DOCTOR OF PHILOSOPHY

Multivariate GARCH and portfolio optimisation

a comparative study of the impact of applying alternative covariance methodologies

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Multivariate GARCH and portfolio optimisation: A comparative study of the impact of applying alternative covariance methodologies

By

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ABSTRACT

This thesis investigates the impact of applying different covariance modelling techniques on the efficiency of asset portfolio performance. The scope of this thesis is limited to the exploration of theoretical aspects of portfolio optimisation rather than developing a useful tool for portfolio managers. Future work may entail taking the results from this work further and producing a more practical tool from a fund management perspective.

The contributions made by this thesis to the knowledge of the subject are that it extends literature by applying a number of different covariance models to a unique dataset that focuses on the 2007 global financial crisis. The thesis also contributes to the literature as the methodology applied also enables a distinction to be made in respect to developed and emerging/frontier regional markets. This has resulted in the following findings:

First, it identifies the impact of the 2007–2009 financial crisis on time-varying correlations and volatilities as measured by the dynamic conditional correlation model (Engle 2002). This is examined from the perspective of a United States (US) investor given that the crisis had its origin in the US market. *Prima facie* evidence is found that economic structural adjustment has resulted in long-term increases in the correlation between the US and other markets. In addition, the magnitude of the increase in correlation is found to be greater in respect to emerging/frontier markets than in respect to developed markets.

Second, the long-term impact of the 2007–2009 financial crisis on time-varying correlations and volatilities is further examined by comparing estimates produced by different covariance models. The selected time-varying models (DCC, copula DCC, GO-GARCH: MM, ICA, NLS, ML; EWMA and SMA) produce statistically significantly different correlation and

volatility estimates. This finding has potential implication for the estimation of efficient portfolios.

Third, the different estimates derived using the selected covariance models are found to have a significant impact on the calculated weights and turnovers of efficient portfolios. Interestingly, however, there was no significant difference between their respective returns. This is the main finding of the thesis, which has potentially very important implications for portfolio management.

ACKNOWLEDGEMENTS

I would like to thank first and foremost my Director of Studies, Dr Timothy Rodgers, for his continuous support over the last few years. I'm also grateful to Dr Karl Shutes for helping me in choosing this topic of multivariate GARCH models and showing me R. I can't forget Dr Keith Redhead, who helped me to start my PhD. In addition, I'm thankful to Dr Sailesh Tanna, Dr Jia Miao and Dr Hui Pan for their suggestions, which enabled me to improve my work. I deeply appreciate the support given to me by my line managers, Dr Shinder Thandi, Mrs Eileen McAuliffe and Dr Graham Sadler.

I'm grateful to my wife, Agnieszka, for her patience, understanding and love. Furthermore, I thank my mother, Maria, and my brother, Mariusz, for giving me motivation and hope.

Finally, I would like to thank to all those who haven't been mentioned yet but supported me on my way towards my PhD, especially my whole family and friends.

I dedicate this PhD thesis to

my father, Mariusz, and my grandfather, Marian.

IMPORTANT INFORMATION

Some parts of this PhD thesis (mainly Chapter 4 but also a part of the literature review in Chapter 2 and a part of the data description in Chapter 3) have been recently published as a chapter in a book, *Advances in Financial Risk Management: Corporates, Intermediaries and Portfolios* (Niklewski and Rodgers 2013). The proofs are attached at the back of the thesis. In addition, I have used some parts of my MSc dissertation (Niklewski 2008) in a part of the literature review in Chapter 2.

ETHICAL APPROVAL

Coventry University ETHICS

Low Risk Research Ethics Approval

Where NO human participants are involved and/or when using secondary data - Undergraduate or Postgraduate or Member of staff evaluating service level quality

Project Title

Multivariate GARCH and portfolio optimisation: A comparative study of the impact of applying alternative covariance methodologies

Principal Investigator Certification

I believe that this project **does not require research ethics approval**.	X
I confirm that I have answered all relevant questions in the checklist honestly.	X
I confirm that I will carry out the project in the ways described in the checklist. I will immediately suspend research and request a new ethical approval if the project subsequently changes the information I have given in the checklist.	X

Principal Investigator

Name: Jacek Niklewski ....

Date: 02/12/2013 ....

Student's Supervisor (if applicable)

I have read the checklist and confirm that it covers all the ethical issues raised by this project fully and frankly. I confirm that I have discussed this project with the student and agree that it does not require research ethics approval. I will continue to review ethical issues in the course of supervision.

Name: Timothy Rodgers ....

Date: 03/12/2013 ....

Low Risk Research Ethics Approval Checklist

Applicant Details

Project ref:	P19331
Full name:	Jacek Niklewski
Faculty:	[BES] Business, Environment and Society
Department:	[EF] Economics, Finance and Accounting
Module code:	
Supervisor:	Timothy Rodgers
Project title:	Multivariate GARCH and portfolio optimisation: A comparative study of the impact of applying alternative covariance methodologies
Date(s):	26/01/2009
Created:	02/12/2013 20:27

Project Details

PhD thesis

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Questions	Yes	No
Will the project involve human participants?		X

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Questions	Yes	No
Will the project involve human patients/clients, health professionals, and/or patient (client) data and/or health professional data?		X
Will any invasive physical procedure, including collecting tissue or other samples, be used in the research?		X
Is there a risk of physical discomfort to those taking part?		X
Is there a risk of psychological or emotional distress to those taking part?		X
Is there a risk of challenging the deeply held beliefs of those taking part?		X
Is there a risk that previous, current or proposed criminal or illegal acts will be revealed by those taking part?		X
Will the project involve giving any form of professional, medical or legal advice, either directly or indirectly to those taking part?		X

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Will this project involve you disclosing personal data to the participants other than your name and the University as your contact and e-mail address?		X
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Will this project potentially place you in the situation where you may receive unwelcome media attention?		X
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Informed Consent of the Participant

Questions	Yes	No
Are any of the participants under the age of 18?		X
Are any of the participants unable mentally or physically to give consent?		X
Do you intend to observe the activities of individuals or groups without their knowledge and/or informed consent from each participant (or from his or her parent or guardian)?		X

Participant Confidentiality and Data Protection

Questions	Yes	No
Will the project involve collecting data and information from human participants who will be identifiable in the final report?		X
Will information not already in the public domain about specific individuals or institutions be identifiable through data published or otherwise made available?		X
Do you intend to record, photograph or film individuals or groups without their knowledge or informed consent?		X
Do you intend to use the confidential information, knowledge or trade secrets gathered for any purpose other than this research project?		X

Gatekeeper Risk

Questions	Yes	No
Will this project involve collecting data outside University buildings?		X
Do you intend to collect data in shopping centres or other public places?		X
Do you intend to gather data within nurseries, schools or colleges?		X
Do you intend to gather data within National Health Service premises?		X

Other Ethical Issues

Questions	Yes	No
Is there any other risk or issue not covered above that may pose a risk to you or any of the participants?		X
Will any activity associated with this project put you or the participants at an ethical, moral or legal risk?		X

Other Documents Submitted

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1 Statement of objectives and Overview

In this chapter I introduce the topic and give some background to my thesis. Furthermore, I define the scope of my work and I state the contribution of my PhD thesis to the academic literature. Finally, I present the structure of thesis in terms of the subsequent chapters.

1.1 Introduction and Background

Asset diversification is a concept that has a long history. We can even see the basic principles identified by William Shakespeare in *The Merchant of Venice* (1600). We find Antonio saying:

> 'My ventures are not in one bottom trusted,
>
> Nor to one place; nor is my whole estate
>
> Upon the fortune of this present year:
>
> Therefore my merchandise makes me not sad.'

In the earlier part of the twentieth century we see academics starting to take a serious interest in portfolio management issues, for example, Hicks (1935). Modern portfolio theory, however, as we know it today, did not appear until the middle of the century. In 1952 Markowitz published his seminal paper for which he later won a Nobel Prize. His work changed the way practitioners and academics perceive the portfolio selection problem. Markowitz's mean-variance approach is based on three key inputs: expected returns, variances and correlations.

Even though the mean-variance model is most popular among practitioners and academics, it is not free of assumptions, simplifications and drawbacks (IMF 2011). One of them is that it assumes the use of constant correlation estimates. Evidence found in the literature, however, suggests that correlation tends to change over time due to, for example, globalisation (Goetzmann *et al*. 2005), macroeconomic factors (Jithendranathan 2005) and stock market cycle (Longin and Solnik 2001). Interest in the issue of the changing nature of correlation relationships has increased in recent years in response to the impact of the 2007–2009 financial crisis on global markets. This had immense impact not only on the financial industry but also on the economy in general. Many investors lost their money and through this their trust in mean-variance model has weakened (IMF 2011). As a consequence, there has been a drive in academia to examine whether or not we can produce a better and more efficient version of Markowitz's original model.

Correlation and variance are key parameters in Markowitz's model; therefore, many in the academic world believe that if we can better model them we should be able to produce better portfolio models. Recent advances in autoregressive conditional heteroskedasticity (ARCH) based methodologies introduced by Nobel Prize laureate, Engle, in 1982, now enable us to model volatility and correlation better, by using time-varying models. In this thesis, I make use of multivariate generalised autoregressive conditional heteroskedasticity (GARCH) models to examine if the application of time-varying based methodologies can improve portfolio selection in relation to the mean-variance approach.

1.2 Statement of Research Questions and Scope of Thesis

The research questions identified by this thesis are as follows:

- What was the impact of the 2007–2009 financial crisis on correlation and volatility estimates?
- What is the effect of using different covariance models on correlation and volatility estimates?
- What is the impact of applying different covariance modelling techniques on portfolio performance?

The scope of this thesis does not extend to developing a practical tool for portfolio managers but rather to explore the theoretical issues. However, potential future work may involve taking the results from this thesis and refining them in order to produce a more practical tool that would be more useful to fund managers. Given this scope, transaction costs and asymmetry effect are not fully explored in my work.

Transaction costs are partially taken into consideration in Chapter 6 by using portfolio turnover multiplied by estimated average transaction costs as a proxy of their total. Transaction costs depend on a number of factors, for example, the volume of shares traded and the market specific factors. Potential asymmetry effects are partially addressed in Chapters 4–6 by taking into consideration modelling volatilities and the distribution (copula approach). Asymmetry is not, however, taken into consideration in the correlation equation.

1.3 CONTRIBUTIONS AND FINDINGS OF THE THESIS

1.3.1 CONTRIBUTIONS OF THE THESIS TO THE LITERATURE

The contributions made can be identified on a chapter-by-chapter basis. The contributions of Chapter 4 is that it extends prior research (Celık 2012, Cheung *et al.* 2008, Kearney and Potì 2006, Syllignakis and Kouretas 2011) by examining on *long-term* impact of the 2007 financial crisis on the time-varying correlation and volatility linkage between regional financial markets. This focuses specifically on the differences between US-developed market relationships and US-emerging/frontier market relationships. It does this using multivariate GARCH methodology. The novelty of my work is that studies in this area focus on developed markets and relatively few examine emerging/frontier markets.

The novel contribution of Chapter 5 is that whilst a number of studies in the literature have examined the relative performance of different conditional covariance models (Boswijk and van der Weide 2006, Caporin and McAleer 2014, Engle 2002), they do not make comparisons between the *specific* methodologies I have chosen in this thesis. Another novel aspect that I explore is the long-term impact of a crisis period on *relative* performance of these specific models. Furthermore, I extend Chapter 4 by comparing how individual models differ in respect to correlations and volatilities before and after the 2007 financial crisis. This has important implications from a portfolio perspective as it can help determine the most efficient time-varying methods to use in respect to correlation and volatility estimation. The chapter also discusses the model-specific differences found in respect to developed and emerging/frontier markets. This issue will become increasingly important given the globalisation of investment portfolios (Goetzmann *et al*. 2005, You and Daigler 2010).

In Chapter 6 I estimate efficient portfolios. My dataset enables me to optimise using conditional covariance models centred on a major financial crisis and also take account of regional developed and emerging/frontier market perspectives. Although model comparison is found elsewhere in the literature (Cha and Jithendranathan 2009, Engle 2002, Giamouridis and Vrontos 2007), my thesis is novel in respect the specific group of covariance models that I have chosen in this thesis. It is novel in respect to the distinction I draw between developed and emerging/frontier markets. My work makes a further contribution in relation to portfolio optimisation given there is little in the literature in respect to the treatment of transaction costs.

1.3.2 FINDINGS OF THE THESIS

The main findings of the thesis are:

First, I identify the impact of the 2007–2009 financial crisis on correlation and volatility measured by time-varying methodology, namely the dynamic conditional correlation (DCC) model (Engle 2002). This is examined from the perspective of a United States (US) investor given that the crisis had its origin in the US market. This approach is novel because it examines the magnitude of the impact on correlations and volatilities. I find prima facie evidence that economic structural adjustment has resulted in long-term increases in the correlation between the US and other markets, and that the magnitude of the increase in correlation appears to be greater in respect to emerging/frontier markets.

Second, I extend the examination of the long-term impact of the 2007–2009 financial crisis on correlation and volatility by comparing estimates produced by different covariance models. I find the correlation and volatility estimates produced by selected time-varying models are statistically significantly different; this suggests that there are implications for how we should estimate an efficient portfolio.

The selected time-varying models are:

DCC (dynamic conditional correlation) (Engle 2002) and the extension of the DCC model COPULA DCC (COP in short) (Patton 2006), GO-GARCH ML (ML in short) (generalised orthogonal generalised autoregressive conditional heteroskedasticity based on maximum likelihood estimation) (van der Weide 2002), GO-GARCH NLS (NLS in short) (generalised orthogonal generalised autoregressive conditional heteroskedasticity based on non-linear least squares estimation) (van der Weide 2006), GO-GARCH ICA (ICA in short) (generalised orthogonal generalised autoregressive conditional heteroskedasticity based on independent component analysis estimation) (Broda and Paolella 2009), GO-GARCH MM (MM in short) (generalised orthogonal generalised autoregressive conditional heteroskedasticity based on method of moments estimation) (Boswijk and van der Weide 2011), simple moving average (SMA) and exponentially weighted moving average (EWMA).

Third, which is the main finding of this thesis, although market conditions have a big impact on time-varying correlations and volatilities (which in turn have a significant impact on portfolio weights), there is no corresponding improvement in the returns-based performance of a portfolio estimated by using time-varying methodologies (for all selected time-varying methods).

1.4 METHODOLOGY

I have used DCC, COPULA DCC, GO-GARCH: MM, ICA, NLS, ML, EWMA and SMA models in my thesis for estimation of correlations and volatilities. The differences in means and location parameters are tested by using the Welch (1938) t and the Wilcoxon (1945) rank sum tests.

DCC, COPULA DCC, GO-GARCH: MM, ICA, and EWMA are found as the most promising methodologies for identifying efficient portfolios. The main issue that I face in Chapter 6 is how to deal with the complexity of the task of comparing portfolio performance. There are many possible testing approaches I could take. The models finally selected are compared in portfolio context in terms of the criteria: realised returns, realised cumulative returns, conditional Sharpe ratio and portfolio turnover.

1.5 STRUCTURE OF THE THESIS

The thesis is organised as follows. Chapter 2 presents the literature review. Chapter 3 discusses the data and identifies the financial crisis period. The substantive analysis in the thesis is presented in Chapters 4, 5 and 6. Chapter 4 analyses the impact of the financial crisis on correlations and volatilities based on the DCC model. Chapter 5 extends Chapter 4 by examining the impact of the financial crisis on correlations and volatilities based on different selected covariance models. Chapter 6 tests the relative performance of different selected covariance models in portfolio context. Chapter 7 draws conclusions, gives recommendations and outlines future work.

The appendix has been divided among the relevant chapters.

2 Literature review

2.1 Introduction

The objective of this chapter is to identify the gap in the literature that will provide the basis for this thesis. In Section 2.2 I give a brief overview of investment portfolio theory. This is followed in Section 2.3 with an examination of how correlation and volatilities change over time and in different market conditions. Section 2.4 then looks at different ways of measuring time-varying correlations and volatilities and in Section 2.5 I examine ways of testing different covariance measurement methodologies in the context of portfolio efficiency. Finally, in Section 2.6 I identify the gap in the literature that the substantive research in this thesis will be based around.

2.2 Investment portfolio theory

2.2.1 Brief history of portfolio theory

Markowitz is called the father of modern portfolio theory (MPT). His seminal work published in 1952 discusses expected (mean) returns and variance of returns as portfolio selection criteria. Many of the ideas that Markowitz uses can, however, be identified in earlier literature.

The notions of diversification and covariance can be identified, for example, in Shakespeare's '*The Merchant of Venice*' (1600). We find Antonio saying:

> 'My ventures are not in one bottom trusted,
>
> Nor to one place; nor is my whole estate

Upon the fortune of this present year:

Therefore my merchandise makes me not sad.'

From an academic perspective we see in Hicks' (1935) theory of investment the introduction of ideas that will later prove to be central pillars of MPT. He discussed the notion of risk within the context of investment. Although he never specifically defined risk in terms of standard deviation of returns, the concept is implicit in his analysis. We can also identify ideas in Hicks' work that were later found in Markowitz's portfolio theory; for example, the investor's desire for low risk and high return.

Around the same time as Hicks, Marschak (1938) introduced the notion of choice under assumptions of uncertainty (Arrow 1991). Preferences for investment were represented by indifference curves in the mean-variance space. Although these models were not direct representations of portfolio theory, later commentators have identified that they are central to the probabilistic notions of expected return and risk that are central to MPT (Constantinides and Malliaris 1995).

Other concepts that later proved to be central to the portfolio theory are also found in the literature of the 1930s. For example, Williams (1938) introduced the notion of making investments in large number of securities to eliminate risk. It was argued that risk can be eliminated completely mainly because of the law of large numbers. There were still, however, ideas missing that would later prove to be central to MPT; he did not, for example, consider relationships between returns of securities which means, that diversification will reduce but not eliminate all risk.

Leavens (1945) argued that the literature of his day discussed diversification in general terms but did not indicate why it was desirable. Markowitz (1999) argued that he intuitively understood the concept of covariance but did not provide any theoretical model.

Portfolio theory was developed simultaneously by both Markowitz and Roy in 1952. Roy (1952) developed a model that was different to Markowitz's in two aspects. First, Markowitz allowed only long positions (non-negative investments) whereas Roy did not imply any restrictions on short selling (negative investments). Second, Roy recommended a specific portfolio whereas Markowitz offered a possibility of choosing an optimal portfolio from a range of efficient frontiers that depend on an investor's risk aversion.

After Markowitz's seminal paper (1952) we see the theory developing along a number of different avenues; for example, Hicks (1962), Markowitz (1956, 1959 and 1987), Sharpe (1963 and 1964) and Tobin (1958). I start the remainder of this section by presenting the standard Markowitz model. I then subsequently discuss the important issues relating to it identified in the literature. This is done from the perspective of the objectives of this author's thesis.

2.2.2 MARKOWITZ'S MODEL

Markowitz (1952) proposed the theory of portfolio selection that is known in literature as mean-variance analysis. This framework is an approximation of the expected utility framework, which is based on the utility function that measures an investor's satisfaction with returns. It is generally accepted in textbook literature that the mean-variance framework is a good approximation of the expected utility framework, since at least one of two conditions in practice is fulfilled (Fabozzi *et al*. 2007, Levy and Markowitz 1979, Levy and Post 2005, Samuelson 1970, Tobin 1958). These conditions are:

- normal distribution is a good approximation of distribution of returns;
- quadratic function is a good approximation of utility function.

The mean-variance analysis builds on two key parameters: the expected return and the variance (or the standard deviation) of returns as a measure of the risk of the asset or portfolio. When choosing a portfolio, the investor faces a trade-off between return and risk. A rational entity will want higher returns and lower risk; however, generally, the higher the expected return, the larger the risk (Fabozzi and Markowitz 2011). The investment that dominates all other investments is called mean-variance-efficient (Markowitz 1952).

The expected return of a portfolio (i.e. $E(R_p)$) of n assets can be calculated as a weighted average of expected returns of assets (Markowitz 1952):

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) \tag{1.1}$$

Whereas the variance of portfolio returns (i.e. σ_p^2):

$$\sigma_P^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j>i}^{n} w_i w_j \sigma_{ij} = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j>i}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{1.2}$$

where w_i is weight of asset (relative amount invested in security) i in the portfolio, $E(R_i)$ is expected return of asset i, σ_i^2 is variance of asset i returns, σ_{ij} is covariance between asset i and j returns, σ_i is standard deviation of asset i returns, ρ_{ij} is correlation between asset i and j returns.

These Markowitz equations are used widely in the investment industry and are seen as fundamental to the efficient management of investment portfolios (Syriopoulos and Roumpis 2009, Vrontos *et al.* 2013).

2.2.2.1 MEASURING RISK-RETURN RELATIONSHIP

In his original seminal paper, Markowitz (1952) identified the possibility of developing the concept of the efficiency frontier in the context of measuring optimal risk-return combinations. This has been extended and developed in the subsequent literature (Markowitz 1959, Fabozzi and Markowitz 2011). The use of notion of an optimal portfolio is likely to be a central feature of my thesis.

Form practical perspective there is problematic to identify the whole efficiency frontier. A common approach identified in the literature is to focus on specific efficient portfolios. For example, Cha and Jithendranathan (2009) use minimum variance, low risk and high risk portfolios. On the other hand, Giamouridis and Vrontos (2007) focus on minimum variance and specific-target-return based portfolios.

2.2.2.2 MEAN-VARIANCE PORTFOLIO OPTIMISATION

The classical mean-variance portfolio optimisation can be represented via three principle methodologies. These are: risk minimisation formulation, expected return maximisation formulation and risk aversion formulation (Fabozzi *et al*. 2007, Markowitz 1952, Markowitz 1959).

Although a portfolio can be based on unconstrained optimisation (for example, Jorion 1992), the additional constraints of portfolio being long-only is often added. The effect of this is that none of the assets' weights can be negative. This could be because of legal or practical reasons (Fabozzi *et al*. 2007, Jorion 1992, Markowitz 1952, Markowitz 1959).

2.2.3 Developments and issues within Modern Portfolio Theory

In the following section I'm going to discuss some of the issues and development related to the Markowitz model that can be identified in the literature. Those aspects will be considered in my PhD thesis later.

2.2.3.1 Alternative risk measures

Standard deviation or *variance* is not the best measure of risk. This was even identified by Markowitz himself (1959). One of the reasons behind it is the fact that the distribution of returns is not normal, which can be identified by empirical evidence, e.g. Mandelbrot (1963). For this and other reasons the alternative risk measures can be identified in the portfolio literature. These can be divided into two main categories: dispersion measures and downside measures (Ortobelli *et al*. 2005, Fabozzi *et al*. 2007, Fabozzi and Markowitz 2011).

2.2.3.1.1 Dispersion measures

Dispersion measures treat deviations above the mean and below the mean in the equivalent manner. Standard deviation and variance are the most commonly known representatives of this group. The other dispersion measure is the mean absolute deviation, which is more robust to outliers and simplifies the portfolio optimisation problem to a linear problem. The generalised dispersion measure that nests both the standard deviation (variance) and the mean absolute deviation is called the mean absolute moment (Konno and Yamazaki 1991, Fabozzi *et al*. 2007, Fabozzi and Markowitz 2011).

2.2.3.1.2 Downside measures

The other group of risk measures builds on the fact that standard deviation or variance is a poor measure of risk (Swisher and Kasten 2005). There are at least two reasons why standard deviation (variance) does not measure the risk correctly. First, very often the financial asset returns distribution is asymmetric. Second, standard deviation (variance) measure is based on deviations from the mean value whereas human risk is rather perceived relative to the benchmark level, disaster level or minimum acceptable return (MAR).

Even though the downside measures are theoretically appealing, they have some practical drawbacks. They are computationally much more complicated, not easily aggregated from the individual level into the portfolio level and prone to higher estimation error as they use only a proportion of empirical distribution (Grootveld and Hallerbach 1999, Fabozzi *et al*. 2007).

Possibly the first representatives of this group can be traced back to Markowitz (1952) and Roy (1952). Markowitz proposed semivariance, which is similar to variance but focuses only on adverse deviation (Markowitz 1991). Some theoretical properties of the semivariance approach can be found in Jin *et al*. (2006). At the same time, Roy suggested *safety first* as a measure of risk. It measures the risk as a probability of portfolio return less than the minimum accepted return. Further development of the safety first criterion can be found in Bawa (1975, 1978).

The generalised measure that nests *semivariance* is called the *lower partial moment* (Bawa 1976). This measure builds on two parameters: the power index (which represents the risk aversion) and the target rate of return (which represents the minimum return) (Fabozzi *et al*. 2007, Fabozzi and Markowitz 2011).

One of the most well recognised downside risk measures is *Value at Risk* (VaR) (JP Morgan 1994). The VaR is quite intuitive as it measures the predictive maximum loss at a specified probability level over a given time period (Fabozzi *et al*. 2007, Fabozzi and Markowitz

2011). Despite its positive features it has some serious drawbacks. The main one is that VaR is not a coherent risk measure (Artzner *et al*. 1999, Daníelsson 2011).

To overcome the deficiencies of *VaR*, *Conditional Value at Risk* (CVaR) has been proposed in the literature. CVaR is also called *expected shortfall* (ES) or *expected tail loss* (ETL). CVaR is a coherent risk measure that shows the expected loss, given that the VaR has been exceeded. Another advantage from the portfolio perspective is the fact that the optimisation problem is simplified to a linear problem (Acerbi and Tasche 2002, Fabozzi *et al*. 2007, Daníelsson 2011, Fabozzi and Markowitz 2011).

2.2.3.2 PORTFOLIO OPTIMISATION

2.2.3.2.1 COVARIANCE/CORRELATION ESTIMATION

One of the problems that was identified by Markowitz (1959) is related to the number of covariance/correlation estimates needed as inputs for a portfolio optimisation exercise. For *n* assets in a portfolio one needs as inputs estimates for expected returns (n), variance of returns (n) and covariance or correlation between returns $\left(\frac{n(n-1)}{2}\right)$. The number of covariance/correlation estimates could be problematic when a portfolio becomes large.

To overcome the dimensionality problem of the covariance structure, index models have been developed as alternatives, e.g. the market model (Sharpe 1963), the capital asset pricing model (Lintner 1965, Sharpe 1964), arbitrage pricing theory (Ross 1976), the three factor model (Fama and French 1992) and the four factor model (Carhart 1997).

2.2.3.2.2 EXPECTED VALUE ESTIMATION

The mean-variance optimisation is very sensitive to the changes in inputs, i.e. expected returns, variance of returns and covariance/correlation of returns (Fabozzi and Markowitz

2011). Markowitz's model is derived on expected values of returns, variance of returns and covariance/correlation of returns, which are not known as they depend on future distributions. In practice, the approximations of expected values are based on the historical returns. This is based on the assumption that the future will be similar to the past, which seems to be a strong assumption. These approximations lead to estimation errors that are ignored in the standard portfolio optimisation.

To overcome this deficiency another strand of literature has developed which is called robust portfolio optimisation. It explicitly incorporates the estimation errors into portfolio analysis, e.g. Black and Litterman (1991), Markowitz and Usmen (2003), Fabozzi *et al*. (2007) and Michaud and Michaud (2008).

2.2.3.2.3 HIGHER MOMENTS

As shown by Fabozzi *et al*. (2007), when asset returns follow normal distribution or when an investor's utility is quadratic then the mean-variance analysis can be seen as a special case of general utility maximisation. However, many empirical studies provide evidence that asset returns reject normal distribution as they exhibit asymmetry and fat tails, e.g. de Athayde and Flôres (2004) and Harvey *et al*. (2010). These higher moments (i.e. skewness and kurtosis) can be incorporated into the mean-variance framework by expanding the expected utility function in a Taylor series (e.g. de Athayde and Flôres 2004, Fabozzi *et al*. 2007, Jean 1971 and Harvey *et al*. 2010). A rational investor prefers higher odd moments (e.g. mean and skewness) and lower even moments (e.g. variance and kurtosis) (Fabozzi *et al*. 2007, Scott and Philip 1980). This approach of expanding the expected utility is not limited to the first four moments, but from a practical perspective including orders higher than four is not desirable as the estimation accuracy of higher moments is quite poor because of the high estimation error (Fabozzi *et al*. 2007, Kendall *et al*. 1998). When log and power utility functions are used then the mean-variance optimisation performs very well as it is fairly insensitive to higher moments (Cremers *et al*. 2003, 2005, Levy and Markowitz 1979).

Although in reality financial returns tend not to be normally distributed the mean-variance framework is still used by practitioners. For example, Fabozzi *et al*. (2007: 154) state:

'The beauty of Markowitz's portfolio theory is its simplicity. Despite the abundance of empirical evidence that asset returns are not normally distributed, some practitioners feel that in many practical applications, return distributions are not too far from normal to be of concern.'

2.2.3.3 PORTFOLIO PERFORMANCE MEASURES

One of the key important aspects of portfolio analysis is evaluation of portfolio performance. The early measures focused on portfolio returns only. However, it is crucial to evaluate portfolio performance on a risk-adjusted basis because the higher the risk, the higher the expected return (Reilly and Brown 2012). Within the mainstream literature four key portfolio performance measures that incorporate risk and return (and not just return) can be identified: namely the Treynor ratio (1965), the Sharpe ratio (1966, 1994, 2007), Jensen's alpha (1968) and the information ratio that is the generalised version of the Sharpe ratio (Goodwin 1998).

