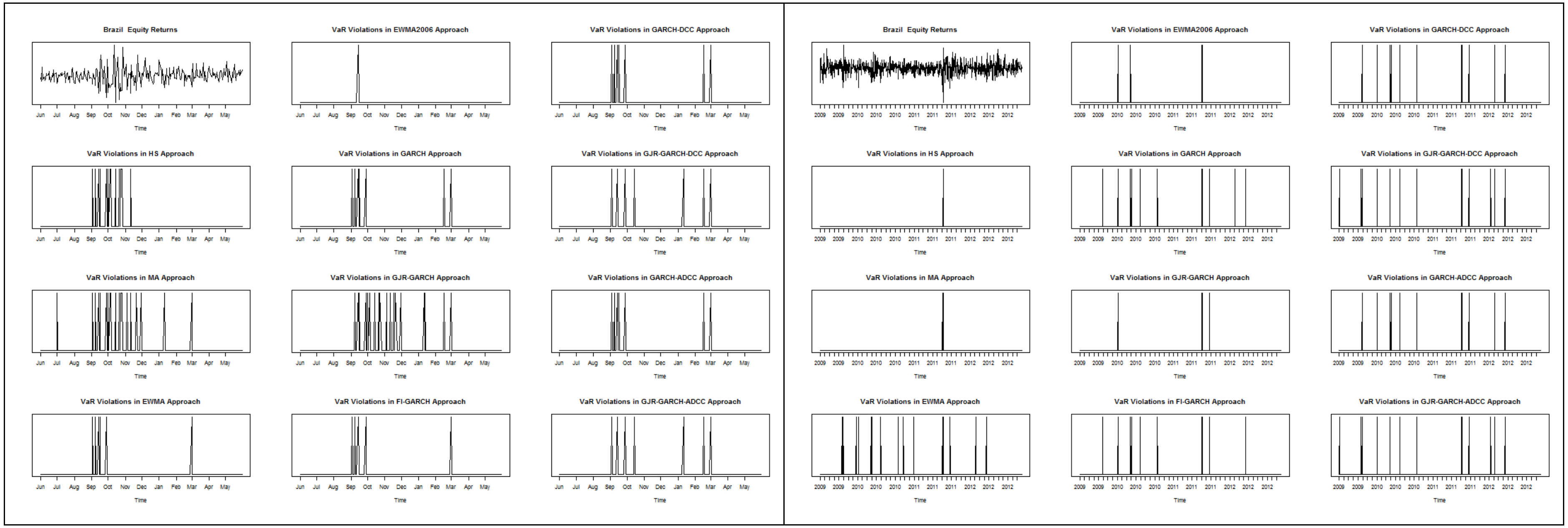
Figure 4.26 – Backtesting Results for Portfolio S7 - United States



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

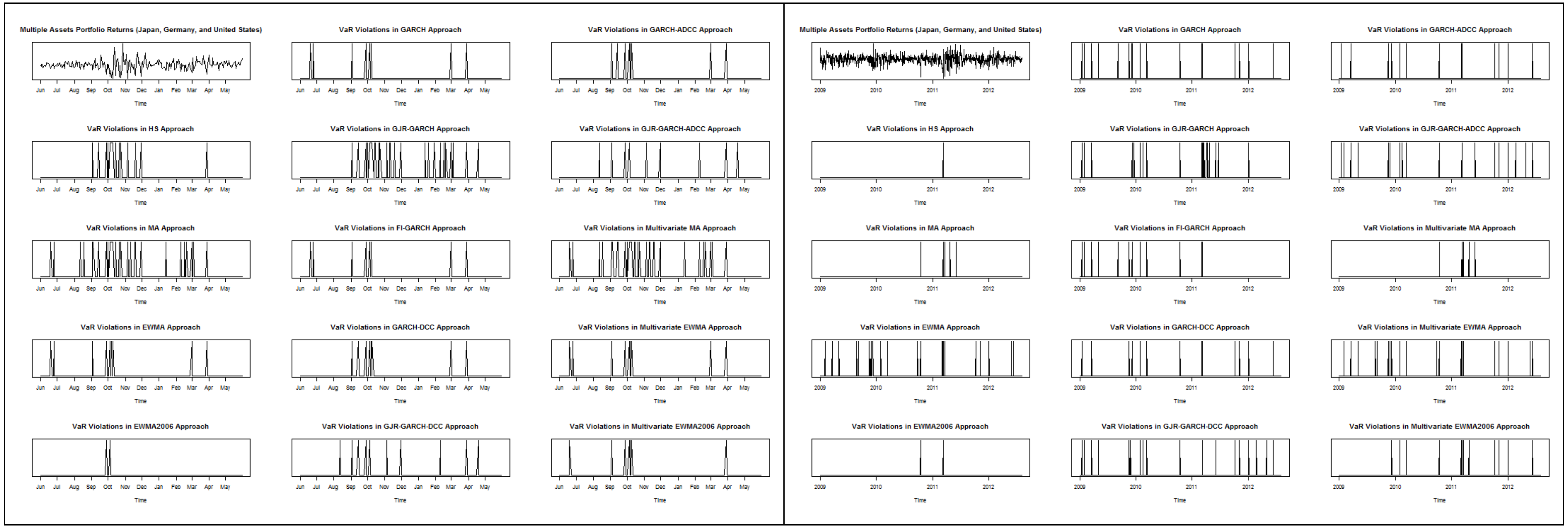
Figure 4.27 – Backtesting Results for Portfolio S8 - Canada



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

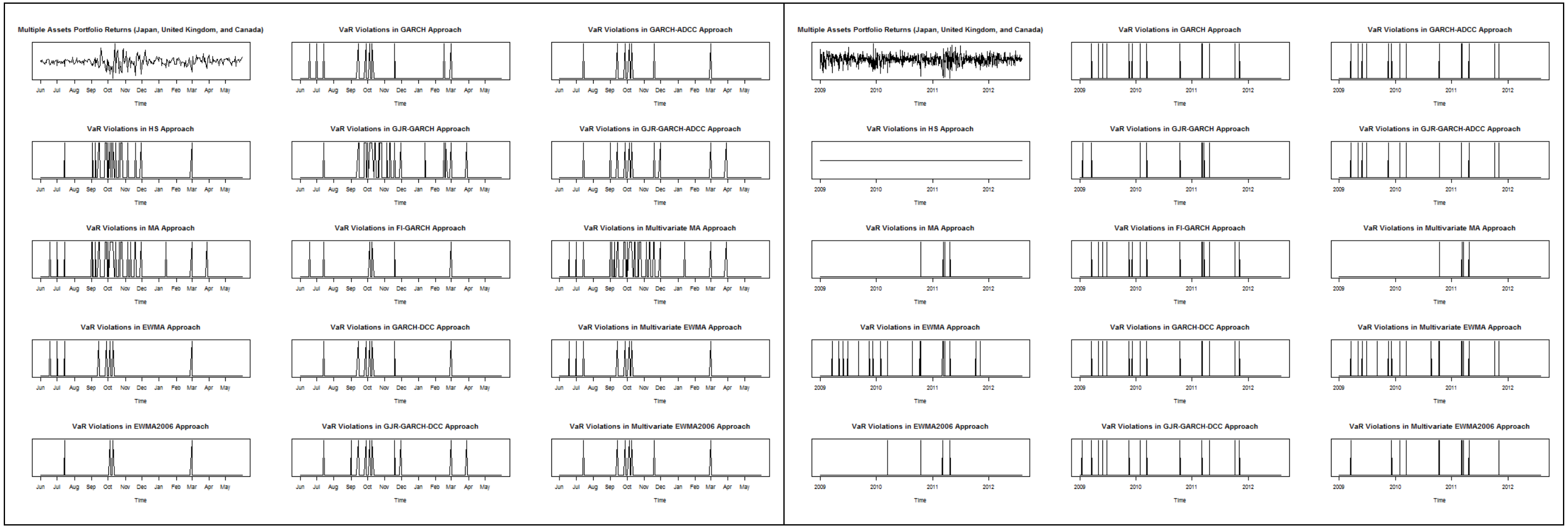
Figure 4.28 – Backtesting Results for Portfolio S9 - Brazil



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

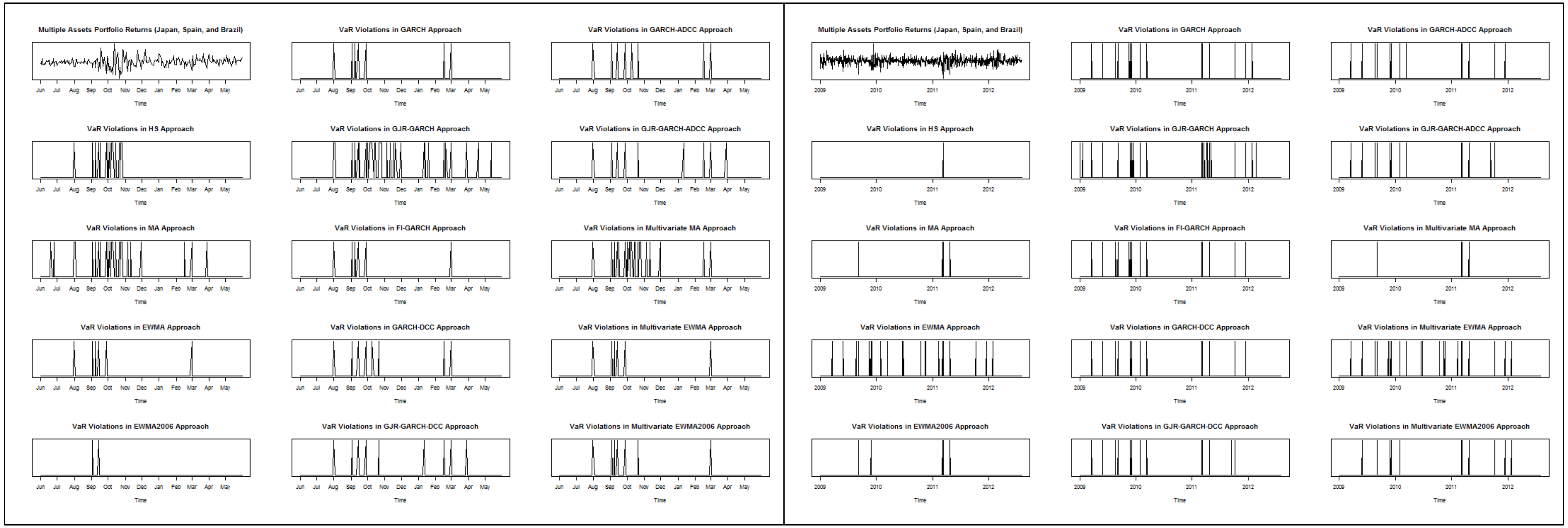
(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

Figure 4.29 – Backtesting Results for Multiple-asset Portfolio M1 (Japan, Germany, United States)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009 (b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

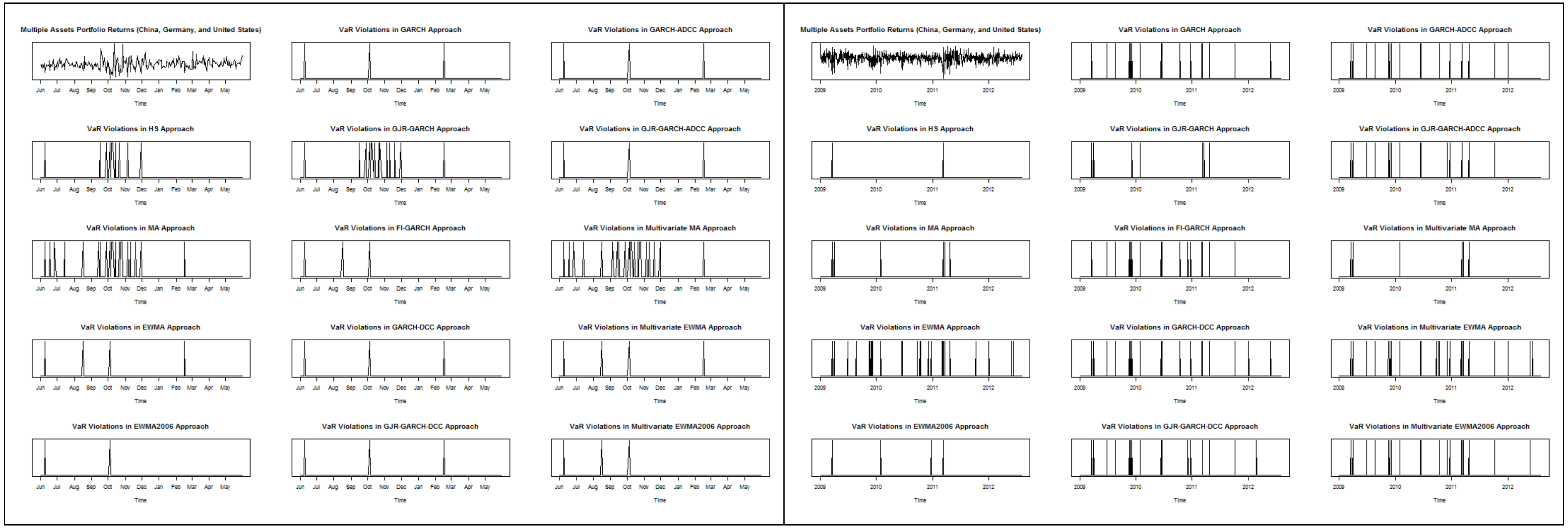
Figure 4.30 – Backtesting Results for Multiple-asset Portfolio M2 (Japan, United Kingdom, Canada)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

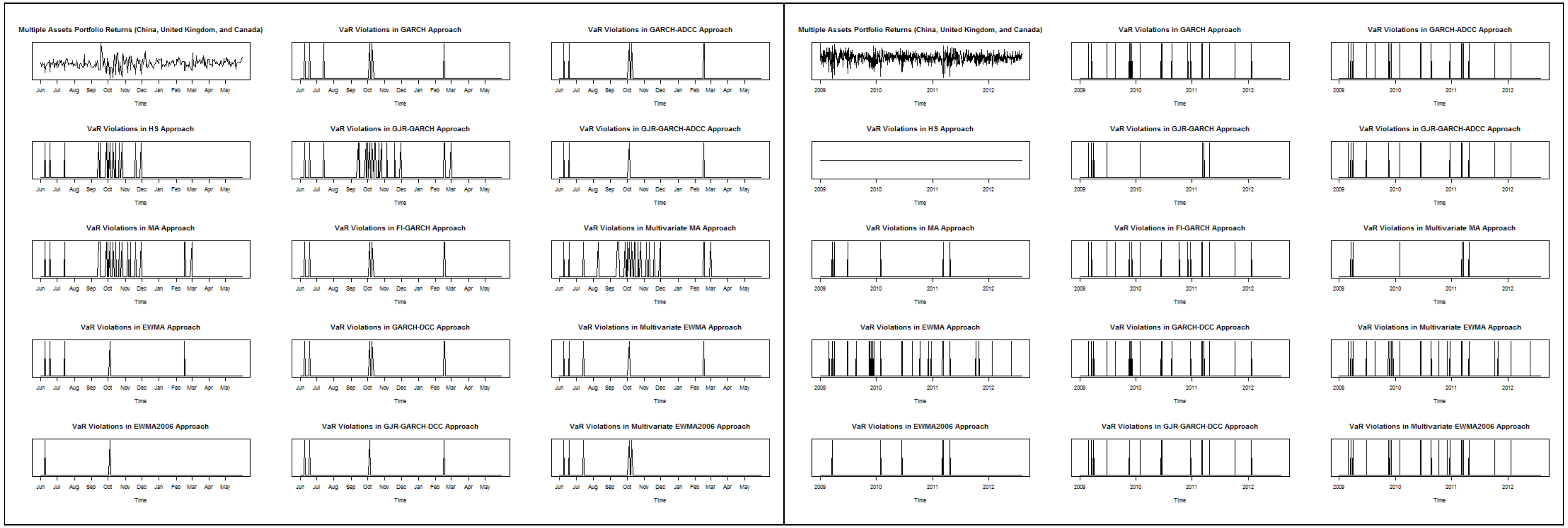
Figure 4.31 – Backtesting Results for Multiple-asset Portfolio M3 (Japan, Spain, Brazil)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

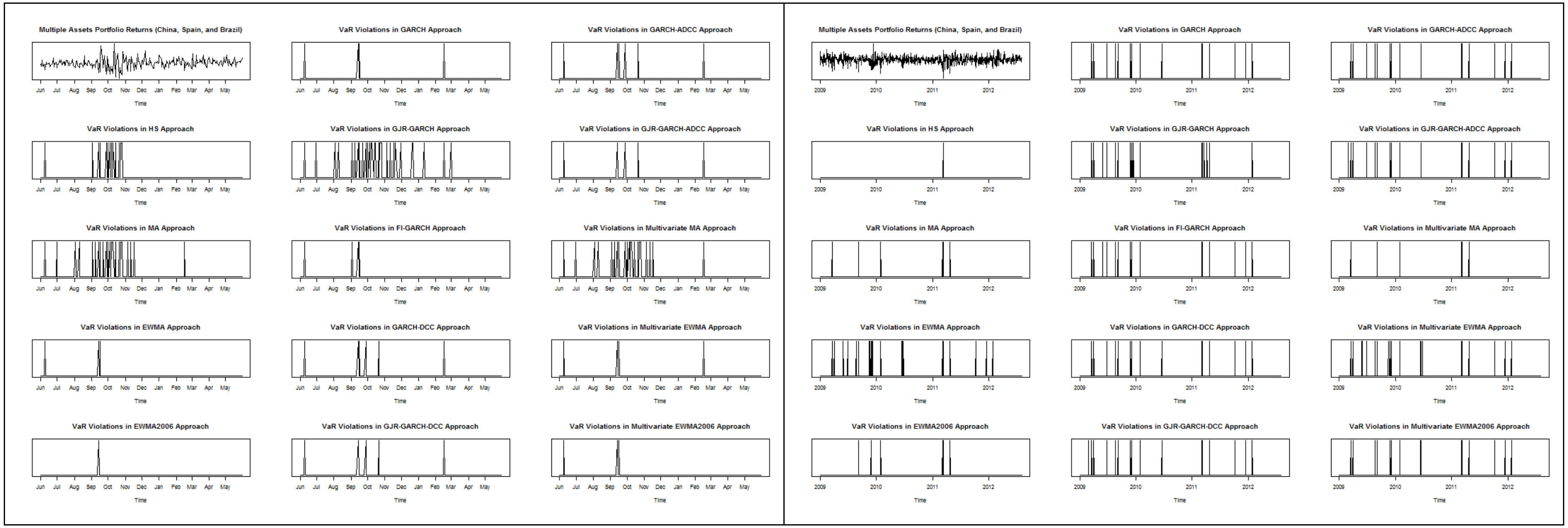
Figure 4.32 – Backtesting Results for Multiple-asset Portfolio M4 (China, Germany, United States)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

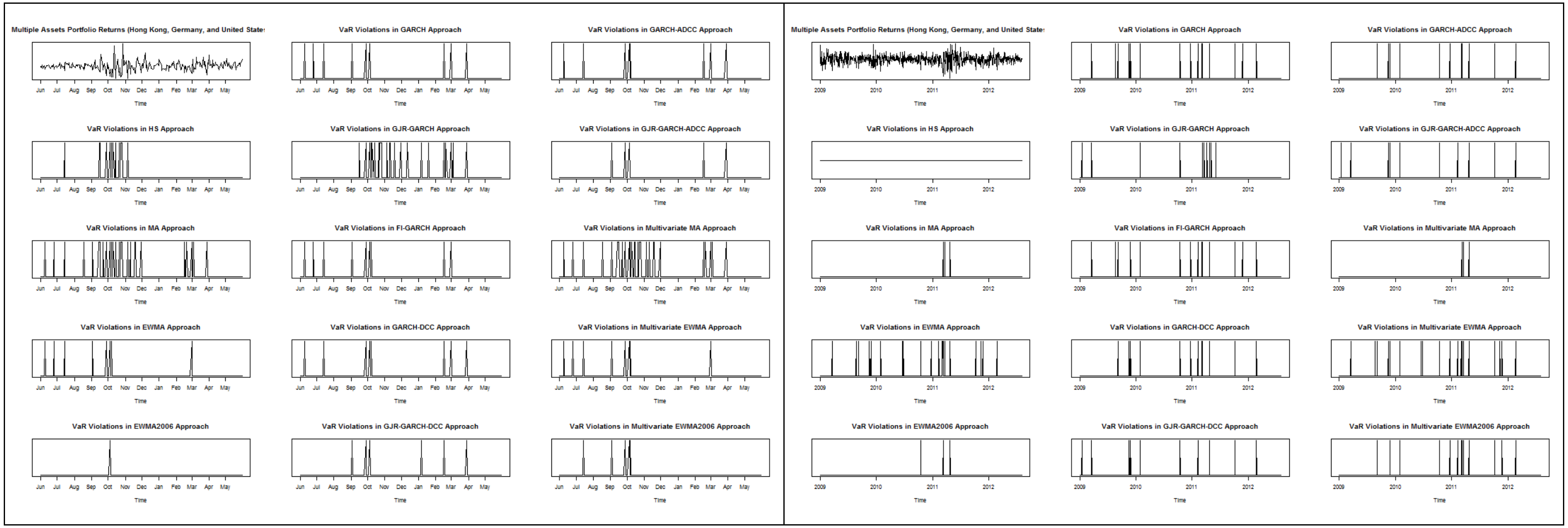
Figure 4.33 – Backtesting Results for Multiple-asset Portfolio M5 (China, United Kingdom, Canada)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

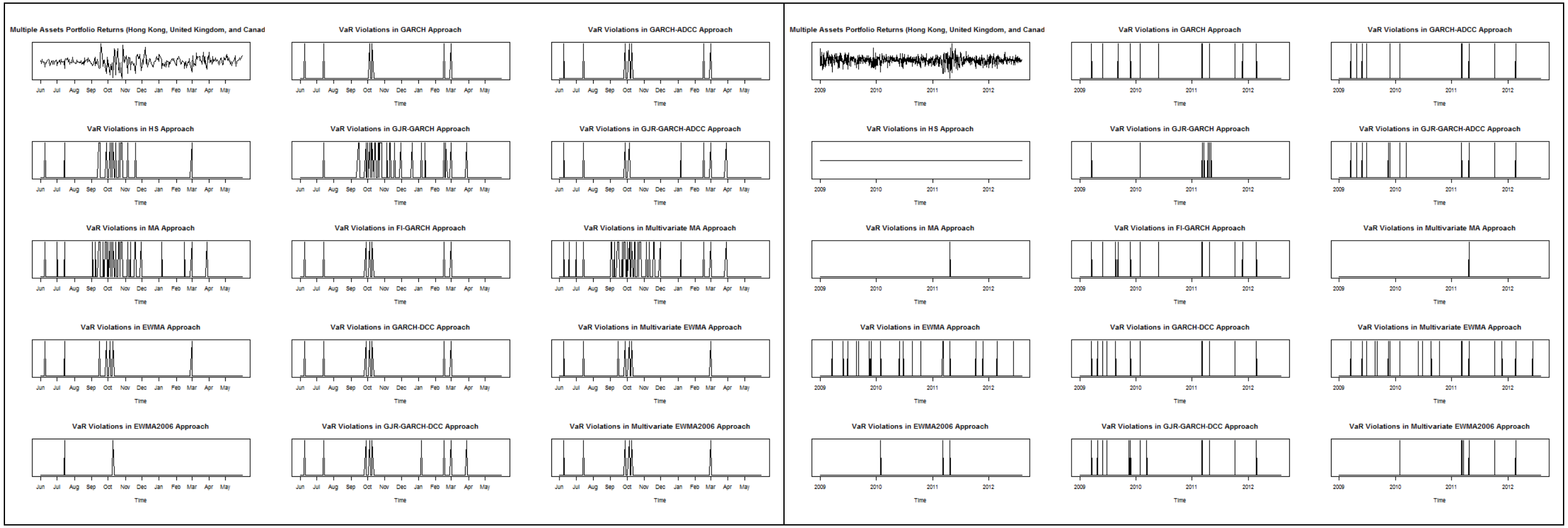
(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

Figure 4.34 – Backtesting Results for Multiple-asset Portfolio M6 (China, Spain, Brazil)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009   (b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

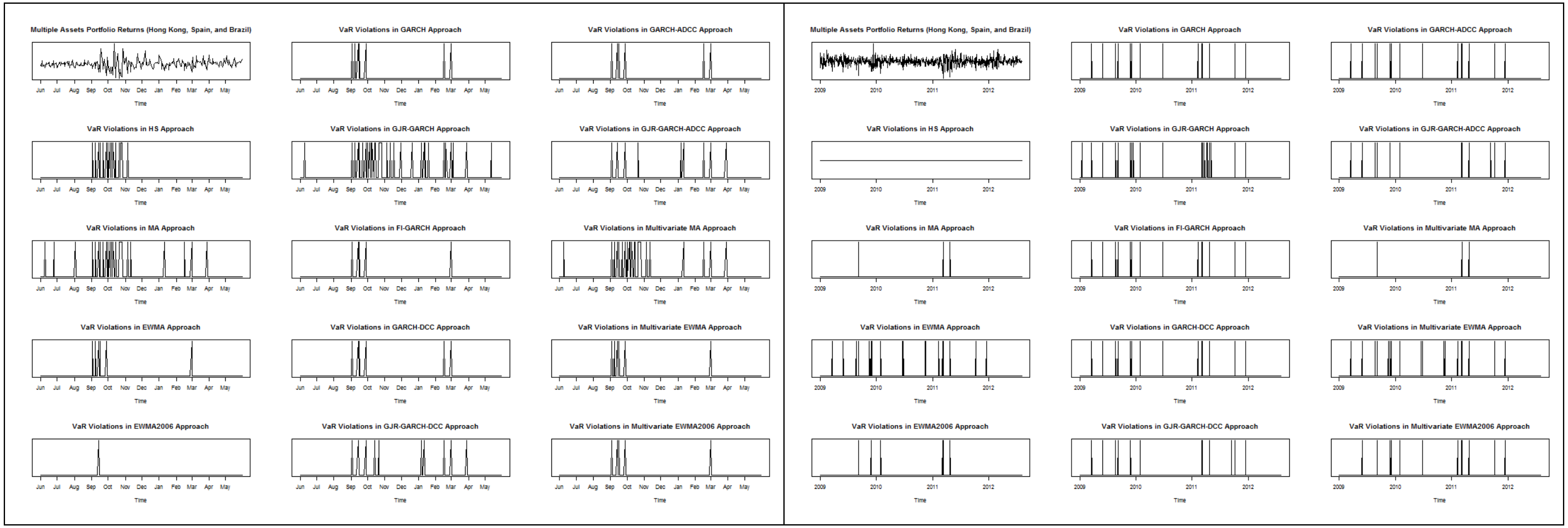
Figure 4.35 – Backtesting Results for Multiple-asset Portfolio M7 (Hong Kong, Germany, United States)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

Figure 4.36 – Backtesting Results for Multiple-assets Portfolio M8 (Hong Kong, United Kingdom, Canada)



(a) the Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

Figure 4.37 – Backtesting Results for Multiple-asset Portfolio M9 (Hong Kong, Spain, Brazil)

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	14	(0.00%)	(80.12%)	(77.42%)	(0.00%)	(0.00%)	(0.00%)
MA	261	19	(0.00%)	(80.12%)	(19.03%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	4	(42.26%)	(80.12%)	(72.37%)	(0.98%)	(68.11%)	(1.58%)
RiskMetrics2006	261	3	(81.27%)	(80.12%)	(79.13%)	(3.59%)	(93.88%)	(7.17%)
GARCH	261	7	(2.38%)	(80.12%)	(53.37%)	(0.61%)	(6.41%)	(0.16%)
GJR-GARCH	261	24	(0.00%)	(80.12%)	(87.16%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	3	(81.27%)	(80.12%)	(79.13%)	(3.59%)	(93.88%)	(7.17%)
DCC	261	7	(2.38%)	(80.12%)	(53.37%)	(0.61%)	(6.41%)	(0.16%)
GJR-DCC	261	6	(7.13%)	(80.12%)	(59.44%)	(11.73%)	(17.06%)	(6.22%)
ADCC	261	7	(2.38%)	(80.12%)	(53.37%)	(0.61%)	(6.41%)	(0.16%)
GJR-ADCC	261	6	(7.13%)	(80.12%)	(59.44%)	(11.73%)	(17.06%)	(6.22%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	2	(0.34%)	(3.88%)	(0.15%)	(0.12%)	(0.01%)	(0.01%)
MA	936	2	(0.34%)	(3.88%)	(0.15%)	(0.12%)	(0.01%)	(0.01%)
EWMA	936	17	(2.43%)	(59.47%)	(3.50%)	(0.11%)	(0.86%)	(0.04%)
RiskMetrics2006	936	3	(1.48%)	(3.88%)	(0.45%)	(0.37%)	(0.09%)	(0.07%)
GARCH	936	11	(60.01%)	(59.47%)	(11.44%)	(14.86%)	(25.07%)	(18.77%)
GJR-GARCH	936	2	(0.34%)	(3.88%)	(0.15%)	(0.12%)	(0.01%)	(0.01%)
FI-GARCH	936	12	(40.60%)	(59.47%)	(0.74%)	(1.56%)	(1.96%)	(1.97%)
DCC	936	11	(60.01%)	(59.47%)	(11.44%)	(14.86%)	(25.07%)	(18.77%)
GJR-DCC	936	14	(15.56%)	(11.05%)	(20.07%)	(4.64%)	(16.09%)	(3.83%)
ADCC	936	11	(60.01%)	(59.47%)	(11.44%)	(14.86%)	(25.07%)	(18.77%)
GJR-ADCC	936	14	(15.56%)	(11.05%)	(20.07%)	(4.64%)	(16.09%)	(3.83%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.5 – Backtesting Results for Portfolio S1 1% One-day VaR - Japan

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	4	(42.26%)	(5.82%)	(72.37%)	(5.59%)	(68.11%)	(7.93%)
MA	261	11	(0.01%)	(5.82%)	(47.21%)	(0.04%)	(0.04%)	(0.00%)
EWMA	261	5	(18.68%)	(5.82%)	(65.79%)	(14.60%)	(37.92%)	(12.75%)
RiskMetrics2006	261	1	(25.22%)	(5.82%)	(93.00%)	(5.82%)	(51.71%)	(8.63%)
GARCH	261	4	(42.26%)	(5.82%)	(72.37%)	(12.46%)	(68.11%)	(16.38%)
GJR-GARCH	261	14	(0.00%)	(5.82%)	(77.42%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	4	(42.26%)	(5.82%)	(72.37%)	(34.79%)	(68.11%)	(40.40%)
DCC	261	4	(42.26%)	(5.82%)	(72.37%)	(12.46%)	(68.11%)	(16.38%)
GJR-DCC	261	3	(81.27%)	(5.82%)	(79.13%)	(30.47%)	(93.88%)	(45.06%)
ADCC	261	4	(42.26%)	(5.82%)	(72.37%)	(12.46%)	(68.11%)	(16.38%)
GJR-ADCC	261	3	(81.27%)	(5.82%)	(79.13%)	(30.47%)	(93.88%)	(45.06%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	2	(0.34%)	(59.47%)	(92.62%)	(20.47%)	(1.35%)	(0.82%)
MA	936	7	(41.71%)	(45.60%)	(74.52%)	(5.50%)	(68.25%)	(7.08%)
EWMA	936	25	(0.00%)	(45.60%)	(24.12%)	(0.41%)	(0.01%)	(0.00%)
RiskMetrics2006	936	9	(90.53%)	(45.60%)	(67.58%)	(24.14%)	(90.98%)	(31.71%)
GARCH	936	17	(2.43%)	(45.60%)	(42.75%)	(7.66%)	(5.78%)	(2.91%)
GJR-GARCH	936	7	(41.71%)	(45.60%)	(74.52%)	(5.50%)	(68.25%)	(7.08%)
FI-GARCH	936	7	(41.71%)	(80.25%)	(74.52%)	(6.11%)	(68.25%)	(7.80%)
DCC	936	17	(2.43%)	(45.60%)	(42.75%)	(7.66%)	(5.78%)	(2.91%)
GJR-DCC	936	16	(4.76%)	(45.60%)	(45.54%)	(11.88%)	(10.64%)	(6.20%)
ADCC	936	17	(2.43%)	(45.60%)	(42.75%)	(7.66%)	(5.78%)	(2.91%)
GJR-ADCC	936	16	(4.76%)	(45.60%)	(45.54%)	(11.88%)	(10.64%)	(6.20%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.6 – Backtesting Results for Portfolio S2 1% One-day VaR – China

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	11	(0.01%)	(5.82%)	(47.21%)	(0.00%)	(0.04%)	(0.00%)
MA	261	24	(0.00%)	(5.82%)	(22.48%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	5	(18.68%)	(5.82%)	(65.79%)	(8.05%)	(37.92%)	(7.25%)
RiskMetrics 2006	261	2	(69.23%)	(94.25%)	(86.02%)	(30.03%)	(91.04%)	(46.41%)
GARCH	261	5	(18.68%)	(5.82%)	(65.79%)	(8.05%)	(37.92%)	(7.25%)
GJR-GARCH	261	27	(0.00%)	(5.82%)	(44.74%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	4	(42.26%)	(5.82%)	(72.37%)	(8.68%)	(68.11%)	(11.82%)
DCC	261	5	(18.68%)	(5.82%)	(65.79%)	(8.05%)	(37.92%)	(7.25%)
GJR-DCC	261	5	(18.68%)	(5.82%)	(65.79%)	(8.05%)	(37.92%)	(7.25%)
ADCC	261	5	(18.68%)	(5.82%)	(65.79%)	(8.05%)	(37.92%)	(7.25%)
GJR-ADCC	261	5	(18.68%)	(5.82%)	(65.79%)	(8.05%)	(37.92%)	(7.25%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	1	(0.04%)	(1.44%)	(96.31%)	(1.44%)	(0.21%)	(0.01%)
MA	936	4	(4.69%)	(78.28%)	(85.29%)	(22.14%)	(13.64%)	(8.53%)
EWMA	936	16	(4.76%)	(78.28%)	(45.54%)	(11.95%)	(10.64%)	(6.24%)
RiskMetrics 2006	936	4	(4.69%)	(78.28%)	(85.29%)	(2.31%)	(13.64%)	(0.92%)
GARCH	936	15	(8.84%)	(78.28%)	(48.43%)	(14.33%)	(18.34%)	(9.62%)
GJR-GARCH	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
FI-GARCH	936	16	(4.76%)	(78.28%)	(45.54%)	(11.95%)	(10.64%)	(6.24%)
DCC	936	15	(8.84%)	(78.28%)	(48.43%)	(14.33%)	(18.34%)	(9.62%)
GJR-DCC	936	14	(15.56%)	(78.28%)	(51.41%)	(10.28%)	(29.49%)	(8.48%)
ADCC	936	15	(8.84%)	(78.28%)	(48.43%)	(14.33%)	(18.34%)	(9.62%)
GJR-ADCC	936	14	(15.56%)	(78.28%)	(51.41%)	(10.28%)	(29.49%)	(8.48%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.7 – Backtesting Results for Portfolio S3 1% One-day VaR - Hong Kong

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	17	(0.00%)	(56.33%)	(90.85%)	(0.00%)	(0.00%)	(0.00%)
MA	261	31	(0.00%)	(18.75%)	(85.90%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	7	(2.38%)	(18.75%)	(53.37%)	(0.34%)	(6.41%)	(0.09%)
RiskMetrics 2006	261	1	(25.22%)	(92.56%)	(93.00%)	(92.56%)	(51.71%)	(51.68%)
GARCH	261	10	(0.05%)	(3.84%)	(37.10%)	(2.27%)	(0.14%)	(0.05%)
GJR-GARCH	261	25	(0.00%)	(72.52%)	(2.10%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	7	(2.38%)	(56.33%)	(53.37%)	(13.21%)	(6.41%)	(3.88%)
DCC	261	10	(0.05%)	(3.84%)	(37.10%)	(2.27%)	(0.14%)	(0.05%)
GJR-DCC	261	10	(0.05%)	(56.33%)	(37.10%)	(6.22%)	(0.14%)	(0.16%)
ADCC	261	10	(0.05%)	(3.84%)	(37.10%)	(2.27%)	(0.14%)	(0.05%)
GJR-ADCC	261	10	(0.05%)	(56.33%)	(37.10%)	(6.22%)	(0.14%)	(0.16%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	3	(1.48%)	(1.42%)	(88.95%)	(0.60%)	(5.09%)	(0.10%)
MA	936	8	(64.68%)	(24.37%)	(71.02%)	(0.03%)	(84.03%)	(0.06%)
EWMA	936	21	(0.10%)	(78.93%)	(32.59%)	(0.01%)	(0.28%)	(0.00%)
RiskMetrics 2006	936	2	(0.34%)	(3.84%)	(92.62%)	(11.72%)	(1.35%)	(0.49%)
GARCH	936	12	(40.60%)	(9.98%)	(57.64%)	(13.53%)	(60.57%)	(15.43%)
GJR-GARCH	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
FI-GARCH	936	13	(25.88%)	(9.98%)	(54.49%)	(19.51%)	(44.00%)	(19.05%)
DCC	936	12	(40.60%)	(9.98%)	(57.64%)	(13.53%)	(60.57%)	(15.43%)
GJR-DCC	936	16	(4.76%)	(9.98%)	(45.54%)	(58.60%)	(10.64%)	(38.29%)
ADCC	936	12	(40.60%)	(9.98%)	(57.64%)	(13.53%)	(60.57%)	(15.43%)
GJR-ADCC	936	16	(4.76%)	(9.98%)	(45.54%)	(58.60%)	(10.64%)	(38.29%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.8 – Backtesting Results for Portfolio S4 1% One-day VaR - Germany

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	14	(0.00%)	(79.19%)	(19.77%)	(0.00%)	(0.00%)	(0.00%)
MA	261	26	(0.00%)	(18.75%)	(13.13%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	6	(7.13%)	(18.75%)	(59.44%)	(12.70%)	(17.06%)	(6.74%)
RiskMetrics 2006	261	2	(69.23%)	(92.56%)	(86.02%)	(9.16%)	(91.04%)	(17.64%)
GARCH	261	7	(2.38%)	(18.75%)	(53.37%)	(9.67%)	(6.41%)	(2.78%)
GJR-GARCH	261	27	(0.00%)	(18.75%)	(44.74%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	6	(7.13%)	(18.75%)	(59.44%)	(12.70%)	(17.06%)	(6.74%)
DCC	261	7	(2.38%)	(18.75%)	(53.37%)	(9.67%)	(6.41%)	(2.78%)
GJR-DCC	261	10	(0.05%)	(60.50%)	(37.10%)	(2.00%)	(0.14%)	(0.04%)
ADCC	261	7	(2.38%)	(18.75%)	(53.37%)	(9.67%)	(6.41%)	(2.78%)
GJR-ADCC	261	10	(0.05%)	(60.50%)	(37.10%)	(2.00%)	(0.14%)	(0.04%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
MA	936	2	(0.34%)	(1.35%)	(92.62%)	(2.47%)	(1.35%)	(0.11%)
EWMA	936	18	(1.18%)	(93.76%)	(35.31%)	(0.24%)	(2.73%)	(0.05%)
RiskMetrics 2006	936	1	(0.04%)	(1.48%)	(96.31%)	(1.48%)	(0.21%)	(0.01%)
GARCH	936	12	(40.60%)	(9.98%)	(14.04%)	(2.65%)	(23.87%)	(3.26%)
GJR-GARCH	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
FI-GARCH	936	11	(60.01%)	(9.98%)	(11.44%)	(5.32%)	(25.07%)	(7.21%)
DCC	936	12	(40.60%)	(9.98%)	(14.04%)	(2.65%)	(23.87%)	(3.26%)
GJR-DCC	936	14	(15.56%)	(9.98%)	(51.41%)	(69.32%)	(29.49%)	(60.81%)
ADCC	936	12	(40.60%)	(9.98%)	(14.04%)	(2.65%)	(23.87%)	(3.26%)
GJR-ADCC	936	14	(15.56%)	(9.98%)	(51.41%)	(69.32%)	(29.49%)	(60.81%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.9 – Backtesting Results for Portfolio S5 1% One-day VaR - United Kingdom