To overcome some of these deficiencies a large number of extensions and alternative measures have been proposed in the literature (Reilly and Brown 2012). For example, Jensen's measure has been further developed to incorporate multifactor models to be used instead of just single factor model (Roll and Ross 1984). An alternative measure was also proposed by Fama (1972); here the overall portfolio performance is seen as being explained by investor's risk, manager's risk, diversification and net selectivity. Another example is the Sortino ratio (Sortino and Price 1994), which uses the downside risk as well as the MAR instead of variance and mean values. Different group of measures emphasise portfolio holdings rather then returns (Grinblatt and Titman 1993, Daniel *et al*. 1997). Performance attribution analysis breaks down portfolio managers' skills into two groups: ability to select superior securities and superior timing. The portfolio performance measure that has been proposed by Brinson *et al*. (1986) consists of allocation and selection effect. There is also another strand of literature that focuses only on market timing skills (Merton 1981).

The literature related to the portfolio performance evaluation is quite extensive and the aforementioned discussion presents only the main strands.

2.3 FACTORS INFLUENCING CORRELATION BETWEEN MARKETS AND VOLATILITY

A large number of studies have examined the benefits of portfolio internationalisation, for example Laopodis (2005), Lucey and Muckley (2011) and Meric *et al*. (2008). Using historical data from 1966-1971, Solnik (1995) estimated that non-diversifiable risk was about 27% in the US and about 44% in Germany. He found that a well-diversified international portfolio reduced this risk by about half for the US investor and that the benefits were even greater for the German investor. The size of such potential benefits will, however, change over time in response to changes in the correlation between markets. In this section I examine how volatile correlations are from a short and a long-term perspective. This is important from the perspective of my thesis as high levels of volatility in correlation would suggest that I should be using time-variant measures such as those, for example, estimated based on multivariate GARCH-based methodologies. Correlation is often highly volatile and can be influenced in both the long term and the short term by a number of variables.

Harvey (2000) examined the reasons why international diversification reduces risk. He argued that if markets were completely segmented then the benefits of internationalisation would depend on country-level variance and total skewness. If, on the other hand, markets were completely integrated he argues that covariance and co-skewness are key to the relationship.

2.3.1 IMPACT OF GLOBALISATION

Many time series studies have identified that, although correlation levels between markets can vary considerably over time, there is a clear upward trend. It is generally argued that this reflects the impact of globalisation and increasing market integration; for example, Bekaert *et al*. (2002). This conclusion is borne out by a number of related studies in the literature. Fama and French (1989) and Jagannathan and Wang (1996) identified that as economic production becomes less segmented and more integrated (as measured by business-cycle convergence), financial integration increases. This effect was subsequently found to be particularly apparent in Europe where equity market integration increased significantly after 1996 in response to rapid economic and financial integration (Fratzschler 2002, Moore 2007, Moore and Pentecost 2006). A more recent paper by Goetzmann *et al*. (2005) examined this issue on a worldwide basis using a timeframe of 150 years. They argue that there is robust historical evidence that market correlation is strongly influenced by market globalisation. This argument is also supported by You and Daigler (2010), who found a continuation of this globalisation-related trend of increasing integration over time, and by a further study from Yu *et al*. (2010), who identified that in Asia, rates of market integration had increased in 2007-08 after being relatively low between 2002 and 2006. Despite this predominant focus in the literature on the increase in integration over time (for example, Barari 2004, Kearney and Lucey 2004, Swanson 2003), it should be noted, however, that others, such as Schmukler

(2004), argue that there are limits to this integration process. This can be taken as implying that diversification benefits are likely to maintain their importance in equity portfolio allocation.

The impact of globalisation appears greatest in the context of correlation levels between developed and developing markets. For instance, Cha and Oh (2000) showed that correlation between developed and developing markets increased over time. Yu *et al.* (2010) provided an evidence of a different degree of integration between mature and emerging markets, which potentially can be ascribed to political, institutional and economic differences. It seems that the correlation of more developed markets responds differently (more significantly) to asymmetric macroeconomic shocks which could indicate much stronger reaction to the international business cycle (Kizys and Pierdzioch 2006). From the perspective of my thesis it is therefore probably appropriate to examine the correlation between the US and developed markets and also the US and developing markets.

2.3.2 Impact of macroeconomic factors

Elsewhere in the literature others have looked at macroeconomic factors (Araújo 2009, Cai *et al.* 2009, Jithendranathan 2005, Kizys and Pierdzioch 2006, Syllignakis and Kouretas 2011 and Wang and Moore 2008). Results provided by Kizys and Pierdzioch (2006) suggest that international equity correlations cannot be systematically explained by the business cycle. Moreover, neither monetary convergence, nor macroeconomic convergence cannot explain stock market correlation as found by Wang and Moore (2008). On the other hand, Syllignakis and Kouretas (2011) provide evidence that macroeconomic fundamentals like business cycle, monetary policy convergence, inflationary environment and currency risk premium play a key role in the explanation of the conditional correlation, especially during the 2007–2009 financial crisis. Another supporting argument can be found in the study by Jithendranathan

(2005) who argues that macroeconomic variables have an important influence on correlation and additional studies can be identified that suggest that financial integration tends to be higher when countries are in recession (Ragunathan *et al*. 1999). Other researchers, however, have argued that these effects are more likely to be related to market volatility than macroeconomic factors. Both Longin and Solnik (1995) and Solnik *et al*. (1996) argue that higher correlations should be seem in terms of greater volatility in declining bear market phases rather than in terms of the impact of a recession.

2.3.3 Impact of stock market cycle

The assertion that correlation increases during times of high market volatility is a theme that runs throughout a lot of the literature in this area. For example, Karolyi and Stulz (1996), and Ramchand and Susmel (1998) found correlation to be higher between the US and other markets during high-volatility periods. Other researchers relate these differences to the impact of differences in stock market trends rather than to volatility per se. For example, Longin and Solnik (2001) find that the correlation increases during bear market phases and they attribute this to the observation that periods of negative returns are associated with having higher correlation levels that are periods of positive returns. Similarly, it has also been identified in a more recent study by You and Daigler (2010) that the benefits from international diversification are asymmetric; they argue that this results in a reduction in portfolio diversification benefits during bear markets. Elsewhere in the literature other research has tried to explain the reasons for this phenomenon. It is argued by Bekaert and Wu (2000) that the asymmetric impact on correlation of different market phases is possibly due to negative shocks producing two interacting effects, namely an effect relating to changes in investors' expectations of the conditional variance and a second effect relating to increases in leverage as markets fall. It can also be argued from a behavioural finance perspective that increases in correlation as markets fall is consistent with the types of herding behaviour that occur when investors are faced with a relatively uniform set of stimuli (Prechter 1985, 1999). It has been argued that the stock markets are a direct index of social mood reflecting the combined level of optimism or pessimism at a given time (Prechter 2001).

2.3.4 IMPACT OF FINANCIAL CRISIS

There are a number of studies that have looked at the impact of a crisis on correlation levels. Contagion theory (for example, Forbes and Rigobon 2002) would suggest that the impact of a crisis on correlation will often be short term and result in short-lived spikes in correlation. More recently, Tsai and Chen (2010) examined the impact of a number of crises, both financial and non-financial, on correlation among financial markets within the US. The indications were that these resulted in short-term, contagion-related spikes in correlation. Further evidence from the 1997 Asian financial crisis appears to support the argument that market volatility and the phases of the stock market cycle are important factors in determining the impact of a crisis on cross-country market correlation. Schwebach *et al*. (2002) found the impact of the Asian crisis to be similar to that found during business downturns and bear markets. Using world equity benchmark shares, they identified that cross-country correlations increased. These ranged from 0.180 to 0.274 during the first phase of the crisis, rising to 0.451–0.531 during the second phase. In another study, Cho and Parhizgari (2008) appear to confirm the existence of contagion effects across eight South-East Asian markets; they found mean country-pair correlations before and after the crisis were largely statistically significant. Medo *et al*. (2009) quantify the influence of correlation on investment diversification by using the effective portfolio size. They analyse change in effective portfolio size over the period January 1973–April 2008 for 20 stocks from DJIA. They show that during the three crises – October 1987, emerging market 1997 and dot-com bubble 2001-2002 – the effective portfolio size decreases substantially, which indicates an increase in the correlations.

It can be noted that the studies cited in relation to the Asian financial crisis used relatively short data sets. This means that it is not possible to tell from them whether or not the changes found were limited to being short-term contagion effects or whether they represented long-term structural changes. Long-term structural changes would not be surprising. My data set covers a long data period that enables me to perform a much more detailed analysis. Garnaut (1998) argued that the Asian crisis had a major structural impact on the region. He noted that the crisis induced policy reforms (for example, significant cuts in government expenditure) and that these reforms were reinforced by IMF programmes (for example, monetary policy tightening such as increases in interest rates). Garnaut argued that the result would be that markets would be made more effective in allocating resources. These policy induced changes, I would argue (see also Chiang *et al.* (2007)), will potentially induce permanent change in the correlations between markets through changes in the regional 'financial architecture'.

2.4 Modelling of volatility and correlation

2.4.1 Features of financial data

The financial data exhibit different features such as (Brooks 2008, Danielson 2011, Piontek 2004a, 2004b, Tsay 2010):

- Volatility clustering – there are periods of high and low volatility. The high absolute returns tend to follow high absolute returns and small absolute returns tend to follow small absolute returns.
- Leptokurtosis effect – the distribution of returns shows much fatter tails than the normal distribution assumes (i.e. the probability of rare events is much larger).

- Leverage effect – the volatility tends to be larger for price falls than for price rises when the magnitudes of both the price rise and price fall are identical. This is the asymmetric influence of negative and positive information on future level of volatility.
- Skewness – the returns distribution presents some degree of skewness.
- Autocorrelation – of rates of returns especially in periods of low variability.
- Long-run memory effect – high order autocorrelation coefficients of squared returns (errors) are significant, more precisely when autocorrelation coefficients of squared errors sum up to infinity.

2.4.2 UNIVARIATE VOLATILITY MODELS

2.4.2.1 MOVING AVERAGE (MA)

One of the simplest ways to estimate volatility is the moving average (MA) model. The EW-period MA model can be presented as follows (Alexander 1998, Danielson 2011):

$$\sigma_t^2 = \frac{1}{EW}\sum_{i=1}^{EW} \epsilon_{t-i}^2 \tag{1.3}$$

where $\epsilon_t = r_t - \mu_t$ is the demeaned asset's return r_t at time t, σ_t^2 is the variance at time t, EW is the estimation window.

Despite the estimation simplicity, the model has some deficiencies. For example, observations are equally weighted and the choice of estimation windows is rather arbitrary (Alexander 1998, Danielson 2011).

2.4.2.2 EXPONENTIALLY WEIGHTED MOVING AVERAGE (EWMA)

The way to improve the MA model is to treat observation differently, i.e. by assigning higher weight to the most recent observations. JP Morgan (1994) proposed the EWMA model that uses exponential weights. The EW-period EWMA model can be presented as follows (Alexander 1998, Danielson 2011, JP Morgan 1994):

$$\sigma_t^2 = \frac{1-\lambda}{\lambda(1-\lambda^{EW})}\sum_{i=1}^{EW}\lambda^i\epsilon_{t-i}^2 \tag{1.4}$$

where $\epsilon_t = r_t - \mu_t$ is the demeaned asset's return r_t at time t, σ_t^2 is the variance at time t, EW is the estimation window, $0 < \lambda < 1$ is the decay factor.

The model can be rewritten in the following manner (Alexander 1998, Danielson 2011):

$$\sigma_t^2 = (1-\lambda)\epsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 \tag{1.5}$$

JP Morgan suggested $\lambda = 0.94$ for daily data and $\lambda = 0.97$ for monthly data.

Similarly as for the MA, the EWMA model is relatively easy to estimate. However, the main disadvantage of EWMA is the assumption of a constant decay factor for all assets.

2.4.2.3 Autoregressive conditionally heteroskedastic (ARCH)

This is a special class of models very popular in volatility modelling and forecasting. The autoregressive conditional heteroskedasticity (ARCH) model was proposed by Engle (1982). The ARCH (q) can be represented as (Danielson 2011, Yu 2002):

$$\begin{cases} r_t = \mu + u_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_q u_{t-q}^2 \end{cases} \tag{1.6}$$

where $u_t \sim iid(0, \sigma_t^2)$

or

$$\begin{cases} r_t = \mu + \sigma_t \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 (r_{t-1} - \mu)^2 + \cdots + \alpha_q \big(r_{t-q} - \mu\big)^2 \end{cases} \tag{1.7}$$

where $\varepsilon_t \sim iid(0,1)$

The conditional variance of error depends on q lags of squared errors. The h-step-ahead forecast of volatility can be shown as (Yu 2002):

$$\hat{\sigma}_{t+h}^2 = \alpha_0 + \alpha_1 (\hat{r}_{t+h-1} - \mu)^2 + \cdots + \alpha_q \big(\hat{r}_{t+h-q} - \mu\big)^2 \tag{1.8}$$

where $\begin{cases} \hat{r}_{t+h-j} = r_{t+h-j} & 1 \leq h \leq j \\ \big(r_{t\mp h-j} - \mu\big)^2 & h > j \end{cases}$

This model allows the modelling of time-varying variances. However, there are some limitations. Firstly, when modelling financial time series the number q tends to be large. Secondly, the non-negativity constraint of alphas ($\forall_{i=0,\cdots,q}\ \alpha_i \geq 0$) can be violated as the number of alphas increases (Brooks 2008: 391-392, Piontek 2000, Tsay 2010). To overcome some of the deficiencies, the generalised version of ARCH model was developed by Bollerslev (1986).

2.4.2.4 GENERALISED AUTOREGRESSIVE CONDITIONALLY HETEROSKEDASTIC (GARCH)

The conditional variance in the GARCH model depends not only on lagged squared errors but also on lags of conditional variance (Bollerslev 1986). The GARCH (p, q) can be presented as follows (Danielson 2011, Yu 2002):

$$\begin{cases} r_t = \mu + u_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 \end{cases} \tag{1.9}$$

where $u_t \sim iid(0, \sigma_t^2)$

or

$$\begin{cases} r_t = \mu + \sigma_t \varepsilon_t \\ \sigma_t^2 = \alpha_0 + \alpha_1 (r_{t-1} - \mu)^2 + \cdots + \alpha_q \left(r_{t-q} - \mu\right)^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 \end{cases} \tag{1.10}$$

where $\varepsilon_t \sim iid(0,1)$

The h-step-ahead forecast of volatility can be shown as (Yu 2002):

$$\begin{cases} \hat{\sigma}_{t+h}^2 = \alpha_0 + \sum_{i=1}^{m} (\alpha_i + \beta_i) \hat{\sigma}_{t+h-i}^2 - \beta_h \widehat{w}_t - \cdots - \beta_m \widehat{w}_{t+h-m} & h = 1, \cdots, p \\ \hat{\sigma}_{t+h}^2 = \alpha_0 + \sum_{i=1}^{m} (\alpha_i + \beta_i) \hat{\sigma}_{t+h-i}^2 & h = p + 1, \cdots \end{cases} \tag{1.11}$$

where:

$s_t = r_t - \mu,$

$m = max\{p, q\},$

$\alpha_i = 0 \quad for\ i > q,$

$\beta_i = 0 \quad for\ i > p,$

$\widehat{w}_\tau = s_\tau^2 - E(s_\tau^2 | \Im_{\tau-1}) \quad for\ 0 < \tau \le t,$

$\widehat{w}_\tau = 0 \quad for\ \tau \le 0,$

$\hat{\sigma}_\tau^2 = s_\tau^2 \quad for\ 0 < \tau \le t,$

$\hat{\sigma}_\tau^2 = s_\tau^2 = \frac{1}{T}\sum_{i=1}^{T} s_i^2 \quad for\ \tau \leq 0,$

The GARCH (p, q) model can be presented as ARCH (∞). GARCH (1,1) is sufficient to capture all volatility clustering in the data. GARCH is more parsimonious and avoids overfitting (Brooks 2008, Piontek 2004a, 2004b, Tsay 2010). The unconditional variance of error is (Hamilton 1994):

$$var(u_t) = \frac{\alpha_0}{1 - \sum_{i=1}^{q} \alpha_i - \sum_{i=1}^{p} \beta_i} \quad for \sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i < 1 \tag{1.12}$$

If $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \beta_i \geq 1$ then the unconditional variance is not defined.

2.4.2.5 ARCH and GARCH extensions

'Simple' ARCH and GARCH models cannot account for all of those data features presented in Section 2.4.1. Mainly for this reason, but not only, many extensions were proposed in the literature in order to model the financial data more accurately. These are only some examples from the extensive collection (Bollerslev 2008, Brooks 2008): APARCH (Engle 1990), EGARCH (Nelson 1991), FIGARCH (Baillie *et al*. 1996), GARCH-M (Engle *et al*. 1987), GJR GARCH (Glosten *et al*. 1993), GARCH-t (Bollerslev 1987), IGARCH (Engle and Bollerslev 1986), NGARCH (Higgins and Bera 1992) and TGARCH (Zakoian 1994).

2.4.2.6 Alternative univariate volatility models

As well as GARCH models found in the mainstream literature, a number of alternative volatility models can also be identified in the literature for example implied volatility, realised volatility, range-based volatility and stochastic volatility models (Danielson 2011, Fabozzi *et al*. 2007, Tsay 2010).

The implied volatility is based on the Black-Scholes model (Black and Scholes 1973). Given option prices and applying Black-Scholes model, one can derive implied volatility. The main advantage of this volatility measure is its forward-looking nature. However, the key deficiency is that the Black-Scholes model assumes constant volatility and normal innovation. In terms of forecasting future volatility, the empirical studies show mixed picture (Canina and Figlewski 1993, Duque and Paxson 1997, Fung and Hsieh 1991).

Another alternative group of models estimating volatility is based on the idea of calculating the volatility of low-frequency data using high-frequency data (Andersen *et al*. 2001a, 2001b, French, *et al*. 1987). The main advantage of this approach is its simplicity. On the other hand there are some disadvantages, for instance the availability of intraday data, the effects of market microstructure, the problem of choosing the optimal time interval, the overnight return or the diurnal pattern in volume and volatility (Danielson 2011, Tsay 2010).

Information about opening, low, high and closing prices can be used to improve an estimate of volatility (Alizadeh *et al*. 2002, Garman and Klass 1980, Parkinson 1980, Rogers and Satchell 1991, Tsay 2010, Yang and Zhang 2000). One of the disadvantages is that the volatility can be underestimated as the actual range of daily prices can be underestimated by the observed range. This is because we can only observe prices at certain discrete points in time (Tsay 2010).

The stochastic volatility models incorporate innovation into conditional volatility equation (Ghysels *et al*. 1996, Harvey *et al*. 1994, Taylor 1994). Despite the advantages, such as it can be expressed in continuous time form and provide greater flexibility, the stochastic volatility models are much more difficult to estimate as the model uses two innovation terms. Additionally, there is little evidence of their out-of-sample forecast superiority (Danielson 2011, Tsay 2010).

2.4.3 MULTIVARIATE VOLATILITY MODELS

So far I have focused mainly on modelling and forecasting the volatility of one time series. However, in practice there is a need to be able to model and predict the covariances (correlations) between time series. Therefore, we have to move from univariate models to multivariate models. Covariance in finance is used to calculate hedge ratios, portfolio VaR estimates, betas of capital asset pricing models (CAPM), asset weights in portfolio and many more. Multivariate models not only model variances but also covariance (Bauwens *et al*. 2006, Brooks 2008, Silvennoinen and Teräsvirta 2008).

2.4.3.1 MOVING AVERAGE (MA) MODEL

To extend the univariate MA model presented in Section 2.4.2.1 to a multivariate case we need to calculate the covariances. The EW-period moving average is defined as follows (Alexander 1998, Sheppard 2012):

$$H_t = \frac{1}{EW}\sum_{i=1}^{EW} \epsilon_{t-i}\epsilon_{t-i}' \tag{1.13}$$

where $\epsilon_t = r_t - \mu_t$ is the vector of demeaned assets' returns r_t at time t, H_t is the covariance matrix at time t, EW is the estimation window.

Despite the estimation simplicity, the model has some deficiencies. For instance, observations are equally weighted and the choice of estimation windows is rather arbitrary (Alexander 1998, Danielson 2011).

2.4.3.2 EXPONENTIALLY WEIGHTED MOVING AVERAGE (EWMA) MODEL

The univariate EWMA model presented in Section 2.4.2.2 can be extended to a multivariate framework in the following way (Alexander 1998, Danielson 2011, JP Morgan 1994, Sheppard 2012):

$$H_t = (1-\lambda)\epsilon'_{t-1}\epsilon_{t-1} + \lambda H_{t-1} \tag{1.14}$$

where $\epsilon_t = r_t - \mu_t$ is the vector of demeaned assets' returns r_t at time t, H_t is the covariance matrix at time t, $0 < \lambda < 1$ is the decay factor.

As mentioned previously, this model is not only simple to estimate but also the covariance matrix is guaranteed to be positively semi-definite. However, the main drawback is its constant non-estimated decay factor (Alexander 1998, Danielson 2011).

2.4.3.3 MULTIVARIATE GARCH MODELS

Consider that a vector stochastic process $\{r_t\}$ with dimension $N \times 1$. Let $\Im_{t-1}$ denotes the information set generated by the observed series $\{r_t\}$ until time t - 1. I assume that (Bauwens *et al*. 2006):

$$\begin{cases} r_t = \mu_t(\theta) + \epsilon_t \\ \epsilon_t = H_t^{\frac{1}{2}}(\theta) z_t \end{cases} \tag{1.15}$$

where:

θ - vector of parameters,

$\mu_t(\theta)$ - conditional mean $N \times 1$ vector,

$H_t(\theta)$ - conditional variance $N \times N$ matrix,

z_t - iid vector $N \times 1$, that $E(z_t) = 0$ and $Var(z_t) = I_N$

It is worth noting that the conditional variance of r_t is equal to the conditional variance of ϵ_t (Bauwens *et al*. 2006):

$$Var(r_t|\Im_{t-1}) = Var(\epsilon_t|\Im_{t-1}) = H_t^{\frac{1}{2}} Var(z_t|\Im_{t-1}) \left(H_t^{\frac{1}{2}}\right)' = H_t \tag{1.16}$$

H_t is a positive definite matrix ($N \times N$) that may be obtained by e.g. the Cholesky decomposition (Piontek 2006).

The next few sections will focus on the specification of H_t.

2.4.3.4 VEC MODEL

This model was proposed by Bollerslev *et al*. (1988). The VEC model can be presented as follows (Silvennoinen and Teräsvirta 2008):

$$vech(H_t) = c + \sum_{j=1}^{q} A_j vech\left(\epsilon_{t-j}\epsilon'_{t-j}\right) + \sum_{j=1}^{p} B_j vech\left(H_{t-j}\right) \tag{1.17}$$

where *vech* (·) operator stacks the columns of the lower triangular part of a $N \times N$ matrix as a $\frac{N(N+1)}{2} \times 1$ vector and A_j and B_j are $\frac{N(N+1)}{2} \times \frac{N(N+1)}{2}$ matrices of parameters (Silvennoinen and Teräsvirta 2008). Each conditional variance and covariance depends on lagged squared errors, cross-products of errors and lagged conditional variances and covariance. That is why the VEC model is very general. However, high flexibility introduces some disadvantages. Firstly, the number of parameters is equal to $(p+q)\left(\frac{N(N+1)}{2}\right)^2 + \frac{N(N+1)}{2}$, which is large; even for $p = q = 1$ and $N = 3$ the number of parameters equals 78. This makes an estimation demanding. There are restrictive conditions introduced to make the covariance matrix H_t positive definite for all t (Bauwens *et al*. 2006, Brooks 2008: 434, Piontek 2006, Silvennoinen and Teräsvirta 2008). Therefore, a diagonal version of VEC model was proposed.

2.4.3.5 DVEC MODEL

The DVEC model is a restricted version of VEC (Bollerslev *et al*. 1988). This model assumes that A_j and B_j are diagonal matrices. This assumption implies there are fewer parameters to be estimated $(p+q+1)\frac{N(N+1)}{2}$ (e.g. for $p = q = 1$ and $N = 3$ the number of parameters equals 18). Therefore, estimation is less demanding at the cost of flexibility. Each element h_{ijt} depends on lagged values of errors $\epsilon_{it}\epsilon_{jt}$ and its own lagged values. This introduces the lack of transmission effect (Piontek 2006). Even though it is easier to obtain a positive definiteness of the conditional variance matrices for DVEC than VEC, the restrictions are still strong (Bauwens *et al*. 2006, Brooks 2008: 434-435, Engle *et al*. 1995, Piontek 2006, Silvennoinen and Teräsvirta 2008).

2.4.3.6 BEKK MODEL

The solution for the problem of ensuring positive definiteness is a new parameterisation of the conditional variance matrix H_t (Engle *et al*. 1995):

$$H_t = CC' + \sum_{j=1}^{q}\sum_{k=1}^{K} A'_{kj}\epsilon_{t-j}\epsilon'_{t-j}A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K} B'_{kj}H_{t-j}B_{kj} \tag{1.18}$$

where A_{kj}, B_{kj} and C are parameter matrices with the dimension $N \times N$; however, C is lower triangular. This model was proposed by Baba, Engle, Kraft and Kroner and is called the BEKK model (Engle *et al*. 1995). Parameter k ensures the generality of the model; however, when $K > 1$ then identification problems arise (Silvennoinen and Teräsvirta 2008). Under very weak conditions the conditional covariance matrix H_t is positive definite at all times

(Engle *et al*. 1995). The constant term matrix is decomposed into two C and C' to ensure the positive definiteness of H_t. BEKK is almost as general as VEC as it includes all diagonal representations of VEC and almost all positive definite VEC representations (Engle *et al*. 1995). The number of parameters to be estimated $(p+q)KN^2 + \frac{N(N+1)}{2}$ is still large. Assuming that $p = q = 1$, $N = 3$ and $K = 1$ then $(p+q)KN^2 + \frac{N(N+1)}{2} = 24$.

The model can be simplified by assuming that the A_{kj}, B_{kj} matrices are diagonal. The number of parameters decreases to $(p+q)KN + \frac{N(N+1)}{2}$ (e.g. for $p = q = 1$, $N = 3$ and $K = 1$ the number of parameters equals 12) but is still large (Silvennoinen and Teräsvirta 2008).

By using BEKK parameterisation for H_t the positive definiteness is easily obtained; the problem with convergence could be an issue as H_t is not linear in parameters. The interpretation of parameters seems not to be easy (Silvennoinen and Teräsvirta 2008).

2.4.3.7 O-GARCH MODEL

To overcome the estimation problem of a large number of parameters, the O-GARCH model was presented by Alexander (2000). This model tries to express multivariate GARCH by means of univariate GARCH models, i.e. the $N \times N$ conditional variance matrix H_t is modelled using $m \leq N$ univariate GARCH models (Bauwens *et al*. 2006). The error vector process $\{\epsilon_t\}$ can be represented as linear combinations of m uncorrelated factors f_t with unconditional variances of one, where m is usually much smaller than N (Alexander 2000, Bauwens *et al*. 2006, Silvennoinen and Teräsvirta 2008):

$$V^{-\frac{1}{2}}\epsilon_t = u_t = W_m f_t \tag{1.19}$$

where:

$f_t = (f_{1t} \cdots f_{mt})'$ that $E(f_t|\Im_{t-1}) = 0$ and $Var(f_t|\Im_{t-1}) = \Sigma_t = diag\left(\sigma^2_{f_{1t}}, \cdots, \sigma^2_{f_{mt}}\right)$

Each factor is assumed to follow the GARCH (1,1) process, so:

$\sigma^2_{f_{it}} = (1 - \alpha_i - \beta_i) + \alpha_i f_{i,t-1} + \beta_i \sigma^2_{f_{i,t-1}} \quad for\ i = 1, \cdots, m$

$V = diag(v_1, \cdots, v_N)$ and v_i the population variance of ϵ_{it}

W_m is orthogonal $N \times m$ matrix that $W_m = P_m \Lambda_m^{\frac{1}{2}}$

$\Lambda_m = diag(\lambda_1, \cdots, \lambda_m)$ that $\lambda_1 \geq \cdots \geq \lambda_m > 0$ and λ is the eigenvalue of the population correlation matrix of u_t

P_m is $N \times m$ the matrix of corresponding eigenvectors to eigenvalues of the population correlation matrix of u_t

The conditional variance matrix of u_t is equal:

$$V_t = Var(u_t|\Im_{t-1}) = W_m \Sigma_t W_m' \tag{1.20}$$

Therefore, the conditional variance matrix of ϵ_t equals:

$$H_t = Var(\epsilon_t|\Im_{t-1}) = V^{\frac{1}{2}} V_t V^{\frac{1}{2}} = V^{\frac{1}{2}} W_m \Sigma_t W_m' V^{\frac{1}{2}} \tag{1.21}$$

The parameters for the O-GARCH (1,1,m) model are V, W_m, all α_i and all β_i. The number of parameters is equal $\frac{N(m+1)+4m}{2}$ or in extreme cases (i.e. $m = N$). V, W_m are obtained by sample counterparts. The number of factors used is established by principle component analysis.

The advantage of the model is that in practice only a few principle components are enough to explain most of the variability in the system. This means that the estimation process is much easier. However, if the data are weakly correlated then identification problems arise. Another problem for the O-GARCH model is when the components have similar scaling (unconditional variance). Thirdly, if the number of components m is less than N then the rank of the conditional variance matrix is reduced, which can be a problem for some diagnostic tests and applications that use the H_t^{-1} matrix (van der Weide 2002). Finally, the transformation matrix W_m is restricted to be orthogonal. Therefore, van der Weide (2002) showed a generalised version of O-GARCH model.

2.4.3.8 GO-GARCH MODEL – MAXIMUM LIKELIHOOD (ML)

The model can be defined as the O-GARCH model above with two main differences. Firstly, the number of factors equals the number of series (i.e. $m = N$). Secondly, the transformation matrix W is restricted to be invertible, not only orthogonal as in O-GARCH model. W is obtained by using singular value decomposition (Bauwens *et al*. 2006, Silvennoinen and Teräsvirta 2008, van der Weide 2002):

$$W = P\Lambda^{\frac{1}{2}}U \tag{1.22}$$

where: $\Lambda = diag(\lambda_1, \cdots, \lambda_N)$ that $\lambda_1 \geq \cdots \geq \lambda_N > 0$ and λ is the eigenvalue of the population correlation matrix of u_t

P is $N \times N$ the matrix of corresponding eigenvectors to eigenvalues of the population correlation matrix of u_t

U is $N \times N$ orthogonal matrix with $det(U) = 1$

Matrix U can be obtained as a product of rotation matrices (Bauwens *et al*. 2006, van der Weide 2002):

$$U = \prod R_{ij}(\delta_{ij}) \quad -\pi \leq \delta_{ij} \leq \pi \quad i, j = 1, \cdots, N \tag{1.23}$$

where R_{ij} performs a rotation in the plane spanned by e_i and e_j over an angle, δ_{ij}. δ_{ij} are called the Euler angles and may be obtained by ML estimation.

The implied conditional correlation matrix of ϵ_t can be calculated as follows (Bauwens *et al*. 2006, van der Weide 2002):

$$R_t = D_t^{-1} V_t D_t^{-1} \tag{1.24}$$

where: $D_t = (V_t \circ I)^{\frac{1}{2}}$ and $V_t = W \Sigma_t W'$

$\circ$ is a Hadamard product (i.e. an element-wise product)

The model can be estimated using a two-step procedure (van der Weide 2002). In the first step, P and Λ are estimated by exploiting the unconditional variance of u_t (i.e. sample counterparts). In the second step, the conditional information is used to estimate the rotation coefficients of U and all α_i and β_i of N factors. This means that $\frac{N(N+3)}{2}$ (i.e. $\frac{N(N-1)}{2} + 2N$) parameters can be estimated by the log-likelihood function (Bauwens *et al*. 2006, Silvennoinen and Teräsvirta 2008, van der Weide 2002). The number of parameters is quite large.

It is worth mentioning that MGARCH-in-mean models cannot be estimated with O-GARCH and GO-GARCH because of the two-step estimation procedure. Secondly, O-GARCH and GO-GARCH are part of factor GARCH models and therefore are nested in the BEKK model (Bauwens *et al*. 2006).

Allowing the transformation matrix W to be time-varying is one of the possible extensions. Secondly, to use different GARCH models for components (i.e. not only GARCH (1,1)) would be another possible extension (van der Weide 2002).

2.4.3.9 GO-GARCH MODEL – NON-LINEAR LEAST SQUARES (NLS)

The problem of maximising the multivariate likelihood function for high dimensions led to the development of the three-step procedure. This estimation method was proposed by Boswijk and van der Weide (2006). The second step of the two-step procedure is itself divided into two steps. This allows the separation of the estimation of a part of the link matrix W (i.e. U matrix) from univariate GARCH parameters (i.e. $\{\alpha_i, \beta_i\}_{i=1}^{m}$).

The three-step procedure tries to identify U from the autocorrelation structure of $s_t^* s_t^{*\prime}$ where $s_t^* = \Lambda^{-\frac{1}{2}} P' \epsilon_t$. They obtain the estimate for $B = U'AU$ by developing the following regression model:

$$s_t s_t' - I_m = B(s_{t-1} s_{t-1}' - I_m)B + \Gamma_t \quad E(\Gamma_t) = 0 \tag{1.25}$$

using the non-linear least squares method. The estimate for U is obtained from B as A is the diagonal matrix.

The three-step procedure is not only more practical in terms of implementation but is also less prone to convergence problems. However, the main disadvantage is the loss of efficiency.

They apply the O-GARCH, DCC and GO-GARCH models to 10-year daily returns of the Dow Jones Industrial index and the NASDAQ Composite index. They find that patterns are quite similar for volatilities and covariance, with some differences in the heights of the peaks; however, more discrepancy is observed in the estimated correlations between GO-GARCH and two other models. GO-GARCH correlations seem to be like a smoothed version of DCC and O-GARCH. GO-GARCH estimates display lower and upper bands, which is a confirmation of the previous results (van der Weide 2002).

They also perform a test for two five-variate examples of five indices, namely US and European indices. What they find is that the NLS (i.e. three-step) estimator performs as well as the ML (i.e. two-step) estimator or even better. US data exhibit noticeable skewness and kurtosis, which makes the model misspecified. These factors have a bad influence on the ML estimator whereas the NLS estimator seems to be much more robust.

2.4.3.10 GO-GARCH model – Independent Component Analysis (ICA)

Both the two-step procedure and the three-step procedure seem to be too slow when the dimension of the model is high. For that reason, Broda and Paolella (2008) introduce a two-step procedure for estimation of the GO-GARCH model. They use independent component analysis (ICA) as the main tool for the decomposition of a high-dimensional problem into a set of univariate models. The ICA algorithm maximises the conditional heteroskedasticity of the estimated components. Their method is called CHICAGO (conditionally heteroskedastic independent component analysis of generalised orthogonal GARCH models). Their procedure allows them to apply non-Gaussian innovations.

ICA is a more powerful tool than principle components analysis (PCA) in the sense of preserving the interesting features of the data-like clusters. This is because PCA tries to find the direction of the component in which the variance of the data is maximised, whereas ICA tries to find the direction of the component in which the interesting features of the data are kept. This objective leads to different components between ICA and PCA. For details see Hyvarinen (1999a).

Broda and Paolella estimate U by ICA. There are many approaches for solving the ICA problem. It is a matter of choosing an appropriate objective function and optimisation algorithm. This might be expressed in the following 'equation' (Hyvarinen 1999b):

ICA method = objective function + optimisation algorithm

The matrix M defining the transformation:

$$f_t = M_m \epsilon_t \tag{1.26}$$

The aim of ICA is to find $M_m \equiv W_m^{-1}$ such that $y_t = M_m \epsilon_t$ are independent. One of the most important restrictions for ICA is that the independent components must be non-Gaussian. If more than one of components is Gaussian, the matrix W_m is not identifiable.

One of the methods for solving this problem is by maximising negentropy. The central limit theorem states that the distribution of the sum of independent random variables with finite second moments converges to a Gaussian distribution. Let us define $z = W_m^T m$. Then we have $y = m^T \epsilon = m^T W_m f = z^T f$, which means that y is a linear combination of f with weights given by z^T. According to the central limit theorem, $z^T f$ is more Gaussian than any f_i and least Gaussian when it equals one of f_i (only when one of z_i of z is non-zero). Taking m, that maximises the non-Gaussianity of $m^T \varepsilon$. This vector m corresponds to a z that has only one non-zero component. This in turn leads to one of the independent components equals $m^T \varepsilon = z^T f$.

The differential entropy H of a random vector y with density $f(y)$ is defined as (Hyvarinen and Oja 2000):

$$H(y) = -\int f(y) log f(y) dy \tag{1.27}$$

This measure is well known as Shannon's entropy or measure of uncertainty (Shannon 1948). A Gaussian variable has the largest entropy among all random variables of equal variances. Now we can define negentropy *J* (i.e. a measure of non-Gaussianity):

$$J(y) = H(y_{gaussian}) - H(y) \tag{1.28}$$

In practice, however, the density is unknown and an estimate of the negentropy is needed. One of the possible estimators of the negentropy suggested by Hyvarinen (1999a) is:

$$J_G(m) = [E\{G(m^T\epsilon)\} - E\{G(v)\}]^2 \tag{1.29}$$

where *m* is an *m*-dimensional (weight) vector constrained so that $E\{(m^T\epsilon)^2\} = 1$ and *G* is a non-quadratic function. Hyvarinen proposed the following choices of *G* functions:

$$G_1(u) = \log\cosh a_1 u \tag{1.30}$$

$$G_2(u) = exp(-a_2 u^2/2) \tag{1.31}$$

with $1 \leq a_1 \leq 2, a_2 \approx 1$

To summarise, the aim is to find *m* that maximises the negentropy of $m^T\varepsilon$.

The example of a Fast ICA fixed-point algorithm for one and several units was proposed by Hyvarinen (1999a). This algorithm is based on the Newton-Raphson method. It is transformed to a fixed-point iteration. It is worth noting that the convergence is cubic (or at least quadratic).

The second method of solving ICA is by exploiting the time structure of the data set. This approach seems to be more natural for time series data, e.g. financial returns data, as the financial data exhibit GARCH effects. That is why by maximising the autocorrelation of the squared returns one can separate independent components (Broda and Paolella 2008). The fixed-point algorithm was proposed by Hyvarinen *et al*. (2001) based on cross cumulants. The convergence is cubic. For details see Hyvarinen *et al*. (2001).

Broda and Paolella (2008) use the second algorithm; however, they suggest that one may use the first one if the second algorithm fails to converge but this is rare.

They also compare three estimators of matrix U: ML of van der Weide (2002), NLS of Boswijk and van der Weide (2006) and ICA of Broda and Paolella (2008). ML and NLS estimators are virtually unbiased whereas ICA shows a small bias. NLS and ICA are much more robust than ML as they are separated from factor specifications. ICA does not exhibit problems with convergence, conversely to ML. The time of the estimation for their data set shows a big discrepancy between the estimators. The ICA algorithm is 56 and 297 times faster than NLS and ML, respectively. Taking into account all features (i.e. robustness, accuracy, reliability and speed) the ICA estimator looks very promising.

They also apply non-Gaussian distributions for components. They use two special cases of generalised hyperbolic distribution (i.e. normal inverse Gaussian and hyperbolic). They also propose to use the asymmetric power ARCH model for the components instead of GARCH (1,1). However, the problem with using generalised hyperbolic distribution of a weighted sum of independent random variables lies in estimating the cumulative density function, which is needed to calculate portfolio risk measures such as VaR or ES. This problem can be solved by saddle point approximation. This method is not only extremely accurate but also computationally cheap. Their application example considers VaR forecasts for three equally weighted portfolios of ten companies taken from Dow Jones. The data spans the period from 23/09/1992 to 23/03/2007. The VaR forecasts obtained are 1.13% (4.48%) for normal inverse

Gaussian distribution and 1.04% (3.98%) for hyperbolic distribution at a nominal level of 1% (5%). The null hypothesis of correct coverage of the Kupiec test cannot be rejected with a p-value of 0.54 (0.26) for normal inverse Gaussian distribution and 0.85 (0.02) for hyperbolic distribution.

2.4.3.11 GO-GARCH model – Method of Moments (MM)

Boswijk and van der Weide (2009) propose another three-step method for estimation of the GO-GARCH model based on the method of moments. This method is based on the fact that latent factors exhibit heteroskedasticity. All they assume about the factors is that they have persistence in variance and finite fourth moments. This method is very convenient as it does not require optimisation of an objective function. In the third step univariate GARCH models are estimated for latent factors.

The starting point for the derivation of their estimator is the matrix-valued process $S_t = s_t s_t' - I_m$, $F_t = f_t f_t' - I_m$ and in particular their autocorrelation properties. $s_t = V^{-\frac{1}{2}}\epsilon_t$. It is worth noting that the O-GARCH model of Alexander (2000) assumes the standardised principle components $s_t^* = V^{-\frac{1}{2}}P'\epsilon_t$ are independent whereas here the components are conditionally uncorrelated. This is a weaker assumption. Let us define the autocorrelations $\rho_{ik} = corr\left(f_{it}^2, f_{i,t-k}^2\right)$ and the cross-covariances $\tau_{ijk} = cov\left(f_{it}^2, f_{i,t-k} f_{j,t-k}\right)$. Another assumption states that for some integers p, $\min_{1\le i\le m} \max_{1\le k\le p} |\rho_{ik}| > 0$, $\max_{1\le k\le p, 1\le i\le j\le m} \left|\tau_{ijk}\right| > 0$. They define the autocovariance matrices as:

$$\Gamma_k(f) = E(F_t F_{t-k}) \quad k = 1,2,\cdots \tag{1.32}$$

Taking into account all the assumptions, they end up with:

$$\Gamma_k(f) = diag\left((\kappa_1 - 1)\rho_{1k}, \cdots, (\kappa_m - 1)\rho_{mk}\right) \tag{1.33}$$

The autocorrelation matrix then can be defined as:

$$\Phi_k(f) = \Gamma_0(f)^{-\frac{1}{2}}\Gamma_k(f)\Gamma_0(f)^{-\frac{1}{2}} = diag(\rho_{1k}, \cdots, \rho_{mk}) \tag{1.34}$$

The autocovariance and autocorrelation matrices for $s_t = Uf_t$:

$$\Gamma_k(s) = E(S_t S_{t-k}) = E(UF_t U' UF_{t-k} U') = U\Gamma_k(f)U' \tag{1.35}$$

$$\Phi_k(s) = \Gamma_0(s)^{-\frac{1}{2}}\Gamma_k(s)\Gamma_0(s)^{-\frac{1}{2}} = U\Gamma_k(f)U' \tag{1.36}$$

The U matrix can be identified by the eigenvectors of $\Gamma_k(s)$ or $\Phi_k(s)$ as $\Gamma_k(f)$ and $\Phi_k(f)$ are diagonal and U is orthogonal matrix.

The sample estimators for $\Gamma_k(s)$ or $\Phi_k(s)$ are given as follows:

$$\hat{\Gamma}_k(s) = \frac{1}{T}\sum_{t=k+1}^{T} S_t S_{t-k} = \frac{1}{T}\sum_{t=k+1}^{T}(s_t s_t' - I_m)(s_{t-k}s_{t-k}' - I_m) \tag{1.37}$$

$$\hat{\Phi}_k(s) = \hat{\Gamma}_0(s)^{-\frac{1}{2}}\hat{\Gamma}_k(s)\hat{\Gamma}_0(s)^{-\frac{1}{2}} \tag{1.38}$$

However, their experiment suggests that the most efficient estimator of $\hat{U}_k$ uses a symmetric version of $\hat{\Phi}_k(s)$ (i.e. $\frac{1}{2}\left(\hat{\Phi}_k(s) + \hat{\Phi}_k(s)'\right)$).

Obtaining an even more efficient estimator $\hat{U}$ may be possible by combining information from different lags. That is why they follow the Cayley transform to derive the pooled estimator:

$$\widehat{U} = \left(I_m - \sum_{k=1}^{p} w_k (I_m - \widehat{U}_k)(I_m - \widehat{U}_k)^{-1}\right)\left(I_m - \sum_{k=1}^{p} w_k (I_m - \widehat{U}_k)(I_m - \widehat{U}_k)^{-1}\right)^{-1} \quad (1.39)$$

where w_k can be chosen as an equal weight or depending on eigenvalues of $\frac{1}{2}\left(\widehat{\Phi}_k(s) + \widehat{\Phi}_k(s)'\right)$. For details see Boswijk and van der Weide (2009).

They perform a finite sample performance of their estimator of the U matrix. To do this they follow Fan *et al.*'s (2008) approach by defining the square root $d(U, U')$ of a symmetric version of the distance measure $D(U, U')$ for orthogonal matrices. For details see Boswijk and van der Weide (2009). They calculate the root mean square distance of $d(U, U')$ (i.e. RMSD) over 5,000 Monte Carlo replications for different numbers of the observations $T \in \{800, 1600, 3200, 6400\}$ and different values of $p \in \{1, 5, 10, 25, 50, 100, 200\}$. The eigenvalue-weighted estimator always is better than the equally weighted estimator. The optimal lag length is $p = 50$ (all the components have finite kurtosis) or $p = 100$ (some of the components do not have finite kurtosis) depending on the properties of the components. The larger the sample size is the higher lag order is needed.

The maximum likelihood estimator (ML) has a much smaller RMSD than the method of moments estimator (MM). However, a very important fact is that the MM estimator for the process with some of the components not having finite kurtosis (which violates one of the assumptions) has the same behaviour as for the process with all the components with finite kurtosis. The gap between the efficiency of the ML and MM estimators is reduced when different GARCH specifications or non-Gaussian innovations are proposed for the components. When the dimension of the system increases then convergence problems are possible for the ML estimator. The gap between the time needed for estimation of ML and MM grows significantly when the dimension of the system increases.

They also perform two empirical applications for comparison of ML and MM estimates. They first consider the Dow Jones STOXX 600 European stock market sector indices. The data span the period from January 1987 to December 2007. They focus on a trivariate model of three sectors. They find that the estimates obtained for the U matrix as well as the GARCH parameters are different. The estimated variances and covariances are quite similar but the correlations seem to differ more. Generally speaking, more variation can be noticed in series estimated by the ML method than by the MM method. Then they add to the system another 12 sectors and perform the above-mentioned estimation once again. The variances and covariances are similar. The conditional correlations display larger differences; however, the variation in the 15-variate model is small around their unconditional mean. All variances, covariances and correlations in the 15-variate model are much smoother than in the three-variate model.

The second application examines the conditional correlations between the daily returns of American Airlines, South-West Airlines, Boeing, FedEx, crude oil and kerosene. The focus on the data from 19 July 2003 to 12 August 2008. They find that all correlations display the same pattern. MM correlations show more variation than ML correlations.

2.4.3.12 DCC model of Engle

The DCC model was proposed by Engle (2002). This model belongs to a group of multivariate models that can be seen as non-linear combinations of univariate GARCH models. The DCC is a generalised version of the constant conditional correlation (CCC) model of Bollerslev (1990). Other DCC models are by Tse and Tsui (2002) or Christodoulakis and Satchell (2002). However, I will just focus here on Engle's DCC model, which is defined as follows:

$$H_t = D_t R_t D_t \tag{1.40}$$

where

$$D_t = diag\left(h_{11t}^{\frac{1}{2}}, \cdots, h_{NNt}^{\frac{1}{2}}\right) \tag{1.41}$$

h_{iit} can be any univariate GARCH model

$$R_t = diag\left(h_{11t}^{\frac{1}{2}}, \cdots, h_{NNt}^{\frac{1}{2}}\right) Q_t diag\left(h_{11t}^{\frac{1}{2}}, \cdots, h_{NNt}^{\frac{1}{2}}\right) \tag{1.42}$$

$Q_t = (q_{ijt})$ is the $N \times N$ symmetric positive definite matrix defined as:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \tag{1.43}$$

where $u_{it} = \epsilon_{it} / \sqrt{h_{iit}}$,

α and β are non-negative scalars that $\alpha + \beta < 1$,

$\bar{Q}$ is the $N \times N$ unconditional variance matrix of u_t.

The main drawback of the model is that all conditional correlations follow the same dynamic structure. The number of parameters to be estimated equals $(N+1)(N+4)/2$ and is large when N is large (Bauwens *et al*., 2006). Therefore Engle proposed the estimation of the DCC model by a two-step procedure. This is possible as the conditional variance $H_t = D_t R_t D_t$ can be seen as volatility part and correlation part. Instead of using the likelihood function for all the coefficients he suggested replacing R_t by the identity matrix. This leads to a quasi-log-likelihood function that is the sum of log-likelihood functions of N univariate models. In the second step Engle estimates parameters of R_t. This method produces consistent but not efficient estimators. It is possible to compare the log-likelihood function of the two-step procedure with the one-step procedure and of the other models. For details see (Bauwens *et al*. 2006, Engle 2002).

Engle performs a comparison of several correlation estimators. The data-generating process is described by two GARCH models and by six different correlation functions. The simulation is performed 200 times for 1,000 observations. He uses eight different models for estimating correlations: moving average, exponential smoothing, scalar BEKK, diagonal BEKK, orthogonal GARCH, DCC with integrated MA estimation, DCC by log likelihood for the integrated model and DCC by log likelihood for the mean-reverting model. Three different measures for comparison are used. The first is the mean absolute error. The second is the autocorrelation test of the squared standardised residuals. The third test is based on the estimator of VaR for a two-asset portfolio. For details see Engle (2002). Overall the experiment shows that DCC models are very good or the best. When it comes to making a choice between DCC models, the mean-reverting is the best.

2.4.3.13 COPULA DCC MODEL

The DCC model (Engle 2002) can be extended by applying the copula approach. The copula theory was introduced by Sklar (1959). It allows the joint distribution of returns to be modelled by marginal distributions of returns and copula, which characterises the dependence between returns. Patton (2006) further extended the theory of static copula by introducing the concept of conditional (time-varying) copula. This allows the concept of copula to be incorporated into financial time series. The DCC model assumed multivariate-normal distribution; however, by applying copula we can model multivariate distribution in a more flexible and accurate way (Bauwens *et al*. 2012).

Following Ghalanos (2013a, 2013b), the copula GARCH model with joint distribution F can be represented as follows:

$$F(r_t|\mu_t, h_t) = C\big(F_1(r_{1t}|\mu_{1t}, h_{1t}), \dots, F_n(r_{nt}|\mu_{nt}, h_{nt})\big) \tag{1.44}$$

Where F_i is the conditional distribution of the i^{th} asset returns, C is the n-dimensional copula, $r_t = r_{1t}, \dots, r_{nt}$ is the vector of asset returns, $\mu_t = \mu_{1t}, \dots, \mu_{nt}$ is the vector of conditional means, $h_t = h_{1t}, \dots, h_{nt}$ is the vector of conditional variances

For simplicity if we assume that conditional variance follows GARCH (1,1) then the conditional mean and variance can be presented as follows:

$$r_{it} = \mu_{it} + \varepsilon_{it} \tag{1.45}$$

$$\varepsilon_{it} = \sqrt{h_{it}} z_{it} \tag{1.46}$$

$$h_{it} = \omega + \alpha\varepsilon_{it-1}^2 + \beta h_{it-1} \tag{1.47}$$

Where $z_{it} \sim f_i(0,1,\xi_i,\nu_i)$ are i.i.d. random variables and we assume here that they follow standardised skew Student distribution (Fernandez and Steel 1998), ξ is the skew parameter, ν is the shape parameter (Ghalanos 2013a). Please note that in general z_{it} does not have to follow standardised skew Student distribution.

Assuming that the dependence structure of the margins follows the Student copula then the conditional density is given by (Ghalanos 2013b):

$$c_t(u_{1t}, \dots, u_{nt}|R_t, \eta) = \frac{f_t(F_1^{-1}(u_{1t}|\eta), \dots, F_n^{-1}(u_{nt}|\eta)|R_t, \eta)}{\prod_{i=1}^{n} f_i(F_i^{-1}(u_{it}|\eta)|\eta)} \tag{1.48}$$

Where $u_{it} = F_{it}(r_{it}|\mu_{it}, h_{it}, \xi_i, \nu_i)$ is the probability integral transformed residuals, $F_i^{-1}(u_{it}|\eta)$ is the quantile transformation of uniform margins, $f_t(.|R_t, \eta)$ is the multivariate density of the Student distribution, R_t is the conditional correlation that is assumed to follow the DCC model, η is the constant shape parameter and $f_i(.|\eta)$ is the univariate density.

The joint density function of two-step estimation can be described as follows:

$$f(r_t|\mu_t, h_t, R_t, \eta) = c_t(u_{1t}, \dots, u_{nt}|R_t, \eta) \prod_{i=1}^{n} \frac{1}{\sqrt{h_{it}}} f_{it}(z_{it}|\xi_i, \nu_i) \tag{1.49}$$

A similar model was proposed by Ausin and Lopes (2010).

Further details on time-varying copulas in terms of specification, simulation and application can be found in Manner and Reznikova (2012).

2.4.3.14 Alternative multivariate volatility models

In the literature some other multivariate GARCH models can be identified (Bauwens *et al*. 2006, 2012, Danielson 2011, Engle 2009b, Engle and Kelly 2012, Francq and Zakoian 2010, Silvennoinen and Terasvirta 2008, Tsay 2010). The alternative volatility models, for example, realised volatility, stochastic volatility and range-based volatility, which are discussed in Section 2.4.2.6, have their counterparts in multivariate framework (Bauwens *et al*. 2006, 2012, Danielson 2011, Engle 2009b, Francq and Zakoian 2010, Silvennoinen and Terasvirta 2008, Tsay 2010).

2.5 Testing multivariate volatility model performance in a portfolio context

One of the aims of my thesis is the comparison of the different multivariate volatility models. In the literature we can identify a large number of different approaches that we could possibly take; for example, in-sample and out-of-sample comparison (Bauwens *et al*. 2012, Caporin and McAleer 2009, 2012, Clements *et al*. 2009, 2012, Colacito *et al*. 2011, DeMiguel *et al*. 2009a, Engle 2009b, Engle and Colacito 2006, Engle and Sheppard 2001, Giamouridis and Vrontos 2007, Jithendranathan 2007, Laurent *et al*. 2012, Patton and Sheppard 2009, Syriopoulos and Roumpis 2009).

In-sample comparisons can be based on checking whether the mathematical and asymptotic properties of the models are satisfied or whether the models capture the features of financial data (Bauwens *et al*. 2012). The optimal in-sample model does not, however, guarantee the optimal out-of-sample performance, which is the key aspect for the financial industry.

The alternative comparisons are based on the out-of-sample performance, which seems to be important from a practical perspective. We can distinguish two main groups: direct and indirect (Bauwens *et al*. 2012, Patton and Sheppard 2009).

Direct model performance focuses on the direct comparison of covariance forecasts by means of mean absolute error (MAE), mean squared error (MSE), Mincer and Zarnowitz (1969) regression or by loss function differential (Diebold and Mariano 1995, West 1996).

On the other hand, the indirect model performance compares alternative covariance forecasts in the application environment; for example, asset allocation framework, portfolio VaR, hedging strategies, trading strategies, and option pricing (Bauwens *et al*. 2012, Engle and Colacito 2006, Engle and Sheppard 2001, Giamouridis and Vrontos 2007, Jithendranathan 2007, Patton and Sheppard 2009, Syriopoulos and Roumpis 2009).

Although many different alternative approaches to testing can be identified in my thesis I will only focus on the comparison of alternative multivariate volatility models in the portfolio context.

2.6 CONCLUSION

The objective of the PhD thesis is to make a novel contribution to the literature. Given that the seminal articles in this area are no more than a decade old (Engle 2002, van der Weide 2002) there is substantial scope to find a gap in the literature where I can make a contribution.

As identified in Section 2.2, Markowitz showed us that the correlation and standard deviation (variance) is fundamental to identifying an efficient portfolio. I have shown in Section 2.3 that correlation and volatility levels show substantial variation across both the market cycle and time in general. We also found that in a time of crisis correlation can change dramatically (Garnaut 1998, Tsai and Chen 2010). I have therefore identified that the 2007 financial crisis should provide a good opportunity to examine the issue of major changes in correlation in the portfolio context.

I have identified a number of limitations in respect to the current literature that I can examine further in my thesis:

- Much of the current literature examines correlation from the perspective simple constant and rolling correlation based methodologies in respect to stock market integration (Forbes and Rigobon 2002, Goetzmann *et al.* 2001, Longin and Solnik 2001). This is potentially inappropriate in times of financial crisis (for example, 2007) given the tendency for correlations to change rapidly at different points of stock market cycle (Longin and Solnik 2001, You and Daigler 2010). This methodology may not be able to model time related changes in correlation linkages between markets in an adequate manner.

- An issue with respect to the GO-GARCH dynamic correlation model (introduced by van der Weide (2002)) relates to the issue of a constant mixing matrix (Section 2.4.3.8). This issue is particularly important in respect to my dataset due to the possibility of structural changes in market relationships in response to the 2007 crisis.
- Another limitation in the current literature is found in respect to the DCC model (introduced by Engle (2002)). This model does not take into consideration non-normality of financial data. This is likely to be a significant issue with respect to my dataset due to the skewed nature of financial returns during financial crisis.
- It is been suggested by Bauwens *et al*. (2012) that the copula-based variation of the DCC may be most appropriate within a financial portfolio context. This has not been applied to the unique and extreme market conditions as occurred during the 2007 financial crisis in the literature. My work will extend the application of this model in this respect.
- There is no commonly accepted way of measuring portfolio performance in the literature which makes comparing relative performances of different correlation methodologies problematic from portfolio optimisation perspective.
- There are a limited number of comparative studies in the literature in respect to developed and emerging/frontier markets. This is particularly evident in respect to the ways in which correlation linkages develop during times of financial crisis.