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	17	(0.00%)	(18.75%)	(1.77%)	(0.00%)	(0.00%)	(0.00%)
MA	261	33	(0.00%)	(0.24%)	(60.41%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	5	(18.68%)	(3.84%)	(65.79%)	(1.74%)	(37.92%)	(1.68%)
RiskMetrics 2006	261	1	(25.22%)	(95.92%)	(93.00%)	(95.92%)	(51.71%)	(51.84%)
GARCH	261	8	(0.71%)	(0.24%)	(50.54%)	(0.15%)	(2.13%)	(0.02%)
GJR-GARCH	261	39	(0.00%)	(0.24%)	(0.68%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	6	(7.13%)	(18.75%)	(59.44%)	(4.85%)	(17.06%)	(2.58%)
DCC	261	8	(0.71%)	(0.24%)	(50.54%)	(0.15%)	(2.13%)	(0.02%)
GJR-DCC	261	8	(0.71%)	(72.52%)	(47.60%)	(5.60%)	(2.06%)	(0.76%)
ADCC	261	8	(0.71%)	(0.24%)	(50.54%)	(0.15%)	(2.13%)	(0.02%)
GJR-ADCC	261	8	(0.71%)	(72.52%)	(47.60%)	(5.60%)	(2.06%)	(0.76%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	6	(23.74%)	(51.74%)	(78.07%)	(26.10%)	(47.87%)	(24.60%)
MA	936	12	(40.60%)	(51.74%)	(57.64%)	(0.38%)	(60.57%)	(0.50%)
EWMA	936	15	(8.84%)	(59.47%)	(48.43%)	(0.44%)	(18.34%)	(0.28%)
RiskMetrics 2006	936	5	(11.60%)	(51.74%)	(81.66%)	(13.84%)	(28.31%)	(9.44%)
GARCH	936	10	(83.53%)	(59.47%)	(64.19%)	(39.77%)	(87.83%)	(48.22%)
GJR-GARCH	936	6	(23.74%)	(51.74%)	(78.07%)	(26.10%)	(47.87%)	(24.60%)
FI-GARCH	936	10	(83.53%)	(59.47%)	(64.19%)	(54.58%)	(87.83%)	(63.11%)
DCC	936	10	(83.53%)	(59.47%)	(64.19%)	(39.77%)	(87.83%)	(48.22%)
GJR-DCC	936	15	(8.84%)	(59.47%)	(48.43%)	(28.75%)	(18.34%)	(20.09%)
ADCC	936	10	(83.53%)	(59.47%)	(64.19%)	(39.77%)	(87.83%)	(48.22%)
GJR-ADCC	936	15	(8.84%)	(59.47%)	(48.43%)	(28.75%)	(18.34%)	(20.09%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.10 – Backtesting Results for Portfolio S6 1% One-day VaR - Spain

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	20	(0.00%)	(3.84%)	(24.86%)	(0.00%)	(0.00%)	(0.00%)
MA	261	35	(0.00%)	(3.84%)	(33.76%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	8	(0.71%)	(3.84%)	(47.60%)	(0.26%)	(2.06%)	(0.03%)
RiskMetrics 2006	261	4	(42.26%)	(3.84%)	(72.37%)	(4.56%)	(68.11%)	(6.58%)
GARCH	261	9	(0.19%)	(3.84%)	(42.17%)	(0.21%)	(0.58%)	(0.01%)
GJR-GARCH	261	33	(0.00%)	(3.84%)	(48.91%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	8	(0.71%)	(3.84%)	(47.60%)	(0.26%)	(2.06%)	(0.03%)
DCC	261	9	(0.19%)	(3.84%)	(42.17%)	(0.21%)	(0.58%)	(0.01%)
GJR-DCC	261	8	(0.71%)	(3.84%)	(47.60%)	(6.50%)	(2.06%)	(0.90%)
ADCC	261	9	(0.19%)	(3.84%)	(42.17%)	(0.21%)	(0.58%)	(0.01%)
GJR-ADCC	261	8	(0.71%)	(3.84%)	(47.60%)	(6.50%)	(2.06%)	(0.90%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	1	(0.04%)	(1.45%)	(96.31%)	(1.45%)	(0.21%)	(0.01%)
MA	936	5	(11.60%)	(26.84%)	(81.66%)	(0.12%)	(28.31%)	(0.10%)
EWMA	936	24	(0.01%)	(90.85%)	(64.38%)	(0.00%)	(0.03%)	(0.00%)
RiskMetrics 2006	936	5	(11.60%)	(29.33%)	(81.66%)	(3.81%)	(28.31%)	(2.71%)
GARCH	936	20	(0.24%)	(90.85%)	(34.97%)	(0.73%)	(0.64%)	(0.07%)
GJR-GARCH	936	1	(0.04%)	(1.45%)	(96.31%)	(1.45%)	(0.21%)	(0.01%)
FI-GARCH	936	21	(0.10%)	(90.85%)	(49.11%)	(0.40%)	(0.36%)	(0.02%)
DCC	936	20	(0.24%)	(90.85%)	(34.97%)	(0.73%)	(0.64%)	(0.07%)
GJR-DCC	936	23	(0.02%)	(9.98%)	(28.14%)	(4.29%)	(0.04%)	(0.14%)
ADCC	936	20	(0.24%)	(90.85%)	(34.97%)	(0.73%)	(0.64%)	(0.07%)
GJR-ADCC	936	23	(0.02%)	(9.98%)	(28.14%)	(4.29%)	(0.04%)	(0.14%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.11 – Backtesting Results for Portfolio S7 1% One-day VaR - United States

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	22	(0.00%)	(23.25%)	(12.66%)	(0.00%)	(0.00%)	(0.00%)
MA	261	37	(0.00%)	(13.22%)	(89.21%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	10	(0.05%)	(23.25%)	(37.10%)	(0.24%)	(0.14%)	(0.00%)
RiskMetrics 2006	261	3	(81.27%)	(23.25%)	(79.13%)	(29.67%)	(93.88%)	(44.12%)
GARCH	261	11	(0.01%)	(23.25%)	(32.41%)	(0.13%)	(0.03%)	(0.00%)
GJR-GARCH	261	38	(0.00%)	(23.25%)	(78.06%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	10	(0.05%)	(23.25%)	(37.10%)	(0.24%)	(0.14%)	(0.00%)
DCC	261	11	(0.01%)	(23.25%)	(32.41%)	(0.13%)	(0.03%)	(0.00%)
GJR-DCC	261	13	(0.00%)	(13.22%)	(24.20%)	(0.13%)	(0.00%)	(0.00%)
ADCC	261	11	(0.01%)	(23.25%)	(32.41%)	(0.13%)	(0.03%)	(0.00%)
GJR-ADCC	261	13	(0.00%)	(13.22%)	(24.20%)	(0.13%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
MA	936	2	(0.34%)	(15.42%)	(92.62%)	(2.09%)	(1.35%)	(0.10%)
EWMA	936	19	(0.54%)	(15.42%)	(37.46%)	(11.94%)	(1.42%)	(2.53%)
RiskMetrics 2006	936	3	(1.48%)	(1.48%)	(88.95%)	(0.40%)	(5.09%)	(0.07%)
GARCH	936	14	(15.56%)	(15.42%)	(51.41%)	(24.40%)	(29.49%)	(20.26%)
GJR-GARCH	936	1	(0.04%)	(15.42%)	(96.31%)	(15.42%)	(0.21%)	(0.08%)
FI-GARCH	936	15	(8.84%)	(15.42%)	(48.43%)	(28.29%)	(18.34%)	(19.74%)
DCC	936	14	(15.56%)	(15.42%)	(51.41%)	(24.40%)	(29.49%)	(20.26%)
GJR-DCC	936	14	(15.56%)	(15.42%)	(51.41%)	(11.56%)	(29.49%)	(9.53%)
ADCC	936	14	(15.56%)	(15.42%)	(51.41%)	(24.40%)	(29.49%)	(20.26%)
GJR-ADCC	936	14	(15.56%)	(15.42%)	(51.41%)	(11.56%)	(29.49%)	(9.53%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.12 – Backtesting Results for Portfolio S8 1% One-day VaR - Canada

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	13	(0.00%)	(72.52%)	(14.63%)	(0.00%)	(0.00%)	(0.00%)
MA	261	19	(0.00%)	(23.25%)	(59.58%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	6	(7.13%)	(72.52%)	(59.44%)	(0.26%)	(17.06%)	(0.15%)
RiskMetrics 2006	261	1	(25.22%)	(79.19%)	(93.00%)	(79.19%)	(51.71%)	(50.13%)
GARCH	261	7	(2.38%)	(72.52%)	(53.37%)	(0.16%)	(6.41%)	(0.04%)
GJR-GARCH	261	18	(0.00%)	(75.41%)	(10.16%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	5	(18.68%)	(72.52%)	(65.79%)	(2.14%)	(37.92%)	(2.05%)
DCC	261	7	(2.38%)	(72.52%)	(53.37%)	(0.16%)	(6.41%)	(0.04%)
GJR-DCC	261	7	(2.38%)	(72.52%)	(53.37%)	(5.75%)	(6.41%)	(1.61%)
ADCC	261	7	(2.38%)	(72.52%)	(53.37%)	(0.16%)	(6.41%)	(0.04%)
GJR-ADCC	261	7	(2.38%)	(72.52%)	(53.37%)	(5.75%)	(6.41%)	(1.61%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Observations	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	1	(0.04%)	(1.45%)	(96.31%)	(1.45%)	(0.21%)	(0.01%)
MA	936	2	(0.34%)	(1.48%)	(92.62%)	(0.20%)	(1.35%)	(0.01%)
EWMA	936	18	(1.18%)	(98.41%)	(4.48%)	(0.03%)	(0.56%)	(0.01%)
RiskMetrics 2006	936	4	(4.69%)	(51.74%)	(85.29%)	(5.21%)	(13.64%)	(2.04%)
GARCH	936	11	(60.01%)	(93.76%)	(60.88%)	(24.31%)	(76.46%)	(29.46%)
GJR-GARCH	936	4	(4.69%)	(51.74%)	(85.29%)	(2.81%)	(13.64%)	(1.12%)
FI-GARCH	936	10	(83.53%)	(93.76%)	(64.19%)	(18.73%)	(87.83%)	(24.77%)
DCC	936	11	(60.01%)	(93.76%)	(60.88%)	(24.31%)	(76.46%)	(29.46%)
GJR-DCC	936	13	(25.88%)	(1.98%)	(54.49%)	(8.07%)	(44.00%)	(8.07%)
ADCC	936	11	(60.01%)	(93.76%)	(60.88%)	(24.31%)	(76.46%)	(29.46%)
GJR-ADCC	936	13	(25.88%)	(1.98%)	(54.49%)	(8.07%)	(44.00%)	(8.07%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.13 – Backtesting Results for Portfolio S9 1% One-day VaR - Brazil

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	17	(0.00%)	(72.52%)	(0.22%)	(0.00%)	(0.00%)	(0.00%)
MA	261	31	(0.00%)	(14.31%)	(2.17%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	9	(0.19%)	(14.31%)	(42.17%)	(0.09%)	(0.58%)	(0.00%)
RiskMetrics2006	261	2	(69.23%)	(88.24%)	(86.02%)	(11.60%)	(91.04%)	(21.54%)
GARCH	261	8	(0.71%)	(14.31%)	(47.60%)	(0.56%)	(2.06%)	(0.07%)
GJR-GARCH	261	29	(0.00%)	(72.52%)	(3.38%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	8	(0.71%)	(14.31%)	(47.60%)	(0.56%)	(2.06%)	(0.07%)
DCC	261	8	(0.71%)	(72.52%)	(47.60%)	(0.13%)	(2.06%)	(0.01%)
GJR-DCC	261	10	(0.05%)	(56.33%)	(37.10%)	(3.07%)	(0.14%)	(0.07%)
ADCC	261	8	(0.71%)	(72.52%)	(47.60%)	(0.13%)	(2.06%)	(0.01%)
GJR-ADCC	261	9	(0.19%)	(56.33%)	(42.17%)	(8.32%)	(0.58%)	(0.54%)
Multi-MA	261	32	(0.00%)	(14.31%)	(0.90%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	9	(0.19%)	(14.31%)	(42.17%)	(0.09%)	(0.58%)	(0.00%)
Multi-RiskMetrics 2006	261	7	(2.38%)	(14.31%)	(53.37%)	(0.29%)	(6.41%)	(0.08%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	1	(0.04%)	(1.45%)	(96.31%)	(1.45%)	(0.21%)	(0.01%)
MA	936	6	(23.74%)	(3.84%)	(78.07%)	(0.90%)	(47.87%)	(1.00%)
EWMA	936	23	(0.02%)	(24.37%)	(12.35%)	(0.01%)	(0.02%)	(0.00%)
RiskMetrics2006	936	3	(1.48%)	(3.88%)	(0.45%)	(0.37%)	(0.09%)	(0.06%)
GARCH	936	18	(1.18%)	(9.98%)	(4.48%)	(0.31%)	(0.56%)	(0.07%)
GJR-GARCH	936	22	(0.04%)	(9.98%)	(1.29%)	(0.00%)	(0.01%)	(0.00%)
FI-GARCH	936	14	(15.56%)	(9.98%)	(20.07%)	(0.24%)	(16.09%)	(0.21%)
DCC	936	14	(15.56%)	(9.98%)	(20.07%)	(2.83%)	(16.09%)	(2.34%)
GJR-DCC	936	19	(0.54%)	(9.98%)	(39.72%)	(5.93%)	(1.47%)	(1.12%)
ADCC	936	14	(15.56%)	(9.98%)	(20.07%)	(2.83%)	(16.09%)	(2.34%)
GJR-ADCC	936	19	(0.54%)	(9.98%)	(39.72%)	(5.93%)	(1.47%)	(1.12%)
Multi-MA	936	6	(23.74%)	(3.84%)	(78.07%)	(0.90%)	(47.87%)	(1.00%)
Multi-EWMA	936	23	(0.02%)	(24.37%)	(12.35%)	(0.01%)	(0.02%)	(0.00%)
Multi-RiskMetrics 2006	936	15	(8.84%)	(29.33%)	(2.02%)	(0.03%)	(1.58%)	(0.02%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.14 – Backtesting Results for Multiple-asset Portfolio M1 (Japan, Germany, United States) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	20	(0.00%)	(33.39%)	(6.38%)	(0.00%)	(0.00%)	(0.00%)
MA	261	30	(0.00%)	(13.22%)	(0.06%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	8	(0.71%)	(13.22%)	(47.60%)	(0.73%)	(2.06%)	(0.09%)
RiskMetrics2006	261	4	(42.26%)	(33.39%)	(72.37%)	(20.34%)	(68.11%)	(25.32%)
GARCH	261	10	(0.05%)	(13.22%)	(37.10%)	(0.48%)	(0.14%)	(0.01%)
GJR-GARCH	261	27	(0.00%)	(33.39%)	(0.01%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	6	(7.13%)	(13.22%)	(59.44%)	(11.35%)	(17.06%)	(6.02%)
DCC	261	7	(2.38%)	(33.39%)	(53.37%)	(4.17%)	(6.41%)	(1.16%)
GJR-DCC	261	10	(0.05%)	(33.39%)	(37.10%)	(0.98%)	(0.14%)	(0.02%)
ADCC	261	7	(2.38%)	(33.39%)	(53.37%)	(4.17%)	(6.41%)	(1.16%)
GJR-ADCC	261	10	(0.05%)	(33.39%)	(37.10%)	(0.98%)	(0.14%)	(0.02%)
Multi-MA	261	30	(0.00%)	(13.22%)	(0.06%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	8	(0.71%)	(13.22%)	(47.60%)	(0.73%)	(2.06%)	(0.09%)
Multi-RiskMetrics 2006	261	7	(2.38%)	(33.39%)	(53.37%)	(4.17%)	(6.41%)	(1.16%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
MA	936	4	(4.69%)	(3.84%)	(85.29%)	(6.35%)	(13.64%)	(2.48%)
EWMA	936	20	(0.24%)	(59.47%)	(0.71%)	(0.02%)	(0.03%)	(0.00%)
RiskMetrics2006	936	4	(4.69%)	(15.81%)	(85.29%)	(55.40%)	(13.64%)	(22.27%)
GARCH	936	14	(15.56%)	(59.47%)	(51.41%)	(22.99%)	(29.49%)	(19.07%)
GJR-GARCH	936	10	(83.53%)	(15.42%)	(0.32%)	(0.19%)	(1.26%)	(0.34%)
FI-GARCH	936	16	(4.76%)	(59.47%)	(2.69%)	(0.69%)	(1.21%)	(0.32%)
DCC	936	15	(8.84%)	(59.47%)	(23.50%)	(3.11%)	(11.57%)	(2.01%)
GJR-DCC	936	13	(25.88%)	(9.98%)	(54.49%)	(57.94%)	(44.00%)	(55.42%)
ADCC	936	15	(8.84%)	(59.47%)	(23.50%)	(3.11%)	(11.57%)	(2.01%)
GJR-ADCC	936	12	(40.60%)	(59.47%)	(57.64%)	(74.95%)	(60.57%)	(76.26%)
Multi-MA	936	4	(4.69%)	(3.84%)	(85.29%)	(6.35%)	(13.64%)	(2.48%)
Multi-EWMA	936	20	(0.24%)	(59.47%)	(0.71%)	(0.02%)	(0.03%)	(0.00%)
Multi-RiskMetrics 2006	936	13	(25.88%)	(59.47%)	(0.04%)	(0.01%)	(0.10%)	(0.01%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.15 – Backtesting Results for Multiple-asset Portfolio M2 (Japan, United Kingdom, Canada) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	16	(0.00%)	(47.78%)	(1.06%)	(0.00%)	(0.00%)	(0.00%)
MA	261	25	(0.00%)	(14.31%)	(9.52%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	6	(7.13%)	(47.78%)	(59.44%)	(2.05%)	(17.06%)	(1.10%)
RiskMetrics2006	261	2	(69.23%)	(72.52%)	(86.02%)	(15.62%)	(91.04%)	(27.59%)
GARCH	261	7	(2.38%)	(47.78%)	(53.37%)	(1.18%)	(6.41%)	(0.32%)
GJR-GARCH	261	33	(0.00%)	(47.78%)	(1.46%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	6	(7.13%)	(47.78%)	(59.44%)	(2.05%)	(17.06%)	(1.10%)
DCC	261	8	(0.71%)	(47.78%)	(47.60%)	(2.22%)	(2.06%)	(0.28%)
GJR-DCC	261	9	(0.19%)	(47.78%)	(42.17%)	(5.72%)	(0.58%)	(0.35%)
ADCC	261	8	(0.71%)	(47.78%)	(47.60%)	(2.22%)	(2.06%)	(0.28%)
GJR-ADCC	261	9	(0.19%)	(47.78%)	(42.17%)	(5.72%)	(0.58%)	(0.35%)
Multi-MA	261	21	(0.00%)	(47.78%)	(9.12%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	6	(7.13%)	(47.78%)	(59.44%)	(2.05%)	(17.06%)	(1.10%)
Multi-RiskMetrics 2006	261	7	(2.38%)	(47.78%)	(53.37%)	(1.81%)	(6.41%)	(0.49%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	1	(0.04%)	(1.45%)	(96.31%)	(1.45%)	(0.21%)	(0.01%)
MA	936	4	(4.69%)	(51.74%)	(85.29%)	(2.81%)	(13.64%)	(1.12%)
EWMA	936	22	(0.04%)	(59.47%)	(54.07%)	(0.30%)	(0.16%)	(0.01%)
RiskMetrics2006	936	5	(11.60%)	(51.74%)	(81.66%)	(6.78%)	(28.31%)	(4.72%)
GARCH	936	15	(8.84%)	(59.47%)	(48.43%)	(7.41%)	(18.34%)	(4.86%)
GJR-GARCH	936	23	(0.02%)	(1.98%)	(59.16%)	(0.00%)	(0.07%)	(0.00%)
FI-GARCH	936	15	(8.84%)	(59.47%)	(23.50%)	(0.67%)	(11.57%)	(0.43%)
DCC	936	13	(25.88%)	(59.47%)	(54.49%)	(13.05%)	(44.00%)	(12.88%)
GJR-DCC	936	13	(25.88%)	(59.47%)	(54.49%)	(8.91%)	(44.00%)	(8.89%)
ADCC	936	13	(25.88%)	(59.47%)	(54.49%)	(13.05%)	(44.00%)	(12.88%)
GJR-ADCC	936	13	(25.88%)	(59.47%)	(54.49%)	(8.91%)	(44.00%)	(8.89%)
Multi-MA	936	4	(4.69%)	(51.74%)	(85.29%)	(2.81%)	(13.64%)	(1.12%)
Multi-EWMA	936	22	(0.04%)	(59.47%)	(54.07%)	(0.30%)	(0.16%)	(0.01%)
Multi-RiskMetrics 2006	936	11	(60.01%)	(93.76%)	(60.88%)	(15.06%)	(76.46%)	(19.00%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.16 – Backtesting Results for Multiple-asset Portfolio M3 (Japan, Spain, Brazil) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	11	(7.17%)	(0.00%)	(0.01%)	(0.00%)	(0.01%)	(5.82%)
MA	261	21	(31.69%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)	(5.82%)
EWMA	261	4	(72.37%)	(30.68%)	(68.11%)	(36.26%)	(42.26%)	(5.82%)
RiskMetrics2006	261	2	(86.02%)	(16.38%)	(91.04%)	(28.68%)	(69.23%)	(5.82%)
GARCH	261	3	(79.13%)	(30.55%)	(93.88%)	(45.16%)	(81.27%)	(5.82%)
GJR-GARCH	261	15	(25.89%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)	(5.82%)
FI-GARCH	261	3	(79.13%)	(18.60%)	(93.88%)	(30.10%)	(81.27%)	(5.82%)
DCC	261	3	(79.13%)	(30.55%)	(93.88%)	(45.16%)	(81.27%)	(5.82%)
GJR-DCC	261	3	(79.13%)	(30.55%)	(93.88%)	(45.16%)	(81.27%)	(5.82%)
ADCC	261	3	(79.13%)	(30.55%)	(93.88%)	(45.16%)	(81.27%)	(5.82%)
GJR-ADCC	261	3	(79.13%)	(30.55%)	(93.88%)	(45.16%)	(81.27%)	(5.82%)
Multi-MA	261	22	(39.50%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)	(5.82%)
Multi-EWMA	261	4	(72.37%)	(30.68%)	(68.11%)	(36.26%)	(42.26%)	(5.82%)
Multi-RiskMetrics 2006	261	3	(79.13%)	(18.60%)	(93.88%)	(30.10%)	(81.27%)	(5.82%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	2	(0.34%)	(59.47%)	(92.62%)	(6.93%)	(1.35%)	(0.30%)
MA	936	6	(23.74%)	(59.47%)	(78.07%)	(11.46%)	(47.87%)	(11.29%)
EWMA	936	26	(0.00%)	(59.47%)	(75.08%)	(0.00%)	(0.00%)	(0.00%)
RiskMetrics2006	936	4	(4.69%)	(59.47%)	(85.29%)	(65.07%)	(13.64%)	(26.78%)
GARCH	936	16	(4.76%)	(59.47%)	(45.54%)	(8.23%)	(10.64%)	(4.19%)
GJR-GARCH	936	7	(41.71%)	(59.47%)	(74.52%)	(15.82%)	(68.25%)	(18.87%)
FI-GARCH	936	16	(4.76%)	(59.47%)	(45.54%)	(4.37%)	(10.64%)	(2.16%)
DCC	936	18	(1.18%)	(59.47%)	(40.05%)	(7.51%)	(2.95%)	(2.07%)
GJR-DCC	936	16	(4.76%)	(59.47%)	(45.54%)	(12.67%)	(10.64%)	(6.65%)
ADCC	936	16	(4.76%)	(59.47%)	(45.54%)	(18.96%)	(10.64%)	(10.30%)
GJR-ADCC	936	15	(8.84%)	(59.47%)	(48.43%)	(9.45%)	(18.34%)	(6.25%)
Multi-MA	936	6	(23.74%)	(59.47%)	(78.07%)	(11.46%)	(47.87%)	(11.29%)
Multi-EWMA	936	26	(0.00%)	(59.47%)	(75.08%)	(0.00%)	(0.00%)	(0.00%)
Multi-RiskMetrics 2006	936	19	(0.54%)	(59.47%)	(37.46%)	(1.93%)	(1.42%)	(0.32%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.17 – Backtesting Results for Multiple-asset Portfolio M4 (China, Germany, United States) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	14	(0.00%)	(5.82%)	(20.67%)	(0.00%)	(0.00%)	(0.00%)
MA	261	21	(0.00%)	(5.82%)	(9.12%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	5	(18.68%)	(5.82%)	(65.79%)	(9.96%)	(37.92%)	(8.87%)
RiskMetrics2006	261	2	(69.23%)	(5.82%)	(86.02%)	(16.38%)	(91.04%)	(28.68%)
GARCH	261	6	(7.13%)	(5.82%)	(59.44%)	(2.94%)	(17.06%)	(1.57%)
GJR-GARCH	261	19	(0.00%)	(5.82%)	(59.58%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	6	(7.13%)	(5.82%)	(11.38%)	(0.17%)	(5.63%)	(0.09%)
DCC	261	6	(7.13%)	(5.82%)	(11.38%)	(0.17%)	(5.63%)	(0.09%)
GJR-DCC	261	4	(42.26%)	(5.82%)	(72.37%)	(12.36%)	(68.11%)	(16.26%)
ADCC	261	6	(7.13%)	(5.82%)	(11.38%)	(0.17%)	(5.63%)	(0.09%)
GJR-ADCC	261	4	(42.26%)	(5.82%)	(72.37%)	(12.36%)	(68.11%)	(16.26%)
Multi-MA	261	22	(0.00%)	(5.82%)	(12.66%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	5	(18.68%)	(5.82%)	(65.79%)	(9.96%)	(37.92%)	(8.87%)
Multi-RiskMetrics 2006	261	5	(18.68%)	(5.82%)	(65.79%)	(1.55%)	(37.92%)	(1.51%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
MA	936	6	(23.74%)	(59.47%)	(78.07%)	(40.86%)	(47.87%)	(37.61%)
EWMA	936	26	(0.00%)	(45.60%)	(3.57%)	(0.00%)	(0.00%)	(0.00%)
RiskMetrics2006	936	6	(23.74%)	(59.47%)	(78.07%)	(17.13%)	(47.87%)	(16.52%)
GARCH	936	19	(0.54%)	(45.60%)	(5.63%)	(0.22%)	(0.34%)	(0.03%)
GJR-GARCH	936	8	(64.68%)	(45.60%)	(71.02%)	(12.90%)	(84.03%)	(17.47%)
FI-GARCH	936	17	(2.43%)	(45.60%)	(3.50%)	(2.74%)	(0.86%)	(0.97%)
DCC	936	19	(0.54%)	(45.60%)	(37.46%)	(2.09%)	(1.42%)	(0.35%)
GJR-DCC	936	15	(8.84%)	(45.60%)	(48.43%)	(2.70%)	(18.34%)	(1.74%)
ADCC	936	19	(0.54%)	(45.60%)	(37.46%)	(2.09%)	(1.42%)	(0.35%)
GJR-ADCC	936	15	(8.84%)	(45.60%)	(48.43%)	(2.70%)	(18.34%)	(1.74%)
Multi-MA	936	6	(23.74%)	(59.47%)	(78.07%)	(11.46%)	(47.87%)	(11.29%)
Multi-EWMA	936	26	(0.00%)	(45.60%)	(3.57%)	(0.00%)	(0.00%)	(0.00%)
Multi-RiskMetrics 2006	936	21	(0.10%)	(45.60%)	(8.55%)	(0.06%)	(0.10%)	(0.00%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.18 – Backtesting Results for Multiple-asset Portfolio M5 (China, United Kingdom, Canada) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	13	(0.00%)	(5.82%)	(66.96%)	(0.00%)	(0.00%)	(0.00%)
MA	261	23	(0.00%)	(5.82%)	(48.23%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	3	(81.27%)	(5.82%)	(79.13%)	(1.72%)	(93.88%)	(3.68%)
RiskMetrics2006	261	1	(25.22%)	(79.19%)	(93.00%)	(79.19%)	(51.71%)	(50.13%)
GARCH	261	4	(42.26%)	(5.82%)	(72.37%)	(3.75%)	(68.11%)	(5.50%)
GJR-GARCH	261	30	(0.00%)	(5.82%)	(37.29%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	4	(42.26%)	(5.82%)	(72.37%)	(0.78%)	(68.11%)	(1.28%)
DCC	261	6	(7.13%)	(5.82%)	(59.44%)	(1.70%)	(17.06%)	(0.92%)
GJR-DCC	261	5	(18.68%)	(5.82%)	(65.79%)	(12.81%)	(37.92%)	(11.26%)
ADCC	261	6	(7.13%)	(5.82%)	(59.44%)	(1.70%)	(17.06%)	(0.92%)
GJR-ADCC	261	5	(18.68%)	(5.82%)	(65.79%)	(12.81%)	(37.92%)	(11.26%)
Multi-MA	261	22	(0.00%)	(5.82%)	(39.50%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	4	(42.26%)	(5.82%)	(72.37%)	(3.75%)	(68.11%)	(5.50%)
Multi-RiskMetrics 2006	261	3	(81.27%)	(5.82%)	(79.13%)	(1.72%)	(93.88%)	(3.68%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	1	(0.04%)	(1.45%)	(96.31%)	(1.45%)	(0.21%)	(0.01%)
MA	936	6	(23.74%)	(59.47%)	(78.07%)	(15.62%)	(47.87%)	(15.14%)
EWMA	936	22	(0.04%)	(59.47%)	(10.33%)	(0.00%)	(0.05%)	(0.00%)
RiskMetrics2006	936	6	(23.74%)	(51.74%)	(78.07%)	(11.77%)	(47.87%)	(11.58%)
GARCH	936	15	(8.84%)	(59.47%)	(48.43%)	(12.97%)	(18.34%)	(8.67%)
GJR-GARCH	936	17	(2.43%)	(59.47%)	(42.75%)	(0.08%)	(5.78%)	(0.02%)
FI-GARCH	936	15	(8.84%)	(59.47%)	(48.43%)	(5.94%)	(18.34%)	(3.88%)
DCC	936	15	(8.84%)	(59.47%)	(48.43%)	(12.97%)	(18.34%)	(8.67%)
GJR-DCC	936	16	(4.76%)	(45.60%)	(45.54%)	(9.17%)	(10.64%)	(4.70%)
ADCC	936	15	(8.84%)	(59.47%)	(48.43%)	(12.97%)	(18.34%)	(8.67%)
GJR-ADCC	936	16	(4.76%)	(45.60%)	(45.54%)	(9.17%)	(10.64%)	(4.70%)
Multi-MA	936	6	(23.74%)	(59.47%)	(78.07%)	(15.62%)	(47.87%)	(15.14%)
Multi-EWMA	936	22	(0.04%)	(59.47%)	(10.33%)	(0.00%)	(0.05%)	(0.00%)
Multi-RiskMetrics 2006	936	15	(8.84%)	(59.47%)	(48.43%)	(3.02%)	(18.34%)	(1.94%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.19 – Backtesting Results for Multiple-asset Portfolio M6 (China, Spain, Brazil) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	12	(0.00%)	(33.39%)	(10.46%)	(0.00%)	(0.00%)	(0.00%)
MA	261	28	(0.00%)	(5.82%)	(23.16%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	8	(0.71%)	(5.82%)	(47.60%)	(0.50%)	(2.06%)	(0.06%)
RiskMetrics2006	261	1	(25.22%)	(92.56%)	(93.00%)	(92.56%)	(51.71%)	(51.68%)
GARCH	261	9	(0.19%)	(5.82%)	(42.17%)	(1.65%)	(0.58%)	(0.09%)
GJR-GARCH	261	23	(0.00%)	(81.04%)	(48.23%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	9	(0.19%)	(5.82%)	(42.17%)	(0.29%)	(0.58%)	(0.01%)
DCC	261	8	(0.71%)	(5.82%)	(47.60%)	(0.80%)	(2.06%)	(0.10%)
GJR-DCC	261	6	(7.13%)	(72.52%)	(59.44%)	(19.58%)	(17.06%)	(10.46%)
ADCC	261	8	(0.71%)	(5.82%)	(47.60%)	(0.80%)	(2.06%)	(0.10%)
GJR-ADCC	261	5	(18.68%)	(72.52%)	(65.79%)	(19.18%)	(37.92%)	(16.51%)
Multi-MA	261	28	(0.00%)	(5.82%)	(23.16%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	8	(0.71%)	(5.82%)	(47.60%)	(0.50%)	(2.06%)	(0.06%)
Multi-RiskMetrics 2006	261	5	(18.68%)	(33.39%)	(65.79%)	(1.36%)	(37.92%)	(1.33%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
MA	936	3	(1.48%)	(1.45%)	(88.95%)	(1.41%)	(5.09%)	(0.24%)
EWMA	936	22	(0.04%)	(59.47%)	(1.29%)	(0.00%)	(0.01%)	(0.00%)
RiskMetrics2006	936	3	(1.48%)	(3.84%)	(88.95%)	(15.91%)	(5.09%)	(2.53%)
GARCH	936	15	(8.84%)	(59.47%)	(48.43%)	(19.67%)	(18.34%)	(13.40%)
GJR-GARCH	936	10	(83.53%)	(9.98%)	(64.19%)	(5.47%)	(87.83%)	(8.02%)
FI-GARCH	936	14	(15.56%)	(59.47%)	(51.41%)	(33.33%)	(29.49%)	(27.90%)
DCC	936	12	(40.60%)	(51.74%)	(57.64%)	(20.12%)	(60.57%)	(22.43%)
GJR-DCC	936	10	(83.53%)	(9.98%)	(64.19%)	(57.55%)	(87.83%)	(65.96%)
ADCC	936	11	(60.01%)	(51.74%)	(60.88%)	(26.30%)	(76.46%)	(31.65%)
GJR-ADCC	936	10	(83.53%)	(9.98%)	(64.19%)	(57.55%)	(87.83%)	(65.96%)
Multi-MA	936	3	(1.48%)	(1.45%)	(88.95%)	(1.41%)	(5.09%)	(0.24%)
Multi-EWMA	936	22	(0.04%)	(59.47%)	(1.29%)	(0.00%)	(0.01%)	(0.00%)
Multi-RiskMetrics 2006	936	13	(25.88%)	(51.74%)	(54.49%)	(20.76%)	(44.00%)	(20.25%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.20 – Backtesting Results for Multiple-asset Portfolio M7 (Hong Kong, Germany, United States) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	17	(0.00%)	(5.82%)	(1.77%)	(0.00%)	(0.00%)	(0.00%)
MA	261	30	(0.00%)	(5.82%)	(5.03%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	7	(2.38%)	(5.82%)	(53.37%)	(1.42%)	(6.41%)	(0.38%)
RiskMetrics2006	261	2	(69.23%)	(33.39%)	(86.02%)	(57.13%)	(91.04%)	(73.47%)
GARCH	261	6	(7.13%)	(5.82%)	(59.44%)	(4.31%)	(17.06%)	(2.29%)
GJR-GARCH	261	28	(0.00%)	(33.39%)	(2.20%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	7	(2.38%)	(5.82%)	(53.37%)	(1.52%)	(6.41%)	(0.41%)
DCC	261	7	(2.38%)	(5.82%)	(53.37%)	(1.52%)	(6.41%)	(0.41%)
GJR-DCC	261	9	(0.19%)	(5.82%)	(42.17%)	(1.64%)	(0.58%)	(0.09%)
ADCC	261	7	(2.38%)	(5.82%)	(53.37%)	(1.52%)	(6.41%)	(0.41%)
GJR-ADCC	261	8	(0.71%)	(5.82%)	(47.60%)	(5.10%)	(2.06%)	(0.69%)
Multi-MA	261	32	(0.00%)	(5.82%)	(3.32%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	7	(2.38%)	(5.82%)	(53.37%)	(1.42%)	(6.41%)	(0.38%)
Multi-RiskMetrics 2006	261	6	(7.13%)	(5.82%)	(59.44%)	(2.69%)	(17.06%)	(1.44%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
MA	936	1	(0.04%)	(1.06%)	(96.31%)	(1.06%)	(0.21%)	(0.01%)
EWMA	936	20	(0.24%)	(59.47%)	(6.98%)	(2.85%)	(0.19%)	(0.33%)
RiskMetrics2006	936	3	(1.48%)	(20.90%)	(88.95%)	(25.23%)	(5.09%)	(4.01%)
GARCH	936	12	(40.60%)	(59.47%)	(14.04%)	(35.09%)	(23.87%)	(37.78%)
GJR-GARCH	936	8	(64.68%)	(59.47%)	(5.35%)	(0.21%)	(13.95%)	(0.37%)
FI-GARCH	936	14	(15.56%)	(59.47%)	(1.49%)	(3.00%)	(1.88%)	(2.48%)
DCC	936	13	(25.88%)	(59.47%)	(1.06%)	(1.41%)	(2.03%)	(1.48%)
GJR-DCC	936	13	(25.88%)	(59.47%)	(16.91%)	(7.80%)	(20.54%)	(7.81%)
ADCC	936	12	(40.60%)	(59.47%)	(0.74%)	(1.13%)	(1.96%)	(1.44%)
GJR-ADCC	936	12	(40.60%)	(59.47%)	(57.64%)	(48.23%)	(60.57%)	(50.79%)
Multi-MA	936	1	(0.04%)	(1.06%)	(96.31%)	(1.06%)	(0.21%)	(0.01%)
Multi-EWMA	936	20	(0.24%)	(59.47%)	(6.98%)	(2.85%)	(0.19%)	(0.33%)
Multi-RiskMetrics 2006	936	8	(64.68%)	(20.90%)	(0.11%)	(0.09%)	(0.43%)	(0.17%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.21 – Backtesting Results for Multiple-asset Portfolio M8 (Hong Kong, United Kingdom, Canada) 1% One-day VaR

(a) Sub-prime Mortgage Crisis Period of 01 Jun 2008 to 01 Jun 2009

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	261	15	(0.00%)	(72.52%)	(88.05%)	(0.00%)	(0.00%)	(0.00%)
MA	261	25	(0.00%)	(5.82%)	(28.90%)	(0.00%)	(0.00%)	(0.00%)
EWMA	261	6	(7.13%)	(72.52%)	(59.44%)	(0.26%)	(17.06%)	(0.15%)
RiskMetrics2006	261	1	(25.22%)	(79.19%)	(93.00%)	(79.19%)	(51.71%)	(50.13%)
GARCH	261	7	(2.38%)	(72.52%)	(53.37%)	(0.16%)	(6.41%)	(0.04%)
GJR-GARCH	261	32	(0.00%)	(5.82%)	(97.18%)	(0.00%)	(0.00%)	(0.00%)
FI-GARCH	261	5	(18.68%)	(72.52%)	(65.79%)	(1.91%)	(37.92%)	(1.84%)
DCC	261	6	(7.13%)	(72.52%)	(59.44%)	(1.09%)	(17.06%)	(0.59%)
GJR-DCC	261	10	(0.05%)	(72.52%)	(37.10%)	(0.51%)	(0.14%)	(0.01%)
ADCC	261	6	(7.13%)	(72.52%)	(59.44%)	(1.09%)	(17.06%)	(0.59%)
GJR-ADCC	261	9	(0.19%)	(72.52%)	(42.17%)	(1.65%)	(0.58%)	(0.09%)
Multi-MA	261	23	(0.00%)	(5.82%)	(17.08%)	(0.00%)	(0.00%)	(0.00%)
Multi-EWMA	261	6	(7.13%)	(72.52%)	(59.44%)	(0.26%)	(17.06%)	(0.15%)
Multi-RiskMetrics 2006	261	5	(18.68%)	(72.52%)	(65.79%)	(1.91%)	(37.92%)	(1.84%)

* The numbers in parentheses are the p-value to reject the null hypothesis

(b) After-crisis Period of 01 Jun 2009 to 31 Dec 2012

			Coverage Tests		Independence Tests		Joint Tests	
	No of Obs.	No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	936	0	(0.00%)	(0.04%)	(100.00%)	NA	(0.01%)	NA
MA	936	3	(1.48%)	(51.74%)	(88.95%)	(21.77%)	(5.09%)	(3.45%)
EWMA	936	19	(0.54%)	(59.47%)	(39.72%)	(0.26%)	(1.47%)	(0.04%)
RiskMetrics2006	936	6	(23.74%)	(51.74%)	(78.07%)	(11.77%)	(47.87%)	(11.58%)
GARCH	936	14	(15.56%)	(59.47%)	(51.41%)	(17.82%)	(29.49%)	(14.74%)
GJR-GARCH	936	20	(0.24%)	(9.98%)	(44.32%)	(0.03%)	(0.74%)	(0.00%)
FI-GARCH	936	15	(8.84%)	(59.47%)	(23.50%)	(2.12%)	(11.57%)	(1.36%)
DCC	936	15	(8.84%)	(59.47%)	(23.50%)	(2.12%)	(11.57%)	(1.36%)
GJR-DCC	936	12	(40.60%)	(59.47%)	(57.64%)	(20.75%)	(60.57%)	(23.09%)
ADCC	936	15	(8.84%)	(59.47%)	(23.50%)	(2.12%)	(11.57%)	(1.36%)
GJR-ADCC	936	12	(40.60%)	(59.47%)	(57.64%)	(20.75%)	(60.57%)	(23.09%)
Multi-MA	936	3	(1.48%)	(51.74%)	(88.95%)	(21.77%)	(5.09%)	(3.45%)
Multi-EWMA	936	19	(0.54%)	(59.47%)	(39.72%)	(0.26%)	(1.47%)	(0.04%)
Multi-RiskMetrics 2006	936	12	(40.60%)	(93.76%)	(57.64%)	(23.03%)	(60.57%)	(25.47%)

* The numbers in parentheses are the p-value to reject the null hypothesis

Table 4.22 – Backtesting Results for Multiple-asset Portfolio M9 (Hong Kong, Spain, Brazil) 1% One-day VaR

Chapter 5. The Performance of VaR in the Presence of Asset Price Bubbles: A Simulation Analysis

5.1 Introduction

Chapter 4 has analysed the performance of VaR in the financial crisis using a sample of data from nine stock markets. In this chapter, the performance of VaR in the presence of bubbles is studied using simulated data. Financial markets have experienced several crises in the last two decades. Financial turmoils are often caused by an asset price bubble that are difficult to observe. If one can perfectly understand the dynamics of stock price movements, one can make better investment decisions and manage risks more efficiently. However, it is nontrivial as manifold factors influence price movement simultaneously. Practitioners commonly use a Monte Carlo simulation (MCS) to quantify financial risks and allocate financial budgets within their investments. For example, portfolio managers can perform MCS to predict the worst likely loss for their portfolios at a particular confidence level. In order to simulate the stock price paths, they have to adopt models that specify the behaviour of the stock prices. Geometrical Brownian motion, which is the most common approach used in the simulation, generates thousands or millions of stock price paths whose moments of distribution can be analysed to quantify the risks. However, as this motion is a Markov process, the purely random walk series is inadequate for modelling a financial crisis with an unexpected plunge due to the collapse of asset price bubble, which limits the effectiveness of various risk management tools.