Although each different method identified in this chapter (constant correlation, rolling correlations, exponential smoothing based correlations and dynamic conditional correlations) do have some negative aspects it is not possible to rule any of them out entirely at this stage. For this reason, in the following chapters of this thesis I will examine the alternative methodologies in detail in order to identify which one will enable me to identify the most efficient portfolio. This will be the main novel contribution of this thesis.

In Chapter 4 I will explore how to apply the DCC model to the measurement of volatility and correlation during the financial crisis. This will be followed in Chapter 5 by a comparison of DCC and other alternative time-variant methodologies; specifically, COPULA DCC, GO-GARCH ML, GO-GARCH NLS, GO-GARCH ICA, GO-GARCH MM, SMA and EWMA.

The findings from Chapters 4 and 5 will be used to identify which multivariate GARCH methodologies will be used in the comparison of portfolio performance undertaken in Chapter 6. The focus throughout these chapters will be to examine any difference which arise in respect to developed and emerging/frontier markets.

3 Data

In this chapter I discuss the data used in the thesis. The first section identifies the crisis period. After that the data set is presented and summary statistics are discussed. The last section focuses on the distribution of the data.

3.1 Identifying the crisis period

An important issue that I face in this study is identifying the starting and ending points of the financial crisis. This is a potentially problematical issue as their dates are open to interpretation. For the purposes of this thesis, I use 11 May 2007 and 1 January 2010 as these respective dates. In order to identify any long-term structural changes in the conditional correlation, conditional volatility and ratio of conditional volatility relationships I split the data into a number of periods. To enhance the robustness of the results and also ensure that I can account for any 'contamination' of the data from the subsequent euro crisis,[1] a number of different test observation periods are used. I use 62-, 124- and 176-week pre-crisis observation periods and 62- and 124-week post-crisis observation periods. The 124-week sample was chosen on the basis that this represents the maximum post-crisis period of data available for analysis. The 62-week period represents half of this maximum period and the 176-week period prior to the crisis was chosen as it represents a long period of relatively stable correlation.

[1] The first significant developments in the euro crisis were after the end-point of the 2007 financial crisis identified in this thesis. A Eurostat report dated 8 January 2010 first highlighted irregularities in the reporting of the Greek deficit and it was not until April 2010 that the eurozone countries first agreed to set up a safety net of €30 billion for Greece. The subsequent €78 billion bailout of Ireland was agreed in November 2010 and a further bailout of Portugal was agreed in May 2011. The developing crisis appears to have had only a marginal impact on US markets during the period of our analysis. From 1 January 2010 to 4 March 2011 (week 62 in our analysis) the S&P500 rose from 1133 to 1321 and by 11 May 2012 (week 124) it reached 1353. Within the eurozone itself, the DAX 30 first fell by a substantial amount from 25 July 2011 (significantly after our week 62) and, after a period of recovery, started to resume its downward trend from 15 March 2012.

Although problems in the US sub-prime market began to become apparent in 2006, it was not until the middle of May 2007 that stock prices across the US financial sector as a whole began to fall (based on the weekly closing values of Dow Jones US Financials index) and volatility across the market began to increase significantly. Market perceptions in respect to the development of the crisis can be approximated by using the VIX index (Chicago Board Options Exchange Market Volatility Index). This index is often described as a 'fear gauge', given that it reflects market volatility expectations over the following 30 days. From around the middle of 2007, the VIX can be observed as rising above its historical mean levels and remaining high throughout the crisis period. As the crisis began to wane, the VIX began to mean-revert back towards its historical average. For the purposes of this study I have identified the point of approximate reversion to the mean as being the end point of the crisis.[2] It can be argued that the crisis ended earlier than this date, in June 2009, which is the point that the National Bureau of Economic Research (NBER) identified as being the end of the contraction phase of the business cycle (NBER 2012). However, up to the end of 2009 the VIX showed market volatility to be still significantly above its historical average. It was not until January 2010 that President Obama declared that the markets had been stabilised and that in effect the crisis was over (US Treasury 2010). I believe that although our choice for the end date chosen may possibly be a little conservative, this adds to the overall robustness of the analysis.

[2] The mean daily closing value of the VIX over the period 3 January 2000–11 May 2012 was 21.72. The index began to show a significant increase above this level from the middle of 2007, peaking at 79.13 on 20 October 2008. It began to revert to the mean value during 2009 and by 28 December 2009 was at 21.58: approximately the long-term mean. Although there was a subsequent period of high volatility during May and June 2010, the post-crisis mean of 21.15 covering the period 4 January 2010–11 May 2012 approximated to the long-term mean. Data source: Yahoo (2012).

3.2 DATA SET

The source of the data used in this study is MSCI (2012). Weekly data is used that runs from 12 July 2002 to 11 May 2012; this gives 514 observations. I considered using daily, weekly and monthly data. Weekly data is used given that monthly data does not provide enough observation for adequately applying GARCH methodology. In addition, the use of daily data was discounted on the basis that portfolio analysis rarely uses such a short period because of the volatility effect associated with international markets being open and closed at different times during the day (Cappiello *et al*. 2006).

I use weekly MSCI 'standard' indices (based on large and mid capitalisation stocks); these are derived from closing-price-based weekly total returns (adjusted for dividend payments) and are based in US dollars. The weekly closing values and logarithmic returns of the respective indices used in the study are presented in Figure 3.1 and Figure 3.2, respectively.

In my study I make use of the US index and a series of (i) developed market regional indices and (ii) emerging/frontier market regional indices. The constituent countries of the regional indices used are shown below in brackets. My study examines the data from the perspective of a US investor given that the crisis had its origin in the US markets.

Developed regions:

- EMU (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Portugal, Spain);
- EUROPE ex EMU (Denmark, Norway, Sweden, Switzerland, UK);
- PACIFIC (Australia, Hong Kong, Japan, New Zealand, Singapore).

Emerging/frontier regions:

- EM BRIC (Brazil, Russia, India, China);
- EM EUROPE (Czech Republic, Hungary, Poland, Russia, Turkey);
- EM LATIN AMERICA (Brazil, Chile, Colombia, Mexico, Peru);
- EM ASIA (China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand);
- EFM AFRICA (Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tunisia).

The 2007 crisis resulted in equity markets across the world starting to fall significantly towards the end of 2008, with most markets reaching their trough in early 2009 (see Figure 3.1). The returns data in Figure 3.2 show that most markets experienced increases in volatility towards the end of 2008 and also during 2009 as the financial crisis reached its peak.

Figure 3.1 Weekly closing values of nine MSCI indices over the period 12 July 2002 to 11 May 2012

Note: The two vertical lines represent 11 May 2007 and 1 January 2010

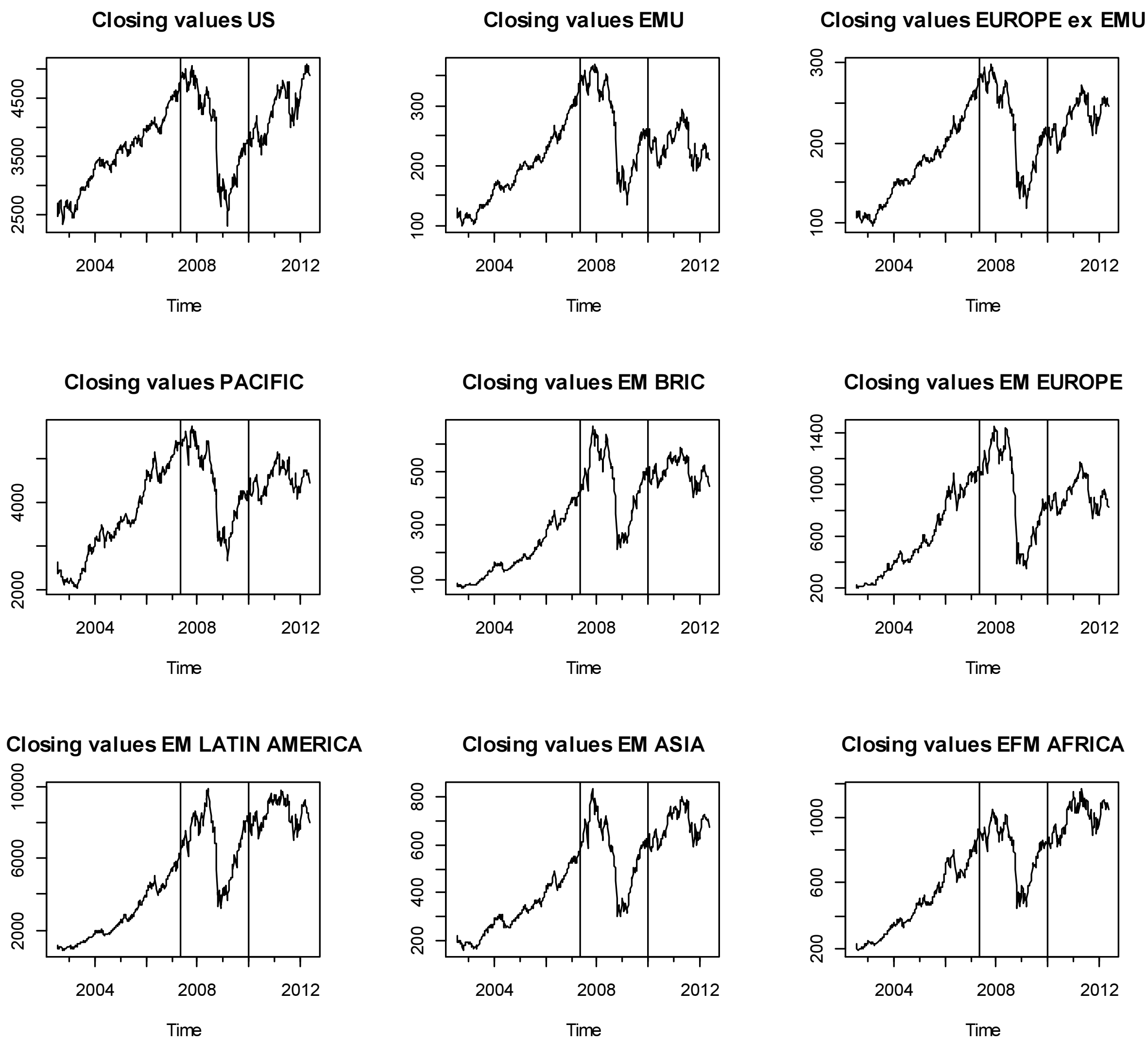
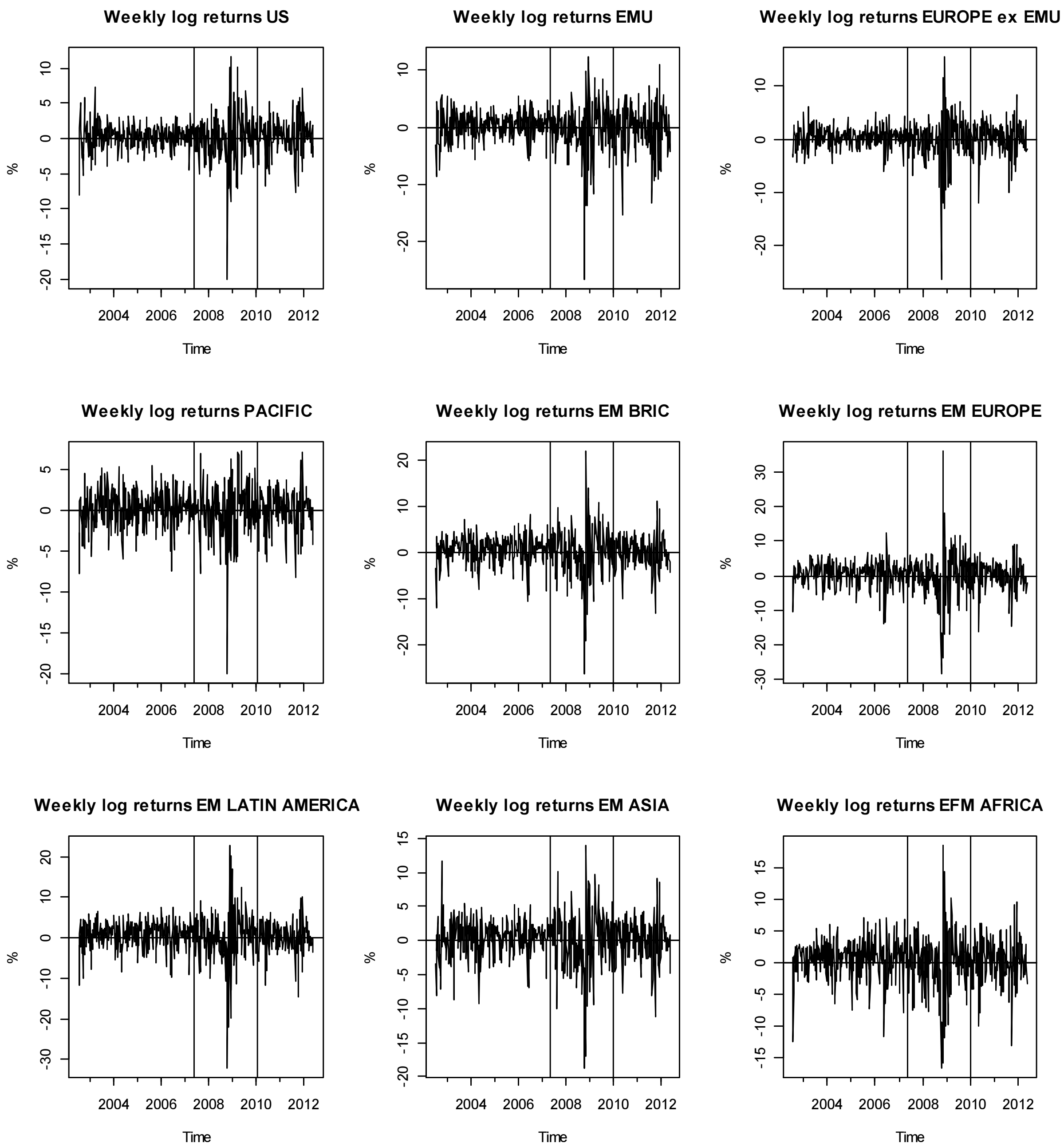


Figure 3.2 Weekly logarithmic returns of nine MSCI indices shown in percentages over the period 12 July 2002 to 11 May 2012

Note: The two vertical lines represent 11 May 2007 and 1 January 2010



3.3 SUMMARY STATISTICS: MEAN, MEDIAN, STANDARD DEVIATION AND UNCONDITIONAL CORRELATION WITH US

Table 3.1 identifies that returns made in emerging/frontier markets over the full sample period covered by the data set were generally higher than those made in their developed market counterparts. The respective mean, median and standard deviation of returns were also on the whole higher in the emerging/frontier regions. This is as would be expected given that higher returns are normally associated with higher risk (volatility). During this period the unconditional correlations between the US and developed world regional indices can be seen as having been generally higher than the correlations between the US and emerging/frontier market indices.

Table 3.1 Summary statistics of weekly percentage returns of nine MSCI indices over the period 12 July 2002 to 11 May 2012

	US	EMU	EUROPE ex EMU	PACIFIC	EM BRIC	EM EUROPE	EM LATIN AMERICA	EM ASIA	EFM AFRICA
Median	0.21	0.51	0.50	0.21	0.82	0.70	0.84	0.54	0.68
Mean	0.12	0.10	0.15	0.10	0.32	0.25	0.38	0.22	0.30
Min.	-20.05	-26.64	-26.45	-20.01	-26.47	-28.46	-32.25	-18.77	-16.74
Max.	11.58	12.37	15.51	7.29	21.92	36.01	22.78	13.95	18.45
Std dev.	2.67	3.65	3.14	2.74	4.06	4.89	4.59	3.44	3.71
Skewness	-0.86	-1.26	-1.50	-1.03	-0.81	-0.44	-1.04	-0.69	-0.53
Kurtosis	7.82	7.04	12.16	5.61	6.44	9.67	8.45	3.60	3.21
Uncond. correlation with US	1.00	0.83	0.83	0.62	0.72	0.62	0.78	0.64	0.63

3.4 DATA DISTRIBUTION

From Table 3.1 we observe negative skewness (the third moment of the distribution) for all the regions, ranging from -1.50 to -0.44. An additional feature of the data set is the high kurtosis (the fourth moment of the distribution) for all the regions, ranging from 3.21 to 12.16. This suggests that the empirical distributions not only have longer left-hand tails but also much fatter tails than normal distribution. This can be confirmed by looking at the histograms (Figure 3.3 and the more detailed view in the appendix in Figure 3.6–Figure 3.14), density plots (Figure 3.4 and the more detailed view in the appendix in Figure 3.15–Figure 3.23), and QQ plots (Figure 3.5 and the more detailed view in the appendix in Figure 3.24–Figure 3.32). I have also performed the statistical test for normality: Jarque-Bera (1980), Shapiro-Wilk (1965), Kolmogorov-Smirnov (Kolmogorov 1933 and Smirnov 1948), and Anderson-Darling (1952) of the weekly returns (Table 3.2). All of the normality tests for all markets reject the null hypothesis of normality at 1% significance level.

Figure 3.3 Histogram plots of weekly returns of nine MSCI indices against fitted normal distribution

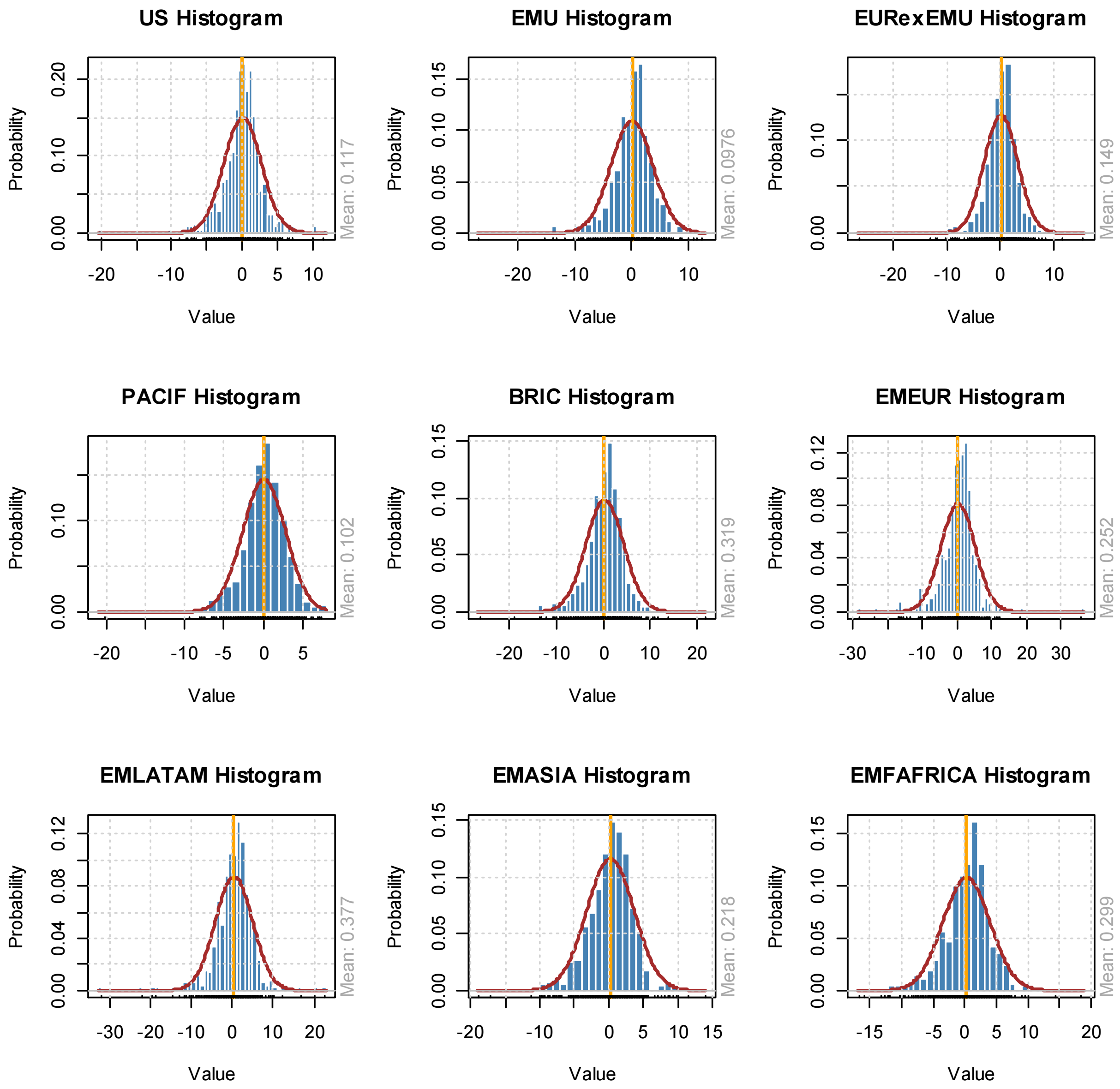


Figure 3.4 Density plots of weekly returns of nine MSCI indices against fitted normal distribution

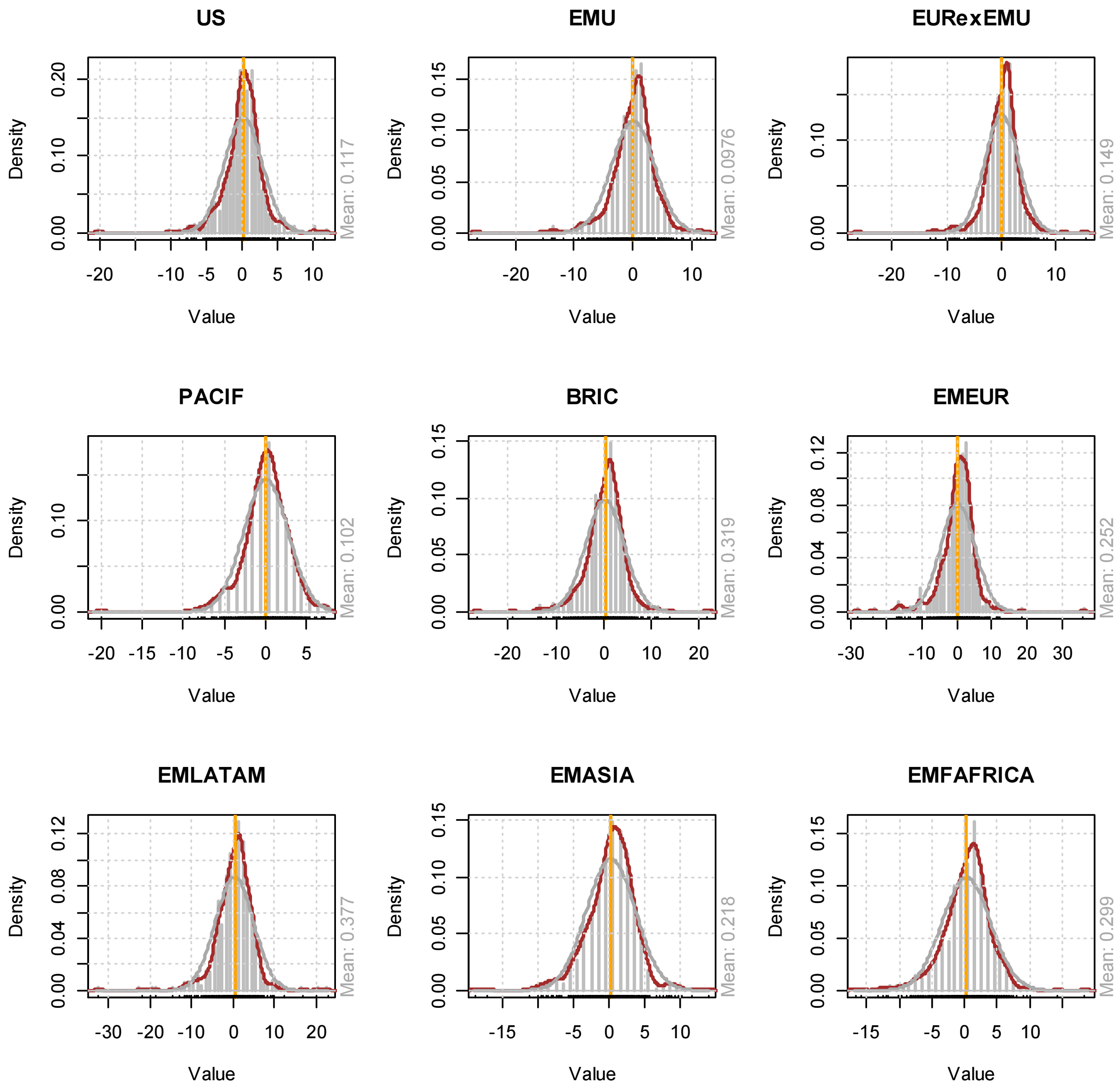


Figure 3.5 QQ plots of weekly returns of nine MSCI indices against normal distribution

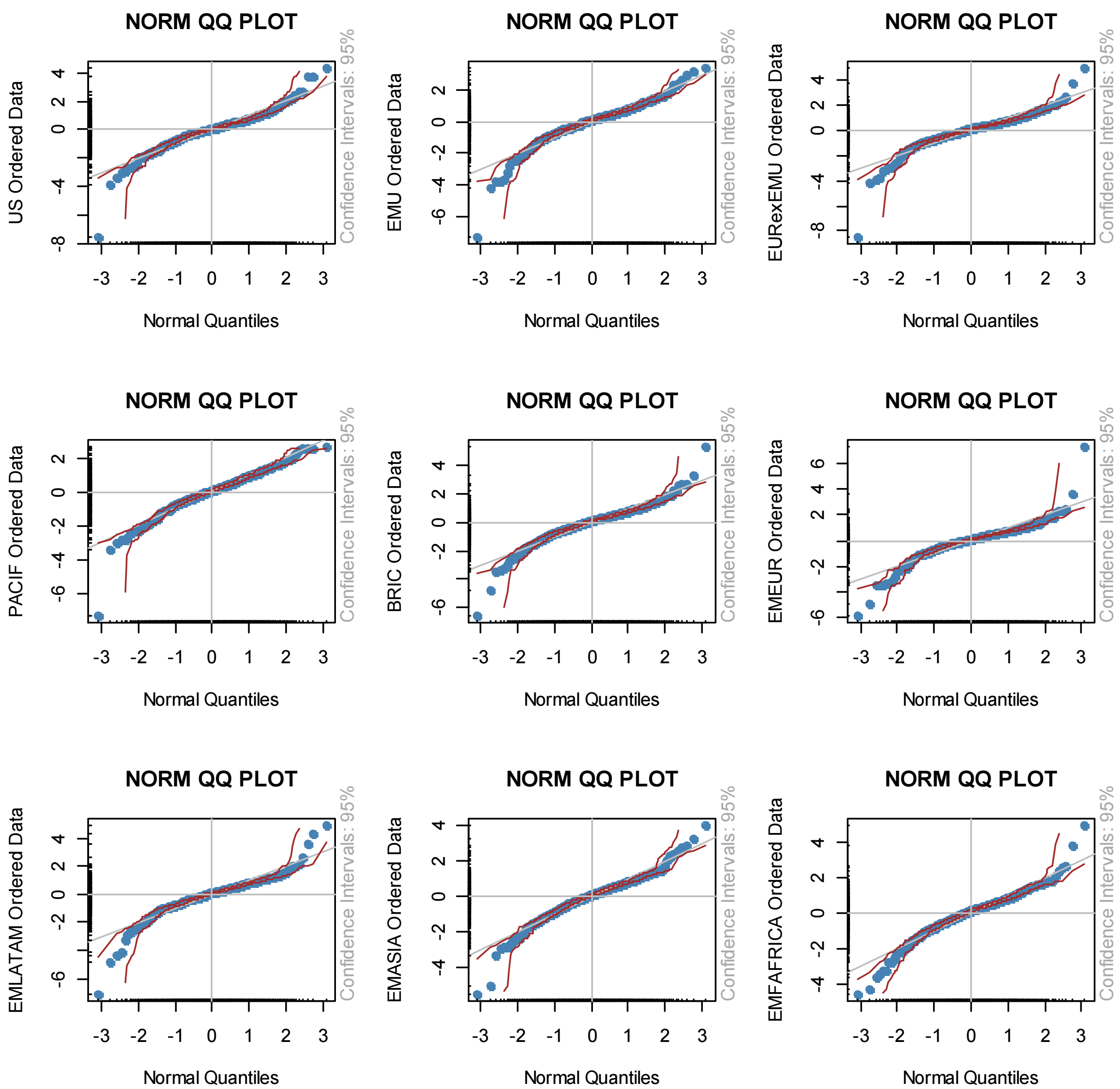


Table 3.2 Normality tests of weekly returns of nine MSCI indices

Index	Sample length	Jarque-Bera test p-value	Shapiro-Wilk test p-value	Kolmogorov-Smirnov test p-value	Anderson-Darling test p-value
US	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
EMU	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
EUROPE ex EMU	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
PACIFIC	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
BRIC	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
EM EUROPE	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
EM LATIN AMERICA	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
EM ASIA	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***
EMF AFRICA	513	0.000***	0.000***	0.000***	0.000***
	513	0.000***	0.000***	0.000***	0.000***