Asset price bubbles refers to asset prices that exceed its fundamental value. In literature, asset price bubbles can be referred as rational bubbles, irrational bubbles, or endogenous bubbles. Rational bubbles occur if investors hold the assets even though the prices exceeded the fundamental value (often referred as the present value of subsequent dividends). They believe the value might be temporarily sustainable due to the divergence of different investors' expectations. Irrational bubbles are referred as investors extrapolate recent prices into future; the asset valuation is not done by following traditional discounted cash flow approach. Endogenous bubbles formed as the market lack of common expectations of what fundamentals really are. The market participants make investment decisions based on different estimates rather than some common priors (e.g. present value of subsequent dividends) about fundamental value, the price bubbles form endogenously. Among the different types of asset price bubbles suggested in the literature, the majority of the empirical studies have focus on rational bubbles due to its conformity with the traditional discounted cash flow theory.

Evans (1991) proposed a model for simulating rational asset price bubbles. It simulates stock price series with periodically collapsing explosive bubbles. However, Evan's bubble model works poorly for generating long and high frequency time series data; stock prices will exhibit constant volatility and the bubble process will have superficial growth and collapse in a single observation. Such features make it an unrealistic option for generating high-frequency (daily) asset prices.

This chapter responds to this weakness of Evan's bubble model by extending it to allow the asset price bubbles to grow and collapse in a gradual manner. More importantly, we introduce a mechanism to incorporate the volatility clustering feature in the asset price series. The enhancement is demonstrated with simulations that compare the average percentage loss during the simulated bubble burst. Our model delivers a stable and realistic result, in contrast to Evan's original model (which produces a wide range of loss with an unlikely sharp rise followed by a sharp fall for daily stock data).

Our model is empirically applied to test the reliability of different VaR measures. The VaR models studied in this work include the historical simulation (HS) approach of Linsmeier and Pearson (1996), the MA approach, Longerstaey and Spencer (1996) RiskMetrics approach, and Zumbach (2006) RiskMetrics2006 (RM2006) approach. We date-stamp the collapse of the bubbles and backtest the VaR measures in the one-year periods before and after the burst, to test their reliability in pre- and post-burst periods. Our results show that the RiskMetrics approach works well in all of the periods and outperforms the other three approaches in 10,000 simulation tests.

The organization of this chapter is as follows. Section 5.2 discusses the relationship between asset price and an asset price bubble and reviews Evan's bubble model. Section 5.3 discusses the problems and practical issues of this model in relation to generating high-frequency (daily) data. Section 5.4 proposes our model and outlines its implementation procedures. Section 5.5 compares our model with Evan's and Section 5.6 shows our model being applied to evaluate the reliability of different VaR approaches with the presence of an asset price bubble. Section 5.7 presents conclusions.

5.2 Asset Prices and Bubbles

Asset price bubbles are often driven by speculative behaviour that bids prices above their fundamental value. Whenever bubbles are present, prices will manifest explosive behaviour. The fundamental value of an asset is the sum of discounted cash flows of all future cash flows. The standard model for stock price at time t is:

$$P_t = E(\frac{P_{t+1} + D_{t+1}}{1+R}) \tag{5.1}$$

where P_t is the real price at time t, D_{t+1} is the real dividends received in the period from t to $t + 1$, and R is the discount rate. By iterating the equation (5.1) forward, stock price P_t can be rewritten as:

$$P_t = \sum_{i=1}^{\infty}\left[\left(\frac{1}{1+r}\right)^i E_t(D_{t+i})\right] + lim_{k\to\infty}\left(\frac{1}{1+r}\right)^k E_t(P_{t+k}) \tag{5.2}$$

$$P_t = p_t^f + b_t \tag{5.3}$$

Such that

$$p_t^f = \sum_{i=1}^{\infty}\left[\left(\frac{1}{1+r}\right)^i E_t(D_{t+i})\right] \tag{5.4}$$

$$b_t = lim_{k\to\infty}\left(\frac{1}{1+r}\right)^k E_t(P_{t+k}) \tag{5.5}$$

As the value p_t^f depends on the expected dividends, p_t^f is considered the fundamental component of the price, while b_t, is considered the rational bubble component that is based on the expectations of the future stock price. From equation (5.5), we can write:

$$E(b_{t+1}) = (1+r)b_t$$

$$b_{t+1} = (1+r)b_t + u_{t+1}. \tag{5.6}$$

where u_t is the random error of the bubble component at time t. Equation (5.6) shows that b_t is an explosive process, which indicates that the stock price will behave explosively if the bubble component b_t is non-zero in equation (5.3).

Diba and Grossman (1988a) propose that the existence of the explosive bubble component b_t in equations (5.3) and (5.6) can be statistically detected by using ADF unit root test and cointegration test. If bubbles are present, equation (5.3) implies the price series P_t is explosive regardless D_t is I(0) or I(1), as the bubble component b_t is an explosive process. From equation (5.6), taking the first differences we obtain a non-stationary ARMA process of equation (5.7).

$$[1-(1+r)L](1-L)b_t = (1-L)u_t \tag{5.7}$$

where L is the lag operator. From equation (5.3), the first differences of P_t contains the non-stationary ARMA process of equation (5.7), it implies that the ΔP_t is explosive and non-stationary. Diba and Grossman (1988a) applies the ADF test in equation (5.8) on the ΔP_t series, the null hypothesis of not explosive is unable to reject and therefore it concludes there was no bubble in the equity market.

$$\Delta y_t = \alpha + \phi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \epsilon_t \tag{5.8}$$

where k is the lag order and ϵ_t is the random error.

Diba and Grossman (1988a) further conducts a cointegration test by examining the relationship between P_t and D_t. If bubbles are present, P_t is explosive and it will not co-move with D_t. So if both P_t and D_t are I(1) and they co-move each other, it will be an evidence that against the presence of price bubbles. The results of cointegration tests suggested by Granger and Engle (1987) produced a mixed result and unable to suggest the existence of price bubbles in the market.

Evans (1991) criticized the empirical tests employed by Granger and Engle (1987) is unrealistic because it assumed that the asset price perpetually grows at an expositive rate and never collapse. The test employed by Diba and Grossman (1988a) has a low power in detecting periodically collapsing bubbles and it biased towards the conclusion of no presence of bubble. It motivates Evans to propose an alternative approach to model the bubbles component by introducing a periodically collapse bubbles series, which timing of collapse is controlled by a Bernoulli process.

5.3 Evan's Bubble Model

The explosive bubbles series can be intuitively modelled in the form of an explosive autoregression AR(1) series. However, Blanchard and Watson (1982) suggest as that no bubble will last forever and all bubbles eventually burst, a simple AR(1) series is inadequate for modelling periodic collapsing behaviour. Evans (1991) suggested the following model to describe such a periodically collapsing explosive bubble process b_t.

$$b_{t+1} = (1+r)b_t u_{t+1}, \quad \text{if } b_t \le \alpha, \tag{5.9}$$

$$b_{t+1} = [\delta + \pi^{-1}(1+r)\theta_{t+1}(b_t - (1+r)^{-1}\delta)]u_{t+1}, \quad \text{if } b_t > \alpha, \tag{5.10}$$

where u_t is an i.i.d. lognormal random variable with unit mean $u_t = exp(y_t - \sigma_b^2/2)$, and θ_t is an i.i.d. Bernoulli process that takes the values of 1 and 0 with probability π and $(1-\pi)$ respectively. The bubble process b_t will grow at a rate r before it reaches the threshold value α; beyond that point, the bubble will grow even faster at a rate of $\pi^{-1}(1+r)$.

It will then fall to an initial value of α with a probability of $(1-\pi)$ in each of the following periods before it bursts.

The fundamental component of the equity price depends solely on expected dividends. Evans (1991) modelled dividends as being generated by a random walk with a drift process, as shown in equation (5.11). The fundamental component in equation (5.4) can be rewritten as equation (5.12) by recursively substituting equation (5.11) itself.

$$D_{t+1} = \mu + D_t + \epsilon_{t+1} \tag{5.11}$$

$$p_t^f = \mu(1+r)r^{-2} + r^{-1}D_t \tag{5.12}$$

where μ is the drift and $\epsilon_t \sim N(0,\sigma_{\Delta_D}^2)$. The equity price series P_t is a summation of the fundamental component p_t^f (dividends series D_t) and the bubble component series b_t. The bubble series is scaled up κ times to ensure that it appropriately affects the equity price.

$$P_t = p_t^f + \kappa b_t \tag{5.13}$$

5.4. Shortcomings of Evan's Bubble Model

5.4.1 Domination of the fundamental component in late observations

Evan's bubble model works well for simulating equity price with periodically collapsing bubbles for short but not long periods. In equation (5.10), the bubble will grow and has a probability of $(1-\pi)$ that it will plunge to the initial value of δ once it reaches above the threshold value of α. Equations (5.11) and (5.12) show that the fundamental component will grow with a positive drift μ and eventually dominate the whole equity price as time t grows. The bubble component will become insignificant as the bubble component b_t will fall back to its initial constant δ when it exceeds the threshold constant value of α.

5.4.2 Superficial growth of the bubble component

Evan's bubble model is suitable for simulating low-frequency (monthly) data, but not for high-frequency (daily) data. Equation (5.10) shows that the bubble will grow faster at a rate of $\pi^{-1}(1+r)$ once it goes beyond the threshold value of α. While such a growth rate may be appropriate for monthly data, it is not for daily data (which is unreasonably high). For example, with a real return $r = 0.02$ and $\phi = 0.8$, the bubble has a 20% probability to burst and the daily equity price will grow to a level of around 3.4 times if the bubble does not burst in 5 consecutive days. It will further grow to a level of 11 times in consecutively 10 days. As the growth rate is superficial and unrealistic in such a short period, Evan's original equations are not suitable for generating daily data.

5.4.3 The bubble completely collapses in a single observation

The final problem with Evan's model is that it suggests that the bubble will collapse back to an initial level of δ in a single observation. Similar to the superficial growth problem, this may be reasonable for monthly data but not for high-frequency daily data. Whenever equity bubbles burst in real cases, equity prices usually consecutively plunge over several days due to bad market sentiment. It is common for bubbles to take several days (rather than a single day) to completely collapse.

5.5 Our Model

5.5.1 The bubble component

We modify Evan's bubble model by introducing controlling parameters in both the bubble and the fundamental component. We relax the bubble growth rate by introducing a parameter of M in equation (5.10); the bubble will now grow at a new rate of $\pi^{-1/M}(1+r)$ when it exceeds the threshold value of α as shown in equation (5.14). The parameter M can be the total number of trading days in a month if one uses it to generate daily data. The bubble will have a probability of $1-\pi_t$ to burst and θ_t is a time-varying i.i.d. Bernoulli process that takes the values of 1 and 0 with probability π_t and $1-\pi_t$ respectively. Once the bubble bursts in time t ($\theta_t = 0$), unlike in Evan's model, the bubble size will not immediately fall back to the initial value but instead reduce to a fraction of its previous level (i.e. $\rho_t b_{t-1}$). The parameter ρ_t is a bubble-collapsing factor with a continuous uniform distribution from a lower bond f_l to an upper bond f_u, i.e. $\rho_t \sim U(f_l, f_u)$. The parameter of ρ_t controls the rate of the bubble's collapse. After the bubble burst, the generation process will shift to using equation (5.15) for all $t \in T_C$ (The set T_C contains all of the observations from when the bubble is starting to collapse until it reaches to the initial value of δ). Under normal circumstances, the probability of a bubble further shrinking may differ from the probability of the bubble first collapsing; one can specify another probability to collapse π_t in the period $t \in T_C$. Equation (5.15) is similar to equation (5.14), although it ensures that the floor value of the bubble series will not fall below its initial level of δ.

$$b_{t+1} = \begin{cases} (1+r)b_t u_{t+1} & \text{if} \quad b_t \le \alpha \\ [\rho_{t+1} b_t + \pi_{t+1}^{-1/M}(1+r)\theta_{t+1}(b_t - \pi_{t+1}^{1/M}(1+r)^{-1}\rho_{t+1} b_t)]u_{t+1} & \text{if} \quad b_t > \alpha \end{cases}, \text{ for } t \notin T_C$$

(5.14)

$$b_{t+1} = max([\rho_{t+1} b_t + \pi_{t+1}^{-1/M}(1+r)\theta_{t+1}(b_t - \pi_{t+1}^{1/M}(1+r)^{-1}\rho_{t+1} b_t)]u_{t+1} \ , \delta), \text{ for} t \in T_C$$

(5.15)

We address the problems of the unrealistic superficial growth rate and allow the bubbles to collapse in multiple observations rather than in a single observation by introducing the following parameters: (1) a bubble collapsing factor ρ_t, (2) a time-varying bubble collapsing probability θ_t and π_t, and (3) a slower growth rate of $\pi_{t+1}^{-1/M}(1+r)$. Our model is hence more realistic for simulating high frequency daily assets price.

5.5.2 The fundamental component

The fundamental component of the equity price depends on expected dividends. The dividend process is assumed to be a random walk with a drift process, as shown in equation (5.16). Unlike in Evan's work, we introduce a lognormal random noise v_t with unit mean and time-varying volatility in the dividend series. Evan used the additive model in equation (5.11) to simulate the dividend process, which may have occasionally resulted a negative value of dividend series due to the random noise $\epsilon_t \sim N(0, \sigma_{\Delta_D}^2)$. The advantage of our multiplicative form in equation (5.16) with lognormal random error is to avoid potential negative dividend series. The fundamental component of the equity price is obtained by recursively substituting the expectation value of equation (5.16) into equation (5.17), which is same as Evan's in equation (5.12).

$$D_t = (\mu + D_{t-1})v_t \tag{5.16}$$

$$p_t^f = \mu(1+r)r^{-2} + r^{-1}D_t \tag{5.17}$$

where μ is the drift, v_t is an i.i.d. lognormal random variable with unit mean $v_t = exp(z_t - \sigma_{D_t}^2 / 2)$, and $\sigma_{D_t}^2$ is the conditional variance of the daily dividend return $z_t \sim N(0, \sigma_{D_t}^2)$ that shown in equation (5.18).

$$\sigma_{D_t}^2 = \psi(\sigma_{\Delta D} S_{t-1})^2 + \beta_1 \sigma_{D_{t-1}}^2 + \beta_2 I_t \sigma_{D_{t-1}}^2 \tag{5.18}$$

where if $v_t < 1, I_t = 1$, else $I_t = 0$. Financial asset returns exhibit volatility clustering is well documented in the literature (Mandelbrot (1963), Akigiray (1989), Lux and Marchesi (2000), Jacobsen and Dannenburg (2003), and Niu and Wang (2013)). The constant volatility feature in Evan's model is inadequate for describing the movement of assets price. Expected future dividends should reflect the current level of market sentiment and investors' speculative behaviour, which will become more volatile when the bubble is nearly burst with a higher bubble level or after a burst with a low bubble level. Accordingly, we define the conditional variance of the daily dividend return in equation (5.18) as an autoregressive equation with a scaled constant volatility $\sigma_{\Delta D}$ factor. The parameter I_t is to capture the asymmetric impacts of bad or good news information on return volatility. The time-varying scaling parameter S_t represents the market speculative sentiment level.

The volatility of the expected dividend is high when the market's speculative sentiment is strong. Markets usually have strong speculative sentiment when the bubble level is at high (i.e. nearly burst) or low (i.e. post-burst) value. In contrast, the speculative sentiment is weak when the bubble is building up and its level is around the mean value. We model the speculative sentiment level using an absolute inverse logistics function that is shown in Figure 5.1 and equation (5.19); the respective logistics function is shown in Figure 5.2 and equation (5.20). To avoid the speculative level going to infinity, we set a lower bound of δ (the bubble component initial value) and an upper bound of α (the bubble component threshold value) for the input of the inverse logistics function. As shown in Figures 5.1 and 5.2, the speculative sentiment level is at its lowest in the middle of the bubble generation process, which implies $a/(1+b)=(\delta+\alpha)/2$; the parameters of a and b in the logistics function are thus set to be $a=\delta+\alpha$ and $b=1$. Given a maximum speculative sentiment level of z, the value of S_t will reach a maximum (i.e. $\hat{S}_t = z$) when the bubble level is reached at the value of α. Substituting $a=\delta+\alpha$, $b=1$ and $\hat{S}_t = z$ into equation (5.19), we obtain $c=(\alpha/\delta)^{1/z}$. To make sure the scaling variable $\hat{S}_t$ that starts at zero is greater than one in equation (5.18), we further set the speculative level indicator S_t as $S_t = \hat{S}_t + 1$.

$$\hat{S}_t = |f^{-1}(B_t)| = \left| \frac{-ln(\frac{a-B_t}{B_t^b})}{ln(c)} \right| \tag{5.19}$$

$$y = f(x) = \frac{a}{1+bc^{-x}} \tag{5.20}$$

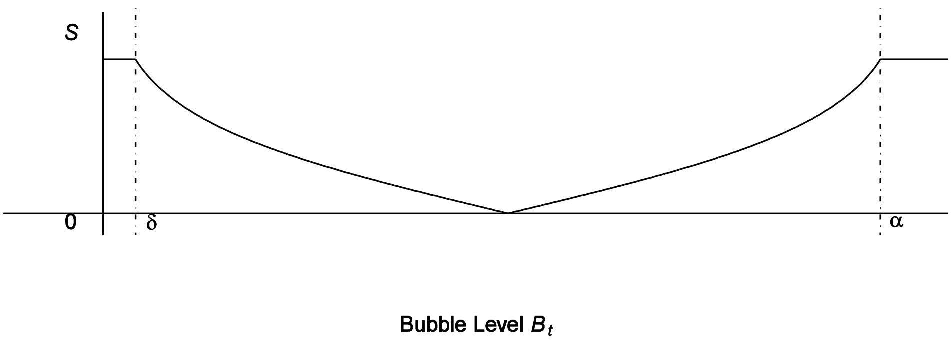


Figure 5.1 – The Inverse Logistics Function with Bubble Level B_t as Input and Speculative Sentiment Level S_t as Output

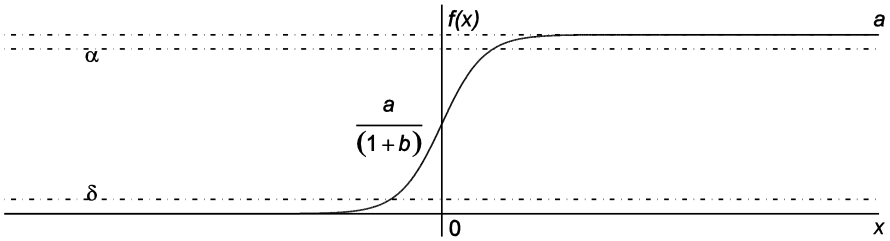


Figure 5.2 – The Logistics Function and Parameter Settings

5.5.3 The equity price series: Combining the fundamental and bubble components

The equity price is generated by adding the fundamental component p_t^f and bubble component b_t together. We scale the bubble component up by κ_t as shown in equation (5.21) in order to let it appropriately affect the equity price. Unlike Evan's model (which uses a constant scaling factor), we introduce a time-varying scaling factor κ_t to avoid the domination problem of the fundamental component in the late observations as time t grows. The time-varying scaling factor κ_t will only be reset when the bubble completely collapses, and it is calculated using equation (5.22). Since the bubble will collapse after it reaches the threshold level of α, equation (5.22) specifies the fundamental component is around $1/\gamma$ times the size of the bubble component, as it ensures the ratio between the bubble threshold level of α to the fundamental value is γ.

$$P_t = p_t^f + \kappa_t b_t \tag{5.21}$$

$$\kappa_t = \frac{\gamma p_t^f}{\alpha} \tag{5.22}$$

5.6 Simulation Results

We simulate 10,000 daily equity price series with each series having a length of 5,040 trading days (i.e. 20 years with 21 trading days per month) by using both Evan's model and our own. We consider 20 years of the monthly real S&P500 equity price index over the period July 1994 to June 2014 for the parameter settings in the simulations. By assuming that the real monthly S&P500 dividend returns distributed normally, we set the mean of the first difference of daily dividends as $\mu = 0.0024$, the sample daily variance as $\sigma^2_{\Delta_D}$ = 0.0295%, and the real daily return as $r = 0.0719\%$. The parameters of ψ, β_1 and β_2 for the conditional AR volatility equation are set to 0.05, 0.8, and 0.15 respectively. To generate the bubble component, the daily variance σ^2_b of the bubble series is 0.01%. The threshold parameter α is set as 2.0, which allows the bubble to grow up to four times its initial level of $\delta = 0.5$. The probability of the bubble bursting is $(1-\pi_t) = 0.05$ (i.e. the bubble will burst within a month (1/20)). The lower bound f_l and upper bound f_u for the bubble collapsing factor ρ_t are 0.8 and 0.5 only, which limit the bubble to shrinking at least 20% ($f_l = 0.8$) and at most 50% ($f_u = 0.5$) of the original size when it bursts. Finally, the bubble component to fundamental component ratio γ is set to 0.25.

Table 5.1 summarizes the parameter settings. To compare our model with Evan's, we perform 10,000 simulations; samples of the generated price series are shown in Figures 5.3, 5.4, 5.5, and 5.6.

	Parameters	Our Model	Evan's Model
Fundamental Component	M	21	-
	μ	0.0024	0.0024
	$\sigma_{\Delta D}^2$	0.03%	0.03%
	ψ	0.05	-
	β_1	0.8	-
	β_2	0.15	-
	z	2	
Bubble Component	δ	0.5	0.5
	α	2	2
	σ_b^2	0.01%	0.01%
	π	0.95	0.8
	f_l	0.8	-
	f_u	0.5	-
	r	0.07%	0.07%
Others	γ	0.25	
	κ	-	150

Table 5.1 – Parameters Used in the Simulations

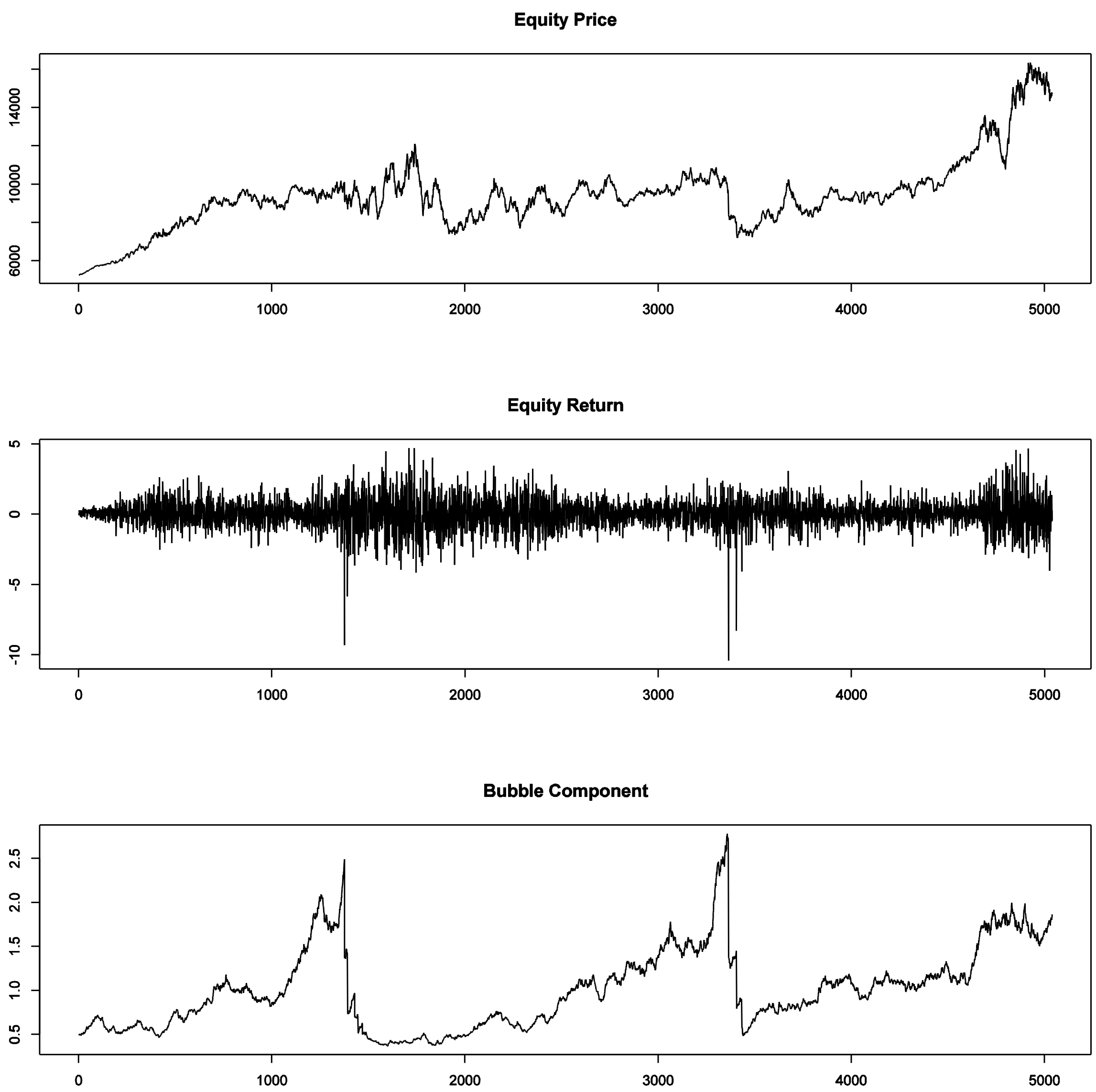


Figure 5.3 – A Sample of Simulated Equity Price Series Generated Using Our Model

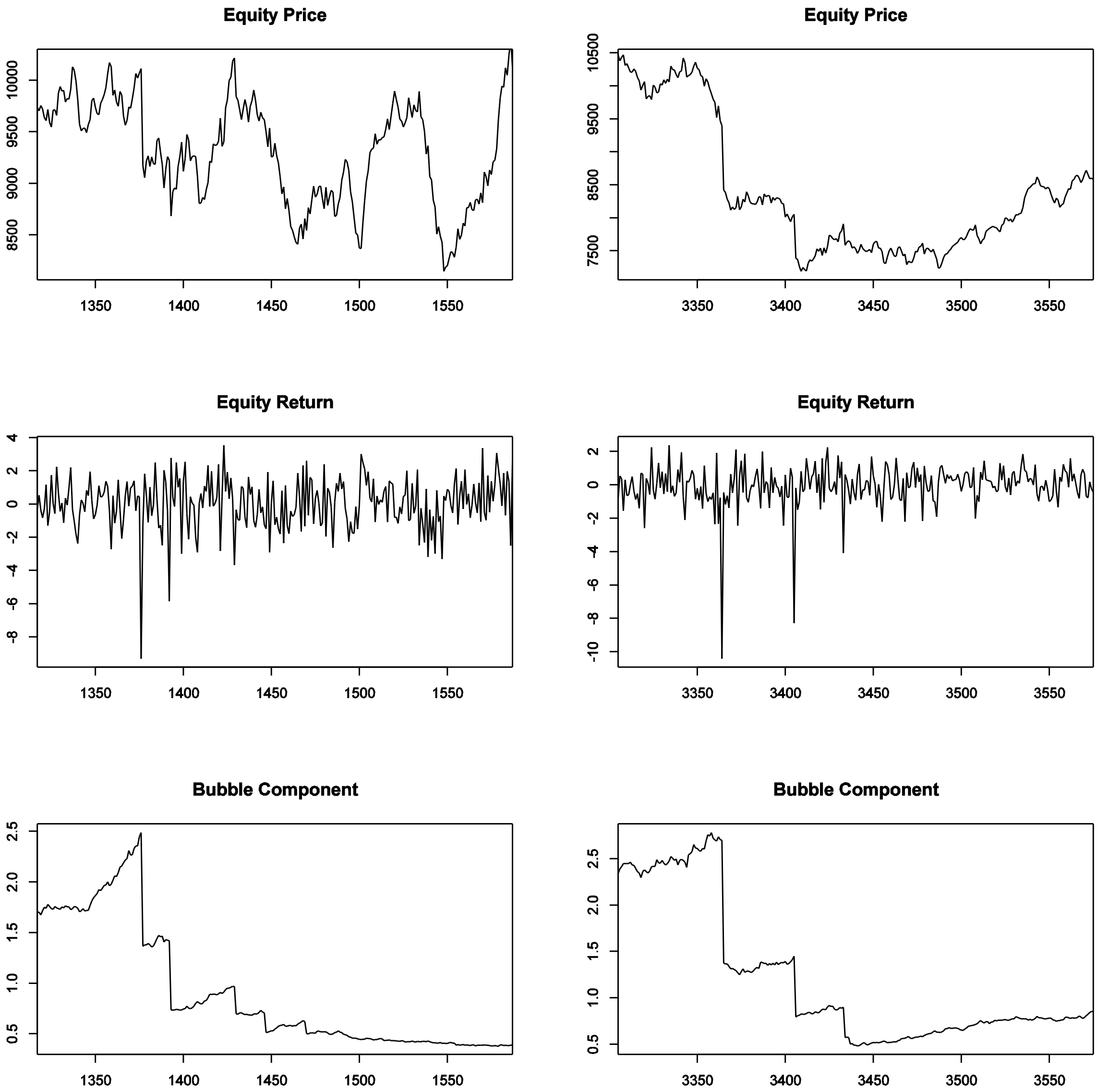


Figure 5.4 – A Closer Look at Figure 5.3 During the Bubble Collapse Period

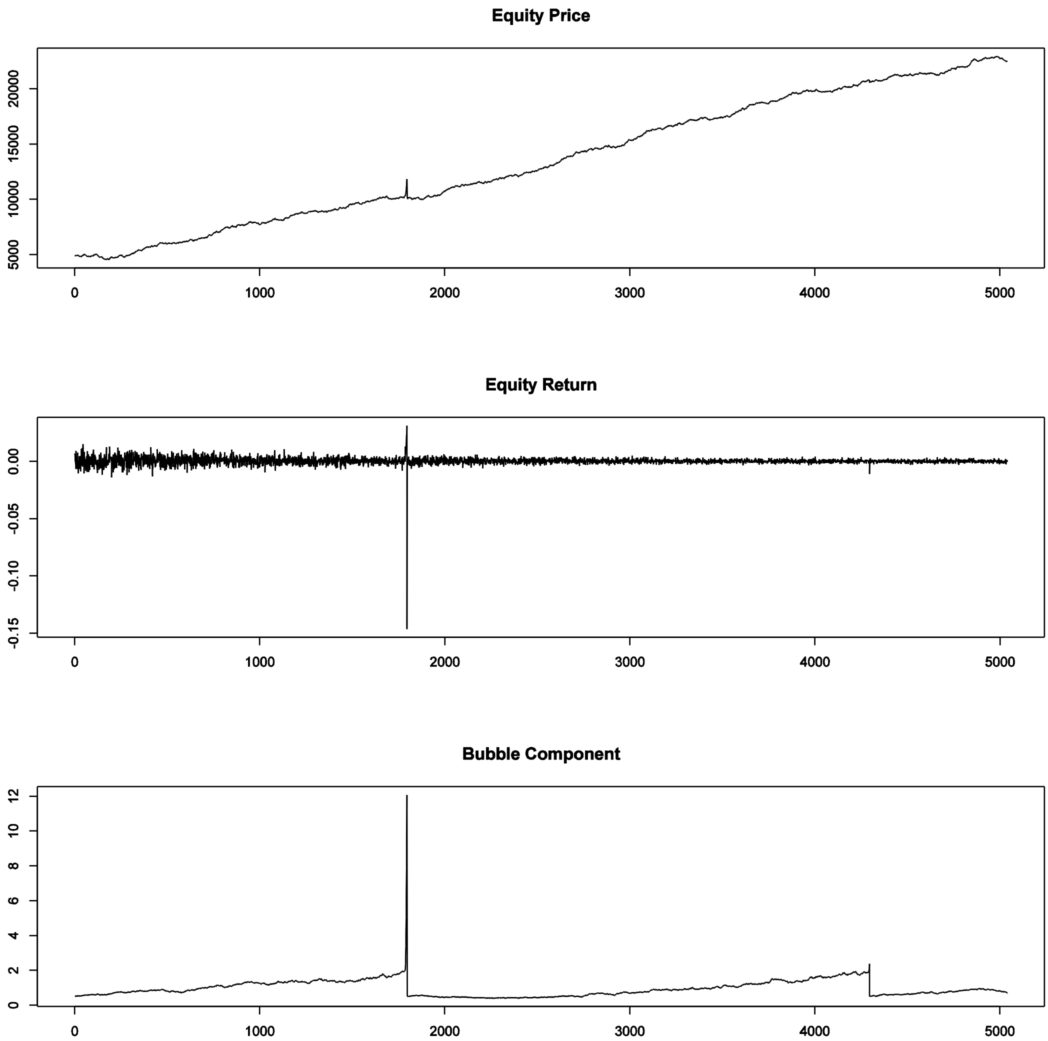


Figure 5.5 – A Sample of Simulated Equity Price Series Generated Using Evan's Model

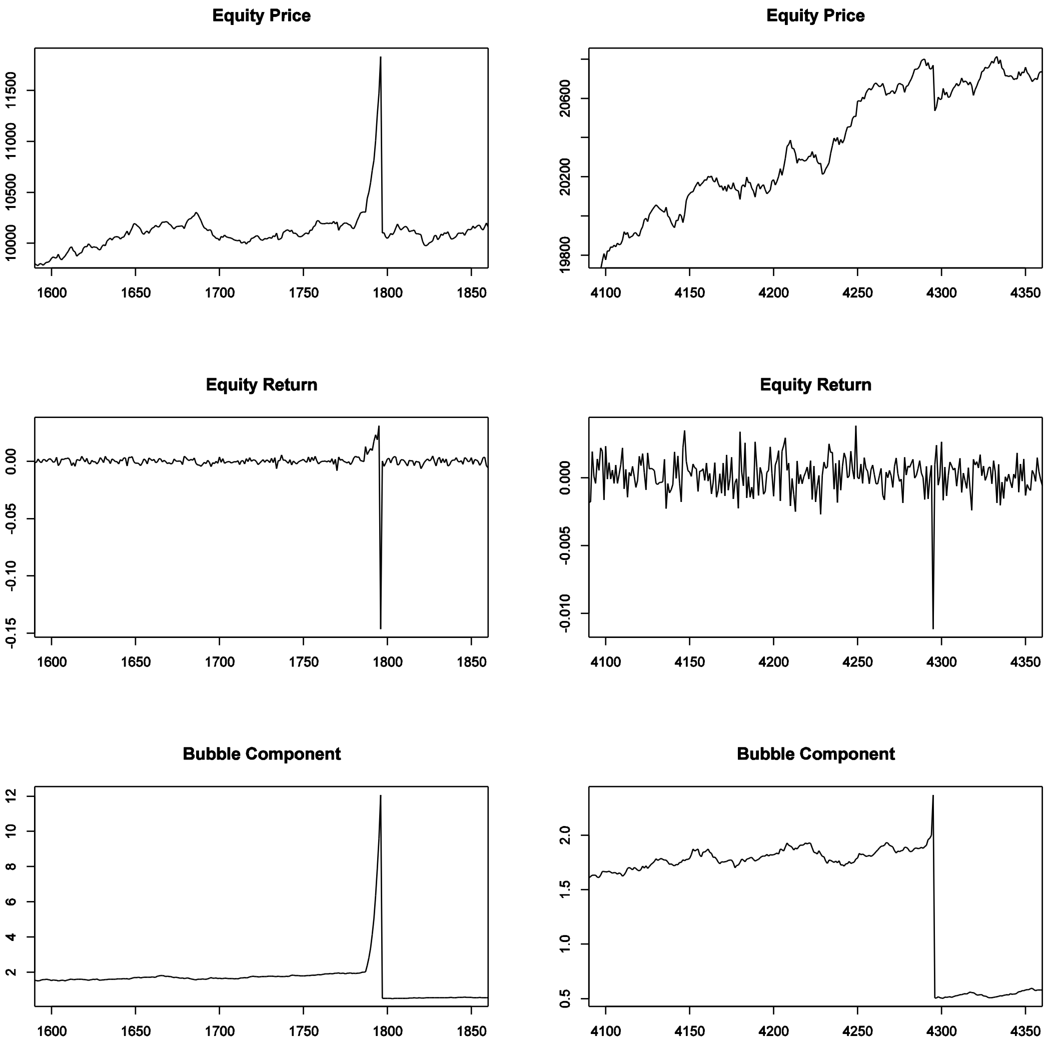


Figure 5.6 – A Closer Look at Figure 5.5 During the Bubble Collapse Period

Figures 5.3 and 5.4, which show a sample of our model's simulations, reveal that bubbles burst in the 1,377th and 3,365th observations. Figures 5.5 and 5.6, which show simulation results using Evan's model, indicate that bubbles instead burst in the 1,797th and 4,296th observations. The third row of Figure 5.5 illustrates the superficial growth property problem of Evan's model. At around the 1,797th observation, the bubble series exhibits a superficial growth before bursting. The bubble size increases around six times in a few days once the value goes beyond the upper threshold value α of 2.0. Furthermore, the bubble value falls from a value of around 12 to its original level of 0.5 in a single day after the bubble burst. The spark in the equity price that it causes make Evan's bubble model unrealistic.