*Notes: The 513 observation period runs from 12 July 2002 to 11 May 2012. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

3.5 APPENDICES

Figure 3.6 Histogram plots of weekly returns of US against fitted normal distribution

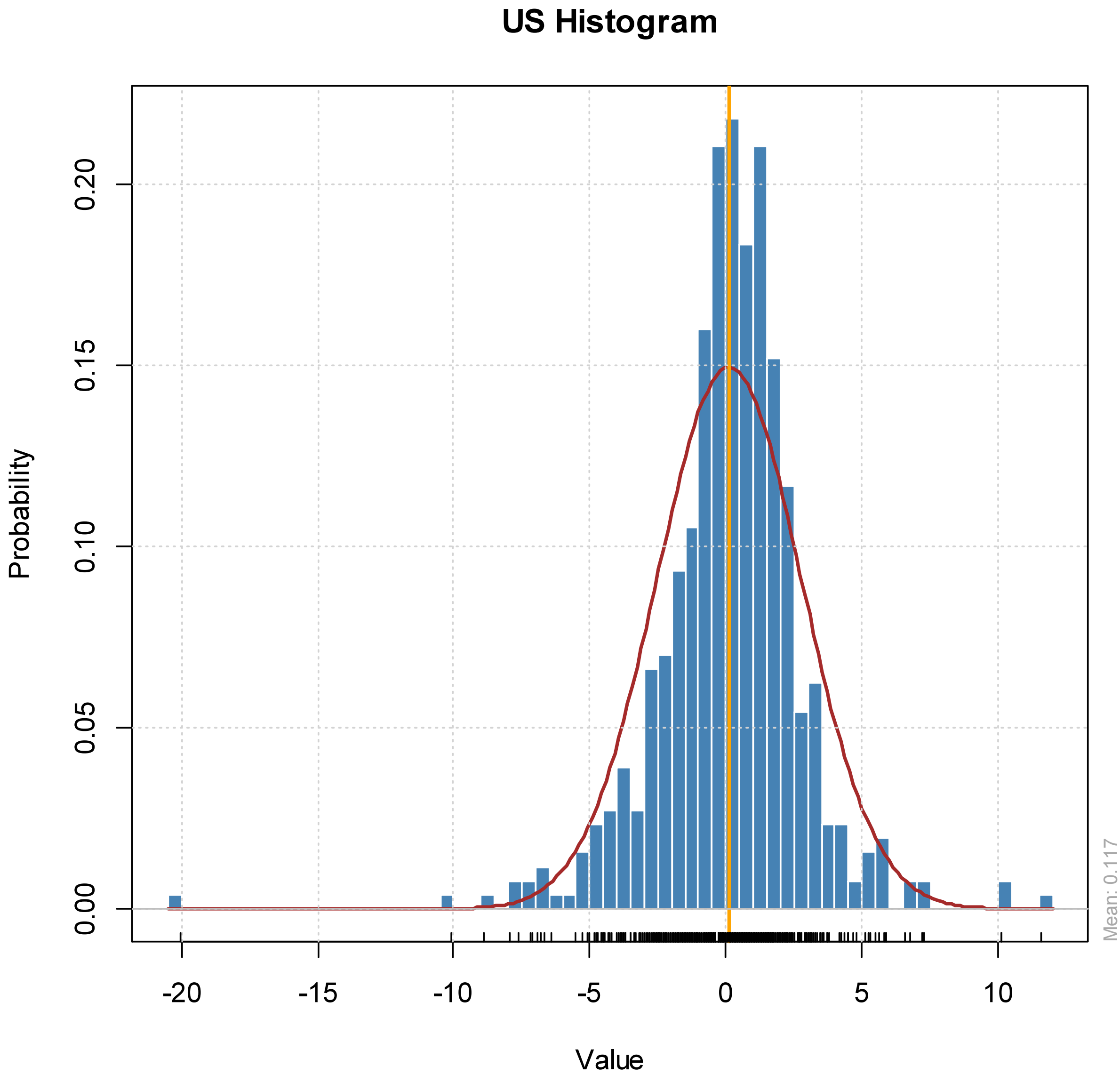


Figure 3.7 Histogram plots of weekly returns of EMU against fitted normal distribution

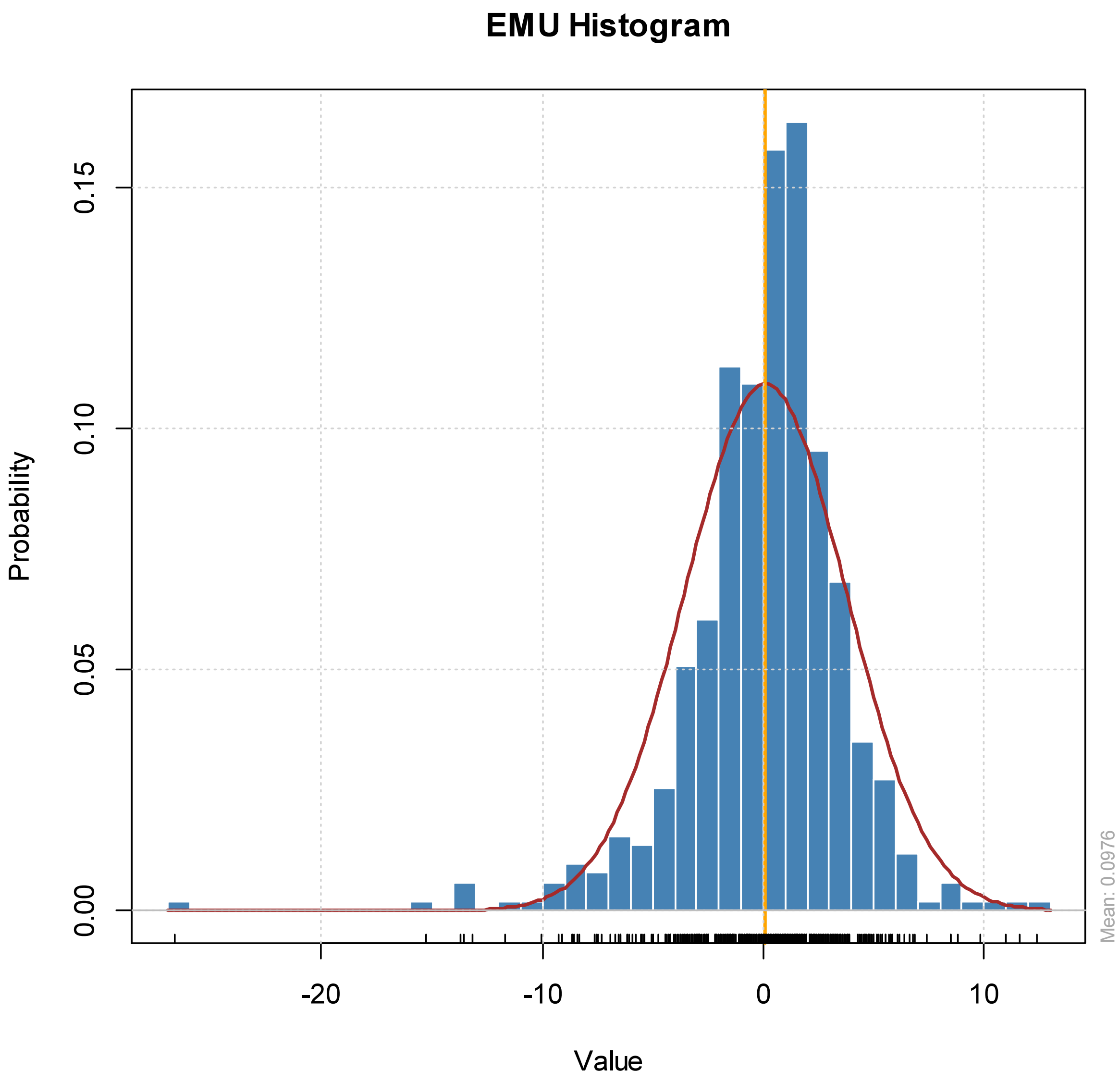


Figure 3.8 Histogram plots of weekly returns of Europe ex EMU against fitted normal distribution

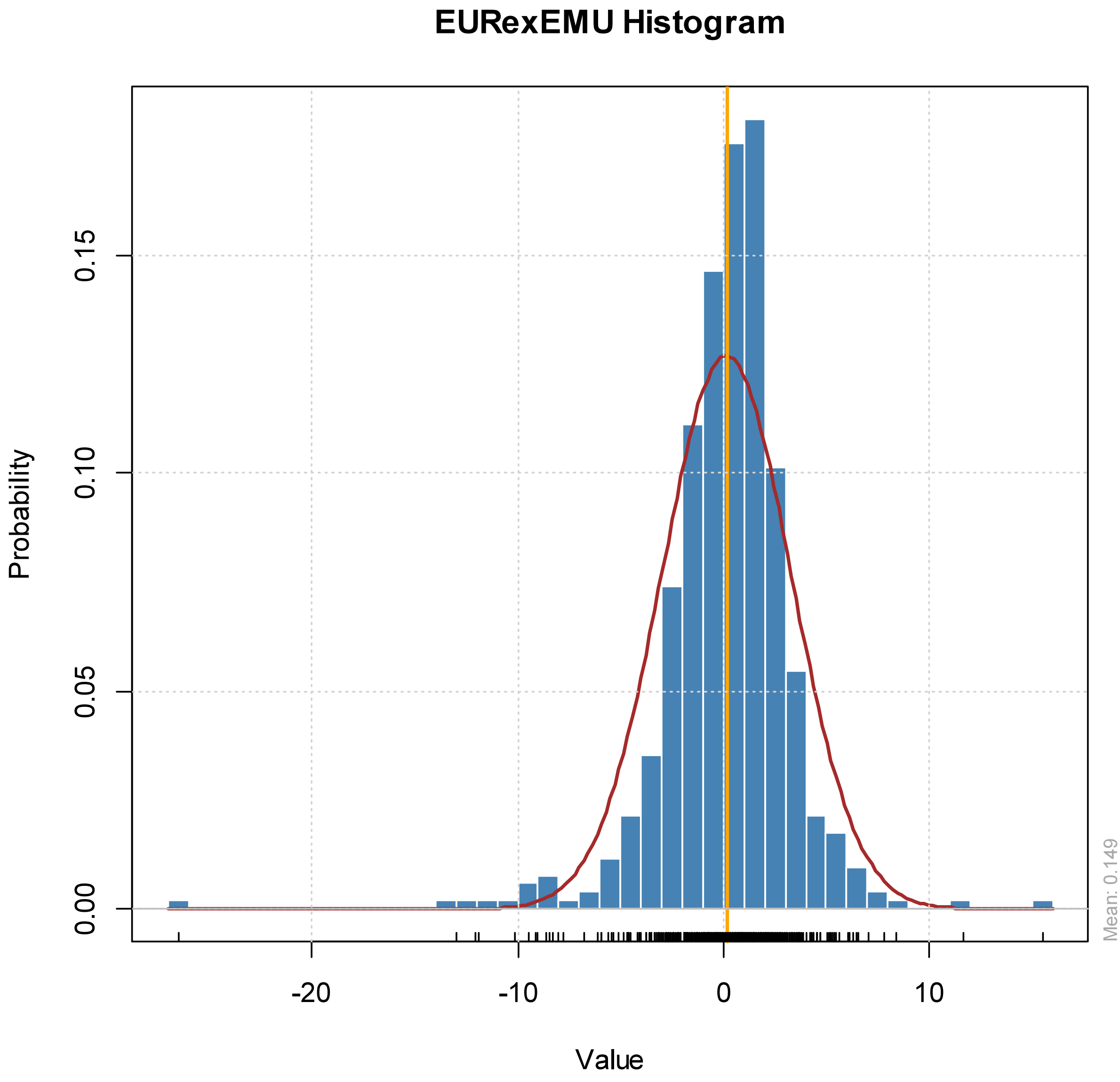


Figure 3.9 Histogram plots of weekly returns of Pacific against fitted normal distribution

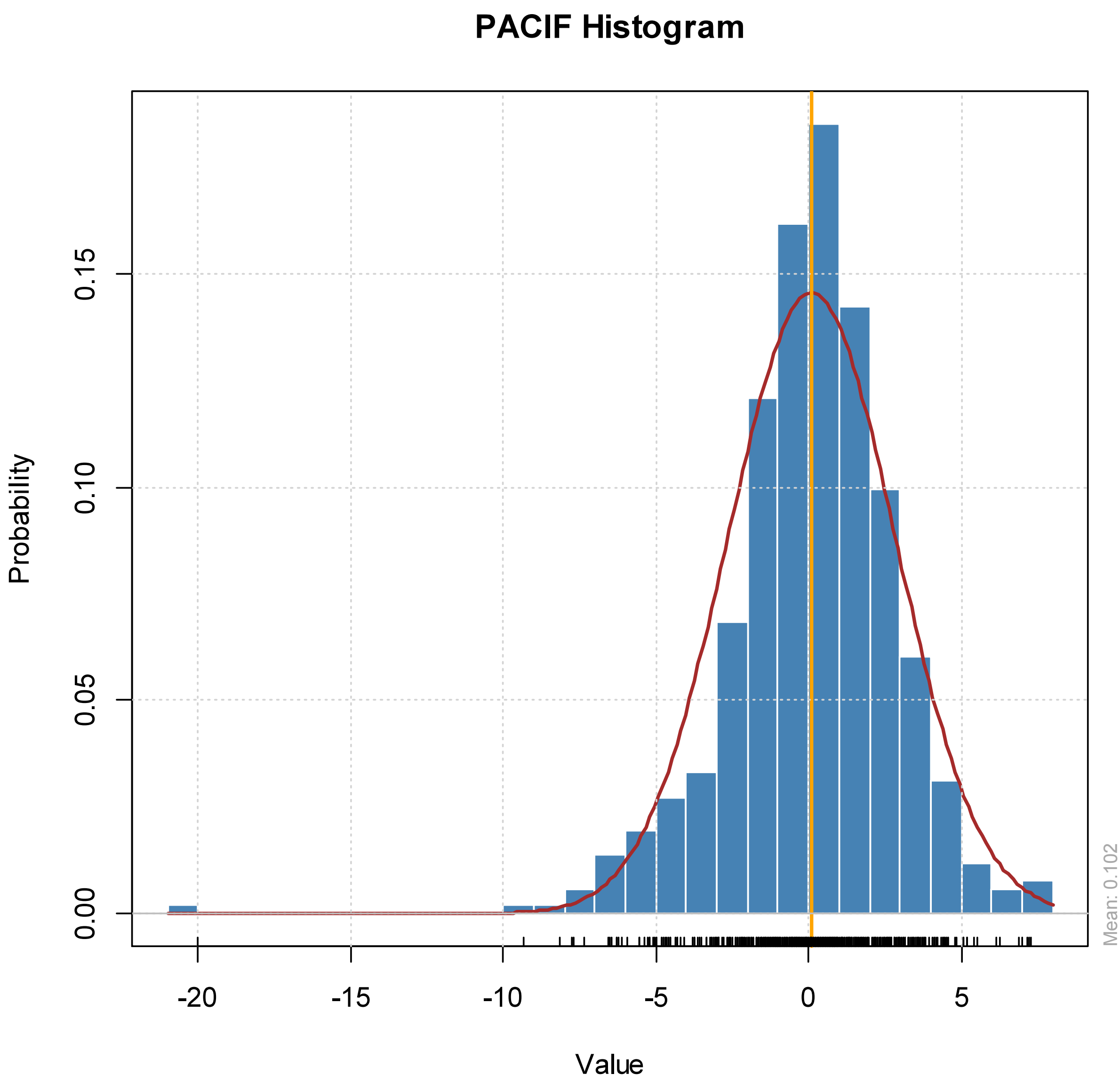


Figure 3.10 Histogram plots of weekly returns of EM BRIC against fitted normal distribution

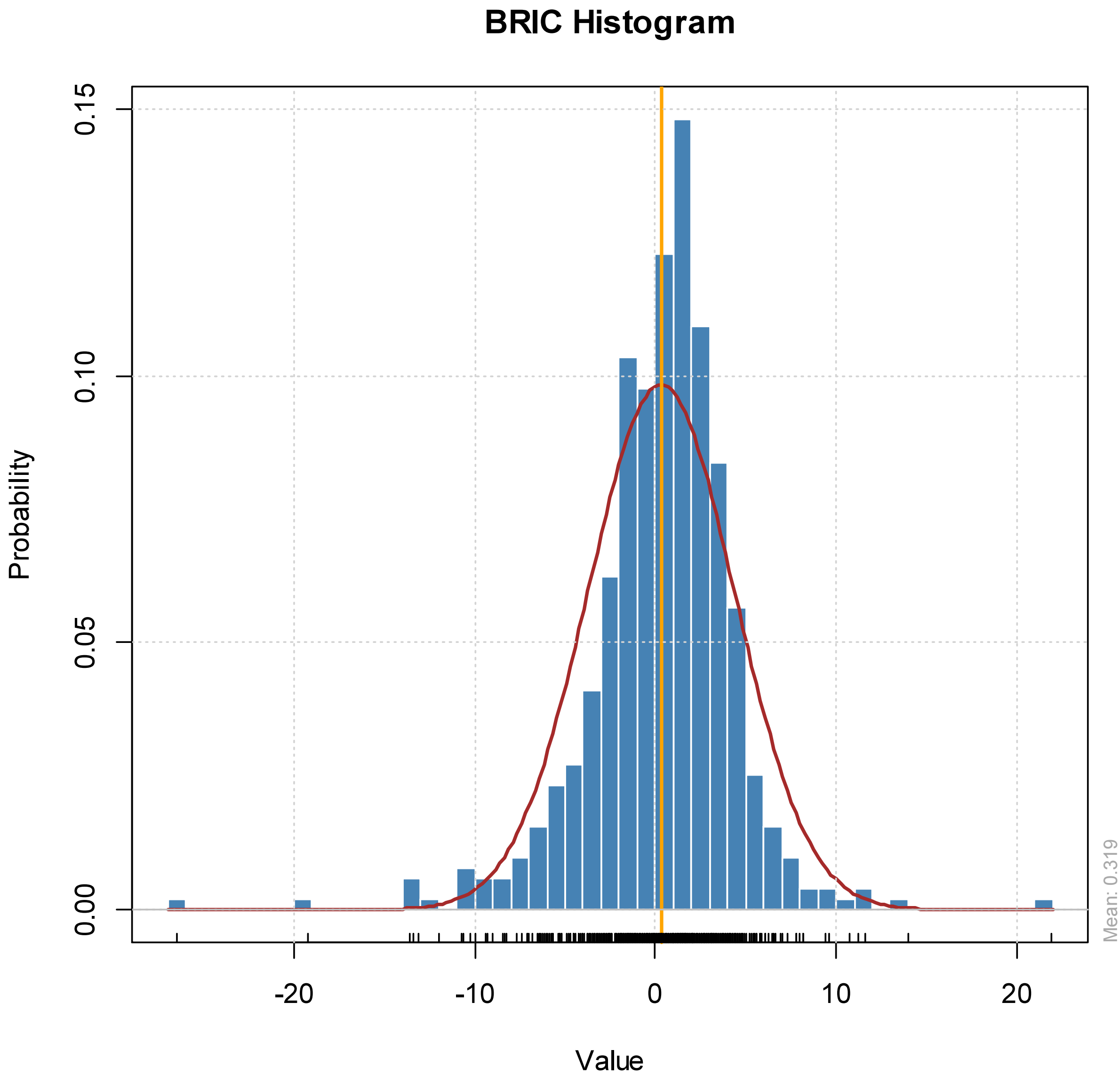


Figure 3.11 Histogram plots of weekly returns of EM Europe against fitted normal distribution

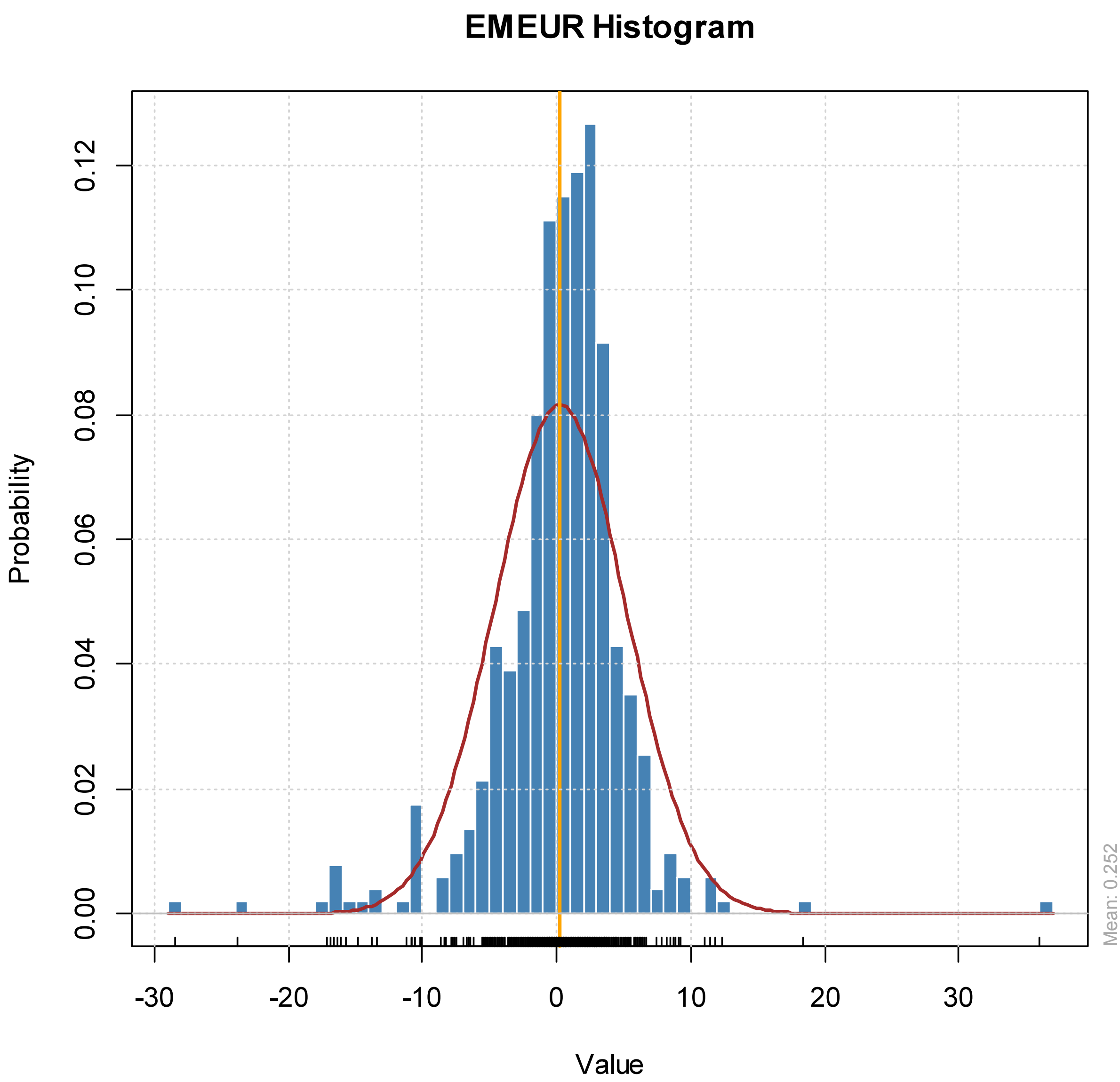


Figure 3.12 Histogram plots of weekly returns of EM Latin America against fitted normal distribution

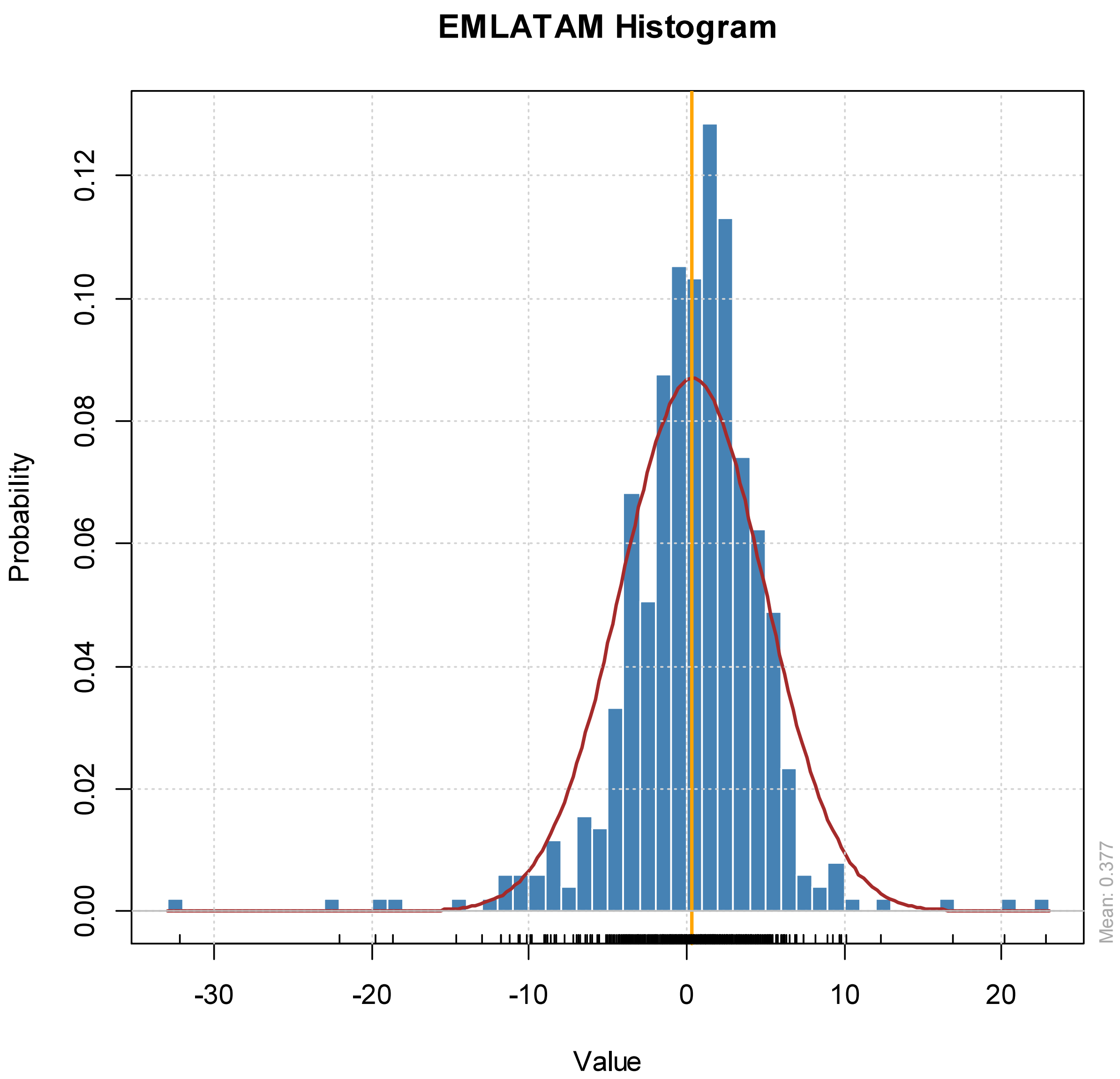


Figure 3.13 Histogram plots of weekly returns of EM Asia against fitted normal distribution

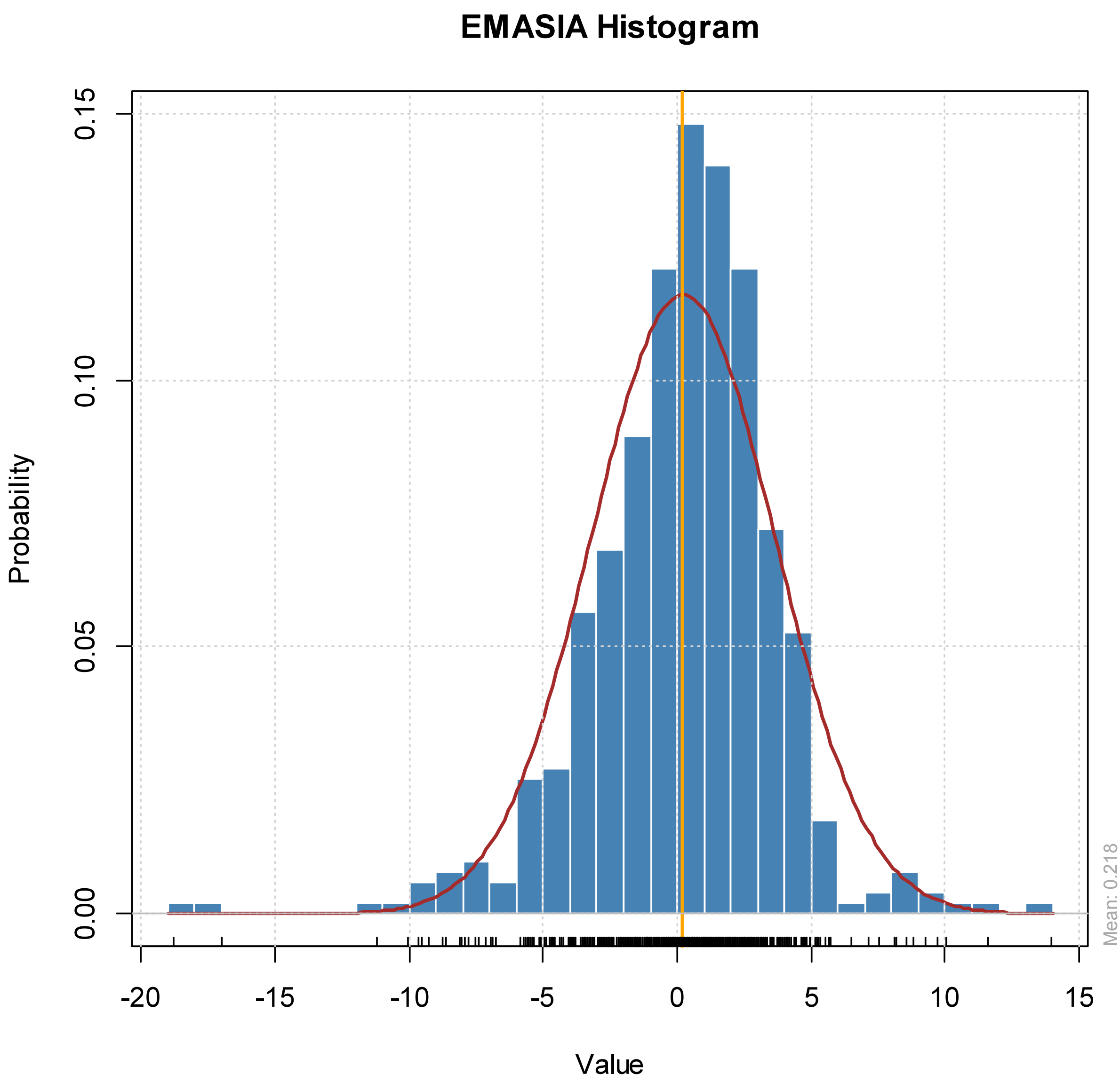


Figure 3.14 Histogram plots of weekly returns of EMF Africa against fitted normal distribution

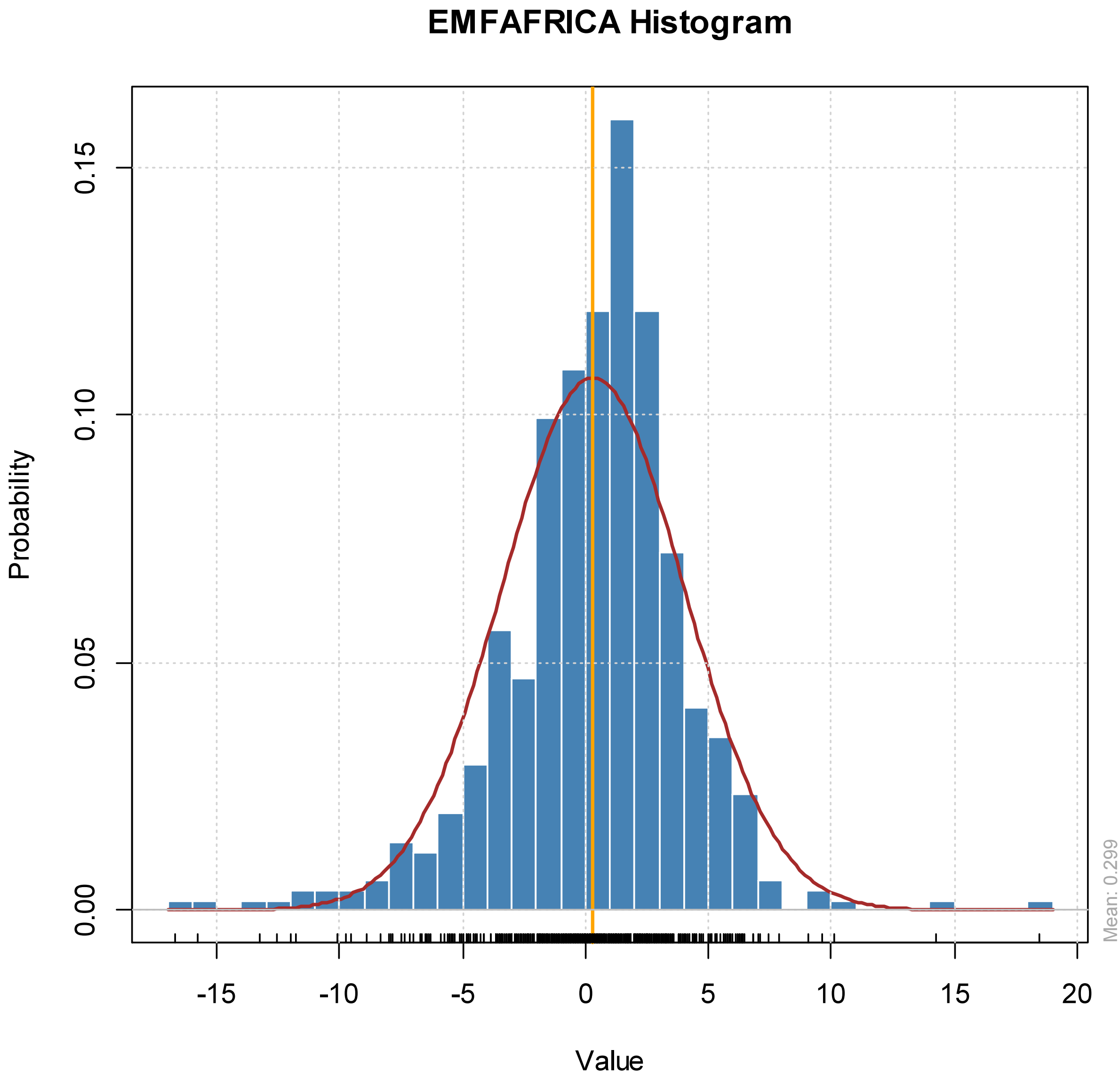


Figure 3.15 Density plots of weekly returns of US against fitted normal distribution

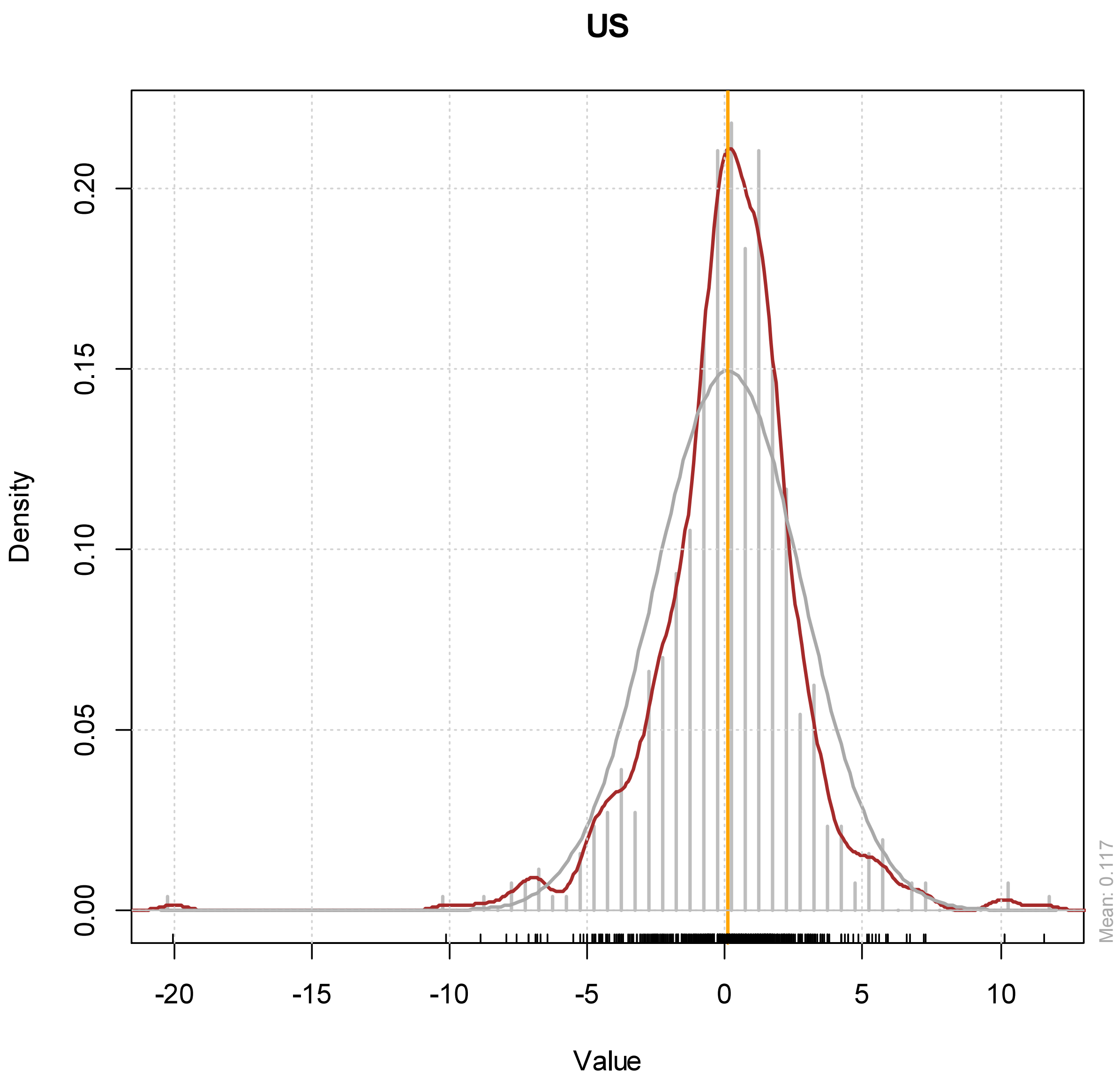


Figure 3.16 Density plots of weekly returns of EMU against fitted normal distribution

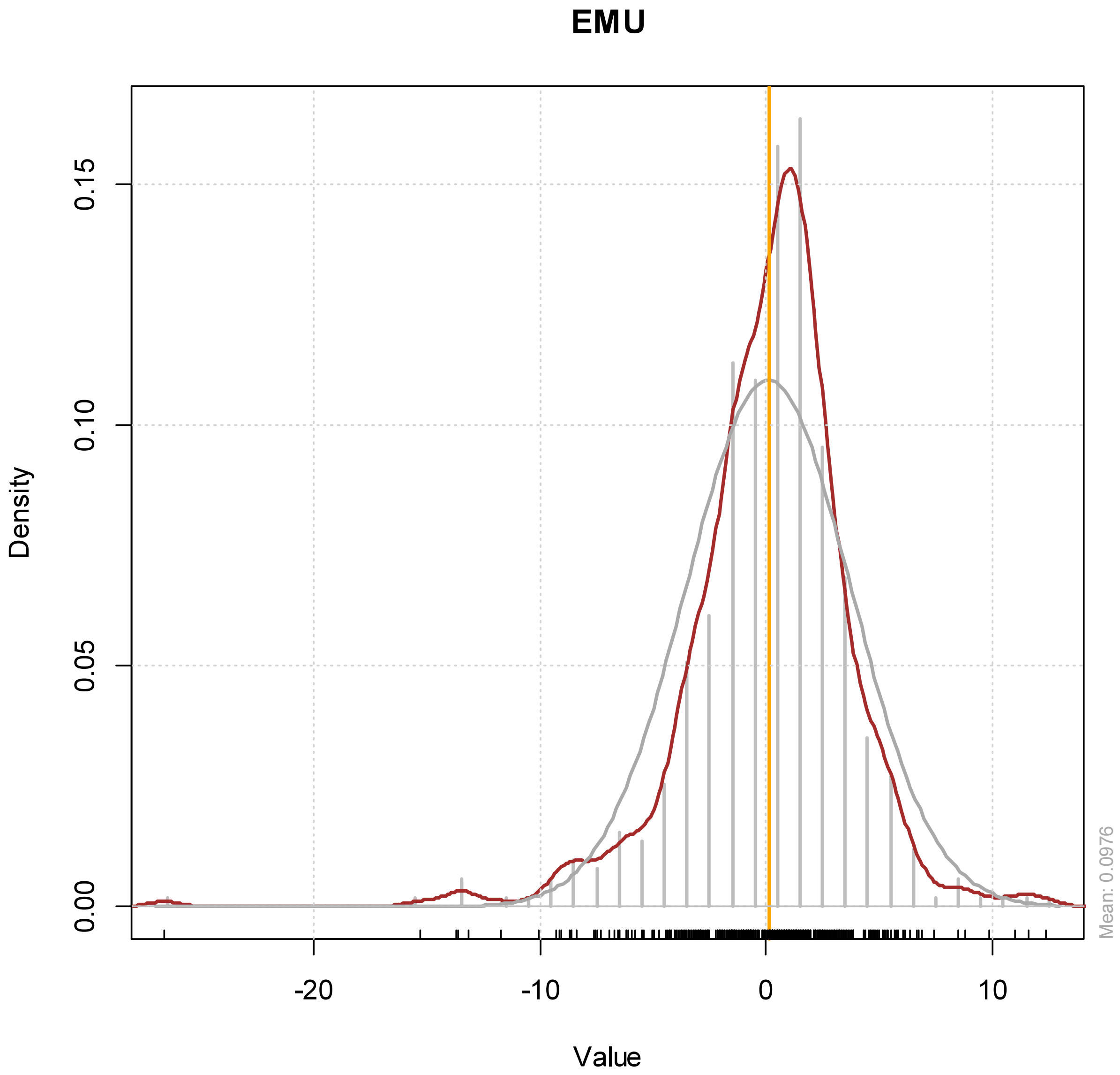


Figure 3.17 Density plots of weekly returns of Europe ex EMU against fitted normal distribution

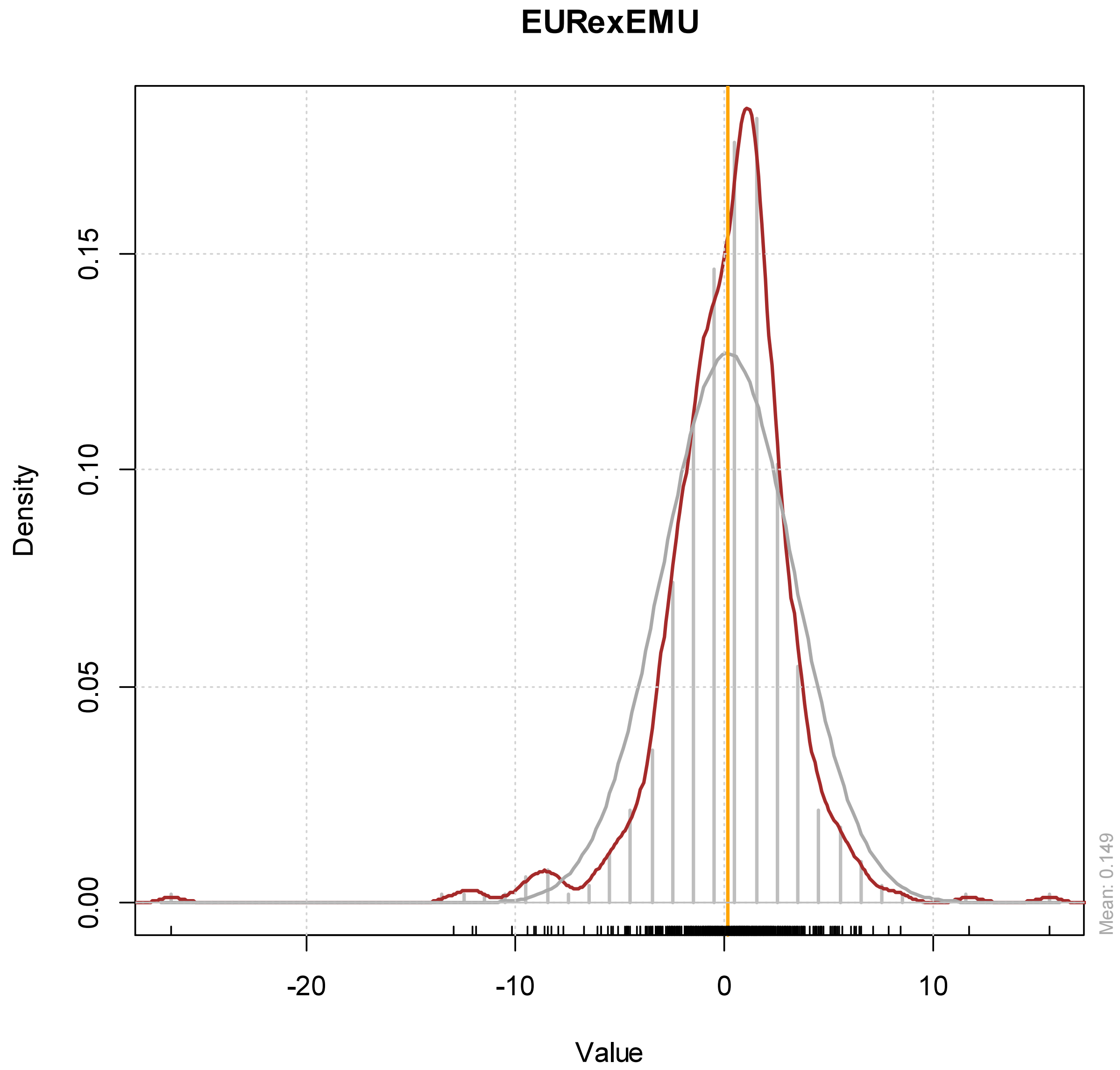


Figure 3.18 Density plots of weekly returns of Pacific against fitted normal distribution

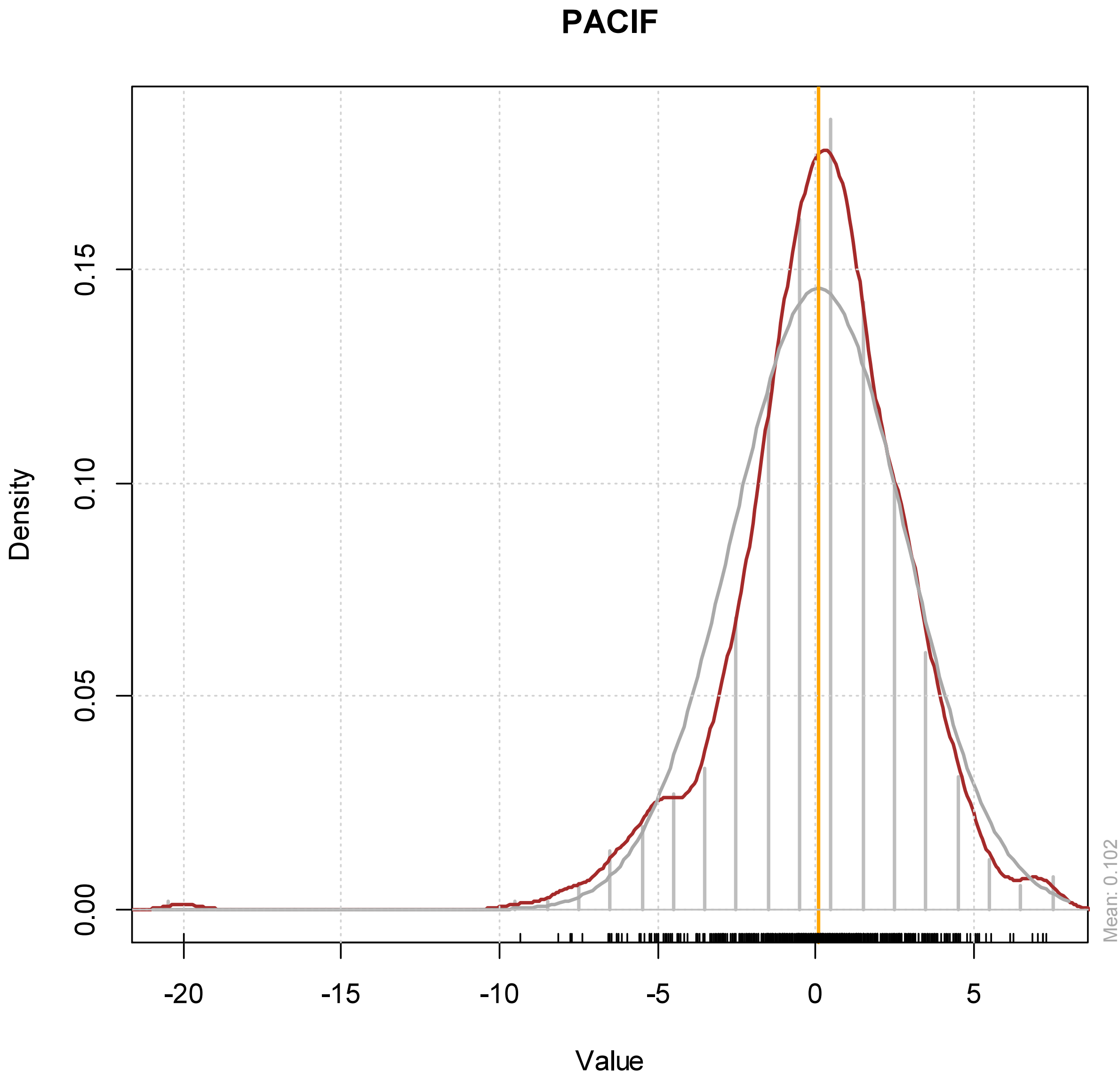


Figure 3.19 Density plots of weekly returns of EM BRIC against fitted normal distribution

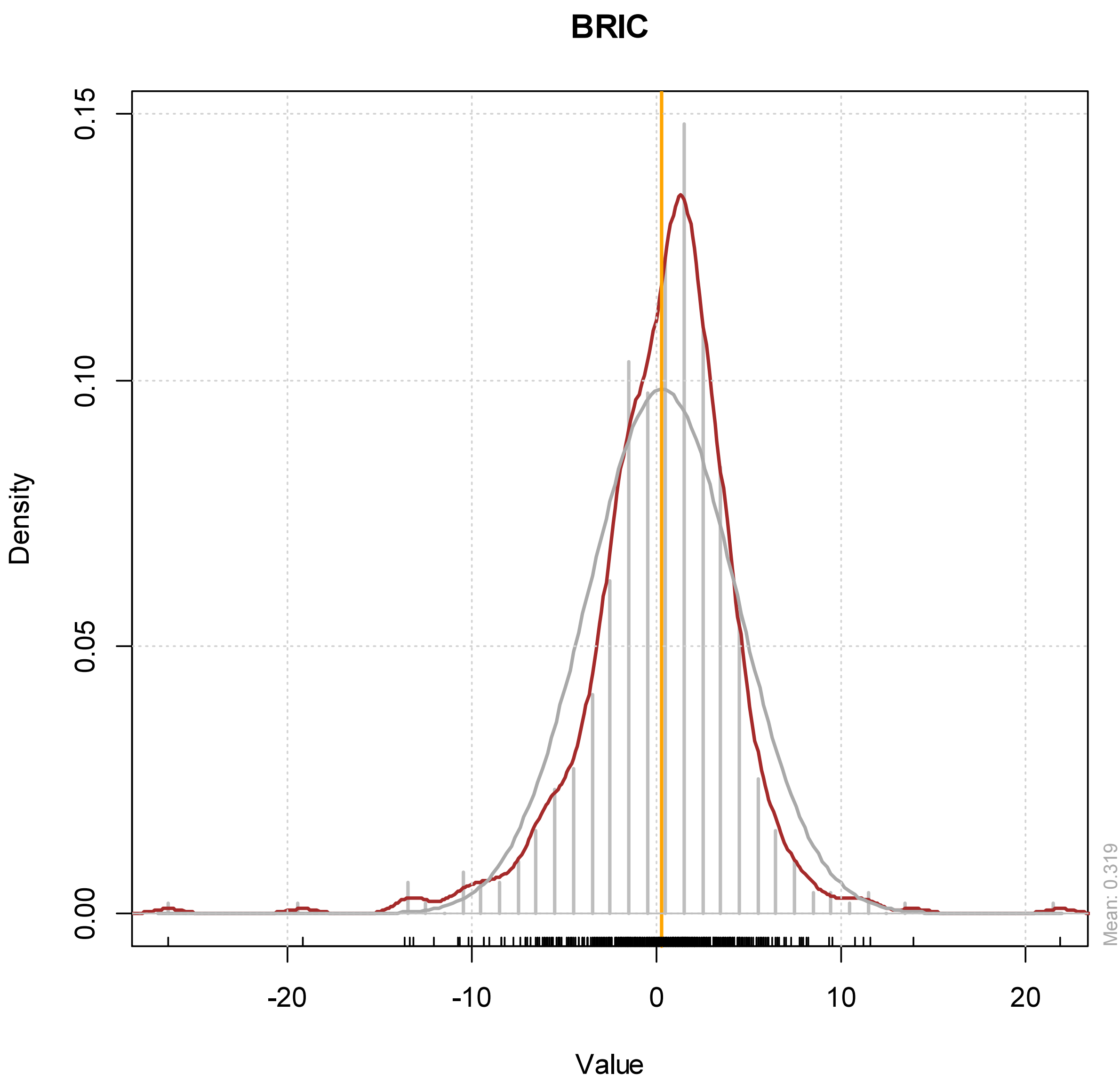


Figure 3.20 Density plots of weekly returns of EM Europe against fitted normal distribution

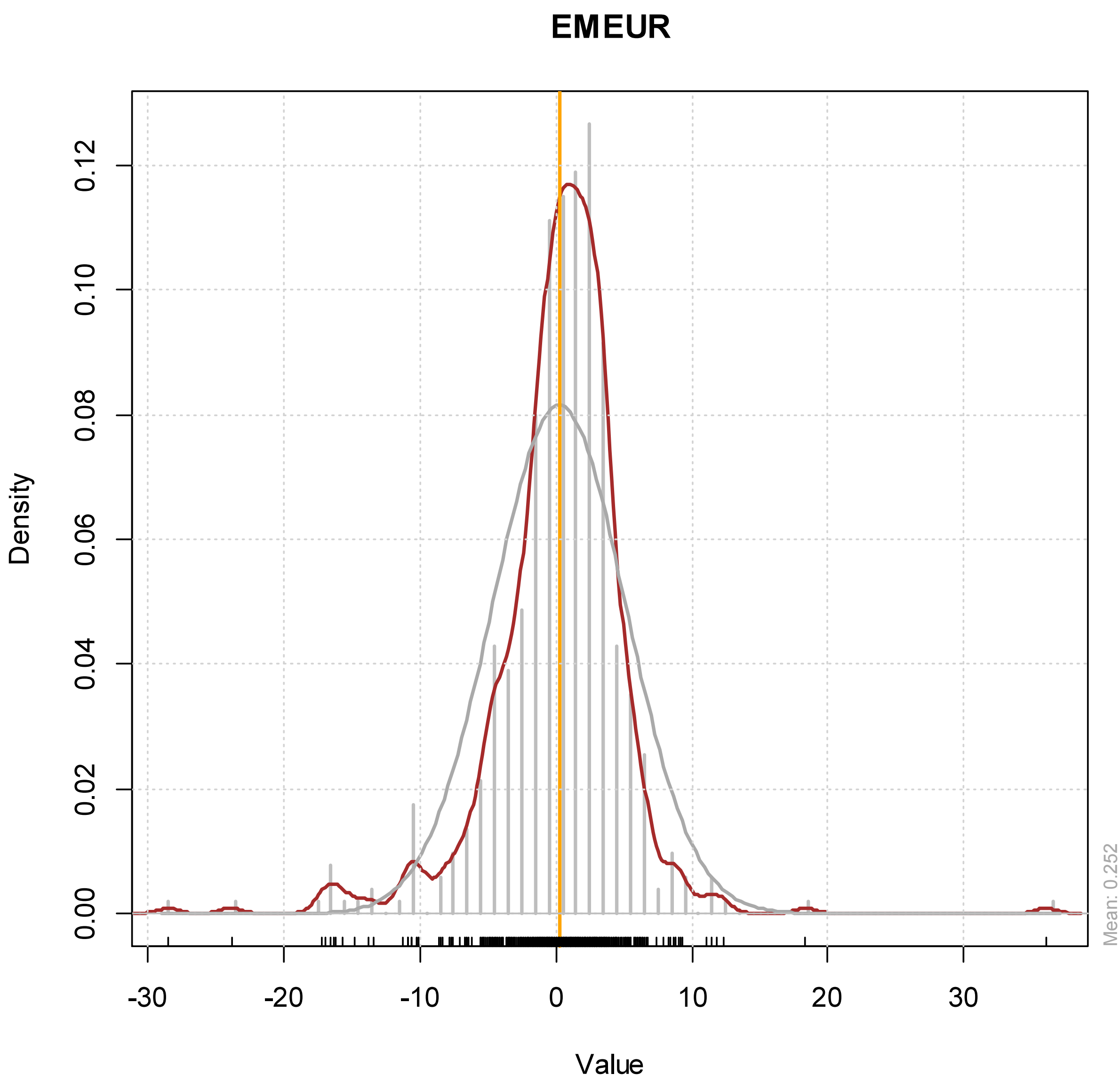


Figure 3.21 Density plots of weekly returns of EM Latin America against fitted normal distribution