In addition, the fundamental component of the equity price will dominate the bubble component in late observations in Evan's model. As shown in the second column of Figure 5.6, the bubble component in the late observations of the simulation becomes insignificant to the equity price series. Another problem of Evan's model can be found in the second row of Figure 5.5, which shows that the equity returns in Evan's model exhibit constant volatility while those in our model exhibit volatility clustering (as shown in the second row of Figure 5.3). The first column in Figure 5.4 shows that the bubble component in our model has progressively collapsed in several observations rather than collapsed in a single observation, as suggested by Evan. Contrasting Figures 5.3 and 5.4 to Figures 5.5 and 5.6 reveals that our model is more realistic than Evan's.

	Number of Simulations	Average number of bubble burst	Average daily loss in bubble burst	Average First Day Percentage Loss in Bubble Burst (quantile)				
				10%	25%	50%	75%	90%
Our Model	10,000	1.89 times	-8.62%	-13.60%	-10.50%	-8.07%	-5.88%	-4.05%
Evan's Model	10,000	2.00 times	-7.88%	-13.29%	-11.26%	-7.88%	-4.50%	-2.47%

Table 5.2 – Summary of the Average First-Day Percentage Loss when Bubbles Collapse

Date	Losses
19/10/1987	-22.62%
26/10/1987	-8.04%
15/10/2008	-7.87%
01/12/2008	-7.70%
09/10/2008	-7.33%
27/10/1997	-7.18%
17/09/2001	-7.13%
29/09/2008	-6.98%
13/10/1989	-6.91%
08/01/1988	-6.85%

Table 5.3 – Largest Daily Percentage Losses in the Dow Jones Industrial Average Since 01 Jan 1987

Table 5.2 summarizes the loss statistics during the average first day of bubble burst in Evan's model as well as ours. The bubbles in both models collapse around twice in 5,040 observations; both instances suggest that the market will experience a financial crisis once every 10 years on average. The average first day loss does not differ significantly between Evan's model and ours, and both models are very similar to real life (as shown in Figure 5.3).

We further compare that descriptive statistics of Evan's model and our model with the nine different stock markets being considered (namely Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil). These nine countries are chosen based on their market capitalization and trading hours. Table 5.4 shows the market capitalization of the nine markets, while Table 5.5 compares the average descriptive statistics of the simulated equity return series with the equity return series of the nine stock markets from 1 July 1994 to 30 June 2014. Table 5.5 shows that the features of the equity price series generated by Evan's model have a high degree of dispersion compared to the real data. The skewness and kurtosis are -7.6562 and 394.2183, with ranges in the nine markets returns from -0.0252 to 0.7075 and 7.5275 to 25.0980 respectively; the equity price generated by Evan's model thus behaves differently from reality. In contrast, the equity price series generated by our model are more consistent with those of the real world, with a mean value of 0.0321%, standard deviation of 1.4122%, skewness of -0.2026, and kurtosis of 8.3430. Similar to the nine stock markets, the LB tests in the return and squared return series show no autocorrelation of the stock return but exhibit volatility clustering. Our model is thus more realistic than Evan's model.

Country	Exchange Name	Index Used	Market Capitalization (USD millions)
*Japan	Tokyo Stock Exchange	NIKKEI 225 STOCK AVERAGE	4,485,449.8
*China	Shanghai Stock Exchange	SHANGHAI SE Composite	3,986,011.9
*Hong Kong	Hong Kong Stock Exchange	HANG SENG	3,324,641.4
*Germany	Deutsche Börse	DAX 30 PERFORMANCE	1,761,712.8
#United Kingdom	London Stock Exchange	FTSE100	6,100,083.0
*Spain	BME Spanish Exchanges	IBEX 35	942,036.0
*United States	New York Stock Exchange	DOW JONES INDUSTRIALS	19,222.875.6
*Canada	Toronto Stock Exchange	S&P/TSX COMPOSITE INDEX	1,938,630.3
*Brazil	BM&F Bovespa	IBOVESPA	823,902.7

*The market capitalization data were obtained from the World Federation of Exchange (WFE), Jan 2015.
#Obtained from the London Stock Exchange Main Market Factsheet, Jan 2015.

Table 5.4 – Market Capitalization of the Nine Exchanges and the Respective Indices Used

	Japan	China	Hong Kong	Germany	United Kingdom	Spain	United States	Canada	Brazil	Our Model (Average)	Evan Model (Average)
Mean	-0.0169%	0.0100%	0.0056%	0.0192%	0.0093%	-0.0132%	0.0230%	0.0196%	0.0280%	0.0321%	0.0306%
Median	0.0000%	0.0000%	0.0000%	0.0591%	0.0121%	0.0412%	0.0273%	0.0497%	0.0000%	0.0351%	0.0260%
Maximum	12.3962%	26.5969%	15.8417%	10.2350%	8.9575 %	12.6141%	9.9751%	8.9447 %	25.0371 %	8.2329%	2.5176%
Minimum	-12.8749%	-20.2324 %	-15.8756%	-9.2804 %	-9.7084%	-10.0603 %	-8.5461%	-10.2830 %	-18.8026%	-11.4968%	-9.5168%
Std. Dev.	1.4867%	1.9490%	1.6346%	1.4804%	1.1597%	1.4504%	1.1294%	1.0786%	2.1634 %	1.4122%	0.3077%
Skewness	-0.4904	0.7075	-0.2106	-0.2738	-0.3048	-0.1641	-0.3361	-0.9248	-0.0252	-0.2026	-7.6562
Kurtosis	9.3207	25.0980	13.1949	7.5275	9.3202	7.9401	11.2387	13.7945	13.7929	8.3430	394.2183
LB(1)	4.7578	3.7350	0.0053	0.3324	2.2736	3.6805	17.4644	0.3001	3.7350	1.9846	6.3940
	(0.0292)	(0.0533)	(0.9419)	(0.5643)	(0.1316)	(0.0551)	(0.0000)	(0.5839)	(0.0533)	(0.1589)	(0.0115)
LB(5)	12.4758	21.0198	12.2743	14.7885	68.9600	28.8390	27.6489	34.1439	21.0198	9.6930	22.8349
	(0.02882)	(0.0008)	(0.0312)	(0.0113)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0844)	(0.0004)
LB(10)	15.6254	53.2327	15.0348	20.1518	85.1596	33.3195	43.1366	48.6212	53.2327	19.2204	34.6294
	(0.1109)	(0.0000)	(0.1308)	(0.0279)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0376)	(0.0001)
LB(20)	21.2902	74.3272	33.9841	35.0362	105.3256	49.0378	66.1449	63.8850	74.3272	38.0312	51.1824
	(0.3802)	(0.0000)	(0.0262)	(0.0199)	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0001)
$LB^2(1)$	133.1383	296.6266	812.0414	206.0478	294.2776	195.4999	191.1259	400.1140	296.6266	117.9616	46.9630
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LB^2(5)$	1958.7815	1225.6235	2172.0516	1571.2044	2389.8137	1210.5841	1739.0591	1669.3076	1225.6235	557.7613	185.9552

	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LB^2(10)$	3506.4569	1681.9321	2639.0255	2805.5106	3888.4935	2127.5497	3363.3591	3695.9362	1681.9321	1132.6540	342.4877
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$LB^2(20)$	4664.4367	2271.9604	3318.1710	4644.2204	6101.9114	3267.1296	5767.4921	6384.7569	2271.9604	2186.0630	647.7547
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

*Numbers in parentheses in LB(n) statistics are at a significant level to reject the null hypothesis of no autocorrelation existing in n lag.

Table 5.5 – Descriptive Statistics of the Equity Return Series of the Nine Stock Markets and the Simulated Equity Series

5.7 VaR Models and the Results of Backtesting

We study both of Linsmeier and Pearson (1996) non-parametric HS approach and the parametric variance-covariance (VCV) approach to calculate the VaR. Both unconditional and conditional variances are applied in the VCV approach, which includes the MA approach, Longerstaey and Spencer (1996) RiskMetrics model, [1] and Gilles Zumbach (2006) RiskMetrics2006 (RM2006) model.[2]

We define T as the total number of observations in the data set, W_E as the size of the estimation windows, and W_T as the testing window for VaR violations. A VaR violation ($\kappa_t = 1$) is recorded if the loss in a particular trading day t exceeds the calculated VaR value. The total number of VaR violations v_1 in the testing period W_T is calculated using equation (5.23), while v_0 in equation (5.24) is the number of days in the testing period without violations.

$$W_E + W_T = T$$

$$\kappa_t = \begin{cases} 1, & \text{if } y_t \le -VaR_t \\ 0, & \text{if } y_t > -VaR_t \end{cases}$$

$$v_1 = \sum \kappa_t \tag{5.23}$$

$$v_0 = W_T - v_1 \tag{5.24}$$

[1] The parameter setting for the RiskMetrics model is $\lambda = 0.94$; technical details can be found in Longerstaey (1996).

[2] The parameters settings for the RM2006 model are $\rho = \sqrt{2}$, $\tau_0 = 1560$ days, $\tau_1 = 4$ days, $\tau_k = 512$ days, and $K = 15$; technical details can be found in Zumbach (2006).

The number and clustering of violations are the two major issues of interest when evaluating the performance of different VaR models. We evaluate the VaR models by testing the number of violations in a given confidence level using Kupiec (1995) unconditional coverage tests, namely the proportion of failures (POF) and time until first failure (TUFF) tests. The POF test is the simplest test for determining whether the observed fail rate (i.e. VaR violations) is significantly different from the selected failure rate p. The null hypothesis of the POF test is $H_0 : p = \hat{p} = \frac{v_1}{W_T}$. Conversely, the TUFF test measures the timing of the first violation to occur. It assumes that the first violation occurs in $v = \frac{1}{p}$ days. For 1% VaR calculations, it is expected that a violation occurs every 100 days. The null hypothesis of the TUFF test is: $H_0 : p = \hat{p} = \frac{1}{v}$.

Independence (i.e. conditional coverage) tests, which include Christoffersen and Pelletier (2004) interval forecast test and Kupiec (1995) mixed-Kupiec test, capture the occurrence of violation clustering. The Christoffersen independence test uses a binary first-order Markov chain and a transition probability matrix to test the independence of the violations, while the Hass (2001) mixed-Kupiec independence test uses the timing of different occurrences to test the independence of the violation.

The joint test considers both the coverage and independence of the violation by combining the LRs of the coverage and independence tests. The Christoffersen joint test combines the LR of the POF test and the Christoffersen independence test, while the mixed-Kupiec joint test combines the LR of the TUFF test and the mixed-Kupiec independence test.

The stock price series used in the backtests are generated from our bubble model using the settings listed in Table 5.1. We explore the reliability of the different VaR models in the before-burst period, the after-burst period, and the whole period. The before-burst period is defined as one year (or 252 trading days) before the bubble burst, while the after-burst period is defined as one year after. The tests are repeated 10,000 times, and the backtesting results are presented in Table 5.6 and 5.7. Table 5.6 shows the average number of VaR violations and the p-values of the backtests while Table 5.7 shows the total numbers of the backtests conducted and the number of backtests that we cannot reject the null hypothesis that the model adequately measures the downside risk at the 5% significance level. Table 5.6 and 5.7 show that the RiskMetrics approach works well for the whole period (20 years with 5,040 observations). The HS, MA and RM2006 approaches perform poorly in the independence tests and join tests. In Table 5.6, the average number of VaR violations of both the HS and MA approaches for the whole period are 59.82 and 64.22 respectively, which is more than the expected number of 50.39 ($5,039 \times 1\%$). Same results are shown in Table 5.7 that only 7,799 out of 10,000 backtests are significant in the HS approach, while we have 5,185 out of 10,000 backtest are significant in the MA approach. The levels of VaR suggested through the HS and MA approaches are too low, which leads to too many violations and losses that frequently exceed expectations. Further, both the HS and MA approaches had poor results in the Mixed-Kupiec independence tests, the p-values are 0.4%, and 0.25% respectively, while there are only 186 out of 10,000 backtests are significant in the HS approach, and 113 out of 10,000 tests are significant in MA approaches. Both the HS and MA approaches failed to react to changing volatility and correlations, leading the violations cases clustered together. In contrast, the RM2006 approach behaves conservatively in the whole period, the average number of VaR violations is 14.38, which is far less than the expected number of 50.39. One might preserve too many capitals far more than regulatory compliance if they adopted the RM2006 approach. Nevertheless, the RM2006 approach yields more promising results with a higher confidence level, a larger number of significant tests in both the before-and after-burst periods. Table 5.6 shows that RM2006 approach has the highest average confidence level among the four approaches in the before- and after-burst periods. The RM2006 approach shows advantages in measuring downside risks around the burst of bubbles when the asset prices are volatile. Table 5.7 shows RM2006 has the largest number of significant backtests results, the number of significant tests are 18,895 out of 18,943 in the before-burst period, while RiskMetrics, HS, and MA are 18,000, 11,196, and 9,911 respectively; similar results are also found in other tests of the before- and after-burst periods.

In summary, RM2006 approach outperforms the other three approaches around the bubble burst periods (before- and after-burst periods). It captures the rapid asset price volatility changes nearby the bubble burst, providing a good measure of the downside risks during financial turmoil. Nevertheless, RiskMetrics performs well without specifically considering any before- or after-burst periods. This may be one of the reasons why practitioners commonly adopt the RiskMetrics. Though the long-memory characteristic of RM2006 calculates the VaR in a relatively conservative manner, it performs well in measuring downside risks in financial turmoil.

				Coverage Tests		Independence Tests		Joint Tests	
	Period	No of Obser-vations	Average No of VaR Violations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	All	5039	59.82	(0.2911)	(0.2008)	(0.3456)	(0.0040)	(0.2595)	(0.0004)
	Before-Burst	252	6.58	(0.1659)	(0.4399)	(0.5441)	(0.1808)	(0.2487)	(0.1572)
	After-Burst	252	2.62	(0.4985)	(0.2408)	(0.7897)	(0.2252)	(0.6745)	(0.2703)
MA	All	5039	64.22	(0.1739)	(0.1903)	(0.3493)	(0.0025)	(0.1620)	(0.0025)
	Before-Burst	252	7.09	(0.1414)	(0.4391)	(0.5213)	(0.1638)	(0.2146)	(0.1399)
	After-Burst	252	5.52	(0.2610)	(0.2131)	(0.5783)	(0.1325)	(0.3630)	(0.1361)
RiskMetrics	All	5039	56.80	(0.4056)	(0.1352)	(0.3902)	(0.3539)	(0.3850)	(0.3467)
	Before-Burst	252	4.14	(0.3914)	(0.4753)	(0.7222)	(0.4487)	(0.5615)	(0.4482)
	After-Burst	252	4.09	(0.3909)	(0.3360)	(0.6934)	(0.3314)	(0.5539)	(0.1361)
RM2006	All	5039	14.33	(0.0000)	(0.0440)	(0.7406)	(0.0006)	(0.0000)	(0.0000)
	Before-Burst	252	1.74	(0.4881)	(0.4456)	(0.9168)	(0.4953)	(0.7029)	(0.5512)
	After-Burst	252	1.94	(0.4879)	(0.3536)	(0.8579)	(0.3918)	(0.6819)	(0.4369)

* The numbers in parentheses are the p-value to reject the null hypothesis that the violations are consistent with the 1% one-day VaR

Table 5.6 – Average Backtesting Results for 1% One-day VaR of the Simulated Equity Series by Our Model

			Coverage Tests		Independence Tests		Joint Tests	
	Period	No. of the VaR backtests	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
HS	All	10,000	7,799	9,677	8,402	186	7,592	198
	Before-Burst	18,943	9,536	17,080	18,440	10,593	11,196	7,976
	After-Burst	17,783	16,789	13,002	17,276	12,160	17,283	13,375
MA	All	10,000	5,185	9,457	8,248	113	5,347	107
	Before-Burst	18,943	8,283	17,026	18,406	9,560	9,911	7,020
	After-Burst	17,783	12,004	12,461	17,198	8,963	13,506	8,103
RiskMetrics	All	10,000	8,782	8,160	9,861	8,730	9,216	8,594
	Before-Burst	18,943	17,225	17,633	18,729	17,366	18,000	16,530
	After-Burst	17,783	16,282	15,299	17,525	15,333	17,176	14,717
RM2006	All	10,000	0	2,859	9,647	21	0	0
	Before-Burst	18,943*	17,632	18,639	18,881	17,375	18,895#	17,504
	After-Burst	17,783*	15,832	16,054	17,665	14,511	17,748	15,113

The number of 18,895 represents there are 18,895 VaR backtests that we cannot reject the null hypothesis that the model adequately measures the downside risk at the 5% significance level. Similar meaning applies in the other cells.

* Backtests are only be performed when the period contains 252 observations. If the bubble burst at late observations (e.g. bubble burst at observation 5,000th of 5,040th), no “after-burst” backtest will be performed.

Table 5.7 – The Number of Significant Backtests in 5% of Significance Level that the Model Adequately Measures the Downside Risks.

5.8 Conclusion

This chapter introduced a modified version of Evan’s model to simulate the path of daily asset prices with multiple periodic collapsing bubbles. Evan’s original model works poorly in generating long and high-frequency (daily) time series data. The equity price in Evan’s model exhibits superficial growth and constant volatility, and the bubble will collapse in a single observation. All of these characteristics show that Evan’s model is inadequate for generating daily asset prices. It also fails in simulating long series data, as the bubble component becomes insignificant to the asset price in late observations.

We modified Evan's bubble model by introducing parameters to control the bubble's size and growth rate and to allow bubbles to have a gradual collapse. One distinguishing feature of our model is that our generated asset prices exhibit volatility clustering, while Evan's has a flawed constant volatility data series. The descriptive statistics revealed that our model has features that are similar to real stock data. The average equity return series of our model has a mean of 0.0321%, a standard deviation of 1.4122%, a skewness of -0.2026, and a kurtosis of 8.3430; in contrast, Evan's model has a mean of 0.0306%, a standard deviation of 0.3077%, a skewness of -7.6562, and a kurtosis of 394.2183. Also, the return series generated from our model shows no autocorrelation of the stock return but does exhibit volatility clustering. Our model is thus more realistic than Evan's model.

Our model overcomes the weakness of the previous work that allows researchers and portfolio managers to simulate daily asset price series with periodic collapsing asset price bubbles. Compare to the widely used Geometrical Brownian motion, our model incorporate rational asset price bubbles to model a financial crisis with unexpected plunge. Practitioners can use our model with Monte Carlo Simulation to quantify financial risks and allocate financial budgets for any unexpected loss.

Furthermore, we applied our model to simulate 10,000 different paths of asset prices to test the reliability of different VaR models. The VaR models under examination include the HS, MA, RiskMetrics, and long-memory RM2006 approaches. We date-stamped the bubble burst and defined the before-burst period as one year (i.e. 252 trading days) before the burst and the after-burst period as one year after. The backtesting results show that both the HS and MA approaches tend to underestimate downside risks, unable to react to a rapidly changing in asset price volatility and correlation during market turmoil. The RiskMetrics approaches performed well when we are without specifically considering any bubble burst period, and the RM2006 approach outperforms the other three approaches in the period around the bubble burst. The empirical tests showed that criticisms that VaR models are unable to capture large financial loss during financial market turmoil are statistically invalid. Practitioners should consider to adopt RM2006 as the VaR model to estimate their downside financial risk.

Chapter 6. The Performance of VaR in the Presence of Asset Price Bubbles: An Empirical Analysis using Bubble Dating Tests

6.1 Introduction

Value at risk has been one of the most popular methods for measuring the downside risk of financial investments in the past decade. The downside risk of a financial investment defines the minimum loss of a portfolio value in a particular period with a certain probability. After the sub-prime mortgage crisis in 2008, practitioners and regulators criticized VaR models for failing to reveal the underlying risk, which led many financial institutions to suffer unexpected losses that were well above the VaR value and resulted in a credit crunch. However, most criticism stems from the lack of statistical support, which may lead to a false picture of the ineffectiveness of VaR.

This chapter is an extension of Chapter 4; unlike in Chapter 4 we define the crisis and non-crisis periods based on subjective judgement; we study Phillips *et al.* (2015) (hereafter PSY) bubble test, which use a backward SADF (BSADF) test to date-stamp the origination and termination dates of bubbles. Diba and Grossman (1988a) and Craine (1993) provide early literature in detecting rational asset price bubbles in equity market. Diba and Grossman (1988a) suggests to detect bubbles by conducting unit root test on first difference of price series and cointegration test on the price and dividend series. Craine (1993) tested the presence of bubbles by using a unit root test on price/dividend ratio. However, as suggested by Evans (1991) (details can be found in Section 5.2), the unit root and cointegration tests assumed rational bubbles will last forever, they have little power to detect bubbles that collapse periodically. In light of the weakest of the previous approaches, researchers focus on developing robust methods to detect periodical collapsing bubbles in asset price series. Hall *et* *al.* (1999) address the issue by making use of dynamic Markov-switching models to generalise the ADF unit root test, allowing the regression parameters to switch values between regimes in the collapsing bubble process. McMillan (2007) uses exponential smooth transition (ESTR) models to explain the boom and bust dynamics in stock price. McMillan (2007) analysed the log dividend-price ratio data for thirteen countries by both the ESTR and asymmetric-ESTR models. The log dividend-price ratio found stationarity only under the asymmetric-ESTR model, it explains the rise of temporary deviations from equilibrium (bubbles) is due to the presence of both transactions costs and noise/fundamental trader interaction. Both Hall *et al.* (1999) and McMillan (2007) are able to detect periodical collapsing bubbles; however; asymptotic distributions of the relevant test statistics cannot be obtained analytically, simulations from the finite sample can be computationally expensive. Recently, Phillips *et al.* (2011) have suggested to use a supremum of a set of recursive right-tailed ADF tests (SADF) to detect the presence of stock bubbles; the test is then be further generalised as PSY test (Phillips *et al.* (2015). The PSY test detects periodical collapsing bubbles and give estimates on the bubbles' origination and termination dates. Unlike the previous approaches, the asymptotic distribution of the test statistics in PSY test can be obtained analytically while estimations of the origination and termination dates of bubbles are consistent.

Against the background of the concern that VaR models fail in financial crisis periods, we perform a series of backtests. However, as our aim is to backtest but not forecast, we explore and slightly modify the date-stamping strategy of the PSY test. Five VaR testing periods are defined: the pre-burst period, the bubble period, the post-burst period, the period between bubbles, and the full period. The bubble period is bounded by the bubble's origination and termination dates, the pre-burst period is defined as two years (around 500 observations) before the bubble's origination date, and the post-burst period is defined as two years after the bubble's termination date. Empirical backtesting tests from the RiskMetrics VaR and RiskMetrics2006 VaR models are then carried out for these periods for six countries (Hong Kong, Germany, the United Kingdom, Spain, the United States, and Canada), proxied by seven indices.

The outline of this chapter is as follows. Section 6.2 discusses the rationale for using the log price/dividend ratio as an indicator of asset price bubbles. Section 6.3 describes the SADF and GSADF tests used to identify asset price bubbles and the date-stamping mechanism. Section 6.4 describes the RiskMetrics and RiskMetrics2006 VaR models as well as the backtesting methods. It also presents the empirical results of the GSADF tests, bubble period identification, and the VaR backtests. Section 6.5 concludes the chapter.

6.2 Asset Prices and Bubbles

Asset price bubbles are usually driven by speculative behaviour that bid an asset price beyond that asset's fundamental value (which is the sum of the discounted cash flows of all future cash flows). If bubbles are present, prices should thus behave explosively. In accordance with Campbell and Shiller (1988), we write the log price of a security as

$$p_t = p_t^f + b_t \tag{6.1}$$

where p_t is the log price at time t, p_t^f is the fundamental value, and b_t is the bubble component.

$$p_t = \frac{\kappa - r}{1-\rho} + (1+\rho)\sum_{i=0}^{\infty} \rho^i d_{t+1+i} + lim_{k\to\infty}\rho^k p_{t+k} \tag{6.2}$$

$$p_t^f = \frac{\kappa - r}{1-\rho} + (1+\rho)\sum_{i=0}^{\infty} \rho^i d_{t+1+i} \tag{6.3}$$

$$b_t = lim_{k\to\infty} \rho^k E_t(p_{t+k}) \tag{6.4}$$

where $\rho = \frac{P}{P+D}$, $\kappa = -ln(\rho) - (1-\rho)\delta$, $\delta = d - p$, r is the continuous return, and ρ_t and δ_t are assumed to be constant over time.

In equation (6.1), the value of p_t^f is considered the fundamental component of the stock price as it depends on the expected dividends. In contrast, the present value of b_t in equation (6.4) is considered the speculative component as it is based on the future expectation of stock prices (not dividends). We can rewrite equation (6.4) as

$$b_t = (1+e^{\delta})b_t + \epsilon_{b,t} = (1+g)b_t + \epsilon_{b,t} \tag{6.5}$$

where g is the growth rate of the bubble component and $\epsilon_{b,t}$ is the random error of the bubble component at time t. Equation (6.5) shows that b_t is an explosive process, which means that the stock price will be explosive if the bubble component b_t is non-zero in equation (6.1).

From equations (6.1) and (6.3), we see that the differences between the log real dividend and log real price are

$$
\begin{aligned}
d_t - p_t &= d_t - \frac{\kappa - r}{1-\rho} + (1+\rho)\sum_{i=0}^{\infty} \rho_i d_{t+1+i} - lim_{k\to\infty}\rho^k p_{t+k} \\
&= -\frac{\kappa - r}{1-\rho} + d_t - \sum_{i=0}^{\infty}(1-\rho)\rho^i d_{t+1+i} - b_t \\
&= -\frac{\kappa - r}{1-\rho} + d_t - \sum_{i=0}^{\infty}(\rho^i - \rho^{i+1}) d_{t+1+i} - b_t \\
&= -\frac{\kappa - r}{1-\rho} - \sum_{i=0}^{\infty}\rho^i \Delta d_{t+1-i} - b_t
\end{aligned}
$$

If bubbles are absent (i.e. $b_t = 0$), the log price/dividend ratio becomes

$$
p_t - d_t = \frac{\kappa - r}{1-\rho} + \sum_{i=0}^{\infty}\rho^i E_t(\Delta d_{t+1+i}) \tag{6.6}
$$

Equation (6.6) implies that the log price/dividend ratio will be stationary if the log dividend d_t is I(1) stationary. If the log dividend is I(1) and the log price-dividend ratio is explosive, this explosive behaviour must thus be caused by a non-zero bubble component b_t.

Similar arguments also apply to the price-dividend (without logarithm) ratio, which starts by analysing financial bubbles using the asset pricing equation:

$$
P_t = \sum_{i=0}^{\infty}\left(\frac{1}{1+r_f}\right)^i E_t(D_{t+i} + U_{t+i}) + B_t \tag{6.7}
$$

where P_t is the asset price at time *t*, r_f is the risk-free rate, D_t is the asset dividend, U_t is unobservable fundamentals, and B_t is the bubble component. Similar to equation (6.5), the expected value of B_t is:

$$E_t(B_{t+1}) = (1+r_f)B_t \tag{6.8}$$

6.3 SADF and GSADF Tests

Phillips *et al.* (2011) have suggested using a supremum of a set of recursive right-tailed augmented Dickey-Fuller (ADF) tests (Dickey and Fuller (1979)) to detect the presence of stock bubbles. Their so-called SADF test applies the right-tailed ADF test with the null hypothesis of a unit root ($\phi = 0$) and the alternative hypothesis of an explosive root ($\phi > 0$).

The regression model used in the SADF test is

$$\Delta y_t = \alpha + \phi y_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta y_{t-j} + \epsilon_t \tag{6.9}$$

where k is the lag order and ϵ_t is the random error.

The SADF test starts by testing the first r_0 fraction of the observations; it then performs the ADF test repeatedly by incrementing r_0 to 1. The forward sequence of the regression starts from the observation 1 to $[Tr_w]$, where [.] is the integer part of the argument, T is the total number of observations, and $r_w \in [r_0, 1]$ is the fraction of the observations. The SADF statistic is

$$SADF_{r_0} = \sup_{r_w \in [r_0, 1]} ADF_{r_w}^{0}$$

The asymptotic distribution of the SADF test with the null hypothesis of the true process is a random walk without drift:

$$SADF_{r_0} \to sup_{r_w \in [r_0,1]} \left\{ \frac{r_w[\int_0^{r_w} WdW - \frac{1}{2}r_w] - W(r_w)\int_0^{r_w} Wdr}{r_w^{\frac{1}{2}}\{r_w\int_0^{r_w} W^2dr - [\int_0 r_w W(r)dr]^2\}^{\frac{1}{2}}} \right\} \tag{6.10}$$

where W is a Wiener process.

By comparing the SADF statistics of the data series with the asymptotic distribution of the Dickey-Fuller *t*-statistic in equation (6.10), we can identify the explosive behaviour of the data series. To date-stamp the explosion, we perform the backward ADF (BADF) test. This test performs the ADF test repeatedly by fixing the starting point of the sample at the first observation while rolling the end point from the observation $[Tr_0]$ to T. If, say, the testing sequence starts from r_1 ($r_1 = 0$ in the BADF test) and ends at r_2, the corresponding BADF test statistic would be $BADF_{r_2}^{r_1}$. Since the BADF test fixes the starting point as the first observation, its BADF test statistic is denoted by $BADF_{r2}$.

The explosion originates at $[Tr_e]$ when $[Tr_e]$ is the first occurrence and the $BADF_{r_e}$ statistic is above the critical value. Furthermore, PSY impose the conditions that the bubble duration must be longer than $log(T)$ and that the termination date of the explosion $[Tr_f]$ must be the first occurrence after the observation $[Tr_e] + log(T)$ when the $BADF_{r_f}$ statistic is below the critical value.

$$\hat{r}_e = \inf_{r_2 \in [r_0,1]} \left\{ r_2 : BADF_{r_2} > cv_{r_2}^{\beta_T} \right\}$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta \frac{log(T)}{T}, 1]} \left\{ r_2 : BADF_{r_2} < cv_{r_2}^{\beta_T} \right\}$$

These authors further suggest that the critical value $cv_{r_2}^{\beta_T}$ should vary with the number of observations in the testing window in order to diverge to infinity and eliminate type I errors for large T, suggesting that $cv_{r_2}^{\beta_T} = \frac{log(log(Tr_s))}{100}$.

The shortcoming of the SADF test is that it may fail if multiple bubbles are present in the sample. Phillips *et al.* (2015) proposed the generalized version of SADF (i.e. the GSADF test) to address this problem. The GSADF test provides the flexibility to allow the starting point of the testing window to change. The GSADF statistic is defined as

$$GSADF_{r_0} = \sup_{r_w \in [r_0, 1]} \left\{ \sup_{r_1 \in [0, 1-r_w]} ADF_{r_w}^{r_1} \right\}$$

Equation (6.11) shows the corresponding asymptotic distribution of the GSADF test with the null hypothesis that the true process is a random walk without drift. The technical details for equation (6.11) can be found in Shi *et al.* (2011).

$$GSADF_{r_0} \to \sup_{r_w \in [r_0, 1]} \sup_{r_1 \in [0, 1-r_w] r_2 = r_1 + r_2} \left\{ \frac{r_w [\int_{r_1}^{r_2} WdW - \frac{1}{2} r_w] - [W(r_1) - W(r_2)] \int_{r_1}^{r_2} W(r) dr}{r_w^{\frac{1}{2}} \{ r_w \int_{r_1}^{r_2} W^2 dr - [\int_{r_1} r_2 W(r) dr]^2 \}^{\frac{1}{2}}} \right\} \quad (6.11)$$

The date-stamping method used in the GSADF test is an extended version of the BADF statistic. The BSADF test performs an SADF test by rolling the starting point of the test window $r_1 \in [0, r_2 - r_0]$ from the observation $[T(r_2 - r_0)]$ to the first observation. For a testing sequence that starts at r_1 and ends at r_2, the corresponding BSADF statistic is defined as

$$BSADF_{r_2} = \sup_{r_1 \in [0, r_2 - r_0]} \{BADF_{r_2}^{r_1}\}$$

Similar to the test of Phillips *et al.* (2011) test, the origination date of a bubble in the GSADF test is $[Tr_e]$ when $[Tr_e]$ is the first occurrence and when the $BSADF_{r_e}$ statistic is above the critical value. The minimum bubble duration in the BSADF statistic is generalized to $\delta log(T)$, where δ is a frequency-dependent parameter. The empirical example that PSY use for detecting bubbles in the S&P500 imposed a minimal condition that bubble duration must exceed one year (i.e. for 1,680 monthly observations, δ is 3.73). Moreover, the termination date of explosion $[Tr_f]$ is the first occurrence after the observation $[Tr_e] + \delta log(T)$ when the $BSADF_{r_2}$ statistic is below the critical value.

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : BSADF_{r_2} > cv_{r_2}^{\beta_T} \right\} \tag{6.12}$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta \frac{log(T)}{T}, 1]} \left\{ r_2 : BSADF_{r_2} < cv_{r_2}^{\beta_T} \right\} \tag{6.13}$$

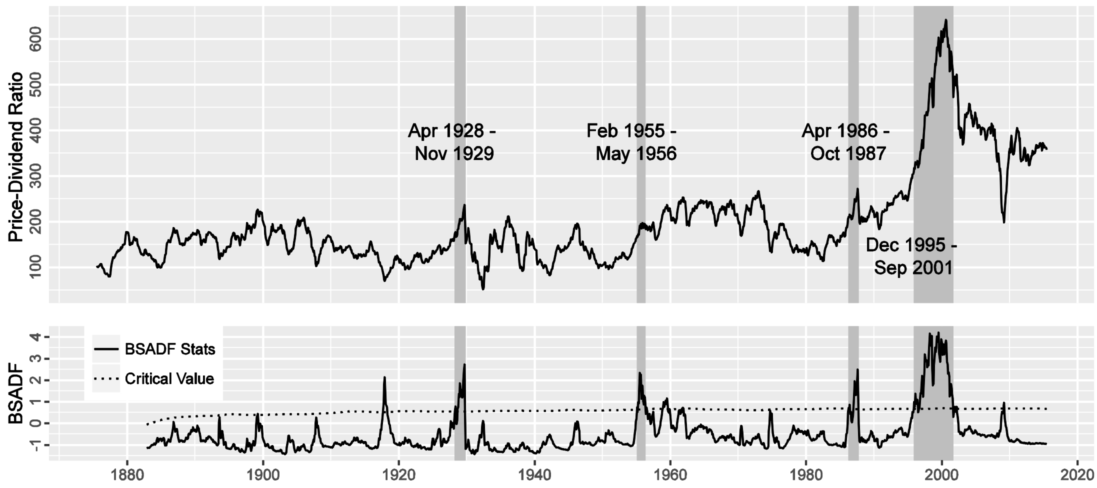
In the GSADF test, the bubble origination date is date-stamped by equation (6.12), which is the end point r_2 of the testing window in the BSADF statistics. However, as the purpose of this paper is backtesting instead of forecasting, we slightly modify the bubble origination date to be the starting point r_1 (instead of r_2) of the testing window in equation (6.14) and removing the minimal bubble duration condition by setting $\delta = 0$. This modified date-stamping strategy for the bubble origination date is referred to as PSY_{r1} hereinafter.

$$\overline{r_e} = \inf_{r_2 \in [r_0, 1]} \left\{ r_1 : BSADF_{r_2} > cv_{r_2}^{\beta_T} \right\} \tag{6.14}$$

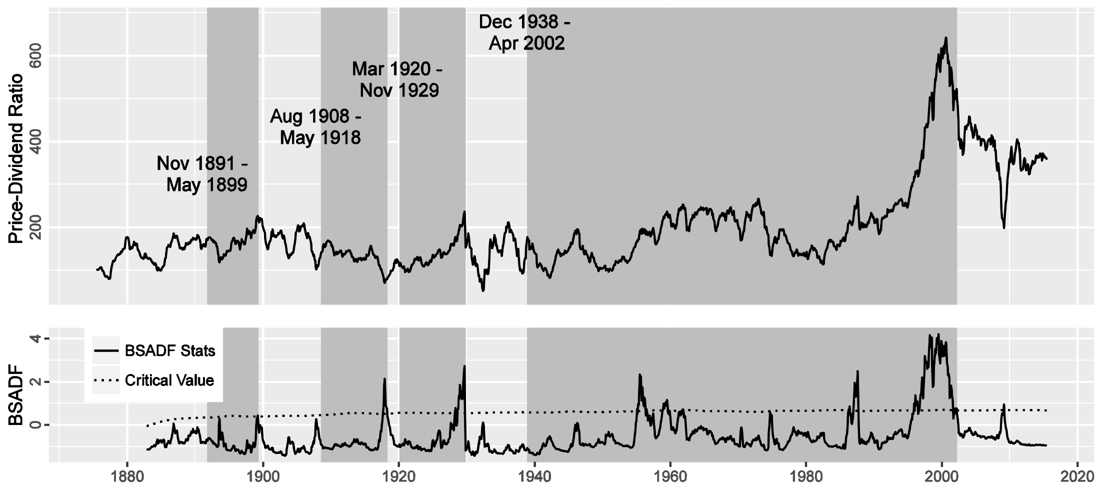
$$\overline{r_f} = \inf_{r_2 \in [\hat{r}_e, 1]} \left\{ r_2 : BSADF_{r_2} < cv_{r_2}^{\beta_T} \right\} \tag{6.15}$$

To illustrate the differences between the original PSY approach and the modified PSY_{r1} approach, we use the S&P500 as an example. Figure 6.1 illustrates the identification results, with the bubble periods highlighted in grey. Figure 6.1a shows that by using the original PSY date-stamping method, bubbles' estimated origination dates are usually close to their termination dates. The original PSY date-stamping is based on picking the end point of the testing window when the whole sample is explosive. The modified PSY_{r1} method sets the bubble origination date as the starting point of the testing window (instead of the end point), which may better illustrate the bubble formation period without arbitrarily imposing the minimal bubble duration parameter δ.

Figure 6.1b shows the results of the PSY_{r1} method, with the bubble period highlighted in grey. Although the bubble period problem lasts for more time, the results related to identifying bubbles in some countries (namely Germany and Hong Kong) are promising; the original PSY method fails to identify any asset price bubbles.



(a) Identification results of using the GSADF test with the original PSY date-stamping method



(b) Identification results of using the GSADF test with PSY_{r1} date-stamping method

Figure 6.1 – Bubble Identification Results in S&P500

6.4 VaR Models and Backtesting Results

To compare the performance of VaR in the pre-burst, bubble, post-burst, and inter-bubble periods, we compute daily VaR using the RiskMetrics model of Longerstaey and Spencer (1996) and the RiskMetrics2006 model of Zumbach (2007). We define T as the total number of observations in the data set, W_E as the size of the estimation windows, and W_T as the testing window for VaR violations. A VaR violation ($\kappa_t = 1$) is recorded if the loss on a particular trading day t exceeded the calculated VaR value. The total number of VaR violations v_1 in the testing period W_T is calculated by equation (6.16), while v_0 in equation (6.17) is the number of days in the testing period without violations.

$$W_E + W_T = T$$

$$\kappa_t = \begin{cases} 1, & \text{if } y_t \leq -VaR_t \\ 0, & \text{if } y_t > -VaR_t \end{cases}$$

$$v_1 = \sum \kappa_t \tag{6.16}$$

$$v_0 = W_T - v_1 \tag{6.17}$$

The number and clustering of violations are the two major issues to consider when evaluating how VaR models perform. We use two unconditional coverage tests, namely POF and TUFF, to evaluate the VaR models by testing the number of violations at a given confidence level. The straightforward POF test examines whether the observed fail rate (i.e. number of VaR violations) is significantly different from the selected failure rate p. The null hypothesis of the POF test is $H_0 : p = \hat{p} = \frac{v_1}{W_T}$. Conversely, the TUFF test measures the timing of the first violation to occur. It assumes that the first violation occurs in $v = \frac{1}{p}$ days. For the 1% VaR calculation, a violation is expected to occur every 100 days. The null hypothesis of the TUFF test is $H_0 : p = \hat{p} = \frac{1}{v}$.