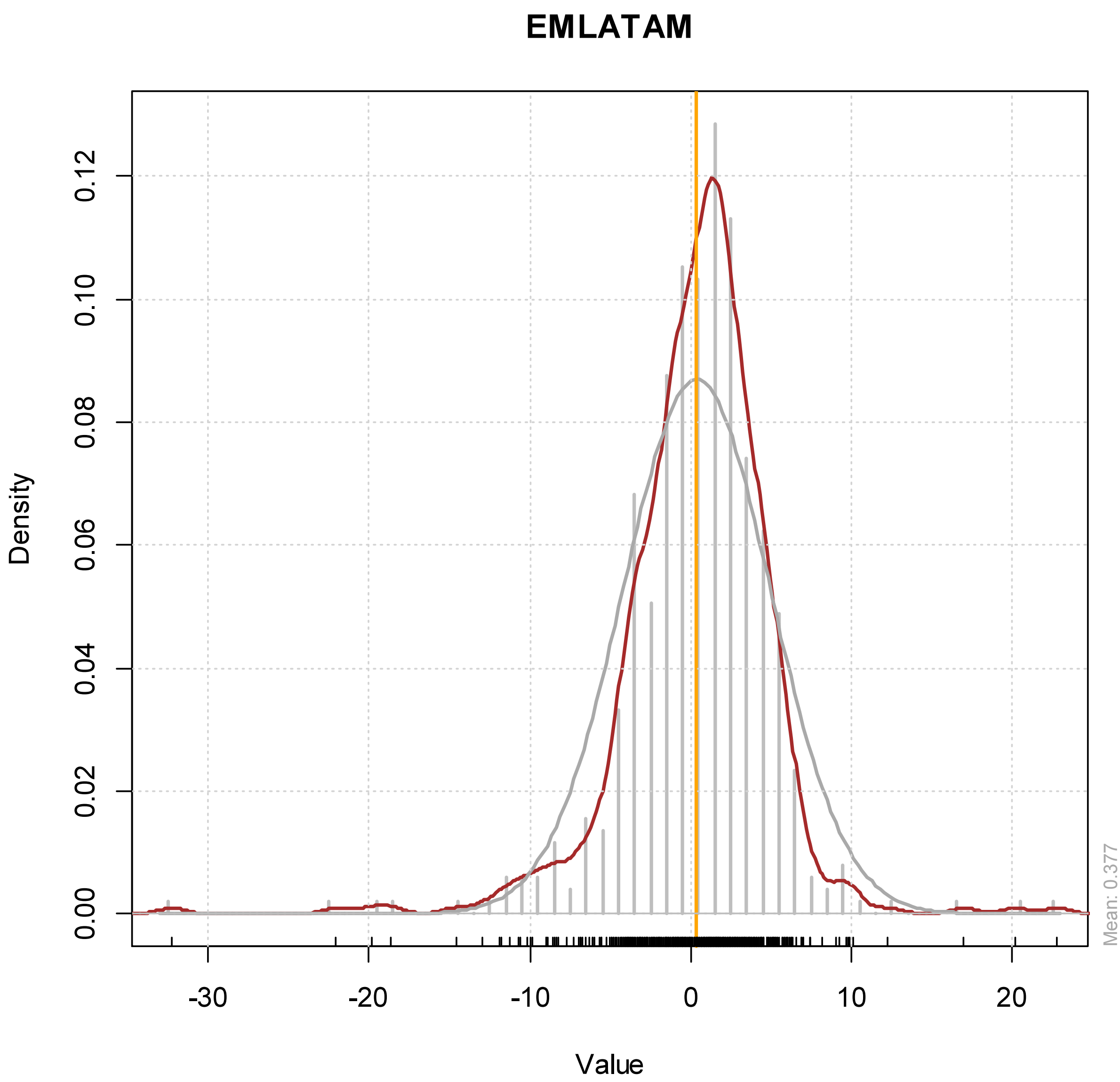


Figure 3.22 Density plots of weekly returns of EM Asia against fitted normal distribution

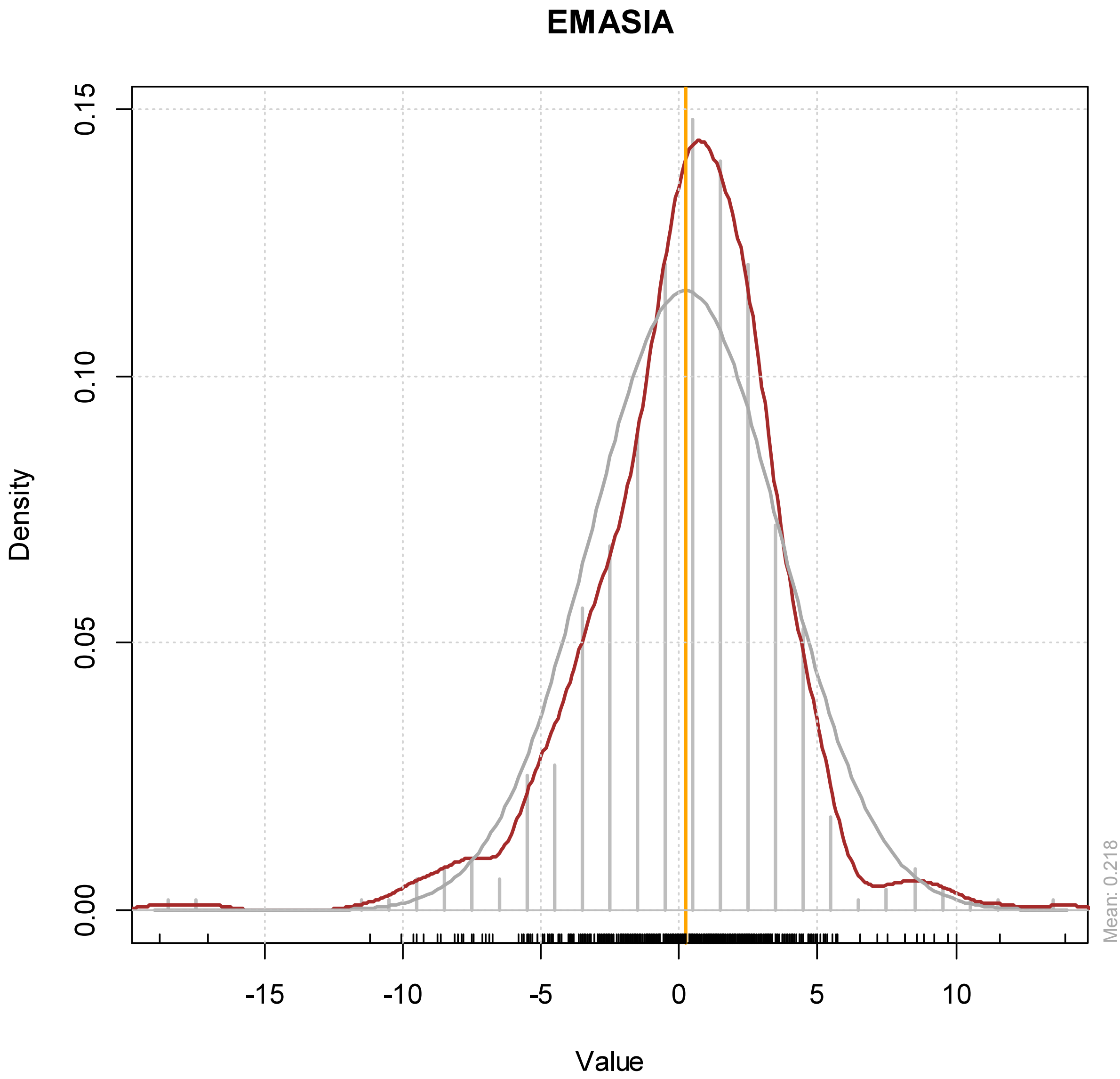


Figure 3.23 Density plots of weekly returns of EMF Africa against fitted normal distribution

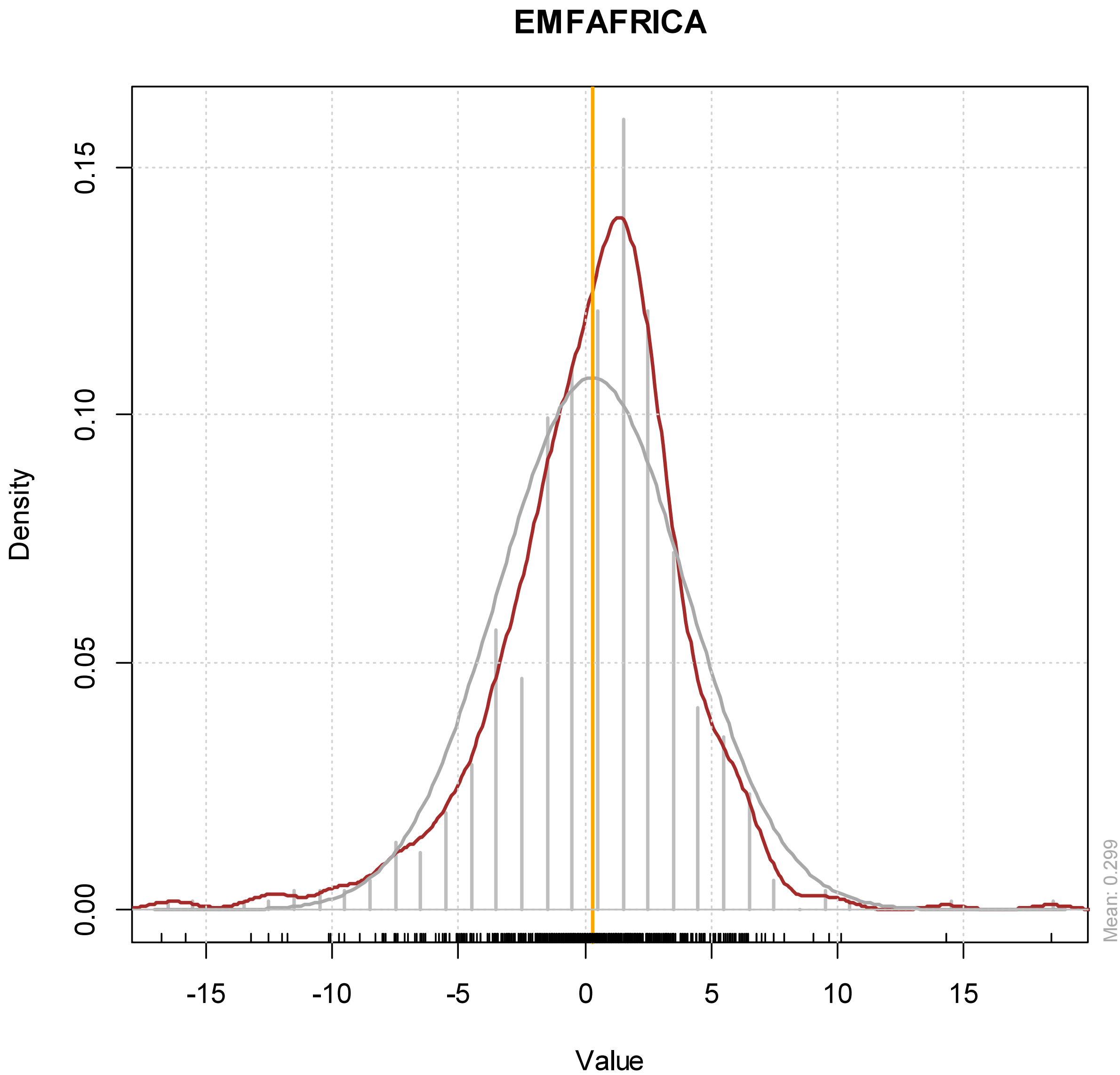


Figure 3.24 QQ plots of weekly returns of US against normal distribution

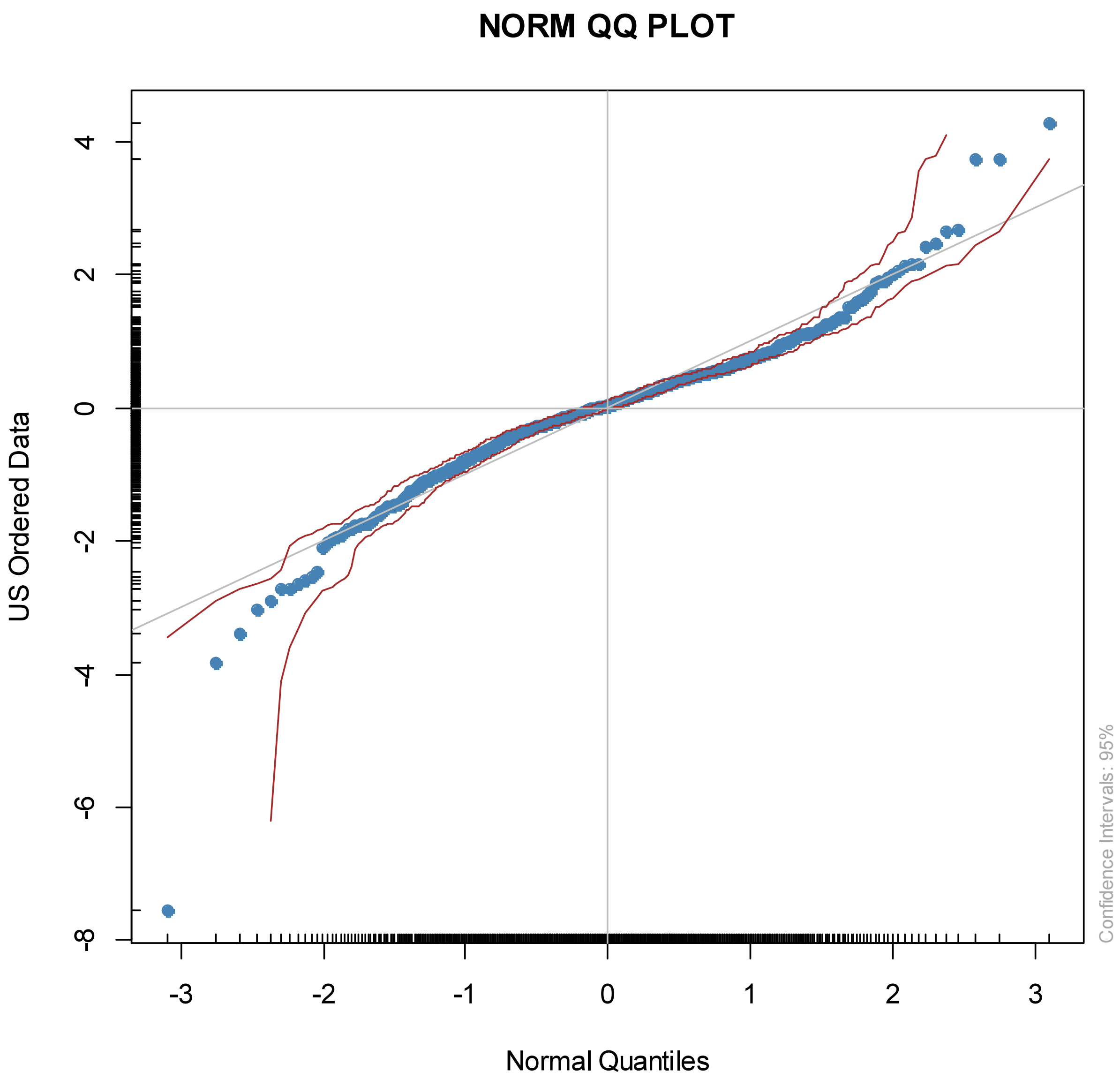


Figure 3.25 QQ plots of weekly returns of EMU against normal distribution

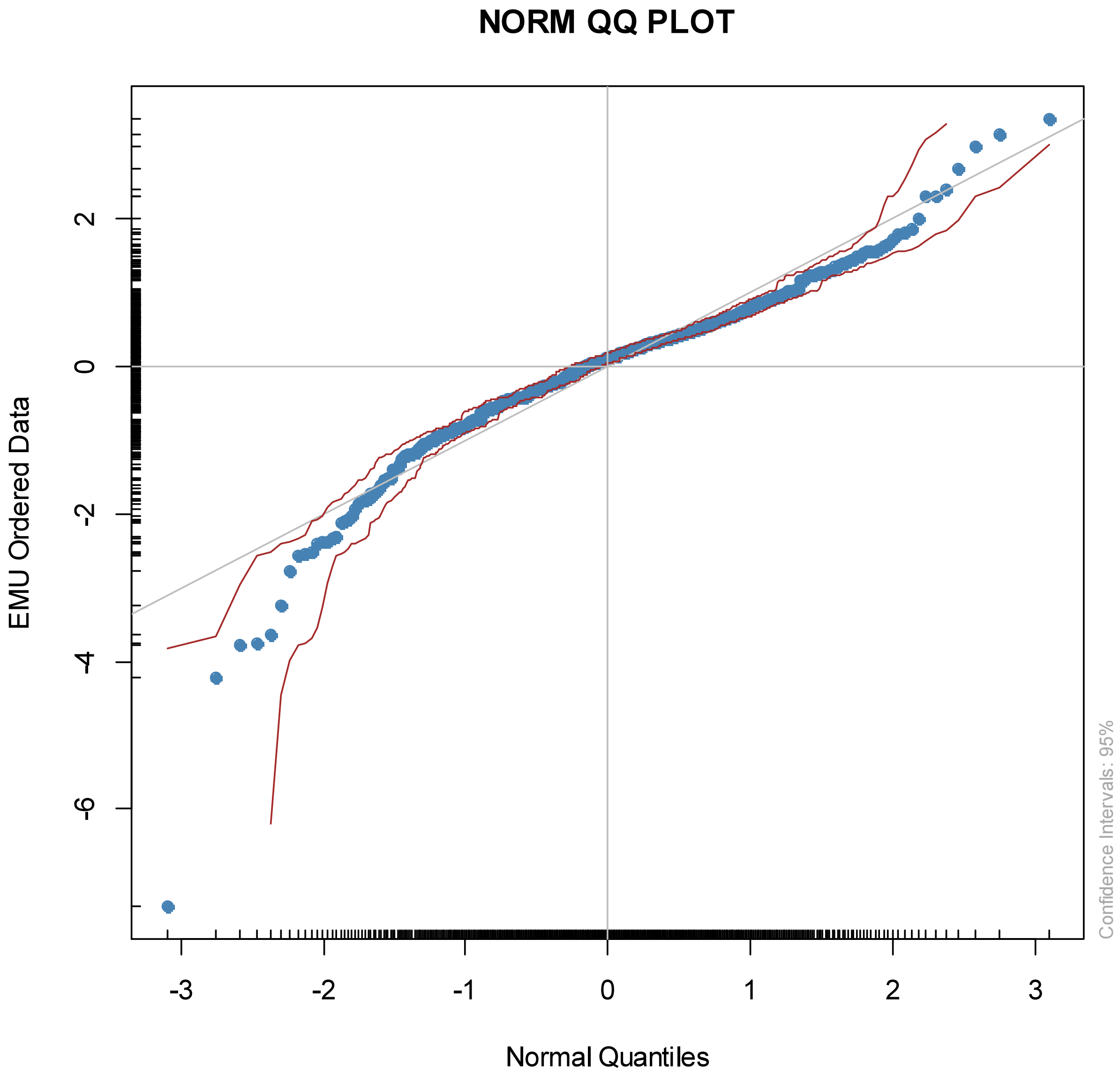


Figure 3.26 QQ plots of weekly returns of Europe ex EMU against normal distribution