Independence tests (i.e. conditional coverage tests), including the interval forecast of test of Christoffersen and Pelletier (2004) and the mixed-Kupiec test of Kupiec (1995), capture the occurrence of violation clustering. Christoffersen's independence test uses a binary first-order Markov chain and a transition probability matrix to test the independence of the violations, while the mixed-Kupiec independence test of Hass (2001) considers the timing of different occurrences to test the independence of the violation.

The joint test considers both the coverage and the independence of the violation by combining the LRs of the coverage and independence tests. The Christoffersen joint test combines the LR of the POF and Christoffersen independence tests, while the mixed-Kupiec joint test combines the LR of the TUFF and mixed-Kupiec independence tests.

Subject to the dividend data availability in Datastream, we employ six stock markets (rather than nine in previous chapter) in our empirical analysis, they are: Hong Kong, Germany, Spain, the United Kingdom, the United States, and Canada. The market capitalizations of the six countries are shown in Table 6.1. As the original papers of Phillips *et al.* (2011) PWY test and Phillips *et al.* (2015) PSY test studied both Nasdaq and S&P500, unlike the previous chapter we study the Dow Jones Index for the U.S. market, we study both Nasdaq and S&P500 in this chapter for comparison purpose.

Country	Exchange Name	Index Used	Market Capitalization (USD million)
*Hong Kong	Hong Kong Stock Exchange	HANG SENG	3,324,641.4
*Germany	Deutsche Börse	DAX 30 PERFORMANCE	1,761,712.8
#United Kingdom	London Stock Exchange	FTSE100	6,100,083.0
*Spain	BME Spanish Exchanges	IBEX 35	942,036.0
*United States	New York Stock Exchange	S&P500, and Nasdaq	19,222.875.6
*Canada	Toronto Stock Exchange	S&P/TSX COMPOSITE INDEX	1,938,630.3

* Data on market capitalization obtained from the World Federation of Exchanges, December 2015.

Data obtained from the London Stock Exchange Main Market Factsheet, January 2015.

Table 6.1 – Stock Exchanges and Respective Indices Used

We define the pre-burst and post-burst periods as two years (or around 500 observations) before and after the bubble, respectively:

$$\text{pre-bubble period: } [[T\overline{r_e}]-\nu, [T\overline{r_e}]] \tag{6.18}$$

$$\text{post-bubble period: } [[T\overline{r_f}], [T\overline{r_f}]+\nu] \tag{6.19}$$

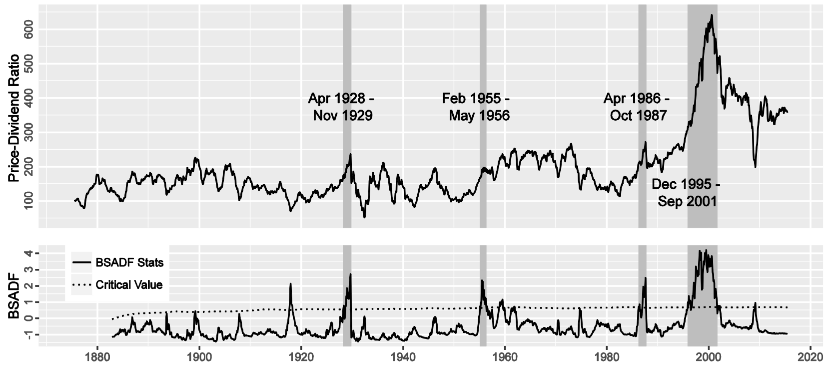
where ν is the time frequency-dependent parameter (with $\nu = 24$ for the monthly data and $\nu \sim 500$ for the daily data.). Using S&P500 as an example, one bubble period identified is 1 April 1986 to 1 October 1987; the pre-burst period runs from 1 April 1984 to 31 March 1986 and the post-bubble period is from 2 October 1987 to 1 October 1989. However, if the pre- and post-burst periods overlap, the periods are not considered in our backtests.

Market data (namely prices and dividends) are mainly obtained from DataStream, although long series monthly S&P500 data are obtained from Professor Robert Shiller's website. In order to ensure a large sample size for the bubble tests, we obtain the data from the base dates that both price and dividend data are available in DataStream, which as shown in Table 6.2.

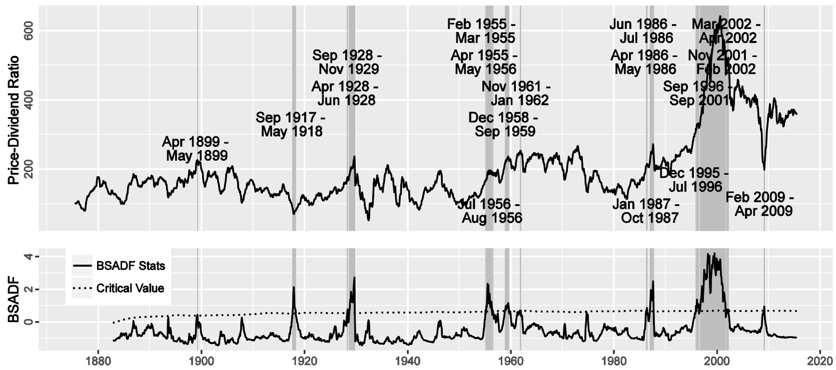
<table>
<tr><th>Country</th><th>Index Used</th><th>Sample Period of Monthly Data in Bubbles Tests</th><th>Sample Period of Daily Data in VaR Backtests</th></tr>
<tr><td rowspan="2">United States</td><td>S&P500</td><td>July 1975 – Dec 2015</td><td>Jan 1950 – Dec 2015</td></tr>
<tr><td>Nasdaq</td><td colspan="2">Jan 1973 – Dec 2015</td></tr>
<tr><td>Hong Kong</td><td>HANG SENG</td><td colspan="2">Jun 1973 – Dec 2015</td></tr>
<tr><td>Germany</td><td>DAX 30 PERFORMANCE</td><td colspan="2">Jan 1973 – Dec 2015</td></tr>
<tr><td>United Kingdom</td><td>FTSE100</td><td colspan="2">Jan 1986 – Dec 2015</td></tr>
<tr><td>Spain</td><td>IBEX 35</td><td colspan="2">Mar 1987 – Dec 2015</td></tr>
<tr><td>Canada</td><td>S&P/TSX COMPOSITE INDEX</td><td colspan="2">Jul 1973 – Dec 2015</td></tr>
</table>

Table 6.2 – Sampling Period for Bubble Tests and VaR Backtests

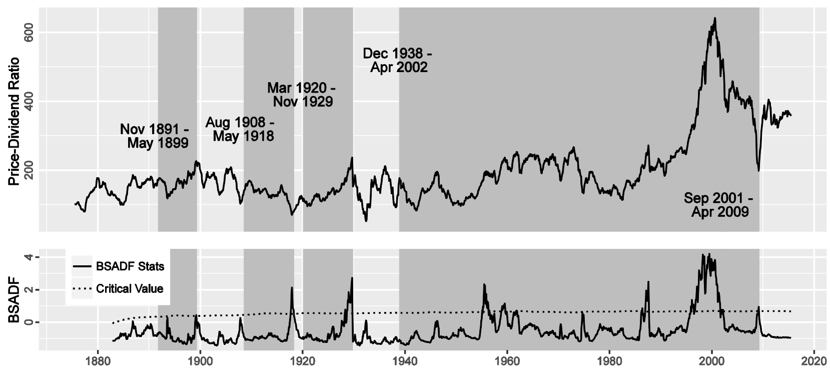
For each sample series, we perform the PSY and PSY_{r1} tests on both price-dividend and logarithmic price-dividend series to date-stamp the bubble origination and termination dates. As an asset price bubble may take time to form and not necessary last long, we also perform the PSY test with a frequency parameter of $\delta = 0$ in equation (6.13), relaxing the minimum bubble duration to zero. Figure 6.2 (a) – (u) displays the date-stamping bubble periods that result from the price-dividend ratio of the seven indices by using: (1) the original PSY test with a minimum bubble duration of 12 months, (2) the PSY test with no minimum bubble duration ($\text{PSY}_{\delta=0}$), and (3) the modified PSY_{r1} test with a bubble origination date that starts from the BADF test's sampling window. Results of the tests using the logarithmic price-dividend ratio are shown in Figure 6.3. As the date-stamping results from considering the price-dividend ratio resemble those from considering the logarithmic price-dividend ratio, we follow PSY to date-stamp bubbles in price-dividend ratio series and further study the results in different VaR tests.



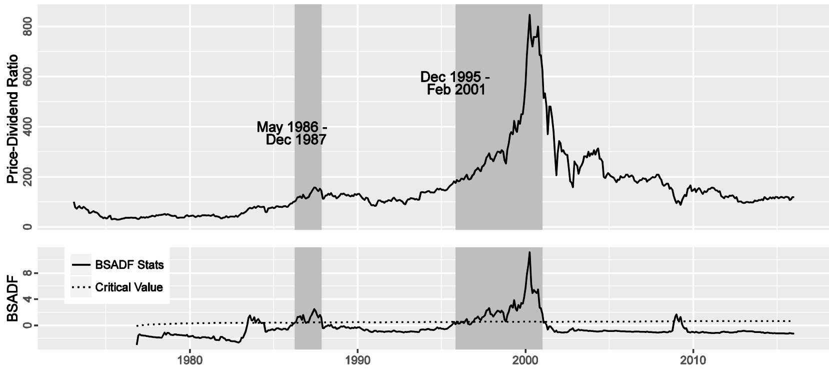
(a) Date-stamping bubble periods in the United States S&P500 price-dividend ratio: PSY test



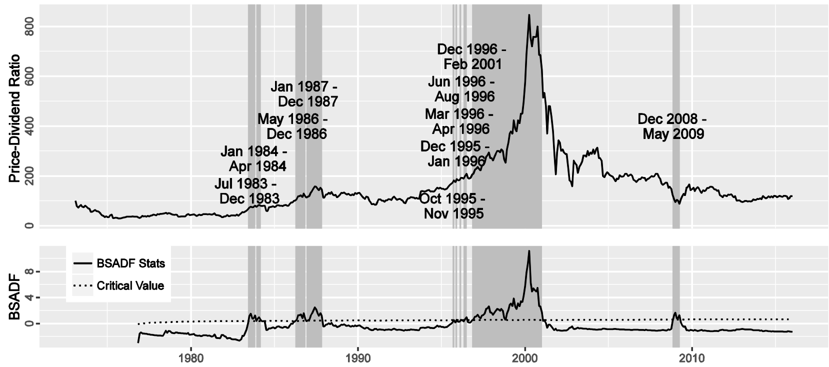
(b) Date-stamping bubble periods in the United States S&P500 price-dividend ratio: $\text{PSY}_{\delta=0}$ test



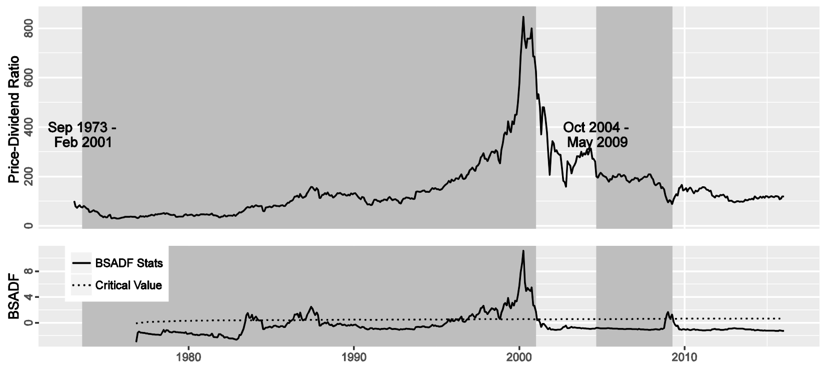
(c) Date-stamping bubble periods in the United States S&P500 price-dividend ratio: PSY_{r1} test



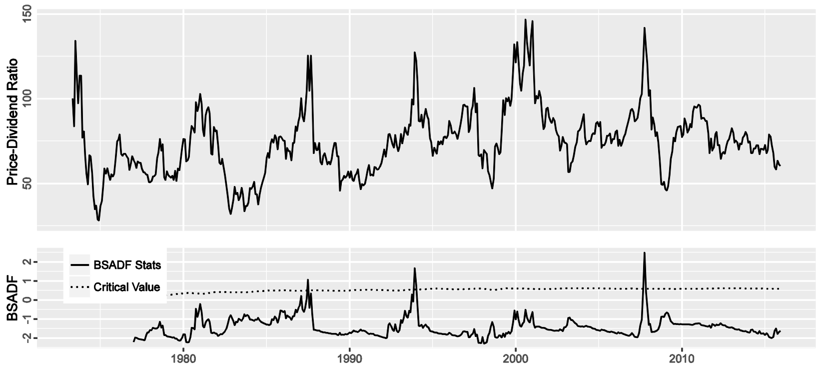
(d) Date-stamping bubble periods in the United States Nasdaq price-dividend ratio: PSY test



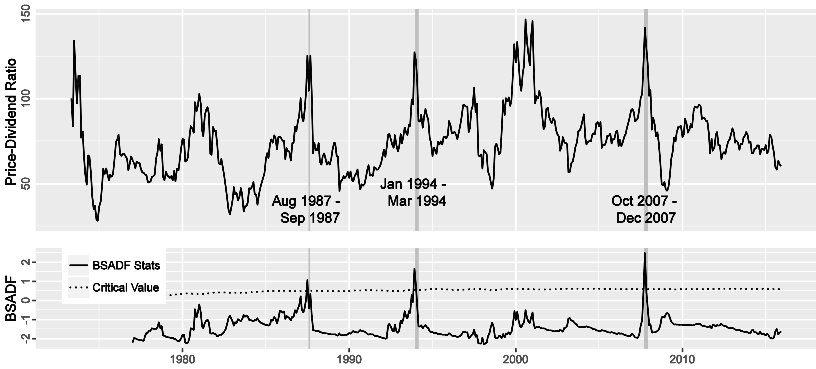
(e) Date-stamping bubble periods in the United States Nasdaq price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



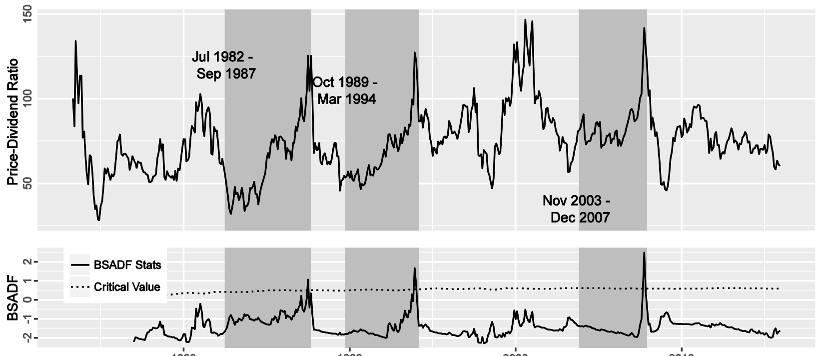
(f) Date-stamping bubble periods in the United States Nasdaq price-dividend ratio: PSY_{r1} test



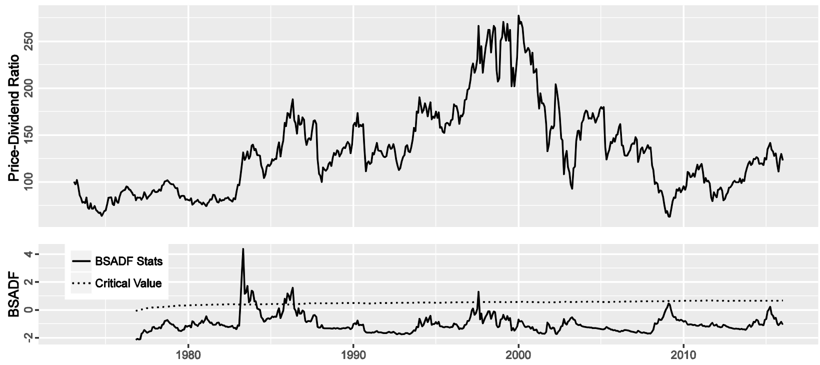
(g) Date-stamping bubble periods in the Hong Kong HSI price-dividend ratio: PSY test



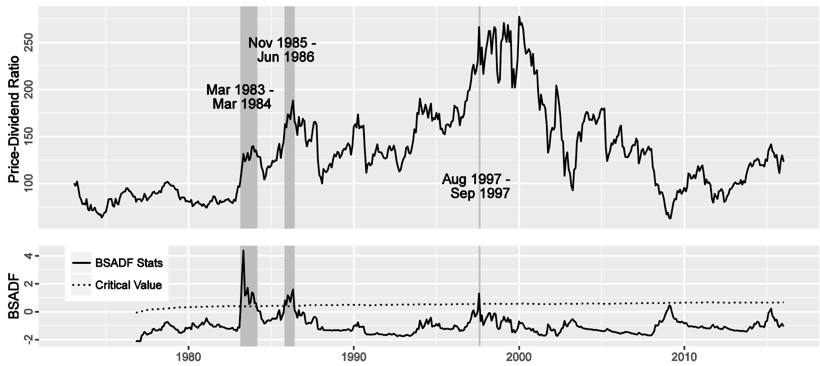
(h) Date-stamping bubble periods in the Hong Kong HSI price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



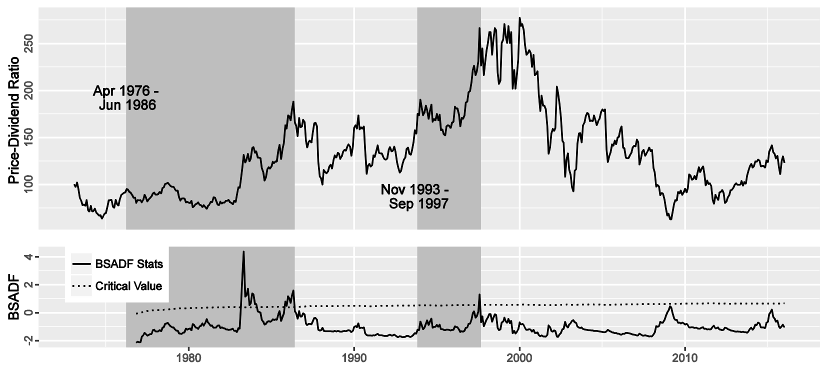
(i) Date-stamping bubble periods in the Hong Kong HSI price-dividend ratio: PSY_{r1} test



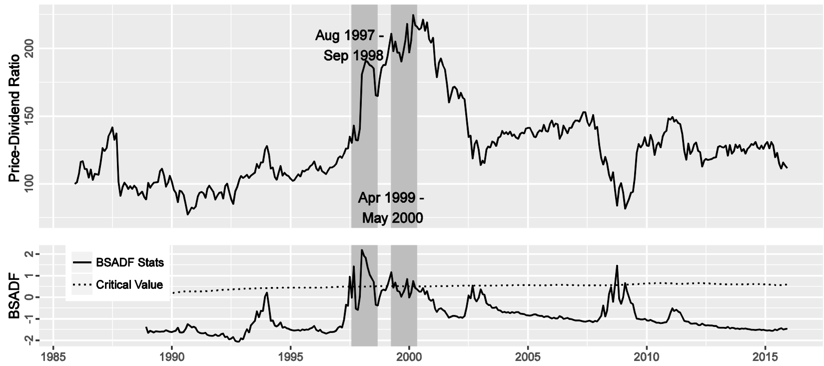
(j) Date-stamping bubble periods in the Germany DAX30 price-dividend ratio: PSY test



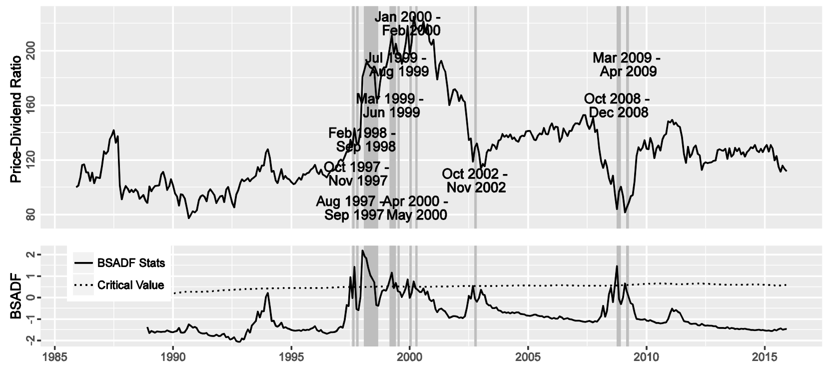
(k) Date-stamping bubble periods in the Germany DAX30 price-dividend ratio: $\text{PSY}_{\delta=0}$ test



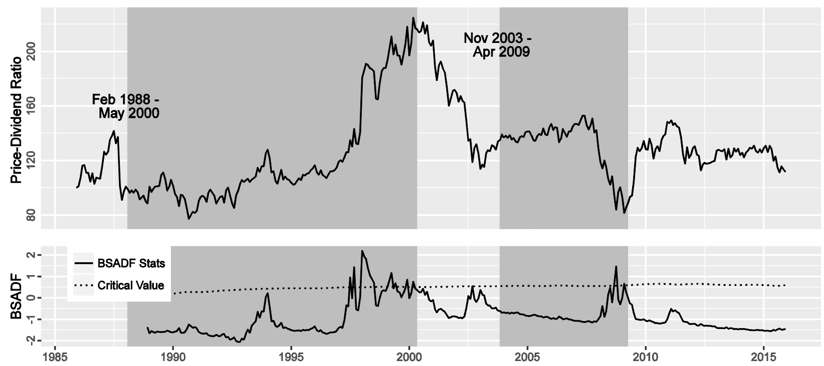
(l) Date-stamping bubble periods in the Germany DAX30 price-dividend ratio: PSY_{r1} test



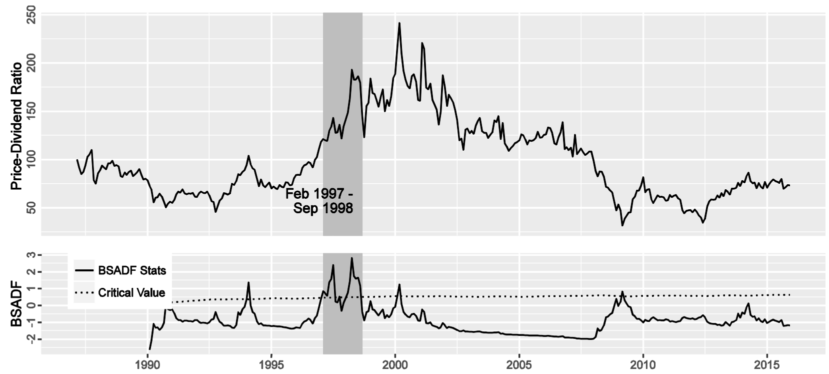
(m) Date-stamping bubble periods in the United Kingdom FTSE100 price-dividend ratio: PSY test



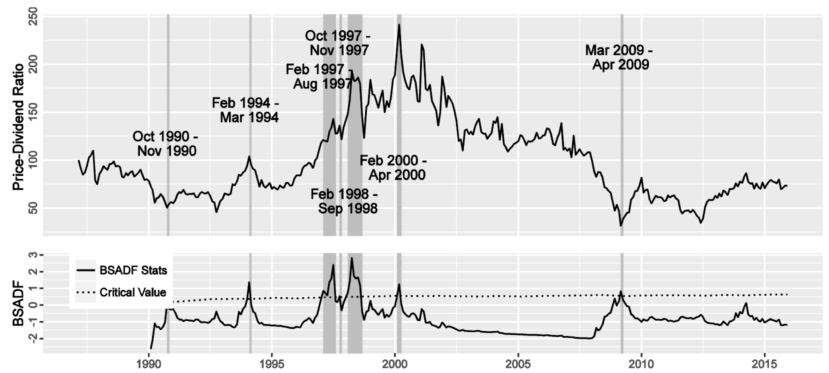
(n) Date-stamping bubble periods in the United Kingdom FTSE100 price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



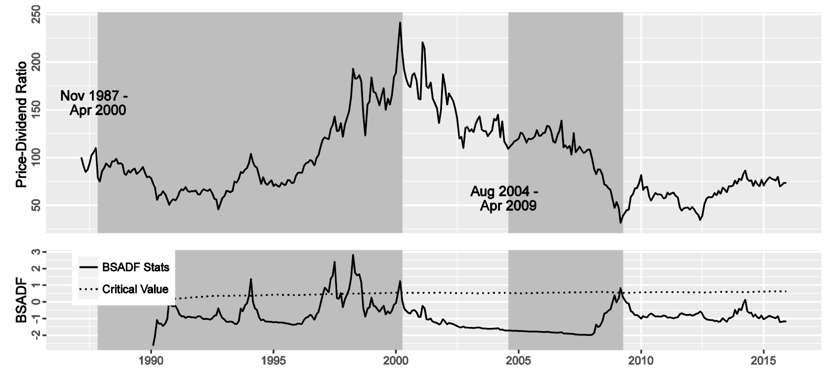
(o) Date-stamping bubble periods in the United Kingdom FTSE100 price-dividend ratio: PSY_{r1} test



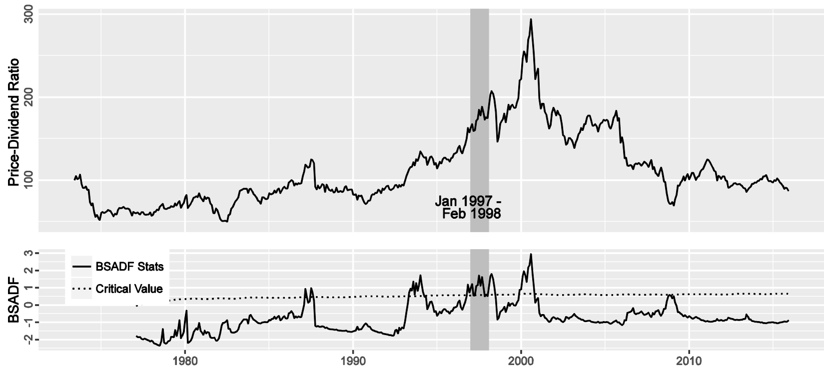
(p) Date-stamping bubble periods in the Spain IBEX35 price-dividend ratio: PSY test



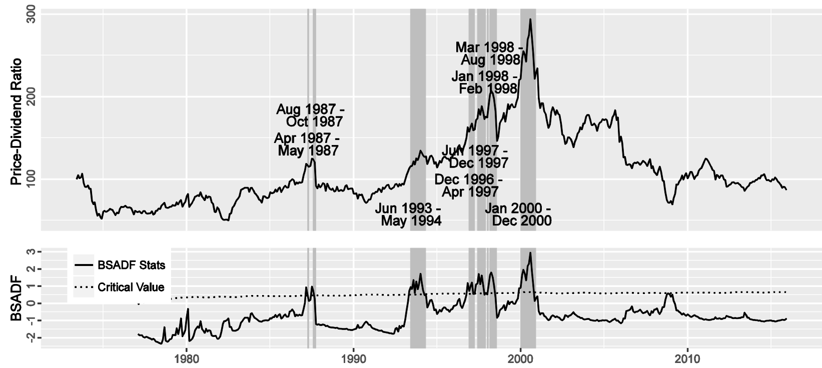
(q) Date-stamping bubble periods in the Spain IBEX35 price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



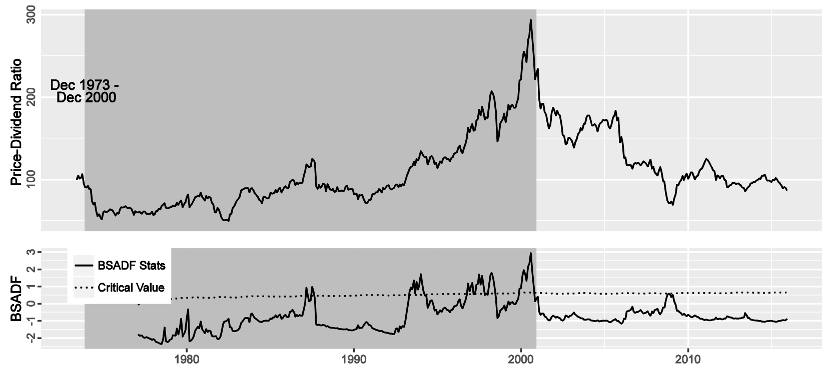
(r) Date-stamping bubble periods in the Spain IBEX35 price-dividend ratio: PSY_{r1} test



(s) Date-stamping bubble periods in the Canada S&P/TSX Composite price-dividend ratio: PSY test



(t) Date-stamping bubble periods in the Canada S&P/TSX Composite price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ Test



(u) Date-stamping bubble periods in the Canada S&P/TSX Composite price-dividend ratio: PSY_{r1} test

Figure 6.2 – Date-stamping Bubble Period of the Price-dividend Ratio for the Six Countries

The six backtest methods used in this study are the POF, TUFF, independent Christoffersen, independent mixed-Kupiec, joint Christoffersen, and the joint mixed-Kupiec tests, which are performed for the six countries as defined in equations (6.18) and (6.19). We perform the VaR backtest for the three date-stamping approaches of the price-dividend ratio for each country. Tables 6.3 to 6.6 show the summarized results, while the full results are presented in Tables 6.7 to 6.13.

	Pre-burst		Bubble		Post-burst		Periods Between Bubbles	
	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006
United States S&P500	12/18	**13/18**	14/18	**18/18**	10/18	**13/18**	1/12	**5/12**
United States Nasdaq	8/12	**11/12**	3/12	**5/12**	8/12	8/12	2/6	**6/6**
Hong Kong HSI	No Bubble Identified							
Germany DAX 30 Performance	No Bubble Identified							
United Kingdom FTSE100	6/6	6/6	9/12	**12/12**	4/6	**6/6**	**6/6**	4/6
Spain IBEX 35	6/6	6/6	2/6	**6/6**	4/6	**6/6**	NA*	
Canada S&P/TSX Composite Index	6/6	6/6	6/6	6/6	2/6	**6/6**	NA*	
Total	38/48	**42/48**	34/54	**47/54**	28/48	**39/48**	9/24	**15/24#**

Table 6.3 – Backtesting Results Using Original PSY Bubble Date-stamping Approach

* Only 1 bubble detected

The results 15/24 represents there are 15 out of 24 VaR backtests that we cannot reject the null hypothesis that the model adequately measures the downside risk at the 5% significance level. Similar meaning applies in the other cells. Details of the test results and testing period are shown in Table 6.7 – 6.13.

	Pre-burst		Bubble		Post-burst		Periods Between Bubbles	
	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics2 006
United States S&P500	NA*		51/72	**58/72**	NA*		32/66	**48/66**
United States Nasdaq	NA*		30/54	**40/54**	NA*		34/48	**35/48**
Hong Kong HSI	7/18	**18/18**	**13/18**	11/18	9/18	**14/18**	2/12	**8/12**
Germany DAX 30 Performance	13/18	**18/18**	15/18	**18/18**	10/18	**18/18**	8/12	8/12
United Kingdom FTSE100	NA*		45/60	**46/60**	NA*		38/54	38/54
Spain IBEX 35	NA*		26/42	**32/42**	NA*		28/36	**29/36**
Canada S&P/TSX Composite Index	NA*		27/48	**47/48**	NA*		25/42	**28/42**
Total	20/36	**36/36**	207/312	**252/312**	19/36	**32/36**	167/270	**194/270#**

Table 6.4 – Backtesting Results Using PSY Bubble Date-stamping Approach Without Minimum Bubble Duration ($\delta = 0$)

* Bubble Periods are highly fragmented, no Pre-Burst and Post-Burst Period be defined.

The results 194/270 represents there are 194 out of 270 VaR backtests that we cannot reject the null hypothesis that the model adequately measures the downside risk at the 5% significance level. Similar meaning applies in the other cells. Details of the test results and testing period are shown in Tables 6.7 – 6.13.

	Pre-burst		Bubble		Post-burst		Periods Between Bubbles	
	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006	RiskMetrics	RiskMetrics 2006
United States S&P500	NA*							
United States Nasdaq	**10/12**	5/12	3/12	**7/12**	7/12	**8/12**	6/6	**3/6**
United Kingdom FTSE100	1/6	1/6	6/12	**7/12**	4/6	**6/6**	2/6	**6/6**
Spain IBEX 35	**10/12**	8/12	1/12	**8/12**	10/12	**12/12**	**4/6**	2/6
Canada S&P/TSX Composite Index	4/6	4/6	0/6	**3/6**	2/6	**6/6**	NA@	
Hong Kong HSI	10/18	**11/18**	6/18	**16/18**	9/18	**15/18**	3/12	**7/12**
Germany DAX 30 Performance	**9/12**	5/12	4/12	**9/12**	7/12	**12/12**	3/6	**2/6**
Total	**44/66**	34/66	20/72	**50/72**	39/66	**59/66**	18/36	**20/36#**

Table 6.5 – Backtesting Results Using PSY_{r1} Bubble Date-stamping Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

* Daily data available in Datastream do not cover the identified bubbles period.

@ Only 1 bubble detected

The results 20/36 represents there are 20 out of 36 VaR backtests that we cannot reject the null hypothesis that the model adequately measures the downside risk at the 5% significance level. Similar meaning applies in the other cells. Details of the test results and testing period are shown in Table 6.7 – 6.13.

	RiskMetrics	RiskMetrics2006
United States S&P500	0/6	0/6
United States Nasdaq	0/6	0/6
Hong Kong HSI	0/6	**1/6**
Germany DAX 30 Performance	0/6	0/6
United Kingdom FTSE100	0/6	**1/6**
Spain IBEX 35	0/6	**1/6**
Canada S&P/TSX Composite Index	0/6	**3/6**
Total	0/42	**6/42***

Table 6.6 – Backtesting Results (Full Sample Period)

* The results 6/42 represents there are 6 out of 42 VaR backtests that we cannot reject the null hypothesis that the model adequately measures the downside risk at the 5% significance level. Similar meaning applies in the other cells. Details of the test results and testing period are shown in Appendix Table 6.7 – 6.13.

Tables 6.3, 6.4, and 6.5 reveal that the RiskMetrics model performs badly in all the pre-burst, bubble, and post-burst periods. The entries in the Table 6.3 to 6.5 represent the total number of backtests is significant. For example, the entry of the backtest result for RiskMetrics2006 of S&P500 in the pre-burst period is 13/18, it represents there are 13 out of 18 backtests are significant in the period. The corresponding individual backtest results can be obtained in Table 6.7(d), it shows that three pre-burst periods are identified (01 Feb 1953 to 31 Jan 1955, 01 Apr 1984 to 31 Mar 1986, and 01 Dec 1993 to 30 Nov 1995). The total number of backtest in the pre-burst periods is 18, while it consists of 6 coverage tests, 6 independence tests, and 6 joint tests. Among the 18 tests, 13 of them are significant at 5% significance level. Table 6.3 summarizes the backtesting results for periods that identified by the original PSY method. In the period of asset price bubble presence, the RiskMetrics model has a result of 3/12 in the tests of the U.S. Nasdaq market. It represents there are 3 out of 12 VaR backtests that we cannot reject the null hypothesis of the model adequately measures the downside risk at the 5% significance level. Alternatively, the RiskMetrics model provides an adequate measure only in 25% (3/12) of the tests. In contrast, the RiskMetrics2006 model outperformed the RiskMetrics model, with a result of 5/12 (41.67%). The poor performance of RiskMetrics model can also been found in the Spanish market (with a result of 2/6 (33%); the RiskMetrics2006 model has a result of 6/6 (100%)) and in the overall figure (with a result of 34/54 (63%); the RiskMetrics2006 model has a result of 47/54 (87%)). For the post-burst periods, the RiskMetrics model underperformed RiskMetrics2006 model in a large extent as well. It has an overall result of 28/48 (58%) while RiskMetrics2006 model has an overall result of 39/48 (81%). Similar results are found in the tests of other periods.

Comparatively poor results of RiskMetrics model are also been found in Table 6.4, which shows the results for the bubble periods that are identified by the $PSY_{\delta=0}$ method. The summarized results are: (1) Pre-burst periods: RiskMetrics model has an overall result of 20/36 (55%) and RiskMetrics2006 model has an overall result of 36/36 (100%); (2) Bubble periods: RiskMetrics model has an overall result of 207/312 (66%) and RiskMetrics2006 model has an overall result of 252/312 (81%); (3) Post-burst periods: RiskMetrics model has an overall result of 19/36 (53%) and RiskMetrics2006 model has an overall result of 32/36 (89%); (4) Periods between bubbles: RiskMetrics model has an overall result of 167/270 (62%) and RiskMetrics2006 model has an overall result of 194/270 (72%). The RiskMetrics2006 model outperforms the RiskMetrics model in all tests.

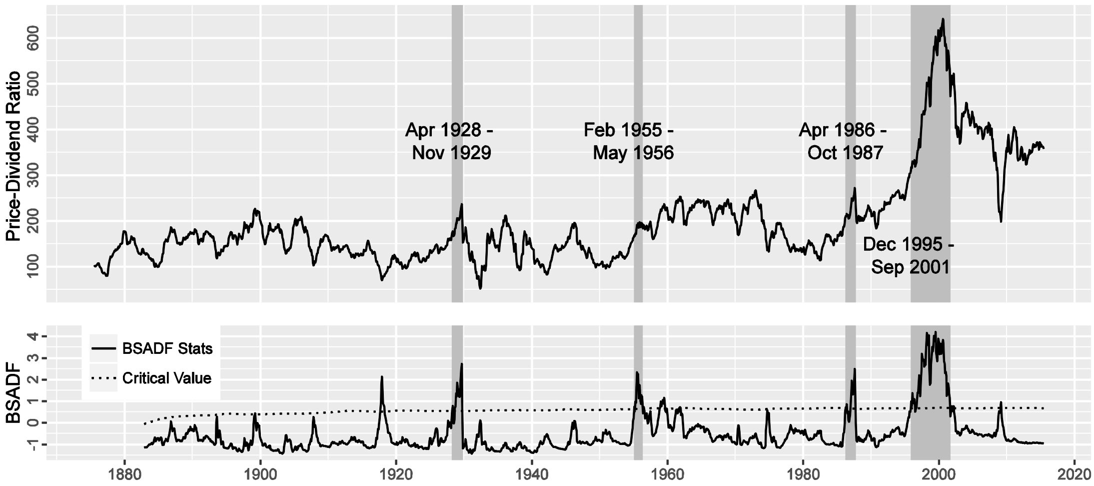
Similar findings are observed for the tests of the PSY_{r1} method in Table 6.5. The summarized results are: (1) Pre-burst periods: RiskMetrics model has an overall result of 44/66 (67%) and RiskMetrics2006 model has an overall result of 34/66 (52%); (2) Bubble periods: RiskMetrics model has an overall result of 20/72 (28%) and RiskMetrics2006 model has an overall result of 50/72 (69%); (3) Post-burst periods: RiskMetrics model has an overall result of 39/66 (59%) and RiskMetrics2006 model has an overall result of 59/66 (89%); (4) Periods between bubbles: RiskMetrics model has an overall result of 18/36 (50%) and RiskMetrics2006 model has an overall result of 20/36 (56%). Except the pre-burst period, the superiority of the RiskMetrics2006 model shows clearly.

In sum, the RiskMetrics2006 model outperforms the RiskMetrics model. It works well in all pre-burst, bubble, and post-burst periods; its results for the coverage, independence, and joint tests are also promising in all six countries (Tables 6.7 to 6.13). However, Table 6.6 shows that both the RiskMetrics and RiskMetrics2006 methods perform badly in the full sample. This poor performance is due to the conservatism of the two VaR methods: they work well in pre-burst, bubble, and post-burst periods but not in the full sample. The VaR model is capable of capturing downside risk during the bubble periods and the long memory characteristic of the RiskMetrics2006 model enables it to perform well in post-burst period. In contrast, the long memory characteristic curse itself is too conservative in normal circumstances, which leads a firm to being too conservative and devoting too much capital to managing downside risks. Simply put, the criticism that VaR models fail in crisis periods is not true, while the RiskMetrics2006 method tends to behave conservatively in normal periods and overstates downside risk in some situations.

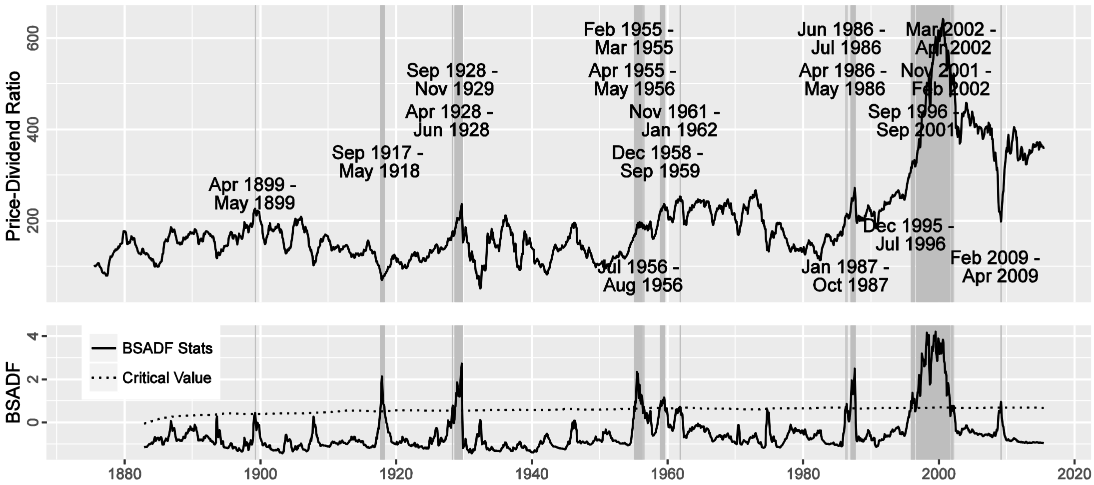
6.5 Conclusion

In chapter 4, we tested the effectiveness of different VaR models in the 2008 sub-prime mortgage crisis period. The crisis and non-crisis periods are identified by subjective judgement and only sub-prime mortgage crisis has been studied, the results may be biased. In this chapter we identify the crisis and non-crisis period by using both the original and modified PSY_{r1} test, and we performed empirical tests to respond to criticism concerning the failure of VaR models in financial crisis periods when asset price bubbles burst. We conducted empirical tests for six selected countries, namely the United Kingdom, Hong Kong, Germany, Spain, the United States, and Canada, proxied by seven indices.

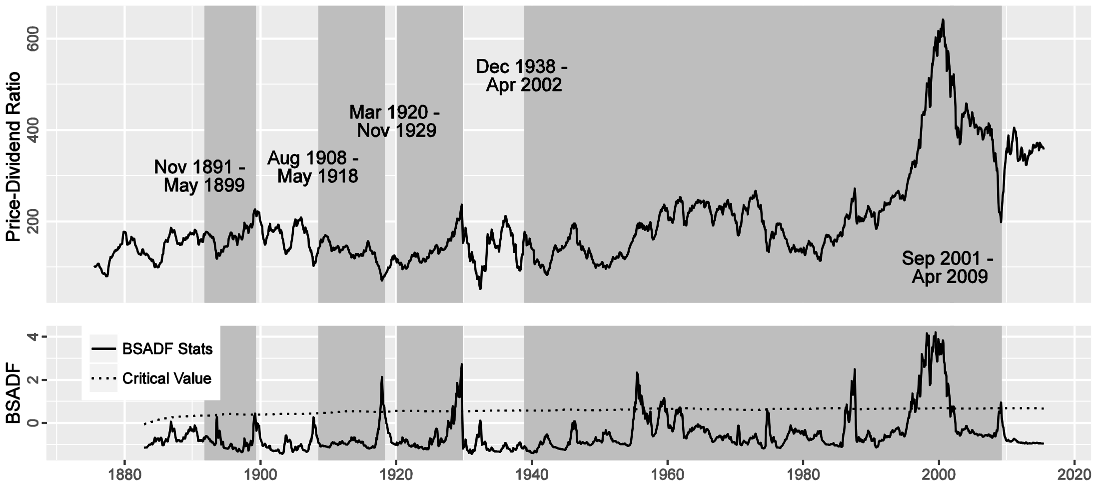
The results of the six backtests allowed us to draw two main conclusions. First, we showed that the RiskMetrics2006 model outperforms the RiskMetrics model. Specifically, the former works well in pre-burst, bubble, and post-burst periods, which may overstate downside risk in a normal period. This result conforms our findings in chapter 4 and practitioners should consider to adopt RiskMetrics2006 as the VaR model to estimate their downside financial risk rather than adopting RiskMetrics. Second, our empirical test results showed that the criticism that VaR models fail in crisis periods is statistically invalid, VaR is still an effective tool to quantify the downside risk subject to having a good volatility model. After the sub-prime mortgage crisis, the Basel III committee responded to the criticism of the failure of VaR and shifted the VaR measure to an Expected Shortfall (ES) (see Acerbi and Tasche, 2002) measure of risk under stress. One shortcoming of VaR is it only defines the minimum loss of a portfolio value in a particular time period with a certain percentage of probability, but not the expected loss ones will suffer. Use ES will help to ensure a more prudent capture of tail risk and capital adequacy during periods of significant financial market stress. However, both the calculation of VaR and ES requires a volatility model, ES will suffer the same criticisms if a flaw volatility model is adopted. Considering this, regulators may consider to stress the practitioners to adopt the long-memory Riskmetrics2006 as the internal volatility model, rather than simply replace the VaR measure with the ES for internal model-based approach in managing the market risk.



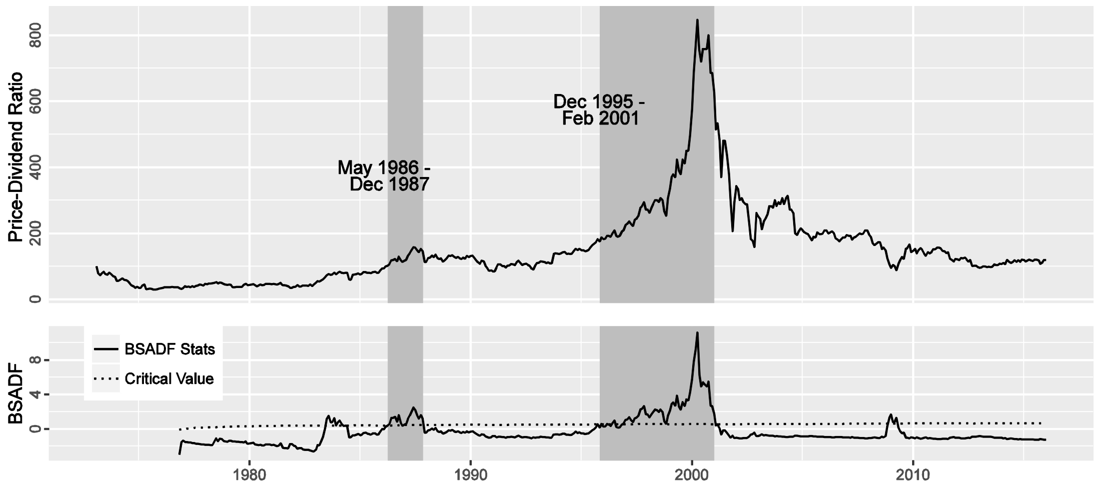
(a) Date-stamping bubble periods in the S&P500 logarithmic price-dividend ratio: PSY test



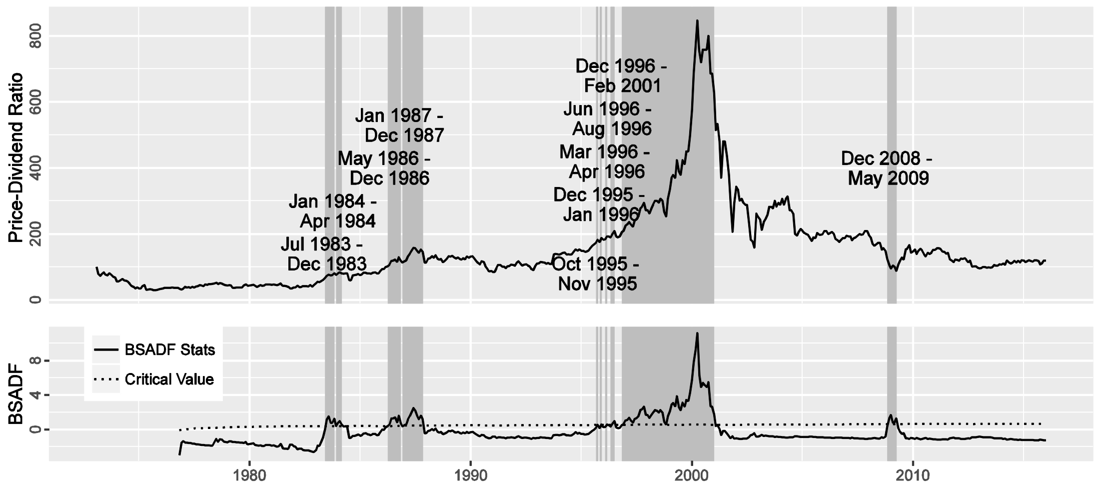
(b) Date-stamping bubble periods in the S&P500 logarithmic price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



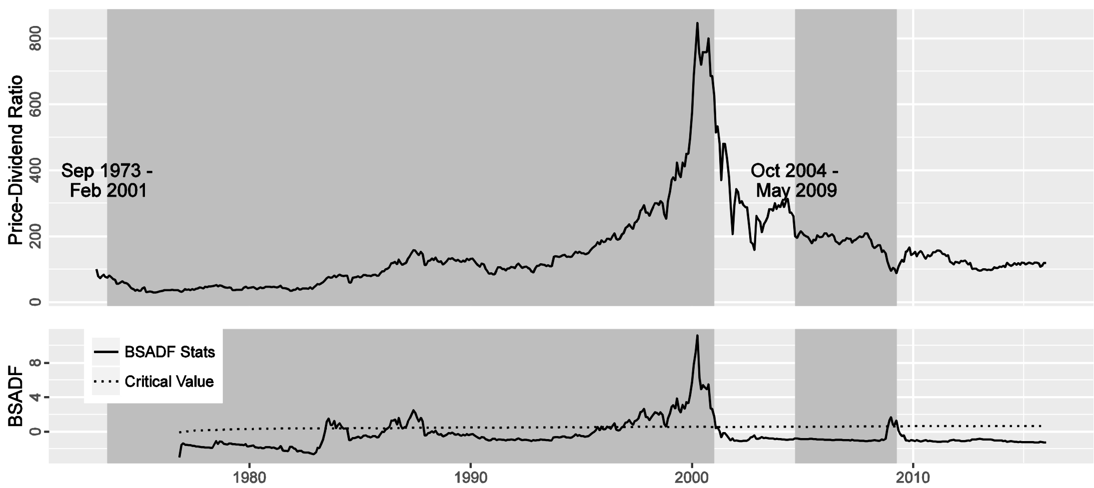
(c) Date-stamping bubble periods in the S&P500 logarithmic price-dividend ratio: PSY_{r1} test



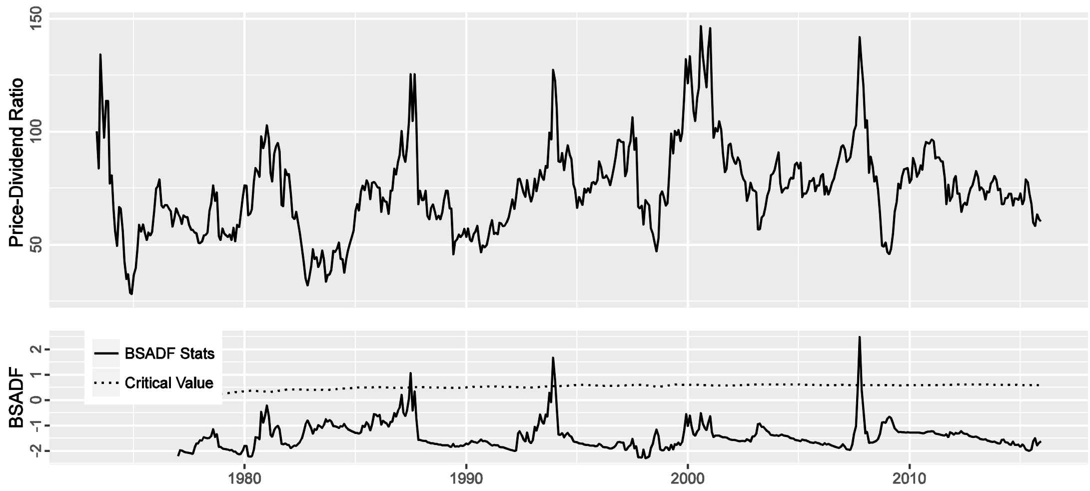
(d) Date-stamping bubble periods in the Nasdaq logarithmic price-dividend ratio: PSY test



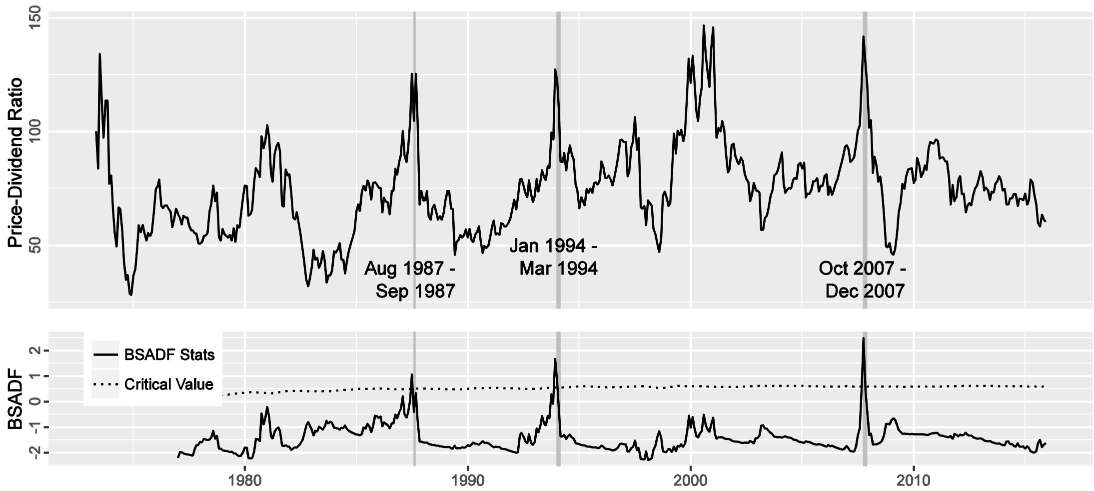
(e) Date-stamping bubble periods in the Nasdaq logarithmic price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ Test



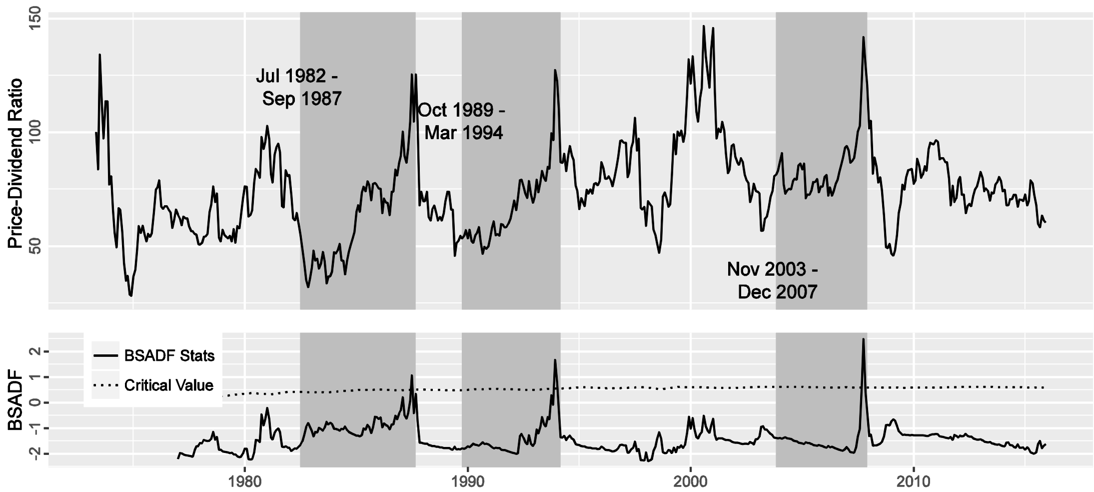
(f) Date-stamping bubble periods in the Nasdaq logarithmic price-dividend ratio: PSY_{r1} test



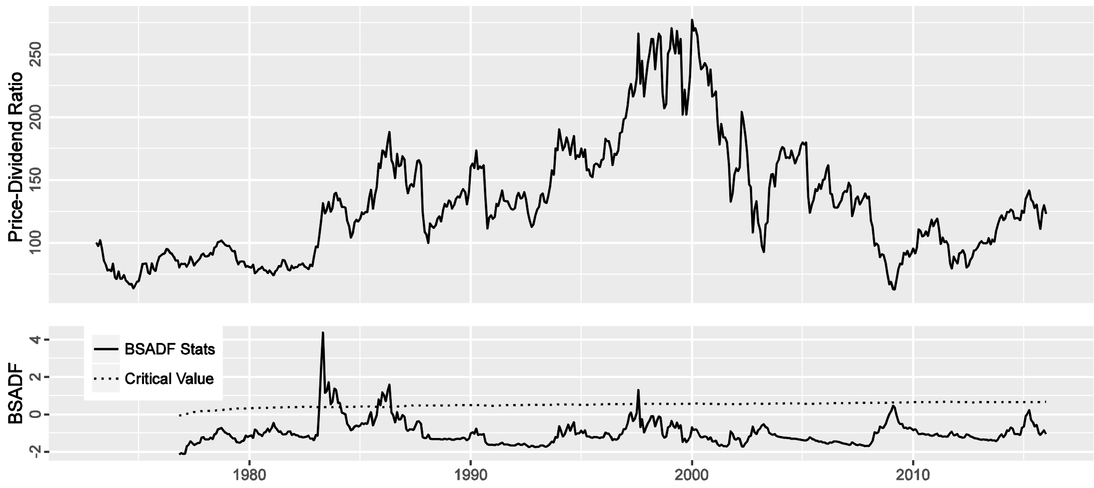
(g) Date-stamping bubble periods in the HSI logarithmic price-dividend ratio: PSY test



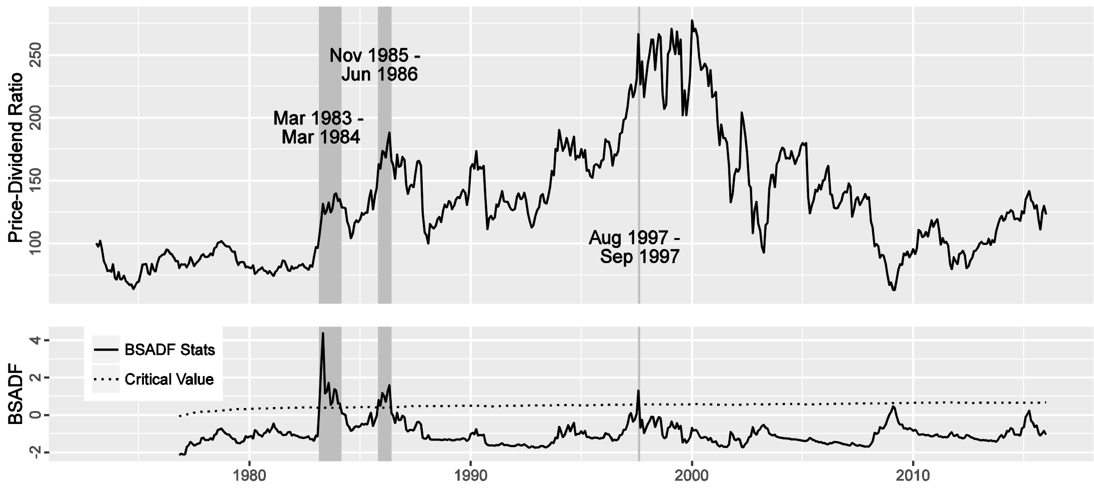
(h) Date-stamping bubble periods in the HSI logarithmic price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



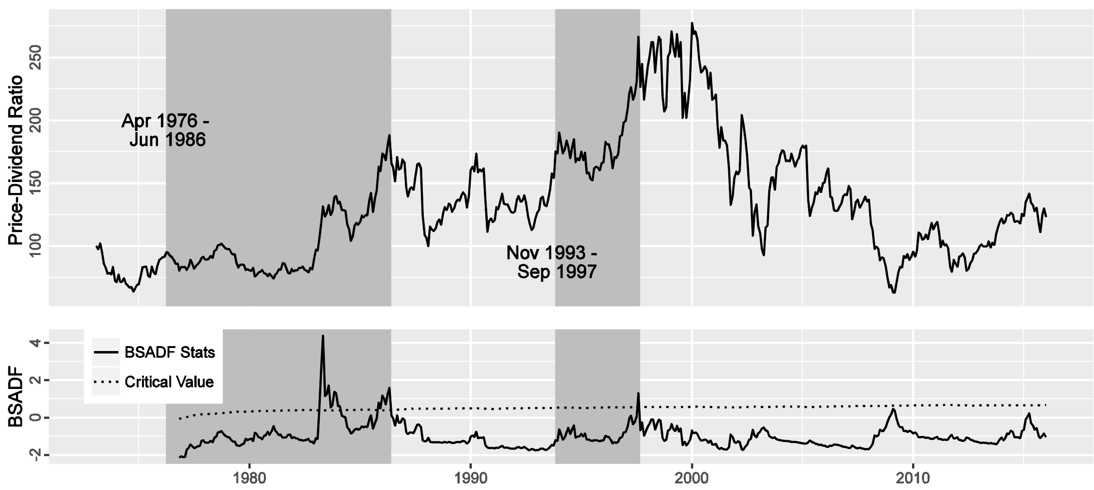
(i) Date-stamping bubble periods in the HSI logarithmic price-dividend ratio: PSY_{r1} test



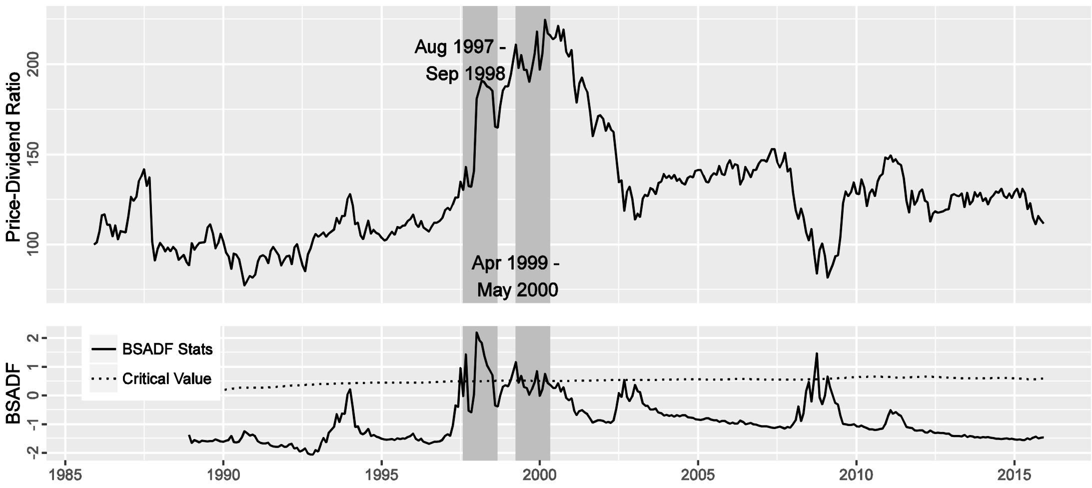
(j) Date-stamping bubble periods in the DAX 30 logarithmic price-dividend ratio: PSY test



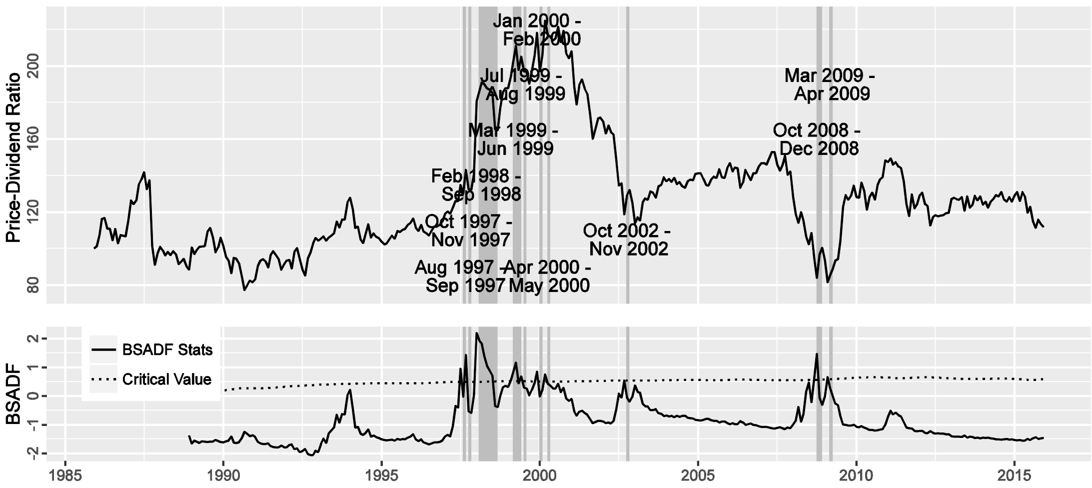
(k) Date-stamping bubble periods in the DAX 30 logarithmic price-dividend ratio: $PSY_{\delta=0}$ test



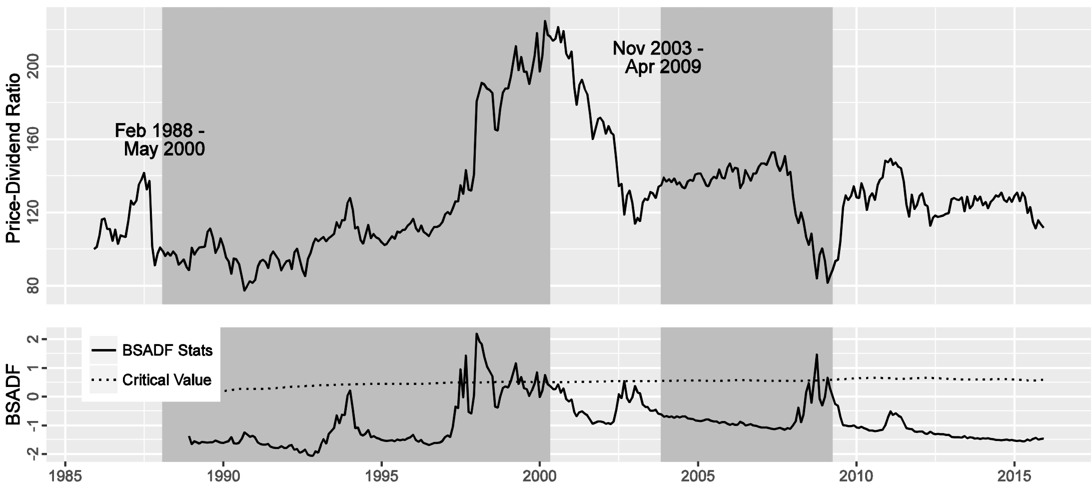
(l) Date-stamping bubble periods in the DAX 30 logarithmic price-dividend ratio: PSY_{r1} test



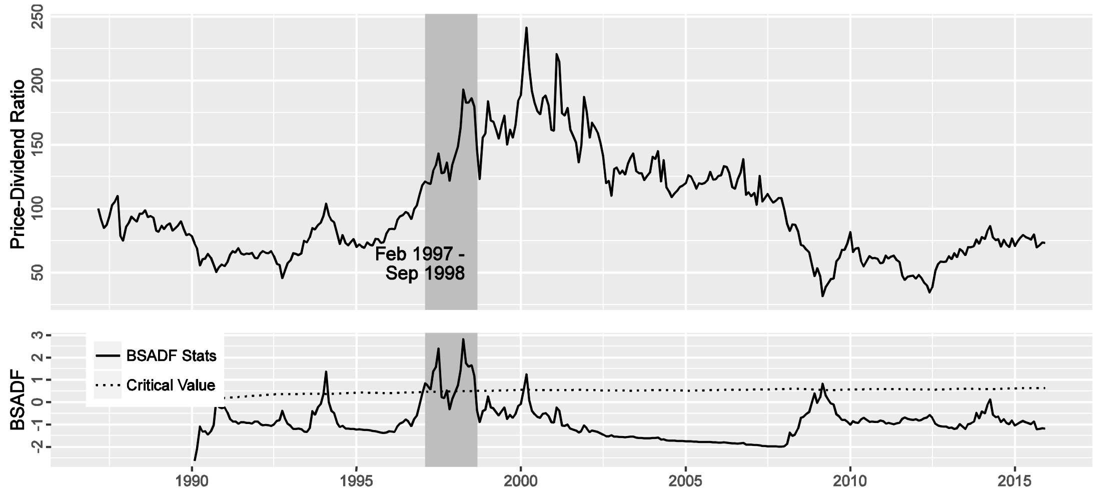
(m) Date-stamping bubble periods in the FTSE100 logarithmic price-dividend ratio: PSY test



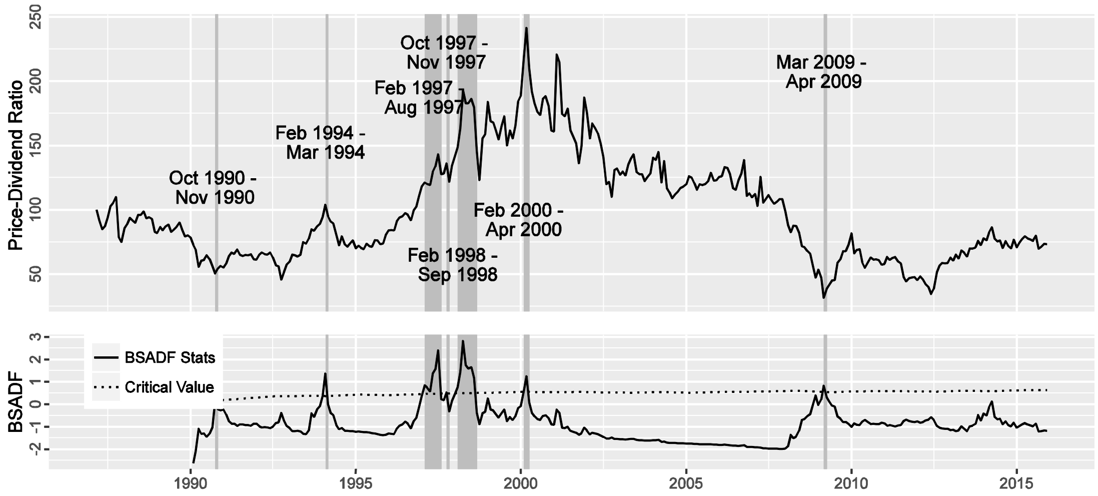
(n) Date-stamping bubble periods in the FTSE100 logarithmic price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



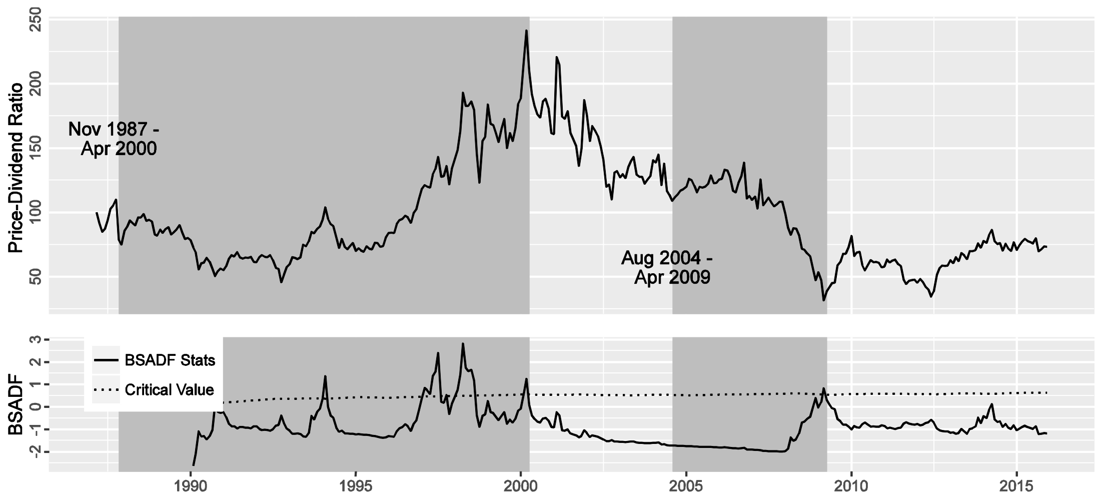
(o) Date-stamping bubble periods in the FTSE100 logarithmic price-dividend ratio: PSY_{r1} test



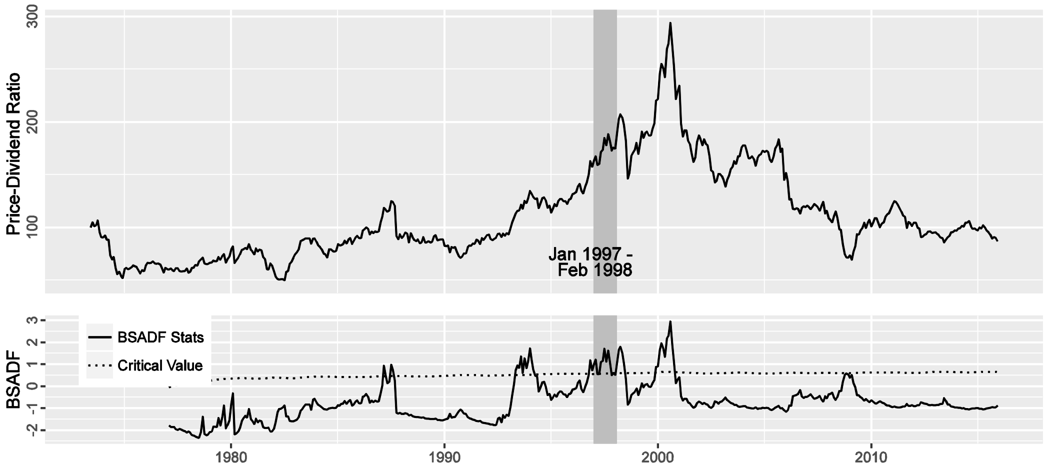
(p) Date-stamping bubble periods in the IBEX 35 logarithmic price-dividend ratio: PSY test



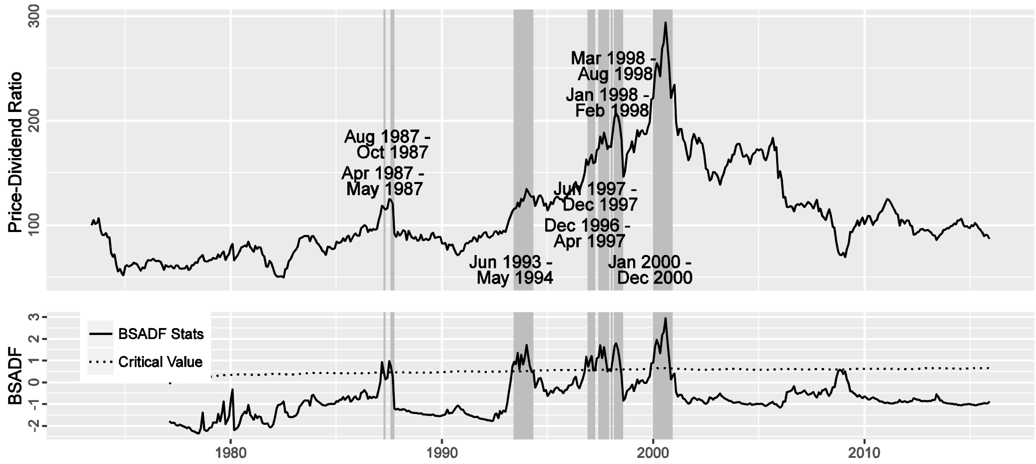
(q) Date-stamping bubble periods in the IBEX 35 logarithmic price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



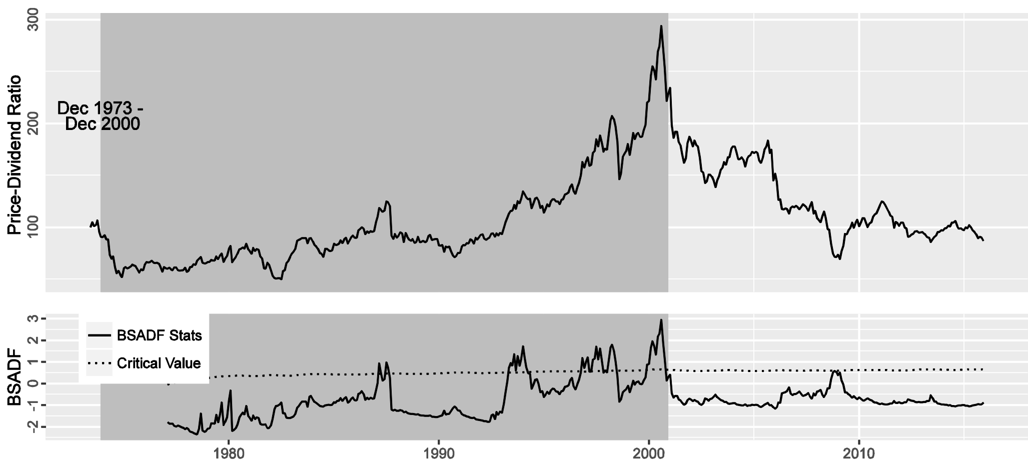
(r) Date-stamping bubble periods in the IBEX 35 logarithmic price-dividend ratio: PSY_{r1} test



(s) Date-stamping bubble periods in the S&P/TSX Composite logarithmic price-dividend ratio: PSY test



(t) Date-stamping bubble periods in the S&P/TSX Composite logarithmic price-dividend ratio: $\mathrm{PSY}_{\delta=0}$ test



(u) Date-stamping bubble periods in the S&P/TSX Composite logarithmic price-dividend ratio: PSY_{r1} test

Figure 6.3 – Date-stamping Bubble Periods of the Logarithmic Price-dividend Ratio for the Six Countries

Table 6.7 – The United States S&P500 Backtests

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	04 Jan 1950 – 31 Dec 2015	343/16606	(0.00%)	(2.39%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.7(a) – The United States S&P500 Backtest Results for RiskMetrics

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	04 Jan 1950 – 31 Dec 2015	95/16606	(0.00%)	(0.44%)	(1.94%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.7(b) – The United States S&P500 Backtest Results for RiskMetrics2006

			Coverage Tests		Independence Tests		Joint Tests	
	Periods	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Feb 1953 – 31 Jan 1955	14/503	(0.10%)	(2.89%)	(37.01%)	(0.26%)	(0.29%)	(0.01%)
	01 Apr 1984 – 31 Mar 1986	3/503	(32.53%)	(12.95%)	(84.94%)	(10.20%)	(60.55%)	(12.70%)
	01 Dec 1993 – 30 Nov 1995	10/506	(5.15%)	(49.94%)	(18.32%)	(6.00%)	(6.19%)	(2.85%)
Bubble Periods	01 Feb 1955 – 01 May 1956	4/315	(64.41%)	(25.50%)	(74.80%)	(17.96%)	(85.36%)	(26.16%)
	01 Apr 1986 – 01 Oct 1987	8/382	(6.09%)	(22.12%)	(55.80%)	(21.21%)	(14.54%)	(11.09%)
	01 Dec 1995 – 01 Sept 2001	37/1452	(0.00%)	(11.05%)	(32.83%)	(0.00%)	(0.00%)	(0.00%)
Post-burst Periods	02 May 1956 – 01 May 1958	15/504	(0.03%)	(5.82%)	(33.69%)	(0.33%)	(0.09%)	(0.01%)
	02 Oct 1987 – 01 Oct 1989	10/505	(5.09%)	(1.98%)	(18.37%)	(0.20%)	(6.14%)	(0.09%)
	02 Sept 2001 – 01 Sept 2003	3/498	(33.56%)	(4.82%)	(84.86%)	(23.06%)	(61.77%)	(26.46%)
Periods between Bubbles	02 May 1956 – 31 Mar 1996	200/10047	(0.00%)	(5.82%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)
	02 Oct 1987 – 30 Nov 1995	40/2065	(0.01%)	(1.98%)	(0.72%)	(0.02%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

* Daily data available in Datastream do not cover the identified bubbles period.

Table 6.7(c) – The United States S&P500 Backtest Results for RiskMetrics: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Feb 1953 – 31 Jan 1955	6/503	(67.31%)	(4.82%)	(70.32%)	(11.11%)	(85.08%)	(16.12%)
	01 Apr 1984 – 31 Mar 1986	1/503	(2.75%)	(4.63%)	(94.96%)	(4.63%)	(8.78%)	(1.21%)
	01 Dec 1993 – 30 Nov 1995	4/506	(62.30%)	(49.94%)	(80.05%)	(81.33%)	(85.83%)	(87.39%)
Bubble Periods	01 Feb 1955 – 01 May 1956	2/315	(48.52%)	(25.50%)	(87.28%)	(49.07%)	(77.38%)	(59.11%)
	01 Apr 1986 – 01 Oct 1987	4/382	(92.68%)	(52.09%)	(77.08%)	(55.14%)	(95.44%)	(69.27%)
	01 Dec 1995 – 01 Sept 2001	15/1452	(89.98%)	(11.05%)	(57.56%)	(6.55%)	(84.82%)	(8.96%)
Post-burst Periods	02 May 1956 – 01 May 1958	3/504	(32.33%)	(13.92%)	(84.95%)	(8.91%)	(60.30%)	(11.21%)
	02 Oct 1987 – 01 Oct 1989	5/505	(98.21%)	(1.98%)	(3.39%)	(0.25%)	(10.54%)	(0.53%)
	02 Sept 2001 – 01 Sept 2003	2/498	(12.70%)	(4.82%)	(89.88%)	(14.15%)	(30.96%)	(10.05%)
Periods between Bubbles	02 May 1956 – 31 Mar 1996	55/10047	(0.00%)	(13.92%)	(31.23%)	(0.19%)	(0.00%)	(0.00%)
	02 Oct 1987 – 30 Nov 1995	15/2065	(18.90%)	(1.98%)	(9.67%)	(1.97%)	(10.62%)	(1.78%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

* Daily data available in Datastream do not cover the identified bubbles period.

Table 6.7(d) – The United States S&P500 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Feb 1955 – 01 Mar 1955	0/20	(52.61%)	(19.87%)	(100.00%)	NA	(81.79%)	NA
	01 Apr 1955 – 01 May 1956	2/273	(64.11%)	(82.94%)	(86.33%)	(92.91%)	(88.38%)	(94.75%)
	01 Jul 1956 – 01 Aug 1956	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	01 Dec 1958 – 01 Sept 1959	5/191	(6.16%)	(51.02%)	(60.31%)	(9.83%)	(15.23%)	(4.67%)
	01 Nov 1961 – 01 Jan 1962	0/40	(36.99%)	(42.31%)	(100.00%)	NA	(66.90%)	NA
	01 Apr 1986 – 01 May 1986	1/23	(23.25%)	(22.12%)	(75.76%)	(22.12%)	(46.74%)	(23.20%)
	01 Jun 1986 – 01 Jul 1986	1/22	(22.12%)	(4.82%)	(75.18%)	(4.82%)	(45.01%)	(6.72%)
	01 Jan 1987 – 01 Oct 1987	2/190	(94.24%)	(64.59%)	(83.61%)	(89.71%)	(97.63%)	(97.39%)
	01 Dec 1995 – 01 Jul 1996	6/147	(0.48%)	(11.05%)	(22.00%)	(0.59%)	(0.88%)	(0.05%)
	01 Sept 1996 – 01 Sept 2001	28/1262	(0.02%)	(68.60%)	(65.10%)	(0.40%)	(0.08%)	(0.01%)
	01 Nov 2001 – 01 Feb 2002	1/63	(66.60%)	(63.57%)	(85.63%)	(63.57%)	(89.63%)	(81.44%)
	01 Mar 2002 – 01 Apr 2002	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
Periods between Bubbles	02 Mar 1955 – 31 Mar 1955	2/22	(1.99%)	(3.84%)	(51.60%)	(1.08%)	(5.39%)	(0.23%)
	02 May 1956 – 30 Jun 1956	1/42	(44.51%)	(5.82%)	(82.31%)	(5.82%)	(72.86%)	(12.42%)
	02 Aug 1956 – 30 Nov 1958	19/586	(0.00%)	(1.98%)	(64.21%)	(0.02%)	(0.01%)	(0.00%)
	02 Sept 1959 – 31 Oct 1961	9/545	(16.23%)	(12.13%)	(58.21%)	(74.65%)	(32.38%)	(63.99%)
	02 Jan 1962 – 31 Mar 1986	114/6091	(0.00%)	(2.89%)	(0.68%)	(0.00%)	(0.00%)	(0.00%)
	02 May 1986 – 31 May 1986	0/20	(52.61%)	(19.87%)	(100.00%)	NA	(81.79%)	NA
	02 Jul 1986 – 31 Dec 1986	4/127	(5.19%)	(1.98%)	(60.85%)	(1.87%)	(13.26%)	(0.81%)
	02 Oct 1987 – 30 Nov 1995	40/2065	(0.01%)	(1.98%)	(0.72%)	(0.02%)	(0.00%)	(0.00%)
	02 Jul 1995 – 31 Aug 1996	10/296	(0.12%)	(84.69%)	(33.34%)	(0.17%)	(0.34%)	(0.01%)
	02 Sept 2001 – 31 Oct 2001	1/38	(40.10%)	(4.82%)	(81.37%)	(4.82%)	(68.35%)	(9.98%)
	02 Feb 2002 – 28 Feb 2002	0/18	(54.75%)	(17.64%)	(100.00%)	NA	(83.45%)	NA

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Daily data available in Datastream do not cover the identified bubbles period.

Table 6.7(e) – The United States S&P500 Backtest Results for RiskMetrics: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Feb 1955 – 01 Mar 1955	0/20	(52.61%)	(19.87%)	(100.00%)	NA	(81.79%)	NA
	01 Apr 1955 – 01 May 1956	1/273	(22.65%)	(82.94%)	(93.15%)	(82.94%)	(47.95%)	(47.03%)
	01 Jul 1956 – 01 Aug 1956	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	01 Dec 1958 – 01 Sept 1959	1/191	(46.65%)	(53.55%)	(91.81%)	(53.55%)	(76.31%)	(63.31%)
	01 Nov 1961 – 01 Jan 1962	0/40	(36.99%)	(42.31%)	(100.00%)	NA	(66.90%)	NA
	01 Apr 1986 – 01 May 1986	0/23	(49.65%)	(23.25%)	(100.00%)	NA	(79.36%)	NA
	01 Jun 1986 – 01 Jul 1986	1/22	(22.12%)	(4.82%)	(75.18%)	(4.82%)	(45.01%)	(6.72%)
	01 Jan 1987 – 01 Oct 1987	0/190	(5.07%)	(47.06%)	(100.00%)	NA	(14.81%)	NA
	01 Dec 1995 – 01 Jul 1996	3/147	(26.62%)	(11.05%)	(72.27%)	(31.61%)	(50.61%)	(31.15%)
	01 Sept 1996 – 01 Sept 2001	10/1262	(44.18%)	(69.66%)	(68.93%)	(10.70%)	(68.68%)	(12.89%)
	01 Nov 2001 – 01 Feb 2002	1/63	(66.60%)	(63.57%)	(85.63%)	(63.57%)	(89.63%)	(81.44%)
	01 Mar 2002 – 01 Apr 2002	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
Periods between Bubbles	02 Mar 1955 – 31 Mar 1955	1/22	(22.12%)	(3.84%)	(75.18%)	(3.84%)	(45.01%)	(5.55%)
	02 May 1956 – 30 Jun 1956	0/42	(35.82%)	(44.51%)	(100.00%)	NA	(65.57%)	NA
	02 Aug 1956 – 30 Nov 1958	4/586	(41.27%)	(24.77%)	(81.45%)	(12.67%)	(69.55%)	(16.47%)
	02 Sept 1959 – 31 Oct 1961	4/545	(51.23%)	(24.55%)	(80.77%)	(47.32%)	(78.33%)	(55.52%)
	02 Jan 1962 – 31 Mar 1986	25/6091	(0.00%)	(97.62%)	(64.98%)	(0.20%)	(0.00%)	(0.00%)
	02 May 1986 – 31 May 1986	0/20	(52.61%)	(19.87%)	(100.00%)	NA	(81.79%)	NA
	02 Jul 1986 – 31 Dec 1986	3/127	(18.95%)	(1.98%)	(70.20%)	(9.70%)	(39.30%)	(9.00%)
	02 Oct 1987 – 30 Nov 1995	15/2065	(18.90%)	(1.98%)	(9.67%)	(1.97%)	(10.62%)	(1.78%)
	02 Jul 1995 – 31 Aug 1996	5/296	(27.80%)	(86.42%)	(67.80%)	(36.33%)	(50.94%)	(35.66%)
	02 Sept 2001 – 31 Oct 2001	1/38	(40.10%)	(4.82%)	(81.37%)	(4.82%)	(68.35%)	(9.98%)
	02 Feb 2002 – 28 Feb 2002	0/18	(54.75%)	(17.64%)	(100.00%)	NA	(83.45%)	NA

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Daily data available in Datastream do not cover the identified bubbles period.

Table 6.7(f) – The United States S&P500 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

Table 6.8 – The United States Nasdaq Backtest Results

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	03 Jan 1973 – 31 Dec 2015	254/11217	(0.00%)	(0.55%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.8 (a) – The United States Nasdaq Backtest Results for RiskMetrics

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	03 Jan 1973 – 31 Dec 2015	90/11217	(2.93%)	(0.00%)	(0.01%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.8(b) – The United States Nasdaq Backtest Results for RiskMetrics2006

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 May 1984 – 30 Apr 1986	7/522	(45.67%)	(17.64%)	(68.62%)	(18.61%)	(69.87%)	(22.55%)
	01 Dec 1993 – 30 Nov 1995	13/522	(0.40%)	(51.02%)	(32.35%)	(0.45%)	(0.98%)	(0.05%)
Bubble Periods	01 May 1986 – 01 Dec 1987	15/414	(0.00%)	(28.89%)	(0.10%)	(0.00%)	(0.00%)	(0.00%)
	01 Dec 1995 – 01 Feb 2001	27/1350	(0.12%)	(11.05%)	(29.36%)	(0.28%)	(0.29%)	(0.02%)
Post-burst Periods	02 Dec 1987 – 01 Dec 1989	10/523	(6.26%)	(97.57%)	(53.20%)	(9.43%)	(14.53%)	(5.02%)
	02 Feb 2001 – 01 Feb 2003	0/305	(1.33%)	(16.99%)	(100.00%)	NA	(4.66%)	NA
Periods between Bubbles	02 Dec 1987 – 30 Nov 1995	56/2087	(0.00%)	(97.57%)	(26.62%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.8(c) – The United States Nasdaq Backtest Results for RiskMetrics: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 May 1984 – 30 Apr 1986	2/522	(10.54%)	(4.80%)	(93.01%)	(13.79%)	(26.84%)	(8.64%)
	01 Dec 1993 – 30 Nov 1995	5/522	(92.24%)	(51.02%)	(75.56%)	(78.62%)	(94.82%)	(87.46%)
Bubble Periods	01 May 1986 – 01 Dec 1987	10/414	(1.43%)	(28.89%)	(1.78%)	(0.06%)	(0.30%)	(0.01%)
	01 Dec 1995 – 01 Feb 2001	14/1350	(89.19%)	(11.05%)	(58.79%)	(3.03%)	(85.55%)	(4.39%)
Post-burst Periods	02 Dec 1987 – 01 Dec 1989	2/523	(10.45%)	(12.60%)	(90.13%)	(28.20%)	(26.57%)	(16.00%)
	02 Feb 2001 – 01 Feb 2003	0/305	(1.33%)	(16.99%)	(100.00%)	NA	(4.66%)	NA
Periods between Bubbles	02 Dec 1987 – 30 Nov 1995	18/2087	(51.79%)	(12.60%)	(14.57%)	(9.37%)	(28.16%)	(11.21%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.8(d) – The United States Nasdaq Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Jul 1983 – 01 Dec 1983	2/110	(43.90%)	(19.87%)	(78.45%)	(38.59%)	(71.41%)	(47.48%)
	01 Jan 1984 – 01 Apr 1984	3/65	(3.27%)	(15.42%)	(58.69%)	(1.41%)	(8.81%)	(0.44%)
	01 May 1986 – 01 Dec 1986	6/153	(0.59%)	(28.89%)	(21.02%)	(0.53%)	(1.02%)	(0.05%)
	01 Jan 1987 – 01 Dec 1987	9/239	(0.10%)	(66.60%)	(0.19%)	(0.00%)	(0.00%)	(0.00%)
	01 Oct 1995 – 01 Nov 1995	1/23	(23.25%)	(4.82%)	(75.76%)	(4.82%)	(46.74%)	(6.96%)
	01 Dec 1995 – 01 Jan 1996	1/22	(22.12%)	(11.05%)	(75.18%)	(11.05%)	(45.01%)	(13.24%)
	01 Mar 1996 – 01 Apr 1996	1/22	(22.12%)	(4.82%)	(75.18%)	(4.82%)	(45.01%)	(6.72%)
	01 Jun 1996 – 01 Aug 1996	3/44	(1.05%)	(11.05%)	(50.21%)	(1.21%)	(3.02%)	(0.16%)
	01 Dec 1996 – 01 Feb 2001	20/1089	(1.30%)	(9.98%)	(38.68%)	(0.60%)	(3.14%)	(0.15%)
Periods between Bubbles	02 Dec 1983 – 31 Dec 1983	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Apr 1984 – 30 Apr 1986	7/543	(51.68%)	(41.20%)	(69.21%)	(26.07%)	(74.94%)	(31.69%)
	02 Dec 1986 – 31 Dec 1986	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	02 Dec 1987 – 30 Sept 1995	55/2043	(0.00%)	(97.57%)	(25.70%)	(0.00%)	(0.00%)	(0.00%)
	02 Nov 1995 – 30 Nov 1995	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Jan 1996 – 28 Feb 1996	1/42	(44.51%)	(4.82%)	(82.31%)	(4.82%)	(72.86%)	(10.61%)
	02 Apr 1996 – 31 May 1996	1/44	(46.69%)	(23.25%)	(82.73%)	(23.25%)	(74.95%)	(37.63%)
	02 Aug 1996 – 30 Nov 1996	0/86	(18.86%)	(88.24%)	(100.00%)	NA	(42.13%)	NA

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Bubble Periods are too fragment, no Pre-Burst and Post-Burst Period be defined.

Table 6.8(e) – The United States Nasdaq Backtest Results for RiskMetrics: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Jul 1983 – 01 Dec 1983	1/110	(92.25%)	(81.04%)	(89.18%)	(81.04%)	(98.61%)	(96.70%)
	01 Jan 1984 – 01 Apr 1984	0/65	(25.30%)	(68.60%)	(100.00%)	NA	(52.03%)	NA
	01 May 1986 – 01 Dec 1986	5/153	(2.56%)	(28.89%)	(13.35%)	(0.30%)	(2.69%)	(0.08%)
	01 Jan 1987 – 01 Dec 1987	5/239	(13.89%)	(66.60%)	(7.98%)	(2.13%)	(7.21%)	(1.72%)
	01 Oct 1995 – 01 Nov 1995	0/23	(49.65%)	(23.25%)	(100.00%)	NA	(79.36%)	NA
	01 Dec 1995 – 01 Jan 1996	1/22	(22.12%)	(11.05%)	(75.18%)	(11.05%)	(45.01%)	(13.24%)
	01 Mar 1996 – 01 Apr 1996	1/22	(22.12%)	(4.82%)	(75.18%)	(4.82%)	(45.01%)	(6.72%)
	01 Jun 1996 – 01 Aug 1996	2/44	(8.36%)	(30.02%)	(65.86%)	(2.32%)	(20.31%)	(1.46%)
	01 Dec 1996 – 01 Feb 2001	9/1089	(55.29%)	(31.48%)	(69.84%)	(18.34%)	(77.79%)	(22.85%)
Periods between Bubbles	02 Dec 1983 – 31 Dec 1983	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Apr 1984 – 30 Apr 1986	2/543	(8.93%)	(3.95%)	(93.14%)	(11.70%)	(23.53%)	(6.64%)
	02 Dec 1986 – 31 Dec 1986	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	02 Dec 1987 – 30 Sept 1995	18/2043	(58.13%)	(12.60%)	(14.92%)	(9.37%)	(30.36%)	(11.50%)
	02 Nov 1995 – 30 Nov 1995	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Jan 1996 – 28 Feb 1996	1/42	(44.51%)	(4.82%)	(82.31%)	(4.82%)	(72.86%)	(10.61%)
	02 Apr 1996 – 31 May 1996	0/44	(34.70%)	(46.69%)	(100.00%)	NA	(64.26%)	NA
	02 Aug 1996 – 30 Nov 1996	0/86	(18.86%)	(88.24%)	(100.00%)	NA	(42.13%)	NA

* The numbers in parentheses are the p-values for rejecting the null hypothesis

\# Bubble Periods are too fragment, no Pre-Burst and Post-Burst Period be defined.

Table 6.8(f) – The United States Nasdaq Backtest Results for RiskMetrics2006: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	03 Jan 1973 – 31 Aug 1973#	0/173	(6.22%)	(54.47%)	(100.00%)	NA	(17.57%)	NA
	01 Oct 2002 – 30 Sept 2004	4/523	(57.28%)	(28.56%)	(80.37%)	(40.06%)	(82.71%)	(49.91%)
Bubble Periods	01 Sept 1973 – 01 Feb 2001	174/7154	(0.00%)	(2.82%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)
	01 Oct 2004 – 01 May 2009	23/1196	(0.44%)	(71.55%)	(34.20%)	(5.22%)	(1.11%)	(0.97%)
Post-burst Periods	02 Feb 2001 – 01 Feb 2003	1/521	(2.32%)	(59.83%)	(95.05%)	(59.83%)	(7.59%)	(6.62%)
	02 May 2009 – 01 May 2011	14/520	(0.13%)	(93.00%)	(37.83%)	(0.20%)	(0.40%)	(0.01%)
Periods between Bubbles	02 Feb 2001 – 30 Sept 2004	5/955	(10.35%)	(59.83%)	(81.85%)	(14.22%)	(25.88%)	(9.10%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Due to data availability, period trimmed from 01 Sept 1971 – 31 Aug 1973 to 03 Jan 1973 – 31 Aug 1973

Table 6.8(g) – The United States Nasdaq Backtest Results for RiskMetrics: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	03 Jan 1973 – 31 Aug 1973#	0/173	(6.22%)	(54.47%)	(100.00%)	NA	(17.57%)	NA
	01 Oct 2002 – 30 Sept 2004	0/523	(0.12%)	(2.28%)	(100.00%)	NA	(0.52%)	NA
Bubble Periods	01 Sept 1973 – 01 Feb 2001	69/7154	(76.14%)	(0.02%)	(0.05%)	(0.00%)	(0.23%)	(0.00%)
	01 Oct 2004 – 01 May 2009	7/1196	(11.82%)	(12.26%)	(77.39%)	(39.15%)	(28.31%)	(27.86%)
Post-burst Periods	02 Feb 2001 – 01 Feb 2003	1/521	(2.32%)	(59.83%)	(95.05%)	(59.83%)	(7.59%)	(6.62%)
	02 May 2009 – 01 May 2011	2/520	(10.70%)	(4.29%)	(90.10%)	(4.92%)	(27.07%)	(3.48%)
Periods between Bubbles	02 Feb 2001 – 30 Sept 2004	1/955	(0.04%)	(59.83%)	(96.35%)	(59.83%)	(0.18%)	(0.15%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Due to data availability, period trimmed from 01 Sept 1971 – 31 Aug 1973 to 03 Jan 1973 – 31 Aug 1973

Table 6.8(h) – The United States Nasdaq Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

Table 6.9 – Hong Kong HSI Backtest Results

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	01 Jun 1973 – 31 Dec 2015	209/11110	(0.00%)	(1.55%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.9(a) – Hong Kong HSI Backtest Results for RiskMetrics

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	01 Jun 1973 – 31 Dec 2015	78/11110	(0.09%)	(0.22%)	(12.68%)	(0.00%)	(0.12%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.9(b) – Hong Kong HSI Backtest Results for RiskMetrics2006

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Aug 1985 – 31 Jul 1987	11/522	(2.68%)	(14.31%)	(49.09%)	(18.49%)	(6.79%)	(7.00%)
	01 Jan 1992 – 31 Dec 1993	14/523	(0.14%)	(74.45%)	(0.39%)	(0.00%)	(0.01%)	(0.00%)
	01 Oct 2005 – 30 Sept 2007	14/520	(0.13%)	(2.89%)	(37.83%)	(0.63%)	(0.40%)	(0.03%)
Bubble Periods	01 Aug 1987 – 01 Sept 1987	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	01 Jan 1994 – 01 Mar 1994	2/42	(7.62%)	(2.89%)	(65.05%)	(4.35%)	(18.74%)	(2.43%)
	01 Oct 2007 – 01 Dec 2007	1/45	(47.78%)	(26.63%)	(82.92%)	(26.63%)	(75.94%)	(41.91%)
Post-burst Periods	02 Sept 1987 – 01 Sept 1989	11/523	(2.72%)	(35.64%)	(22.05%)	(0.49%)	(4.11%)	(0.15%)
	02 Mar 1994 – 01 Mar 1996	5/391	(59.53%)	(61.53%)	(4.54%)	(1.33%)	(11.73%)	(2.29%)
	02 Dec 2007 – 01 Dec 2009	9/522	(13.17%)	(34.52%)	(13.79%)	(0.54%)	(10.68%)	(0.43%)
Periods between Bubbles	02 Sept 1987 – 31 Dec 1993	36/1653	(0.00%)	(35.64%)	(0.72%)	(0.00%)	(0.00%)	(0.00%)
	02 Mar 1994 – 30 Sept 2007	66/3543	(0.00%)	(47.06%)	(4.19%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.9(c) – Hong Kong HSI Backtest Results for RiskMetrics: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Aug 1985 – 31 Jul 1987	2/522	(10.54%)	(84.69%)	(90.12%)	(39.32%)	(26.74%)	(21.32%)
	01 Jan 1992 – 31 Dec 1993	3/523	(28.68%)	(30.38%)	(85.23%)	(5.47%)	(55.73%)	(6.77%)
	01 Oct 2005 – 30 Sept 2007	5/520	(92.93%)	(60.34%)	(75.51%)	(44.23%)	(94.88%)	(57.03%)
Bubble Periods	01 Aug 1987 – 01 Sept 1987	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	01 Jan 1994 – 01 Mar 1994	2/42	(7.62%)	(2.89%)	(65.05%)	(4.35%)	(18.74%)	(2.43%)
	01 Oct 2007 – 01 Dec 2007	0/45	(34.16%)	(47.78%)	(100.00%)	NA	(63.62%)	NA
Post-burst Periods	02 Sept 1987 – 01 Sept 1989	5/523	(91.89%)	(35.64%)	(3.26%)	(0.10%)	(10.14%)	(0.21%)
	02 Mar 1994 – 01 Mar 1996	2/391	(28.40%)	(61.53%)	(88.58%)	(52.81%)	(55.75%)	(48.90%)
	02 Dec 2007 – 01 Dec 2009	5/522	(92.24%)	(34.52%)	(75.56%)	(7.11%)	(94.82%)	(11.81%)
Periods between Bubbles	02 Sept 1987 – 31 Dec 1993	12/1653	(23.91%)	(35.64%)	(7.37%)	(0.20%)	(10.10%)	(0.21%)
	02 Mar 1994 – 30 Sept 2007	27/3543	(13.74%)	(47.06%)	(20.30%)	(2.21%)	(14.75%)	(1.77%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.9(d) – Hong Kong HSI Backtest Result for RiskMetrics2006: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Jul 1980 – 30 Jun 1982	15/522	(0.05%)	(11.05%)	(34.56%)	(0.11%)	(0.14%)	(0.00%)
	01 Oct 1987 – 30 Sept 1989	11/522	(2.68%)	(12.13%)	(22.10%)	(0.28%)	(4.07%)	(0.09%)
	01 Nov 2001 – 31 Oct 2003	6/522	(73.75%)	(38.99%)	(70.85%)	(69.08%)	(88.16%)	(77.88%)
Bubble Periods	01 Jul 1982 – 01 Sept 1987	29/1349	(0.02%)	(21.00%)	(25.88%)	(0.47%)	(0.06%)	(0.02%)
	01 Oct 1989 – 01 Mar 1994	27/1152	(0.01%)	(9.98%)	(2.47%)	(0.01%)	(0.00%)	(0.00%)
	01 Nov 2003 – 01 Dec 2007	25/1065	(0.02%)	(66.60%)	(27.27%)	(7.89%)	(0.05%)	(0.34%)
Post-burst Periods	02 Sept 1987 – 01 Sept 1989	11/523	(2.72%)	(35.64%)	(22.05%)	(0.49%)	(4.11%)	(0.15%)
	02 Mar 1994 – 01 Mar 1996	5/523	(91.89%)	(47.06%)	(3.26%)	(1.19%)	(10.14%)	(2.30%)
	02 Dec 2007 – 01 Dec 2009	9/522	(13.17%)	(34.52%)	(13.79%)	(0.54%)	(10.68%)	(0.43%)
Periods between Bubbles	02 Sept 1987 – 30 Sept 1989	11/543	(3.49%)	(35.64%)	(21.15%)	(0.49%)	(4.95%)	(0.18%)
	02 Mar 1994 – 31 Oct 2003	42/2523	(0.22%)	(47.06%)	(0.50%)	(0.00%)	(0.02%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.9(e) – Hong Kong HSI Backtest Results for RiskMetrics: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Jul 1980 – 30 Jun 1982	3/522	(28.86%)	(96.06%)	(85.21%)	(16.33%)	(55.96%)	(18.16%)
	01 Oct 1987 – 30 Sept 1989	5/522	(92.24%)	(12.13%)	(3.27%)	(0.05%)	(10.16%)	(0.11%)
	01 Nov 2001 – 31 Oct 2003	1/522	(2.30%)	(2.43%)	(95.05%)	(2.43%)	(7.53%)	(0.60%)
Bubble Periods	01 Jul 1982 – 01 Sept 1987	13/1349	(89.27%)	(21.00%)	(61.48%)	(2.50%)	(87.31%)	(3.71%)
	01 Oct 1989 – 01 Mar 1994	9/1152	(43.78%)	(9.98%)	(70.64%)	(8.33%)	(68.94%)	(10.28%)
	01 Nov 2003 – 01 Dec 2007	9/1065	(60.16%)	(86.42%)	(69.52%)	(52.94%)	(80.81%)	(59.76%)
Post-burst Periods	02 Sept 1987 – 01 Sept 1989	5/523	(91.89%)	(35.64%)	(3.26%)	(0.10%)	(10.14%)	(0.21%)
	02 Mar 1994 – 01 Mar 1996	2/523	(10.45%)	(47.06%)	(90.13%)	(46.18%)	(26.57%)	(24.26%)
	02 Dec 2007 – 01 Dec 2009	5/522	(92.24%)	(34.52%)	(75.56%)	(7.11%)	(94.82%)	(11.81%)
Periods between Bubbles	02 Sept 1987 – 30 Sept 1989	5/543	(85.09%)	(35.64%)	(3.12%)	(0.10%)	(9.65%)	(0.21%)
	02 Mar 1994 – 31 Oct 2003	18/2523	(12.73%)	(47.06%)	(11.77%)	(0.78%)	(9.20%)	(0.60%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.9(f) – Hong Kong HSI Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

Table 6.10 – Germany DAX 30 Backtest Results

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	01 Jan 1973 – 31 Dec 2015	196/11218	(0.00%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.10(a) – Germany DAX 30 Backtest Results for RiskMetrics

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	01 Jan 1973 – 31 Dec 2015	54/11218	(0.00%)	(0.87%)	(2.85%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.10(b) – Germany DAX 30 Backtest Results for RiskMetrics2006

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Mar 1981 – 28 Feb 1983	11/521	(2.65%)	(49.94%)	(49.05%)	(24.29%)	(6.71%)	(9.48%)
	01 Nov 1983 – 31 Oct 1985	11/523	(2.72%)	(2.89%)	(49.13%)	(1.79%)	(6.87%)	(0.58%)
	01 Aug 1995 – 31 Jul 1997	10/523	(6.26%)	(41.20%)	(53.20%)	(12.42%)	(14.53%)	(6.69%)
Bubble Periods	01 Mar 1983 – 01 Mar 1984	4/263	(43.04%)	(0.24%)	(76.06%)	(0.43%)	(69.96%)	(0.74%)
	01 Nov 1985 – 01 Jun 1986	3/151	(28.27%)	(8.92%)	(72.64%)	(12.15%)	(52.82%)	(13.81%)
	01 Aug 1997 – 01 Sept 1997	1/22	(22.12%)	(15.42%)	(75.18%)	(15.42%)	(45.01%)	(17.14%)
Post-burst Periods	02 Mar 1984 – 01 Mar 1986	9/521	(13.04%)	(49.94%)	(57.34%)	(16.85%)	(27.19%)	(12.63%)
	02 Jun 1986 – 01 Jun 1988	12/523	(1.09%)	(63.49%)	(26.94%)	(0.00%)	(2.13%)	(0.00%)
	02 Sept 1997 – 01 Sept 1999	12/522	(1.07%)	(40.10%)	(27.00%)	(0.28%)	(2.10%)	(0.05%)
Periods between Bubbles	02 Mar 1984 – 31 Oct 1985	8/435	(11.54%)	(49.94%)	(58.36%)	(11.66%)	(24.91%)	(8.19%)
	02 Jun 1986 – 31 Jul 1997	45/2914	(0.62%)	(63.49%)	(19.29%)	(0.00%)	(1.02%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.10(c) – Germany DAX 30 Backtest Results for RiskMetrics: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Mar 1981 – 28 Feb 1983	3/521	(29.04%)	(65.67%)	(85.20%)	(52.72%)	(56.20%)	(50.24%)
	01 Nov 1983 – 31 Oct 1985	3/523	(28.68%)	(76.36%)	(85.23%)	(71.41%)	(55.73%)	(64.49%)
	01 Aug 1995 – 31 Jul 1997	6/523	(74.09%)	(41.20%)	(70.87%)	(89.10%)	(88.30%)	(93.44%)
Bubble Periods	01 Mar 1983 – 01 Mar 1984	1/263	(24.77%)	(28.31%)	(93.02%)	(28.31%)	(51.07%)	(28.81%)
	01 Nov 1985 – 01 Jun 1986	1/151	(65.67%)	(8.92%)	(90.78%)	(8.92%)	(89.99%)	(21.36%)
	01 Aug 1997 – 01 Sept 1997	1/22	(22.12%)	(15.42%)	(75.18%)	(15.42%)	(45.01%)	(17.14%)
Post-burst Periods	02 Mar 1984 – 01 Mar 1986	3/521	(29.04%)	(29.85%)	(85.20%)	(77.73%)	(56.20%)	(69.60%)
	02 Jun 1986 – 01 Jun 1988	4/523	(57.28%)	(61.38%)	(80.37%)	(28.35%)	(82.71%)	(37.41%)
	02 Sept 1997 – 01 Sept 1999	3/522	(28.86%)	(40.10%)	(85.21%)	(7.55%)	(55.96%)	(9.10%)
Periods between Bubbles	02 Mar 1984 – 31 Oct 1985	2/435	(20.52%)	(29.85%)	(89.18%)	(57.92%)	(44.41%)	(44.07%)
	02 Jun 1986 – 31 Jul 1997	19/2914	(4.38%)	(61.38%)	(11.34%)	(4.24%)	(3.74%)	(2.08%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.10(d) – Germany DAX 30 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Apr 1974 – 31 Mar 1976	1/523	(2.28%)	(17.62%)	(95.06%)	(17.62%)	(7.47%)	(3.00%)
	01 Nov 1991 – 31 Oct 1993	5/521	(92.58%)	(71.43%)	(3.27%)	(7.02%)	(10.19%)	(11.68%)
Bubble Periods	01 Apr 1976 – 01 Jun 1986	48/2652	(0.02%)	(19.87%)	(88.89%)	(0.22%)	(0.08%)	(0.01%)
	01 Nov 1993 – 01 Sept 1997	19/1001	(1.11%)	(3.84%)	(39.09%)	(7.56%)	(2.75%)	(2.07%)
Post-burst Periods	02 Jun 1986 – 01 Jun 1988	12/523	(1.09%)	(63.49%)	(26.94%)	(0.00%)	(2.13%)	(0.00%)
	02 Nov 1993 – 01 Nov 1995	10/522	(6.19%)	(2.89%)	(53.16%)	(10.82%)	(14.39%)	(5.76%)
Periods between Bubbles	02 Jun 1986 – 31 Oct 1993	27/1935	(9.91%)	(63.49%)	(5.67%)	(0.00%)	(4.17%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.10(e) – Germany DAX 30 Backtest Results for RiskMetrics: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	01 Apr 1974 – 31 Mar 1976	1/523	(2.28%)	(17.62%)	(95.06%)	(17.62%)	(7.47%)	(3.00%)
	01 Nov 1991 – 31 Oct 1993	3/521	(29.04%)	(48.71%)	(0.87%)	(1.86%)	(1.83%)	(2.54%)
Bubble Periods	01 Apr 1976 – 01 Jun 1986	10/2652	(0.02%)	(76.36%)	(78.32%)	(5.99%)	(0.11%)	(0.10%)
	01 Nov 1993 – 01 Sept 1997	9/1001	(74.41%)	(57.83%)	(68.60%)	(97.78%)	(87.37%)	(98.74%)
Post-burst Periods	02 Jun 1986 – 01 Jun 1988	4/523	(57.28%)	(61.38%)	(80.37%)	(28.35%)	(82.71%)	(37.41%)
	02 Nov 1993 – 01 Nov 1995	4/522	(57.57%)	(58.32%)	(80.35%)	(63.53%)	(82.90%)	(72.07%)
Periods between Bubbles	02 Jun 1986 – 31 Oct 1993	11/1935	(3.79%)	(61.38%)	(5.02%)	(1.05%)	(1.70%)	(0.41%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.10(f) – Germany DAX 30 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

Table 6.11 – The United Kingdom FTSE100 Backtest Results

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	01 Jan 1986 – 31 Dec 2015	151/7826	(0.00%)	(1.32%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.11(a) – The United Kingdom FTSE100 Backtest Results for RiskMetrics

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	01 Jan 1986 – 31 Dec 2015	43/7826	(0.00%)	(0.03%)	(23.92%)	(0.02%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.11(b) – The United Kingdom FTSE100 Backtest Results for RiskMetrics2006

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Aug 1995 – 31 Jul 1997	10/523	(6.26%)	(41.20%)	(53.20%)	(63.10%)	(14.53%)	(40.68%)
Bubble Periods	01 Aug 1997 – 01 Sept 1998	8/283	(1.15%)	(9.98%)	(49.43%)	(18.55%)	(3.26%)	(3.91%)
	01 Apr 1999 – 01 May 2000	4/283	(51.05%)	(13.22%)	(73.44%)	(35.13%)	(76.03%)	(43.32%)
Post-burst Period	02 May 2000 – 01 May 2002	10/522	(6.19%)	(99.20%)	(53.16%)	(1.64%)	(14.39%)	(0.84%)
Period between Bubbles	02 Sept 1998 – 31 Mar 1999	2/151	(70.26%)	(68.60%)	(81.62%)	(56.51%)	(90.49%)	(73.22%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Exclude the overlapped period

Table 6.11(c) – The United Kingdom FTSE100 Backtest Results for RiskMetrics: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Aug 1995 – 31 Jul 1997	3/523	(28.68%)	(34.99%)	(85.23%)	(56.13%)	(55.73%)	(52.68%)
Bubble Periods	01 Aug 1997 – 01 Sept 1998	3/283	(91.99%)	(9.98%)	(79.95%)	(36.08%)	(96.34%)	(52.22%)
	01 Apr 1999 – 01 May 2000	2/283	(60.07%)	(13.22%)	(86.58%)	(25.41%)	(85.96%)	(38.94%)
Post-burst Period	02 May 2000 – 01 May 2002	3/522	(28.86%)	(32.32%)	(85.21%)	(62.87%)	(55.96%)	(58.09%)
Period between Bubbles	02 Sept 1998 – 31 Mar 1999	0/151	(8.15%)	(65.67%)	(100.00%)	NA	(21.92%)	NA

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.11(d) – The United Kingdom FTSE100 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Original PSY method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Aug 1997 – 01 Sept 1997	1/22	(22.12%)	(9.98%)	(75.18%)	(9.98%)	(45.01%)	(12.21%)
	01 Oct 1997 – 01 Nov 1997	1/23	(23.25%)	(16.52%)	(75.76%)	(16.52%)	(46.74%)	(18.72%)
	01 Feb 1998 – 01 Sept 1998	5/152	(2.49%)	(64.59%)	(55.84%)	(16.97%)	(6.82%)	(4.64%)
	01 Mar 1999 – 01 Jun 1999	2/67	(18.70%)	(38.99%)	(72.37%)	(27.70%)	(39.33%)	(23.00%)
	01 Jul 1999 – 01 Aug 1999	1/22	(22.12%)	(21.00%)	(75.18%)	(21.00%)	(45.01%)	(21.56%)
	01 Jan 2000 – 01 Feb 2000	1/22	(22.12%)	(1.10%)	(75.18%)	(1.10%)	(45.01%)	(1.87%)
	01 Apr 2000 – 01 May 2000	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	01 Oct 2002 – 01 Nov 2002	0/24	(48.73%)	(24.37%)	(100.00%)	NA	(78.57%)	NA
	01 Oct 2008 – 01 Dec 2008	2/44	(8.36%)	(2.89%)	(65.86%)	(0.85%)	(20.31%)	(0.58%)
	01 Mar 2009 – 01 Apr 2009	1/23	(23.25%)	(0.24%)	(100.00%)	(0.24%)	(49.02%)	(0.49%)
Periods between Bubbles	02 Sept 1997 – 30 Sept 1997	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Nov 1997 – 31 Jan 1998	1/65	(68.60%)	(36.76%)	(85.86%)	(36.76%)	(90.70%)	(61.40%)
	02 Sept 1998 – 28 Feb 1999	2/128	(55.45%)	(68.60%)	(80.03%)	(56.51%)	(81.33%)	(68.44%)
	02 Jun 1999 – 30 Jun 1999	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Aug 1999 – 31 Dec 1999	0/110	(13.70%)	(92.25%)	(100.00%)	NA	(33.10%)	NA
	02 Feb 2000 – 31 Mar 2000	0/43	(35.25%)	(45.60%)	(100.00%)	NA	(64.91%)	NA
	02 May 2000 – 30 Sept 2002	15/630	(0.31%)	(99.20%)	(39.19%)	(0.13%)	(0.87%)	(0.01%)
	02 Nov 2002 – 30 Sept 2008	35/1542	(0.00%)	(64.59%)	(24.23%)	(0.01%)	(0.00%)	(0.00%)
	02 Dec 2008 – 28 Feb 2009	1/64	(67.60%)	(33.39%)	(85.75%)	(33.39%)	(90.17%)	(57.46%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.11(e) – The United Kingdom FTSE100 Backtest Results for RiskMetrics: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Aug 1997 – 01 Sept 1997	1/22	(22.12%)	(9.98%)	(75.18%)	(9.98%)	(45.01%)	(12.21%)
	01 Oct 1997 – 01 Nov 1997	1/23	(23.25%)	(16.52%)	(75.76%)	(16.52%)	(46.74%)	(18.72%)
	01 Feb 1998 – 01 Sept 1998	1/152	(65.12%)	(64.59%)	(90.81%)	(64.59%)	(89.69%)	(81.24%)
	01 Mar 1999 – 01 Jun 1999	1/67	(70.57%)	(38.99%)	(86.08%)	(38.99%)	(91.70%)	(64.34%)
	01 Jul 1999 – 01 Aug 1999	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	01 Jan 2000 – 01 Feb 2000	1/22	(22.12%)	(1.10%)	(75.18%)	(1.10%)	(45.01%)	(1.87%)
	01 Apr 2000 – 01 May 2000	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	01 Oct 2002 – 01 Nov 2002	0/24	(48.73%)	(24.37%)	(100.00%)	NA	(78.57%)	NA
	01 Oct 2008 – 01 Dec 2008	2/44	(8.36%)	(2.89%)	(65.86%)	(0.85%)	(20.31%)	(0.58%)
	01 Mar 2009 – 01 Apr 2009	0/23	(49.65%)	(23.25%)	(100.00%)	NA	(79.36%)	NA
Periods between Bubbles	02 Sept 1997 – 30 Sept 1997	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Nov 1997 – 31 Jan 1998	0/65	(25.30%)	(68.60%)	(100.00%)	NA	(52.03%)	NA
	02 Sept 1998 – 28 Feb 1999	0/128	(10.87%)	(79.59%)	(100.00%)	NA	(27.63%)	NA
	02 Jun 1999 – 30 Jun 1999	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	02 Aug 1999 – 31 Dec 1999	0/110	(13.70%)	(92.25%)	(100.00%)	NA	(33.10%)	NA
	02 Feb 2000 – 31 Mar 2000	0/43	(35.25%)	(45.60%)	(100.00%)	NA	(64.91%)	NA
	02 May 2000 – 30 Sept 2002	4/630	(32.36%)	(32.32%)	(82.10%)	(67.42%)	(59.88%)	(65.23%)
	02 Nov 2002 – 30 Sept 2008	12/1542	(36.24%)	(94.25%)	(66.43%)	(3.41%)	(60.12%)	(3.99%)
	02 Dec 2008 – 28 Feb 2009	0/64	(25.67%)	(67.60%)	(100.00%)	NA	(52.56%)	NA

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.11(f) – The United Kingdom FTSE100 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Feb 1986 – 31 Jan 1988	0/520	(0.12%)	(2.34%)	(100.00%)	NA	(0.54%)	NA
Bubble Periods	01 Feb 1988 – 01 May 2000	53/3196	(0.06%)	(41.20%)	(18.12%)	(61.21%)	(0.12%)	(23.47%)
	01 Nov 2003 – 01 Apr 2009	37/1413	(0.00%)	(67.60%)	(34.39%)	(0.00%)	(0.00%)	(0.00%)
Post-burst Period	02 May 2000 – 01 May 2002	10/522	(6.19%)	(99.20%)	(53.16%)	(1.64%)	(14.39%)	(0.84%)
Period between Bubbles	02 May 2000 – 31 Oct 2003	17/914	(1.96%)	(99.20%)	(42.19%)	(0.25%)	(4.75%)	(0.07%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.11(g) – The United Kingdom FTSE100 Backtest Results for RiskMetrics: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Feb 1986 – 31 Jan 1988	0/520	(0.12%)	(2.34%)	(100.00%)	NA	(0.54%)	NA
Bubble Periods	01 Feb 1988 – 01 May 2000	17/3196	(0.35%)	(4.67%)	(66.98%)	(60.51%)	(1.28%)	(17.59%)
	01 Nov 2003 – 01 Apr 2009	13/1413	(75.94%)	(95.09%)	(62.30%)	(1.57%)	(84.56%)	(2.34%)
Post-burst Period	02 May 2000 – 01 May 2002	3/522	(28.86%)	(32.32%)	(85.21%)	(62.87%)	(55.96%)	(58.09%)
Period between Bubbles	02 May 2000 – 31 Oct 2003	5/914	(13.22%)	(32.32%)	(81.45%)	(71.77%)	(31.32%)	(52.45%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.11(h) – The United Kingdom FTSE100 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

Table 6.12 – Spain IBEX 35 Backtest Results

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	03 Mar 1987 – 31 Dec 2015	136/7523	(0.00%)	(0.49%)	(1.53%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.12(a) – Spain IBEX 35 Backtest Results for RiskMetrics

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	03 Mar 1987 – 31 Dec 2015	48/7523	(0.07%)	(0.49%)	(31.75%)	(0.13%)	(0.20%)	(0.01%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.12(b) – Spain IBEX 35 Backtest Results for RiskMetrics2006

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Feb 1995 – 31 Jan 1997	10/523	(6.26%)	(25.50%)	(53.20%)	(31.49%)	(14.53%)	(18.08%)
Bubble Period	01 Feb 1997 – 01 Sept 1998	10/412	(1.38%)	(85.02%)	(23.09%)	(0.15%)	(2.36%)	(0.03%)
Post-burst Period	02 Sept 1998 – 01 Sept 2000	8/523	(25.88%)	(5.82%)	(10.37%)	(0.90%)	(14.07%)	(1.01%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.12(c) – Spain IBEX 35 Backtest Result for RiskMetrics: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Feb 1995 – 31 Jan 1997	4/523	(57.28%)	(56.85%)	(80.37%)	(79.08%)	(82.71%)	(84.67%)
Bubble Period	01 Feb 1997 – 01 Sept 1998	3/412	(56.00%)	(46.65%)	(83.36%)	(89.21%)	(82.54%)	(91.60%)
Post-burst Period	02 Sept 1998 – 01 Sept 2000	3/523	(28.68%)	(5.82%)	(85.23%)	(18.49%)	(55.73%)	(20.20%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.12(d) – Spain IBEX 35 Backtest Result for RiskMetrics2006: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Oct 1990 – 01 Nov 1990	0/24	(48.73%)	(24.37%)	(100.00%)	NA	(78.57%)	NA
	01 Feb 1994 – 01 Mar 1994	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	01 Feb 1997 – 01 Aug 1997	1/130	(78.28%)	(85.02%)	(90.05%)	(85.02%)	(95.52%)	(94.57%)
	01 Oct 1997 – 01 Nov 1997	3/23	(0.14%)	(5.82%)	(33.76%)	(0.15%)	(0.38%)	(0.00%)
	01 Feb 1998 – 01 Sept 1998	6/152	(0.57%)	(62.55%)	(48.10%)	(1.09%)	(1.70%)	(0.10%)
	01 Feb 2000 – 01 Apr 2000	0/44	(34.70%)	(46.69%)	(100.00%)	NA	(64.26%)	NA
	01 Mar 2009 – 01 Apr 2009	0/23	(49.65%)	(23.25%)	(100.00%)	NA	(79.36%)	NA
Periods between Bubbles	02 Nov 1990 – 31 Jan 1994	12/847	(25.13%)	(53.16%)	(15.71%)	(5.86%)	(19.03%)	(5.87%)
	02 Mar 1994 – 31 Jan 1997	12/763	(14.23%)	(24.37%)	(53.55%)	(40.22%)	(28.13%)	(32.59%)
	02 Aug 1997 – 30 Sept 1997	0/42	(35.82%)	(44.51%)	(100.00%)	NA	(65.57%)	NA
	02 Nov 1997 – 31 Jan 1998	0/65	(25.30%)	(68.60%)	(100.00%)	NA	(52.03%)	NA
	02 Sept 1998 – 01 Jan 2000	6/348	(21.83%)	(5.82%)	(64.59%)	(9.09%)	(42.18%)	(8.71%)
	02 Apr 2000 – 28 Feb 2009	46/2325	(0.00%)	(74.48%)	(31.20%)	(0.01%)	(0.01%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.12(e) – Spain IBEX35 Backtest Result for RiskMetrics: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Oct 1990 – 01 Nov 1990	0/24	(48.73%)	(24.37%)	(100.00%)	NA	(78.57%)	NA
	01 Feb 1994 – 01 Mar 1994	0/21	(51.59%)	(21.00%)	(100.00%)	NA	(80.97%)	NA
	01 Feb 1997 – 01 Aug 1997	0/130	(10.60%)	(78.28%)	(100.00%)	NA	(27.08%)	NA
	01 Oct 1997 – 01 Nov 1997	1/23	(23.25%)	(18.75%)	(75.76%)	(18.75%)	(46.74%)	(20.57%)
	01 Feb 1998 – 01 Sept 1998	2/152	(70.90%)	(62.55%)	(81.68%)	(87.81%)	(90.80%)	(94.04%)
	01 Feb 2000 – 01 Apr 2000	0/44	(34.70%)	(46.69%)	(100.00%)	NA	(64.26%)	NA
	01 Mar 2009 – 01 Apr 2009	0/23	(49.65%)	(23.25%)	(100.00%)	NA	(79.36%)	NA
Periods between Bubbles	02 Nov 1990 – 31 Jan 1994	3/847	(2.93%)	(40.60%)	(88.38%)	(21.58%)	(9.21%)	(5.61%)
	02 Mar 1994 – 31 Jan 1997	6/763	(53.78%)	(24.37%)	(75.76%)	(70.20%)	(78.87%)	(75.74%)
	02 Aug 1997 – 30 Sept 1997	0/42	(35.82%)	(44.51%)	(100.00%)	NA	(65.57%)	NA
	02 Nov 1997 – 31 Jan 1998	0/65	(25.30%)	(68.60%)	(100.00%)	NA	(52.03%)	NA
	02 Sept 1998 – 01 Jan 2000	2/348	(38.62%)	(5.82%)	(87.90%)	(16.51%)	(67.91%)	(22.58%)
	02 Apr 2000 – 28 Feb 2009	17/2325	(17.13%)	(15.38%)	(61.67%)	(1.06%)	(34.60%)	(0.92%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.12(f) – Spain IBEX35 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	03 Mar 1987# – 31 Oct 1987	0/174	(6.15%)	(54.01%)	(100.00%)	NA	(17.40%)	NA
	01 Aug 2002 – 31 Jul 2004	7/522	(45.67%)	(79.59%)	(66.24%)	(34.16%)	(68.92%)	(39.05%)
Bubble Periods	01 Nov 1987 – 01 Apr 2000	52/3240	(0.15%)	(2.55%)	(1.02%)	(0.00%)	(0.02%)	(0.00%)
	01 Aug 2004 – 01 Apr 2009	28/1218	(0.01%)	(3.84%)	(67.37%)	(0.07%)	(0.05%)	(0.00%)
Post-burst Periods	02 Apr 2000 – 01 Apr 2002	8/521	(25.48%)	(74.48%)	(10.42%)	(0.22%)	(13.96%)	(0.25%)
	02 Apr 2009 – 01 Apr 2011	8/522	(25.68%)	(39.55%)	(61.74%)	(7.82%)	(46.40%)	(7.99%)
Period between Bubbles	02 Apr 2000 – 31 Jul 2004	18/1130	(6.52%)	(74.48%)	(28.79%)	(0.88%)	(10.38%)	(0.49%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Due to data availability, period trimmed from 01 Nov 1985 – 31 Oct 1987 to 03 Mar 1987 – 31 Aug 1987

Table 6.12(g) – Spain IBEX35 Backtest Results for RiskMetrics: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Periods	03 Mar 1987# – 31 Oct 1987	0/174	(6.15%)	(54.01%)	(100.00%)	NA	(17.40%)	NA
	01 Aug 2002 – 31 Jul 2004	1/522	(2.30%)	(5.78%)	(95.05%)	(5.78%)	(7.53%)	(1.25%)
Bubble Periods	01 Nov 1987 – 01 Apr 2000	20/3240	(1.85%)	(2.55%)	(11.32%)	(7.71%)	(1.78%)	(2.74%)
	01 Aug 2004 – 01 Apr 2009	13/1218	(81.53%)	(49.14%)	(59.62%)	(19.56%)	(84.56%)	(24.90%)
Post-burst Periods	02 Apr 2000 – 01 Apr 2002	3/521	(29.04%)	(15.38%)	(85.20%)	(5.32%)	(56.20%)	(6.65%)
	02 Apr 2009 – 01 Apr 2011	3/522	(28.86%)	(35.92%)	(85.21%)	(14.60%)	(55.96%)	(16.44%)
Period between Bubbles	02 Apr 2000 – 31 Jul 2004	4/1130	(1.18%)	(15.38%)	(86.61%)	(0.47%)	(4.14%)	(0.07%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Due to data availability, period trimmed from 01 Nov 1985 – 31 Oct 1987 to 03 Mar 1987 – 31 Aug 1987

Table 6.12(h) – Spain IBEX35 Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

Table 6.13 – Canada S&P/TSX Composite Backtest Results

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	03 Jul 1973 – 31 Dec 2015	248/11088	(0.00%)	(1.10%)	(0.00%)	(0.00%)	(0.00%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.13(a) – Canada S&P/TSX Composite Backtest Results for RiskMetrics

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Full Period	03 Jul 1973 – 31 Dec 2015	92/11088	(6.34%)	(0.10%)	(79.43%)	(0.00%)	(17.25%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.13(b) – Canada S&P/TSX Composite Backtest Results for RiskMetrics2006

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Jan 1995 – 31 Dec 1996	10/522	(6.19%)	(80.92%)	(53.16%)	(30.11%)	(14.39%)	(17.13%)
Bubble Period	01 Jan 1997 – 01 Feb 1998	5/283	(24.21%)	(55.28%)	(67.09%)	(6.96%)	(46.09%)	(7.21%)
Post-burst Period	02 Feb 1998 – 01 Feb 2000	15/522	(0.05%)	(63.57%)	(44.30%)	(0.07%)	(0.16%)	(0.00%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.13(c) – Canada S&P/TSX Backtest Results for RiskMetrics: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	01 Jan 1995 – 31 Dec 1996	4/522	(57.57%)	(39.21%)	(80.35%)	(94.55%)	(82.90%)	(95.76%)
Bubble Period	01 Jan 1997 – 01 Feb 1998	3/283	(91.99%)	(65.60%)	(79.95%)	(86.87%)	(96.34%)	(94.77%)
Post-burst Period	02 Feb 1998 – 01 Feb 2000	8/522	(25.68%)	(84.69%)	(61.74%)	(15.89%)	(46.40%)	(15.74%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.13(d) – Canada S&P/TSX Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Original PSY Method

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Apr 1987 – 01 May 1987	2/23	(2.19%)	(8.92%)	(52.67%)	(5.02%)	(5.92%)	(1.05%)
	01 Aug 1987 – 01 Oct 1987	1/44	(46.69%)	(27.76%)	(82.73%)	(27.76%)	(74.95%)	(42.57%)
	01 Jun 1993 – 01 May 1994	7/239	(1.50%)	(28.89%)	(18.35%)	(1.70%)	(2.15%)	(0.34%)
	01 Dec 1996 – 01 Apr 1997	4/87	(1.38%)	(2.89%)	(53.21%)	(1.35%)	(3.98%)	(0.22%)
	01 Jul 1997 – 01 Dec 1997	2/110	(43.90%)	(85.58%)	(78.45%)	(3.90%)	(71.41%)	(6.91%)
	01 Jan 1998 – 01 Feb 1998	1/22	(22.12%)	(5.82%)	(75.18%)	(5.82%)	(45.01%)	(7.86%)
	01 Mar 1998 – 01 Aug 1998	6/110	(0.10%)	(42.31%)	(30.65%)	(0.15%)	(0.27%)	(0.00%)
	01 Jan 2000 – 01 Dec 2000	8/240	(0.42%)	(1.10%)	(45.66%)	(0.91%)	(1.26%)	(0.08%)
Periods between Bubbles	02 May 1987 – 31 Jul 1987	0/65	(25.30%)	(68.60%)	(100.00%)	NA	(52.03%)	NA
	02 Oct 1987 – 31 May 1993	32/1477	(0.01%)	(1.98%)	(0.43%)	(0.01%)	(0.00%)	(0.00%)
	02 May 1994 – 30 Nov 1996	12/675	(6.72%)	(37.87%)	(50.95%)	(18.76%)	(15.07%)	(11.04%)
	02 Apr 1997 – 30 Jun 1997	0/64	(25.67%)	(67.60%)	(100.00%)	NA	(52.56%)	NA
	02 Dec 1997 – 31 Dec 1997	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	02 Feb 1998 – 28 Feb 1998	0/20	(52.61%)	(19.87%)	(100.00%)	NA	(81.79%)	NA
	02 Aug 1998 – 31 Dec 1999	7/370	(12.48%)	(1.10%)	(60.28%)	(1.30%)	(26.89%)	(0.98%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.13(e) – Canada S&P/TSX Backtest Results for RiskMetrics: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Bubble Periods	01 Apr 1987 – 01 May 1987	1/23	(23.25%)	(18.75%)	(75.76%)	(18.75%)	(46.74%)	(20.57%)
	01 Aug 1987 – 01 Oct 1987	1/44	(46.69%)	(27.76%)	(82.73%)	(27.76%)	(74.95%)	(42.57%)
	01 Jun 1993 – 01 May 1994	4/239	(33.99%)	(28.89%)	(71.15%)	(65.79%)	(59.22%)	(64.82%)
	01 Dec 1996 – 01 Apr 1997	2/87	(29.77%)	(6.83%)	(75.76%)	(18.34%)	(55.44%)	(21.44%)
	01 Jul 1997 – 01 Dec 1997	1/110	(92.25%)	(87.36%)	(89.18%)	(87.36%)	(98.61%)	(98.28%)
	01 Jan 1998 – 01 Feb 1998	1/22	(22.12%)	(5.82%)	(75.18%)	(5.82%)	(45.01%)	(7.86%)
	01 Mar 1998 – 01 Aug 1998	2/110	(43.90%)	(65.60%)	(78.45%)	(29.15%)	(71.41%)	(38.19%)
	01 Jan 2000 – 01 Dec 2000	3/240	(70.79%)	(1.10%)	(78.24%)	(8.34%)	(89.73%)	(14.65%)
Periods between Bubbles	02 May 1987 – 31 Jul 1987	0/65	(25.30%)	(68.60%)	(100.00%)	NA	(52.03%)	NA
	02 Oct 1987 – 31 May 1993	11/1477	(30.18%)	(1.98%)	(6.82%)	(0.25%)	(11.12%)	(0.30%)
	02 May 1994 – 30 Nov 1996	4/675	(24.96%)	(90.76%)	(82.70%)	(82.71%)	(50.33%)	(72.73%)
	02 Apr 1997 – 30 Jun 1997	0/64	(25.67%)	(67.60%)	(100.00%)	NA	(52.56%)	NA
	02 Dec 1997 – 31 Dec 1997	0/22	(50.61%)	(22.12%)	(100.00%)	NA	(80.16%)	NA
	02 Feb 1998 – 28 Feb 1998	0/20	(52.61%)	(19.87%)	(100.00%)	NA	(81.79%)	NA
	02 Aug 1998 – 31 Dec 1999	5/370	(51.91%)	(1.10%)	(71.09%)	(1.62%)	(75.84%)	(2.62%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Table 6.13(f) – Canada S&P/TSX Backtest Results for RiskMetrics2006: Bubbles Date-stamped by PSY Method Without Minimum Bubble Duration Limit

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	03 Jul 1973 – 30 Nov 1973	0/109	(13.88%)	(93.00%)	(100.00%)	NA	(33.44%)	NA
Bubble Period	01 Dec 1973 – 01 Dec 2000	150/7045	(0.00%)	(3.07%)	(0.17%)	(0.00%)	(0.00%)	(0.00%)
Post-burst Period	02 Dec 2000 – 01 Dec 2002	9/520	(12.92%)	(22.12%)	(0.67%)	(0.01%)	(0.80%)	(0.01%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Due to data availability, period trimmed from 01 Dec 1971 – 30 Nov 1973 to 03 Jul 1973 – 30 Nov 1973

Table 6.13(g) – Canada S&P/TSX Backtest Result for RiskMetrics: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

			Coverage Tests		Independence Tests		Joint Tests	
	Period	Violations/ Observations	POF	TUFF	Christoff-ersen	Mixed-Kupiec	Christoff-ersen	Mixed-Kupiec
Pre-burst Period	03 Jul 1973 – 30 Nov 1973	0/109	(13.88%)	(93.00%)	(100.00%)	NA	(33.44%)	NA
Bubble Period	01 Dec 1973 – 01 Dec 2000	60/7045	(19.91%)	(0.27%)	(54.15%)	(0.04%)	(36.40%)	(0.04%)
Post-burst Period	02 Dec 2000 – 01 Dec 2002	2/520	(10.70%)	(58.43%)	(90.10%)	(79.04%)	(27.07%)	(38.12%)

* The numbers in parentheses are the p-values for rejecting the null hypothesis

Due to data availability, period trimmed from 01 Dec 1971 – 30 Nov 1973 to 03 Jul 1973 – 30 Nov 1973

Table 6.13(h) – Canada S&P/TSX Backtest Results for RiskMetrics2006: Bubbles Date-stamped by Modified PSY Approach with Bubble Origination Date Defined as the Start of the BADF Tests Sampling Window

Chapter 7. Conclusions

7.1 Summary and Main Findings

This chapter summarizes the entire thesis and offers suggestions for future research. This thesis aimed to study the reliability of different VaR approaches in periods with and without asset price bubbles, particular in the crisis period that before and after the bubbles burst. Furthermore, it also proposed a new simulation model that can be used to generate daily asset prices with periodically collapsing explosive bubbles, which is important for improving the effectiveness of various risk management tools.

The document consists of four main empirical chapters. Chapter 3 examined how information spills over among different stock markets and the Chinese stock market's degree of influence in last two decades. Based on the trading hours and market capitalization of different stock exchanges, the nine countries included in our study were Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil. We used the trading hours of the exchanges to classify these countries into three zones and modelled the information spillover directions in a cyclical manner. We examined the spillover effect using the following multivariate GARCH models: the CCC model, Engle (2002) DCC model, and Cappiello *et al.* (2006) ADCC model. The LR tests suggested that the asymmetric GJR-GARCH-DCC model is the best for describing market behaviour. This chapter provided strong evidence of crises across countries; the international financial markets are contagions, while equity markets reflect bad news on volatility but not on correlations. Furthermore, our results showed that the Chinese stock market's influential power on the rest of the world has been gradually increasing in the last two decades.

In Chapter 4, we extensively studied both the parametric and non-parametric VaR approaches using real data. The non-parametric approaches include HS; the univariate parametric approaches include MA, EWMA (RiskMetrics), long memory EWMA (EWMA2006 or RiskMetrics2006), GARCH, GJR-GARCH, and FIGARCH; and the multivariate parametric approaches include DCC, GJR-DCC, ADCC, and GJR-ADCC. We constructed 18 hypothetic portfolios that included nine single-asset and nine multiple-asset portfolios for testing both the univariate and multivariate VaRs. The sub-prime mortgage crisis period was defined from 01 June 2008 to 01 June 2009, while the after-crisis period was defined as 01 June 2009 to 31 December 2012. The empirical results showed that the univariate RiskMetrics2006 approach works well in calculating a single-asset portfolio's VaR. Meanwhile, the multivariate GJR-DCC model that incorporates asymmetric volatility effect in equity markets works well for estimating VaR for multiple-asset portfolios.

Chapter 5 studied the characteristics of financial asset price bubbles using simulation models. We proposed a simulation model that provides a mechanism to simulate daily asset price series with periodically collapsing bubbles. Our model overcomes the weakness of the previous works in two main ways. First, we introduced using an inverse logistics function to model the market's speculative sentiment level in the bubble formation process. Unlike previous work, our simulated asset prices exhibited time-varying volatility clustering, which is more realistic. Second, the rational bubbles were controlled by a time-varying Bernoulli process that allowed bubbles to collapse gradually but not in a single observation. These improvements enabled our model to deliver more stable and realistic results than in previous studies. We applied our simulation model to test the reliability of different VaR estimates. Among the four commonly used approaches of HS, MA, RiskMetrics, and RiskMetrics2006, the RiskMetrics approach outperformed others and did well in the periods before and after the bubbles burst. Our results showed that the criticism that VaR is a flawed risk measure if asset price bubbles present is statistically invalid.

Finally, in Chapter 6 we identified the origination and termination dates of financial bubbles in real data using Phillips *et al.* (2015) GSADF and BSADF tests. Our empirical tests covered six countries (Hong Kong, Germany, the United Kingdom, Spain, the United States, and Canada) over the period March 1987 to January 2014. We date-stamped the bubble origination and termination dates by applying the GSADF and BSADF tests on the log price-dividend ratios of the six markets. As the original BSADF test is forward looking, we modified the date-stamping strategy to make it more suitable for the VaR backtests. The results show that the RiskMetrics2006 model works well in both the before- and after-burst periods, while it tends to overstate downside risks in normal periods without bubbles. Our empirical tests showed that criticisms that VaR models are unable to capture large financial loss during financial turmoil are statistically invalid.

7.2 Conclusion

This study responds to the criticism that the Value-at-Risk (VaR) measure fails in financial crises and the myth that VaR is only applicable during periods without asset price bubbles. We modify and apply the backward SADF test to date-stamp the origination and termination dates of the asset price bubbles of six countries, namely Hong Kong, Germany, the United Kingdom, Spain, the United States, and Canada. The empirical backtesting results presented herein show that both the RiskMetrics model and the RiskMetrics2006 model work well in the periods with and without asset price bubbles. The results of our empirical tests thus show that the criticism of VaR models failing in crisis periods is statistically invalid. The Basel III committee responded to the criticism of the failure of VaR after the sub-prime mortgage crisis by simply shifting the VaR measure to an Expected Shortfall (ES) may not improve the effectiveness of the downside risk measure. The effectiveness of both VaR and ES depends on the volatility model they adopted. As our findings show that VaR performs well in crisis and non-crisis periods, it is suggested that regulators may consider to stress the practitioners to adopt the long-memory Riskmetrics2006 as the internal volatility model, rather than simply replace the VaR measure with the ES for internal model-based approach in managing the market risk.

Another important contribution our study made is that we proposed a simulation model for simulating daily asset price series with periodically collapsing asset price bubble. Our model overcomes the weakness of the previous works in: (1) The simulated asset price in our model exhibits time-varying asymmetric volatility clustering, which is more realistic (see Bollerslev, 1986; John Y. Campbell and Hentschel, 1992). (2) The rational bubbles are controlled by a time-varying Bernoulli process that allows bubbles to collapse gradually but not in a single observation. The descriptive statistics show our model behaves similarly to the real data.

Portfolio managers and practitioners will benefit from our works in having a better model in modelling variations of an asset, allowing them to simulate the price of an asset and its derivatives. Compared our model to the traditional geometrical Brownian motion, our model can simulate an asset price series in a financial crisis with an unexpected plunge due to the collapse of rational asset price bubble, allowing them to make better investment decisions as well as to manage the risks more efficiently.

7.3 Further Research

The empirical findings of this thesis are based on market data for the nine selected countries of Japan, China, Hong Kong, Germany, the United Kingdom, Spain, the United States, Canada, and Brazil. Although these findings yield promising results, they could be made more accurate and comprehensive if additional work is conducted. The future direction of each chapter could be as described below.

Chapter 3 studied the information spillover effect by defining three time zones: Zone A (Japan, China, and Hong Kong); Zone B (the United Kingdom, Germany, and Spain); and Zone C (the United States, Canada, and Brazil). I believe further research should consider more countries in different zones.

Chapter 4 extensively reviewed different univariate and multivariate VaR approaches in a period when financial markets were experiencing crisis. However, we only studied the sub-prime mortgage crisis period of 1 June 2008 to 31 December 2012. We could further backtest the VaR models in different crisis periods, such as the dot-com bubble in 2001 and the Asian financial crisis in 1997.

Chapter 5 proposed a new simulation model for generating daily asset prices with periodically collapsing bubbles. We introduced using an absolute inverse logistics function to incorporate volatility clustering in the simulation series. However, we could further explore how to incorporate an asymmetric conditional variance model when generating asset price, as the impact on stock volatility is asymmetric between good and bad news.

Chapter 6 conducted empirical tests that used Phillips *et al.* (2015) SADF and BSADF tests on the stock log price-dividend ratio to identify the origin and termination dates of financial bubbles. However, due to the availability of dividend data, we only studied the market data from six countries. Future experiments involving more data coverage may provide more comprehensive and convincing results.

References

Acerbi, C. and Tasche, D. (2002) 'On the coherence of expected shortfall', *Journal of Banking & Finance*, 26(7), pp. 1487-1503.

Akigiray, V. (1989) 'Conditional Heteroskedasticity in Time Series of Stock Returns: Evidence and Forecasts', *Journal of Business*, 62(1), pp. 55-80.

Allen, D. E., McAleer, M., Powell, R. J. and Singh, A. K. (2013) *Volatility Spillovers from the US to Australia and China across the GFC*. [Online]. Available at: http://ideas.repec.org/p/dgr/uvatin/20130009.html.

Andrews, D. W. K. (1993) 'Tests for Parameter Instability and Structural Change With Unknown Change Point', *Econometrica*, 61(4), pp. 821-856.

Andrews, D. W. K. and Ploberger, W. (1994) 'Optimal Tests When a Nuisance Parameter Is Present Only under the Alternative', *Econometrica*, 62(6), pp. 1383-1414.

Arslanalp, S., Liao, W., Piao, S. and Seneviratne, D. (2016) *China's Growing Influence on Asian Financial Markets*. [Online]. Available at: http://EconPapers.repec.org/RePEc:imf:imfwpa:16/173.

Bae, K. H., Karolyi, G. A. and Stulz, R. M. (2003) 'A New Approach to Measuring Financial Contagion', *Review of Financial Studies*, 16(3), pp. 717-763.

Baillie, R. T., Bollerslev, T. and Mikkelsen, H. O. (1996) 'Fractionally integrated generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics*, 74(1), pp. 3-30.

Barone-Adesi, G., Giannopoulos, K. and Vosper, L. (1999) 'VaR without correlations for portfolios of derivative securities', *Journal of Futures Markets*, 19(5), pp. 583-602.

Blanchard, O. J. and Watson, M. W. (1982) *Bubbles, Rational Expectations and Financial Markets*. [Online]. Available at: http://www.nber.org/papers/w0945.

Bollerslev, T. (1986) 'Generalized autoregressive conditional heteroskedasticity', *Journal of Econometrics*, 31(3), pp. 307-327.

Bollerslev, T. (1990) 'Modelling the Coherence in Short-Run Nominal Exchange Rates: A

Multivariate Generalized Arch Model', *The review of economics and statistics*, 72(3), pp. pp. 498-505.

Campbell, J. Y. and Hentschel, L. (1992) 'No news is good news', *Journal of Financial Economics*, 31(3), pp. 281-318.

Campbell, J. Y. and Shiller, R. J. (1988) 'The dividend-price ratio and expectations of future dividends and discount factors', *Review of financial studies*, 1(3), pp. 195-288.

Cappiello, L., Engle, R. F. and Sheppard, K. (2006) 'Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns', *Journal of Financial Econometrics*, 4(4), pp. 537-572.

Chow, G. C. (1960) 'Tests of Equality Between Sets of Coefficients in Two Linear Regressions', *Econometrica*, 28(3), pp. 591-605.

Christie, A. A. (1982) 'The stochastic behavior of common stock variances: Value, leverage and interest rate effects', *Journal of Financial Economics*, 10(4), pp. 407-407.

Christoffersen, P. (2009) 'Value–at–Risk Models', in Mikosch, T., Kreiß, J.-P., Davis, R. A. and Andersen, T. G. (eds.) Springer Berlin Heidelberg, pp. 753-766.

Christoffersen, P. and Pelletier, D. (2004) 'Backtesting Value-at-Risk: A Duration-Based Approach', *Journal of Financial Econometrics*, 2(1), pp. 84-108.

Christoffersen, P. F. (1998) 'Evaluating Interval Forecasts', *International Economic Review*, 39(4), pp. 841-862.

Craine, R. (1993) 'Rational bubbles', *Journal of Economic Dynamics and Control*, 17(5), pp. 829-846.

Diba, B. T. and Grossman, H. I. (1988a) 'Explosive Rational Bubbles in Stock Prices?', *The American Economic Review*, 78(3), pp. 520-530.

Diba, B. T. and Grossman, H. I. (1988b) 'The theory of rational bubbles in stock prices', *The Economic Journal*, 98(392), pp. 746-754.

Dickey, D. A. and Fuller, W. A. (1979) 'Distribution of the estimators for autoregressive time series with a unit root', *Journal of the American Statistical Association*, 74(366a), pp. 427-431.

Drakos, A. A., Kouretas, G. P. and Zarangas, L. P. (2010) 'Forecasting financial volatility of the Athens stock exchange daily returns: an application of the asymmetric normal mixture GARCH model', *International Journal of Finance & Economics*, 15(4), pp. 331-350.

Engle, R. (2002) 'Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models', *Journal of Business & Economic Statistics*, 20(3), pp. 339-350.

Engle, R. F. (1982) 'Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation', *Econometrica*, 50(4), pp. 987-1007.

Engle, R. F. and Bollerslev, T. (1986) 'Modelling the persistence of conditional variances', 5(1), pp. 1-50.

Engle, R. F. and Kroner, K. F. (1995) 'Multivariate Simultaneous Generalized ARCH', *Econometric Theory*, 11(01), pp. 122-150.

Engle, R. F. and Ng, V. K. (1993) 'Measuring and Testing the Impact of News on Volatility', *Journal of Finance*, 48(5), pp. 1749-1778.

Eun, C. S. and Shim, S. (1989) 'International Transmission of Stock Market Movements', *The Journal of Financial and Quantitative Analysis*, 24(2), pp. 241-256.

Evans, G. W. (1991) 'Pitfalls in testing for explosive bubbles in asset prices', *The American Economic Review*, 81(4), pp. 922-930.

Forbes, K. J. and Rigobon, R. (2002) 'No Contagion, Only Interdependence: Measuring Stock Market Comovements', *The Journal of Finance*, 57(5), pp. 2223-2261.

Glosten, L. R., Jagannathan, R. and Runkle, D. E. (1993) *On the relation between the expected value and the volatility of the nominal excess return on stocks*. [Online]. Available at: http://ideas.repec.org/p/fip/fedmsr/157.html.

Granger, C. W. J. and Engle, R. F. (1987) 'Co-integration and error correction: representation, estimation, and testing', *Econometrica: journal of the Econometric Society*, 55(2), pp. 251-276.

Hall, S. G., Psaradakis, Z. and Sola, M. (1999) 'Detecting periodically collapsing bubbles: a Markov-switching unit root test', *Journal of Applied Econometrics*, 14(2), pp. 143-154.

Hamao, Y., Masulis, R. W. and Ng, V. (1990) 'Correlations in Price Changes and Volatility across International Stock Markets', *The Review of Financial Studies*, 3(2), pp. 281-307.

Hansen, B. E. (1995) *Approximate Asymptotic P-Values for Structural Change Tests*. [Online]. Available at: http://ideas.repec.org/p/boc/bocoec/297.html.

Hass, M. (2001) *New Methods in Backtesting*.

Jacobsen, B. and Dannenburg, D. (2003) 'Volatility clustering in monthly stock returns', *Journal of Empirical Finance*, 10, pp. 479-503.

Koutmos, G. and Booth, G. G. (1995) 'Asymmetric volatility transmission in international stock markets', *Journal of International Money and Finance*, 14(6), pp. 747-762.

Kuester, K., Mittnik, S. and Paolella, M. S. (2006) 'Value-at-Risk Prediction: A Comparison of Alternative Strategies', *Journal of Financial Econometrics*, 4(1), pp. 53-89.

Kupiec, P. H. (1995) *Techniques for verifying the accuracy of risk measurement models*. [Online]. Available at: http://ideas.repec.org/p/fip/fedgfe/95-24.html.

Linsmeier, T. J. and Pearson, N. D. (1996) *Risk measurement: an introduction to value at risk*. [Online]. Available at: http://ideas.repec.org/p/ags/uiucar/14796.html.

Longerstaey, J. and Spencer, M. (1996) *RiskMetrics, Technical Document*. [Online]. Available at: http://www.riskmetrics.com.

Luttrell, D., Atkinson, T. and Rosenblum, H. (2013) 'Assessing the Costs and Consequences of the 2007-09 Financial Crisis and Its Aftermath', *Economic Letter*, 8(7).

Lux, T. and Marchesi, M. (2000) 'Volatility Clustering in Financial Markets: A Microsimulation of Interacting Agents', *International Journal of Theoretical and Applied Finance*, 03(04), pp. 675-702.

Mandelbrot, B. (1963) 'The Variation of Certain Speculative Prices', *The Journal of Business*, 36(4), p. 394.

McMillan, D. G. (2007) 'Bubbles in the dividend–price ratio? Evidence from an asymmetric exponential smooth-transition model', *Journal of Banking & Finance*, 31(3), pp. 787-804.

Niu, H. and Wang, J. (2013) 'Volatility clustering and long memory of financial time series and financial price model', *Digital Signal Processing: A Review Journal*, 23(2), pp. 489-498.

Oanea, D.-C. and Anghelache, G. (2015) 'Value at Risk Prediction: The Failure of RiskMetrics in Preventing Financial Crisis. Evidence from Romanian Capital Market', *Procedia Economics and Finance*, 20, pp. 433-442.

Pafka, S. and Kondor, I. (2001) 'Evaluating the RiskMetrics methodology in measuring volatility and Value-at-Risk in financial markets', *Application of Physics in Economic Modelling*, 299(1), pp. 305-310.

Phillips, P. C. B., Shi, S. P. and Yu, J. (2013) 'Testing for multiple bubbles 1: Historical episodes of exuberance and collapse in the S&P 500'.

Phillips, P. C. B., Shi, S. P. and Yu, J. (2015) 'Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500', *International Economic Review*, 56(4), pp. 1043-1078.

Phillips, P. C. B., Wu, Y. and Yu, J. (2011) 'Explosive behavior in the 1990s Nasdaq: when did exuberance escalate asset values?', *International Economic Review*, 52(1), pp. 201-226.

Quandt, R. E. (1960) 'Tests of the Hypothesis that a Linear Regression System Obeys Two Separate Regimes', *Journal of the American Statistical Association*, 55(290), pp. 324-330.

Richardson, M. P., Boudoukh, J. and Whitelaw, R. F. (1997) 'The Best of Both Worlds: A Hybrid Approach to Calculating Value at Risk'.

Robert, V. (2011) *International Diversification During the Financial Crisis: A Blessing for Equity Investors?* [Online]. Available at: https://ideas.repec.org/p/dnb/dnbwpp/324.html.

Shi, S. P., Phillips, P. C. B. and Yu, J. (2011) 'Specification sensitivities in right-tailed unit root testing for financial bubbles', *SMU Economics & Statistics Working Paper ...*, (17).

Shiller, R. J. (1981) 'The Use of Volatility Measures in Assessing Market Efficiency*', *The Journal of Finance*, 36(2), pp. 291-304.

Sims, C. A. (1980) 'Macroeconomics and Reality', *Econometrica*, 48(1), pp. 1-48.

Sinha, T. and Chamu, F. (2000) 'Comparing Different Methods of Calculating Value at Risk', *SSRN Electronic Journal*, pp. 1-16.

Szerszen, J. O. B. a. P. J. (2014) *An Evaluation of Bank VaR Measures for Market Risk During and Before the Financial Crisis*. Washington, DC: Federal Reserve Board.

Tesar, L. L. and Werner, I. M. (1995) 'Home bias and high turnover', *Journal of International Money and Finance*, 14(4), pp. 467-492.

Zumbach, G. (2006) *A gentle introduction to the RM 2006 methodology*.

Zumbach, G. O. (2007) 'The Riskmetrics 2006 Methodology', *SSRN Electronic Journal*.