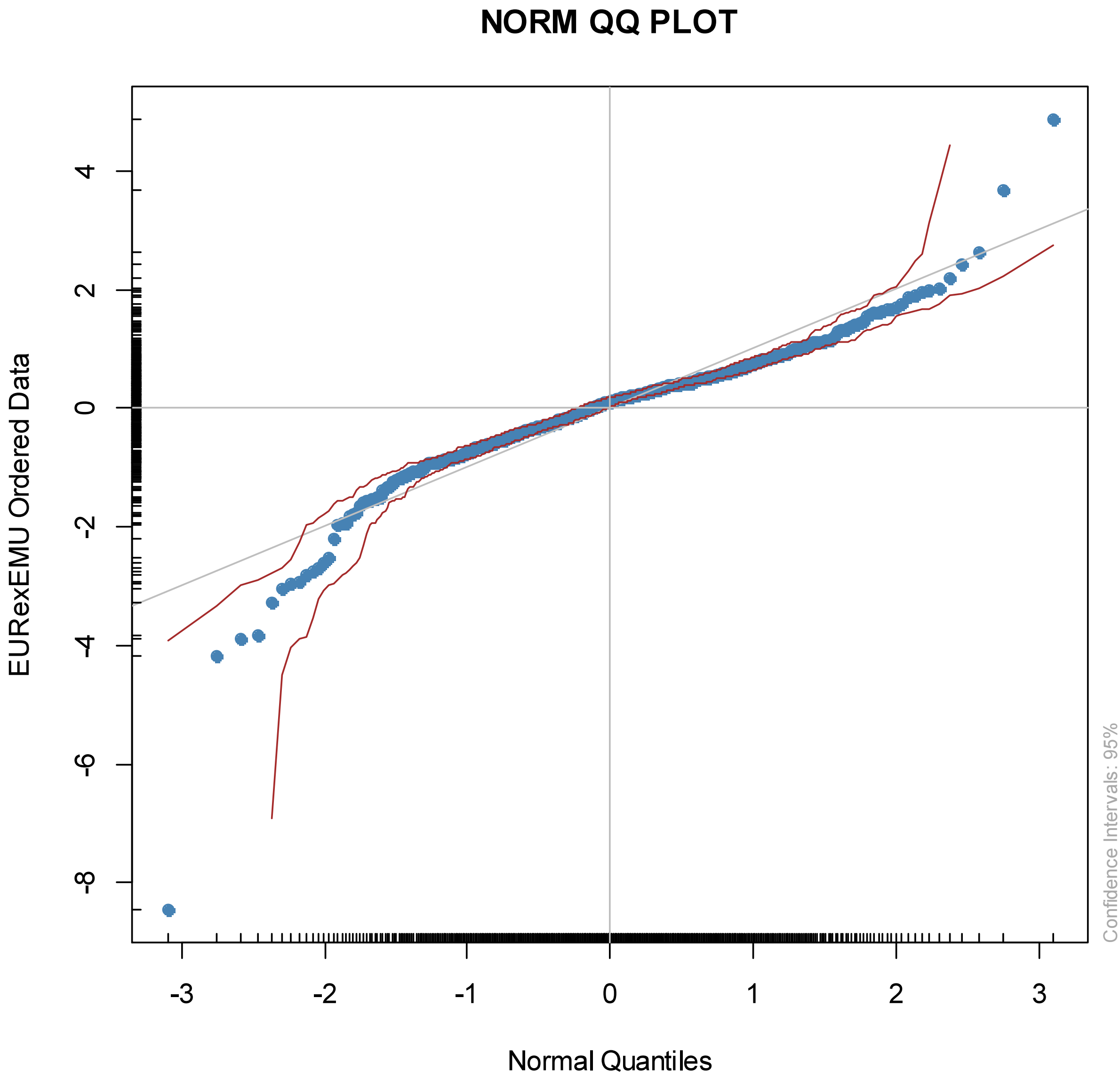


Figure 3.27 QQ plots of weekly returns of Pacific against normal distribution

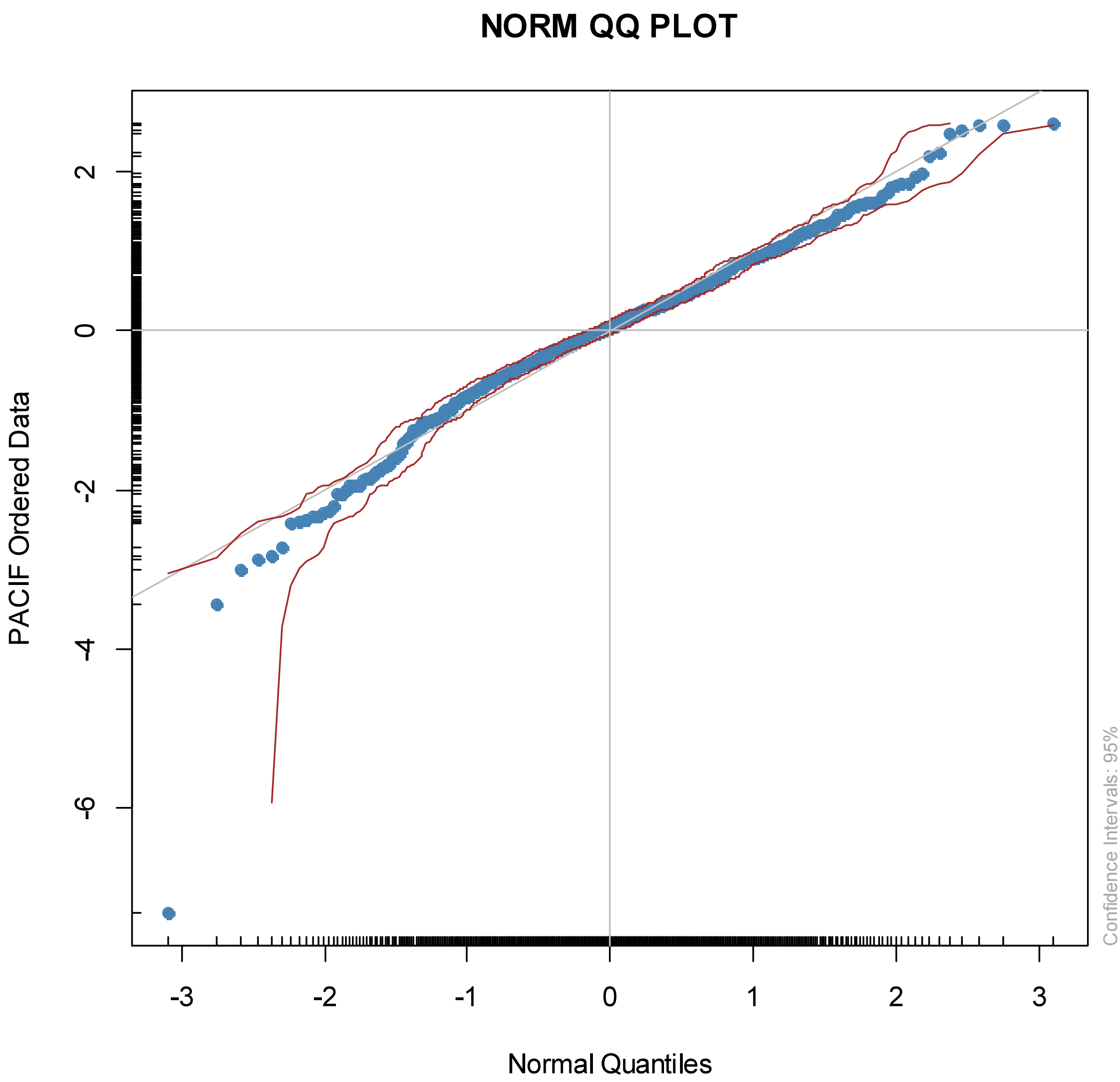


Figure 3.28 QQ plots of weekly returns of EM BRIC against normal distribution

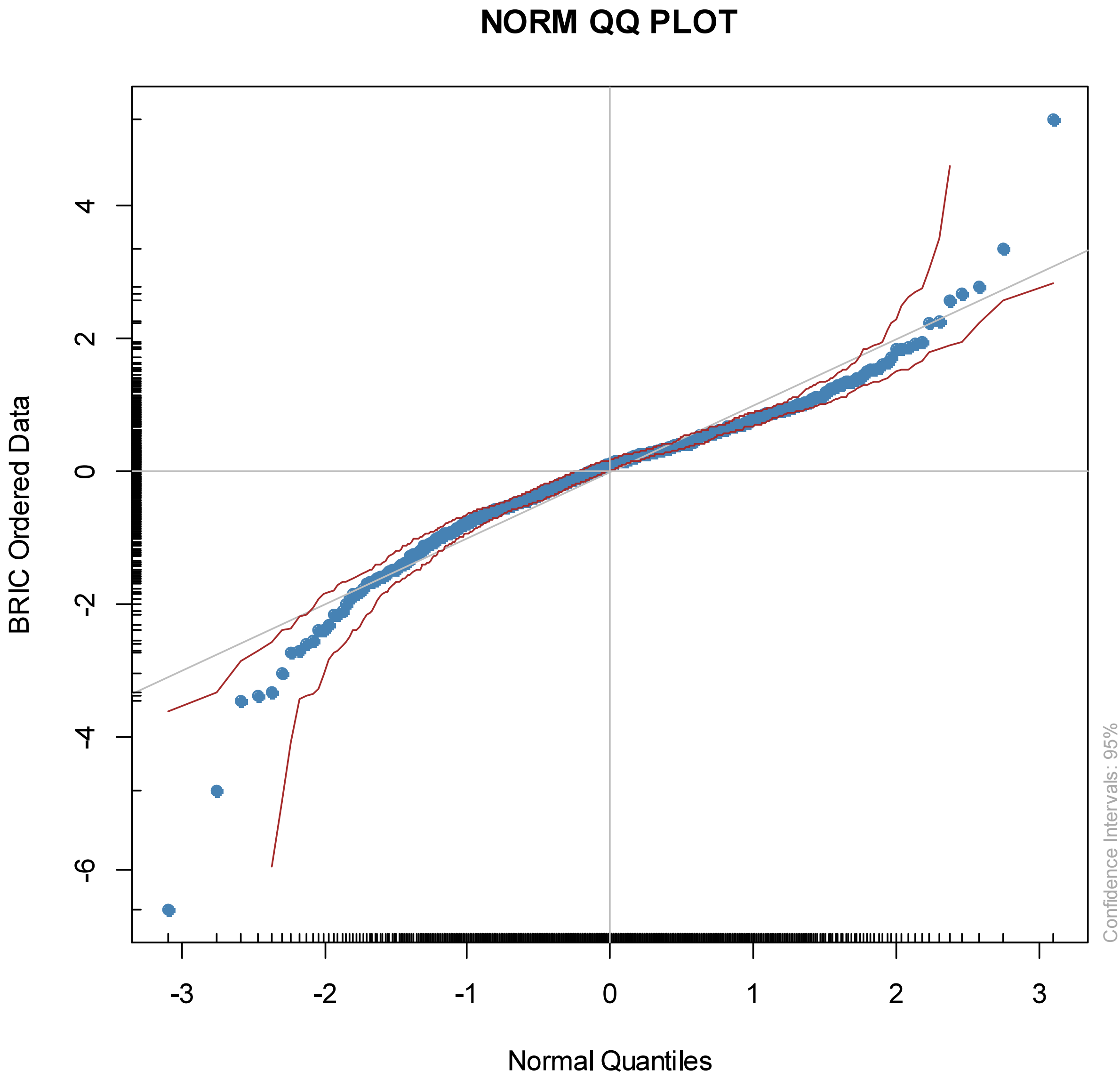


Figure 3.29 QQ plots of weekly returns of EM Europe against normal distribution

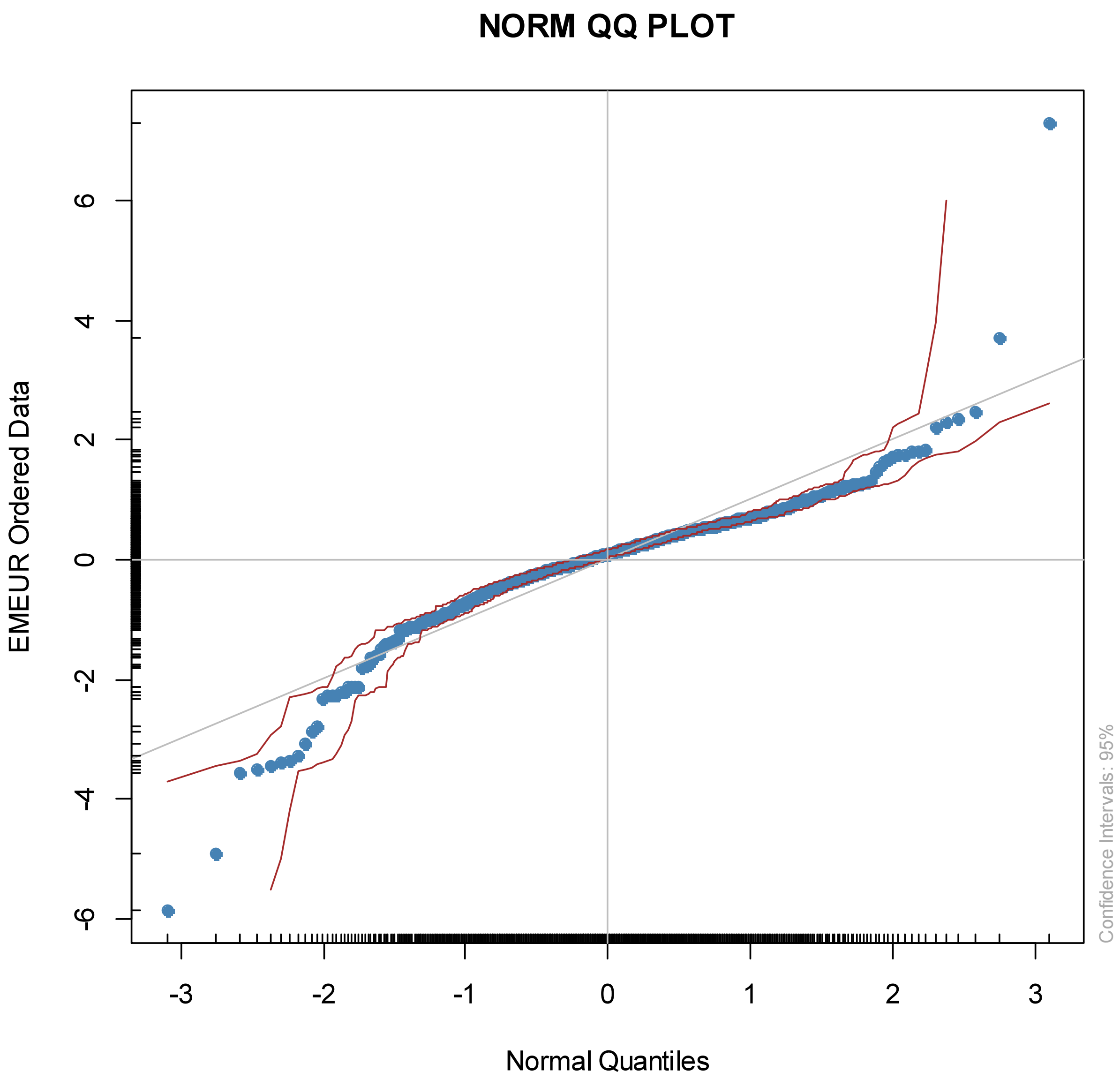


Figure 3.30 QQ plots of weekly returns of EM Latin America against normal distribution

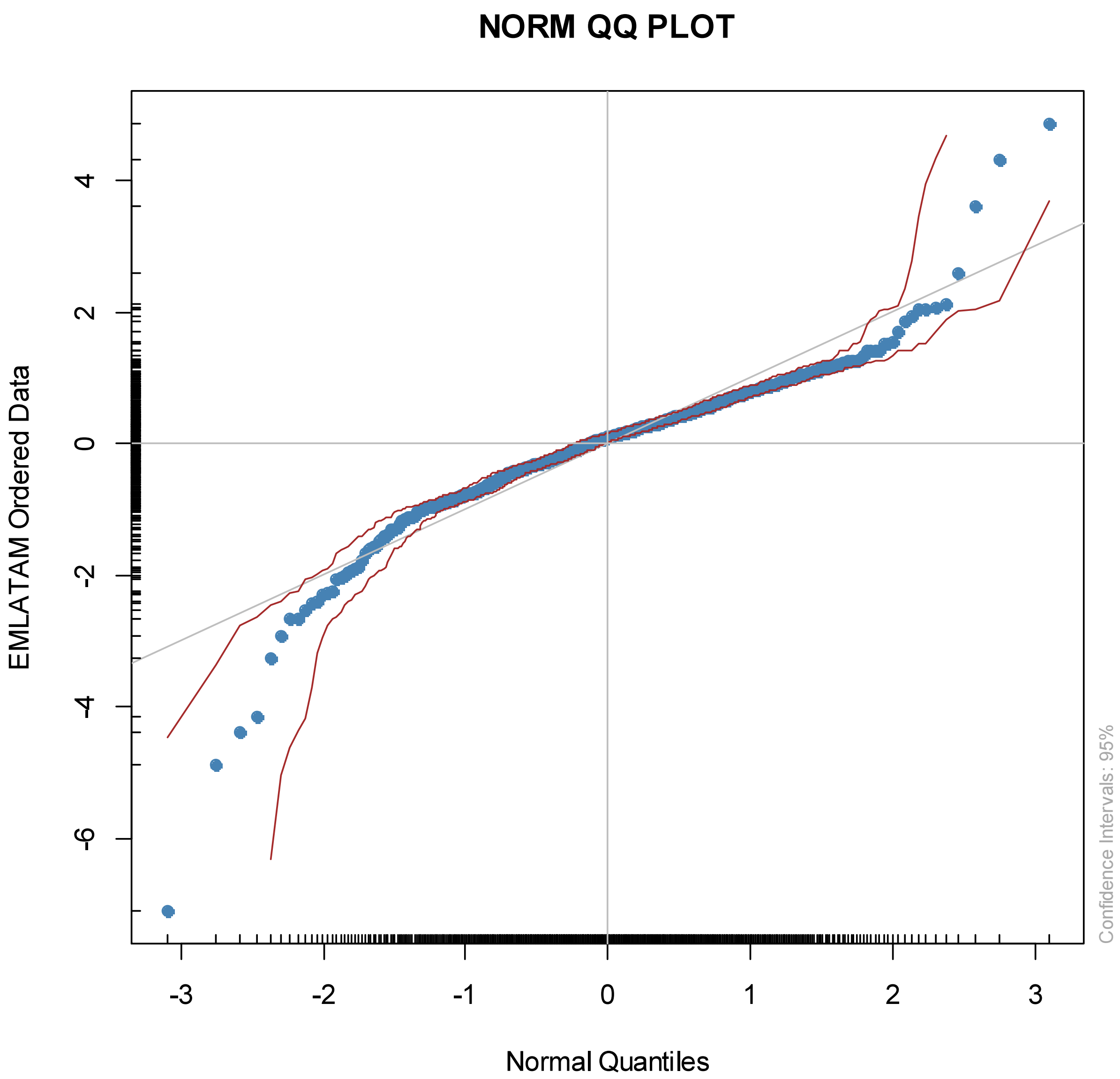


Figure 3.31 QQ plots of weekly returns of EM Asia against normal distribution

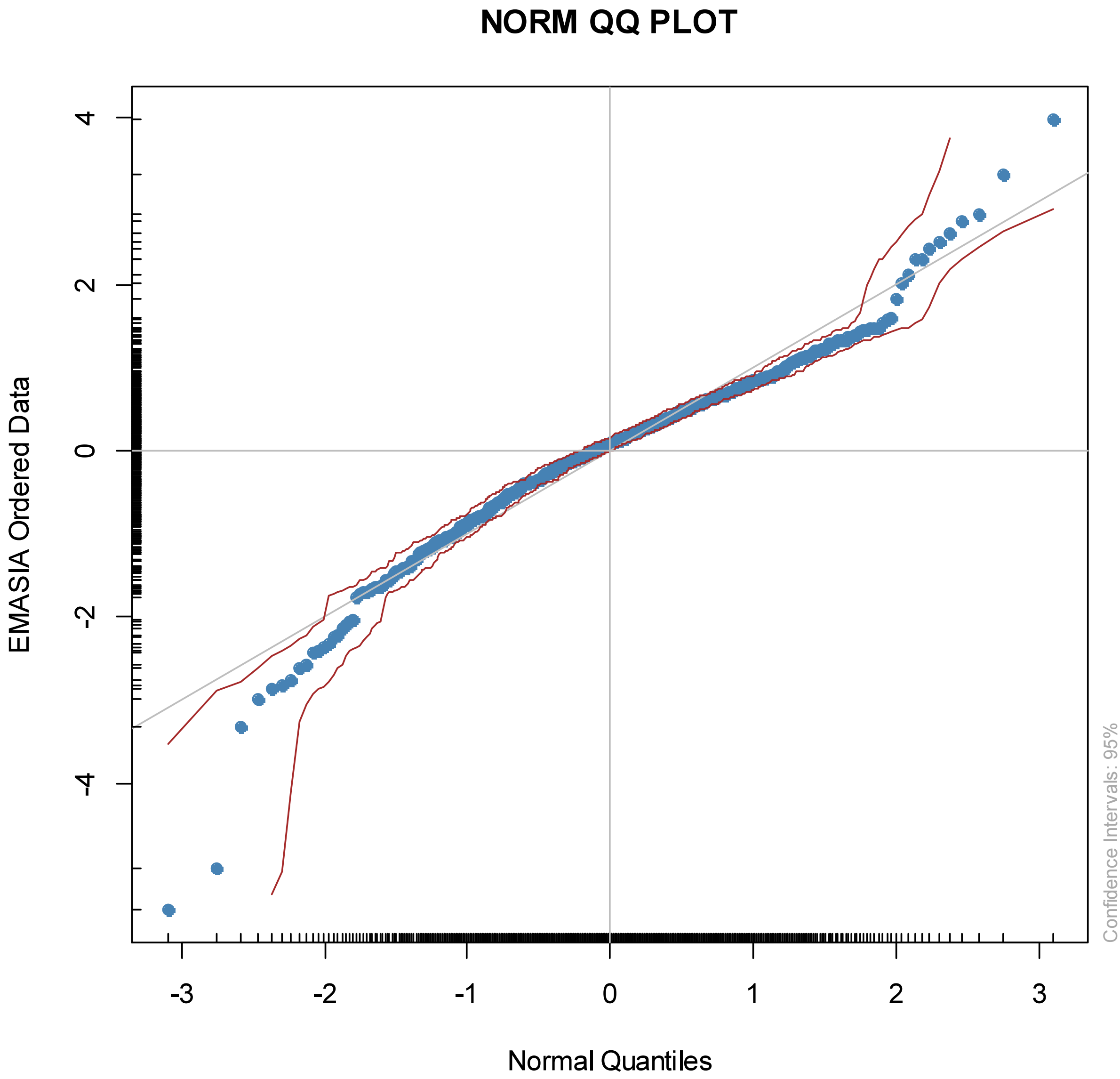
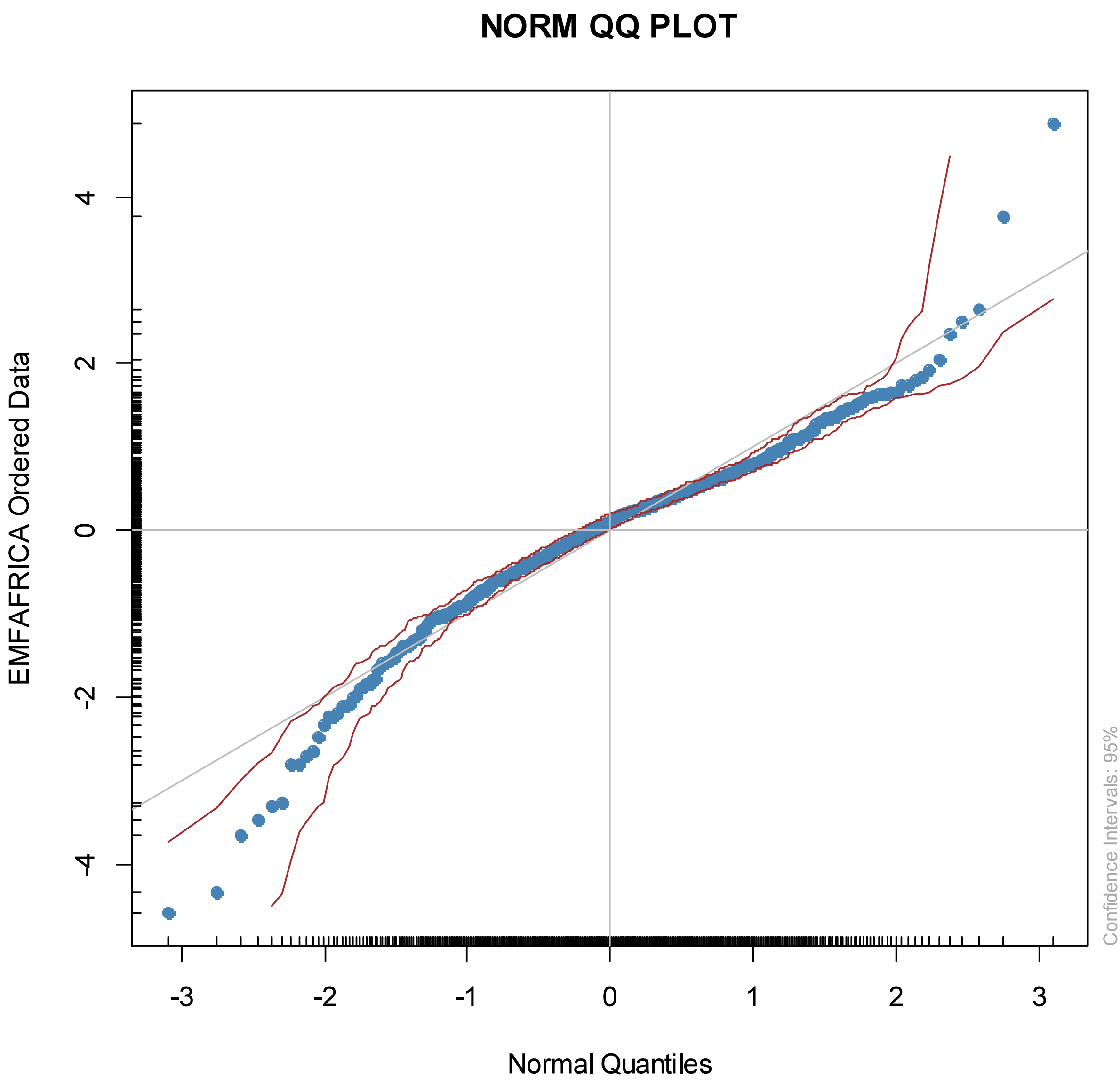


Figure 3.32 QQ plots of weekly returns of EMF Africa against normal distribution



4 MODELLING CORRELATION AND VOLATILITY USING DCC: THE IMPACT OF THE 2007 FINANCIAL CRISIS

4.1 INTRODUCTION, AIMS, OBJECTIVES AND CONTRIBUTION

Although the general trend in both economic integration and market correlation has been for them to increase over time (Goetzmann *et al.* 2005), the long-term impact that the 2007 financial crisis had is questionable. Contagion theory (Forbes and Rigobon 2002) would suggest that the impact of a crisis on correlation will often be short term and result in short-lived spikes in correlation. However, recent evidence from Markwat *et al.* (2009) showed that global contagion events can be long drawn-out processes. The argument made in this chapter is that the impact of a financial crisis may be permanent and structural rather than short-term contagion.

In this chapter I analyse the linkage between US and other markets using DCC correlation. I present the argument that the 2007 financial crisis *may* have had permanent (or persistent) impact in terms of the strength of market correlations. In the hypotheses development section below I argue that this could have arisen due to either changes in structural relationships between markets or changes in behavioural relationships. There is a considerable body of academic evidence to support this argument.

The issue I face in modelling this relationship is whether or not any permanent (or persistent) changes in correlation associated with the 2007 financial crisis can be distinguished from the subsequent Euro crisis. There is a considerable body of academic evidence which suggests that, although the 2007 crisis had a truly global impact, the impact of Euro crisis was more regional in nature. The argument has been made that, although the Euro crisis was serious, it did not threaten the structural integrity of world financial system. We did not, for example, see any major defaults as it was the case in 2007 financial crisis. In the sections below I cite papers in academic literature to support my argument and also provide evidence to this effect from the dataset used in this thesis.

The contribution my study makes to the literature is to extend prior research by focusing on long-term impact of the crisis on the linkage between regional markets rather than individual markets using multivariate GARCH methodology. In addition, it includes both developed as well as emerging/frontier regional markets which gives much wider picture.

The novelty of my work is that whilst most of the studies in the literature focus on developed markets there is relatively small number of studies regarding emerging/frontier markets. This point was made explicit by Chen *et al.* (2002). In addition, majority of academic research focus on individual countries, whereas just a few look from broader (i.e., regional) perspective. A lot of studies focus on short-term impact of a crisis on correlation (Celık 2012, Cheung *et al.* 2008, Syllignakis and Kouretas 2011) and only a few focuses on long-term (Chiang *et al.* 2007). To overcome some of the limitations in modelling correlation found in the literature I employ the multivariate GARCH model. DCC model, introduced by Engle (2002), allows me to address the heteroskedasticity issue mentioned by Forbes and Rigobon (2002) and evolution of cross-market co-movements (Wang and Moore 2008).

The remainder of this chapter is structured as follows. Section 4.2 discusses and presents the hypotheses tested. Section 4.3 describes the data and methodology used. Section 4.4 presents and discusses the results and, finally, Section 4.5 draws some preliminary conclusions.

4.2 HYPOTHESES DEVELOPMENT

4.2.1 Did the impact of financial crisis have permanent impact on the strength of cross sectional correlation?

Prior to 2007, the last major global crisis within financial markets was the 1997 Asian crisis. There is considerable evidence in the literature that this resulted in permanent structural changes in the strength of correlation relationships (for example, Chiang *et al.* 2007). More generally, Wang and Moore (2008) also argue that the structural changes between economies which result from crisis can lead to changes in linkages between stock market returns. Garnaut (1998) argued that the Asian crisis had structural impact on the region. The crisis induced policy reforms and that these reforms were further reinforced by IMF programmes. Chiang *et al.* (2007) argue that the resulting changes in market correlations could be put down to behavioural factors; for example, factors associated with the wake-up-call hypothesis, where investors realise that some sort of similarity exist in the fundamentals of the markets.

There could potentially be similar behavioural explanations to changes in any correlation relationships which occurred as result of the 2007 crisis. We can, however, also argue that any permanent (or persistent) impact could have a financial-structure related explanation. For example, we observe the leverage levels went down significantly as investment banks started to dismantle their derivatives products such as CDOs (Collateralised Debt Obligations) (McKinsey & Company 2012, SIFMA 2014). In addition, we have seen many of the world retail banks increasing their Tier 1 capital ratios in response to new Basel III requirements (McKinsey & Company 2012). I argue in this thesis that this risk reduction in financial system *may* have a long-term and permanent impact on correlation. This provides the basis for Hypothesis 1 below.

The evidence from the Asian financial crisis, cited above, would suggest that such an explanation is plausible. Theoretical evidence from the literature can also be cited to support this argument. Minsky (1992), among others, suggested that a crisis can have a major impact on the 'architecture' of financial markets. Whalen (2008) described the 2007 crisis as a 'Minsky moment' and argued that the crisis has resulted in wide-ranging structural changes across global financial markets.

Crotty (2009) traced the origins of the 2007 financial crisis in the US to the new financial architecture (NFA) of the previous two decades having effectively eliminated the regulatory regime developed in response to the Great Depression of the 1930s. He argued that the NFA resulted in excessive risk-taking, stimulated excessive leverage and also led to the development of financial market complexity and opaqueness. He saw the main consequence of this as being the dramatic increases in the size of the financial sector relative to the rest of the economy.

Crotty argued that the economic and social impact of the NFA has been viewed in most countries as being detrimental and that as a consequence the NFA needed reform. The 2007 crisis can be seen as presenting the opportunity to implement this reform. Moshirian (2011) showed that crisis often leads to the emergence of new national and international financial institutions. One of the responses to the 2007 crisis has been, for example, the Basel III accord (BIS 2012). This is designed to strengthen banks' capital requirements and introduces new regulatory requirements on liquidity and leverage. The crisis also stimulated a worldwide debate on the merits of separating investment banking from commercial banking (which in a US context would be a reintroduction of the Glass–Steagall Act). Other research has suggested that corporate governance structures have undergone re-examination as these have been found to have a significant impact on managerial risk-taking behaviour (King and

Wen 2011). As well as new regulatory responses, the financial architecture has seen massive adjustment through changes in market attitudes to risk. For example, New York Federal reserve chairman Timothy Geithner commented on the huge impact that deleveraging had on financial markets during 2007 (Geithner 2008).

I believe that Whalen (2008) is right in describing the 2007 crisis as a Minsky moment. Furthermore, I argue that the resulting changes to the world's financial architecture, and the consequent changes in levels of integration between its respective financial systems, will have an impact on the long-term correlation between equity markets. I also argue that a further consequence of the crisis may have been that long-term changes have occurred in the relative volatilities of markets, given that the crisis affected developed and emerging/frontier markets in widely differing ways. Such changes, as Gupta and Mollik (2008) identified, can influence correlations. I argue that because of the greater impact of the financial crisis on developed markets, there will possibly be greater similarities in the changes experienced by the US and other developed markets than there will be between the changes experienced by the US and emerging/frontier markets.

In Hypothesis 2 (below) I test whether or not the magnitude of any changes in permanent (structural) correlation differs between developed and emerging/frontier markets. Support for this hypothesis can be identified in the literature. Yu *et al.* (2010) examined the impact of changes in financial linkages on Asian markets. They found a considerable difference with respect to developed and emerging markets. Chiang *et al.* (2007) also found an evidence to suggest that the long-term impact of the Asian financial crisis on the correlation between Thailand and other Asian markets varied considerable between emerging and developed markets (correlation with developed market increased by statistically significant amount, whereas correlation with other emerging markets did not). I would argue that provides a prima facie basis for my Hypothesis 2.

Hypothesis 3 (below) is related to Hypothesis 2. It examines a potential explanation for differences between US and regional markets. While it can be noted that there are a number of potential explanations examined in the literature (for example, Wang and Moore (2008) identify a series of potentially significant explanatory variables), I attempt to explore one potential explanation; specifically the issue of relative market volatilities. There are a number of studies which examine the importance of difference of market volatilities. For example, Aydemir (2008), Cai *et al.* (2009), Knif and Pynnonen (2007), Longin and Solnik (1995), Ramchand and Susmel (1998), Solnik *et al.* (1996) showed that correlation levels and changes in volatility are related. A further study by Gupta and Mollik (2008) found both the volatility of emerging market and the relative volatility of developed and emerging markets influenced the correlation levels between developed and emerging markets. Given the focus of this thesis on difference between developed and emerging/frontier markets, and given the importance of differences in volatilities identified in the literature, this feature provides the basis for Hypothesis 3.

4.2.2 Sample data: Can the impact of 2007 crisis and Euro crisis be distinguished in the data?

I recognise that it is difficult to draw clear and complete boundaries between the 2007 crisis and the subsequent Euro crisis. However, as argued below, I think that for the purpose of this thesis it is possible to distinguish between the impacts of the two crises from a data perspective in most instances.

4.2.2.1 Evidence from literature

A major difference between two crises was that there was no major sovereign debt default in Euro crisis. I would argue therefore that unlike during 2007 crisis there was little significant threat of systematic collapse of the global financial system (Unlike, for example, the thread of collapse associated with the Lehman Brothers bankruptcy of 2008). This meant that the Euro crisis had much less of a *global* impact. We see this in the literature that, for example, Tamakoshi *et al.* (2012) show that the sovereign debt crisis was rather local issue as they found rather no contagion effect. Similar conclusion was drawn by Kazi *et al.* (2014). They provide three possible reasons why European sovereign debt crisis had no contagion effect. First, Greece is regarded as a small economy with a rather small impact on the other countries. Second, the main cause of the European sovereign debt crisis was domestic mishandling of unsustainable levels of public debt. Similar argument can be found in Blundell-Wignall and Slovik (2010) where they argue that there was a heavy exposure of banks to the sovereign debt of the domestic country. Third, quick intervention of European Central Bank as well as International Monetary Fund prevented the European sovereign debt crisis from spreading to other countries.

The consequence of the Euro crisis being mainly limited to Europe is that its impact on the correlation between US and non-Euro area markets was limited and non-permanent. I would argue that although the 2007 crisis had a major impact on the `financial architecture` (for example, deleveraging effect and development of Basel III), the Euro crisis had little effect on the financial architecture outside the Euro area. This is evident from the data below which suggests the impact on relationship between non-Euro markets and the US market was very limited. It should be noted that I do not discount the possibly of the Euro crisis having a significant impact on US-Euro area correlations. This means that the interpretation of this sub-set of the results in this chapter needs to be approached with caution.

4.2.2.2 Evidence from the data

There are four key events that are related to the Euro crisis that have been identified in the footnote in Chapter 3, namely January 2010, April 2010, November 2010 and May 2011. In this sub-section I examine the impact of these events on the conditional volatilities and the relative changes in index values. This is done on the basis that if these key events had little or transitory effect on the different indices it could be argued that the impact of Euro crisis on global financial markets had no lasting impact on these markets (with possible exception of Euro area itself) and therefore the *permanent (or structural)* impact of 2007 global financial crisis on markets can be distinguished from the impact of the Euro crisis.

Figure 4.1 shows that whilst the 2007 crisis had a large and significant influence on market volatilities the four specific dates identified with respect to the Euro crisis had little impact across global markets *in general*. The possible exceptions in respect to this are the EMU and possibly EM EUROPE indices. This suggests that when we look at the correlations with US we may need to be a little careful when interpreting these two particular relationships.

There was an upward trend in the value of all markets during the main period of the Euro crisis (after January 2010). This is shown in Figure 4.2 which shows the index values relative to 12 July 2002. The fact that the indices were rising indicates that markets were relatively relaxed as to the potential impact of this crisis and unlike the 2007 crisis there was no sense of potential systematic collapse. Figure 4.2 shows that there were some short-term corrections that occurred around some of the dates identified but there was nothing to suggest that these were any more than just short-term corrections as the markets continued to trend upwards subsequently.

Figure 4.1 Conditional volatilities of US, developed and emerging/frontier region stock indices

Notes: The graph shows the conditional volatility of the US and respective indices over the period 12 July 2002 to 1 July 2011. The five vertical lines represent: the start of global financial crisis (11 May 2007), the end of global financial crisis (1 January 2010), Euro crisis related events (April 2010, November 2010 and May 2011).

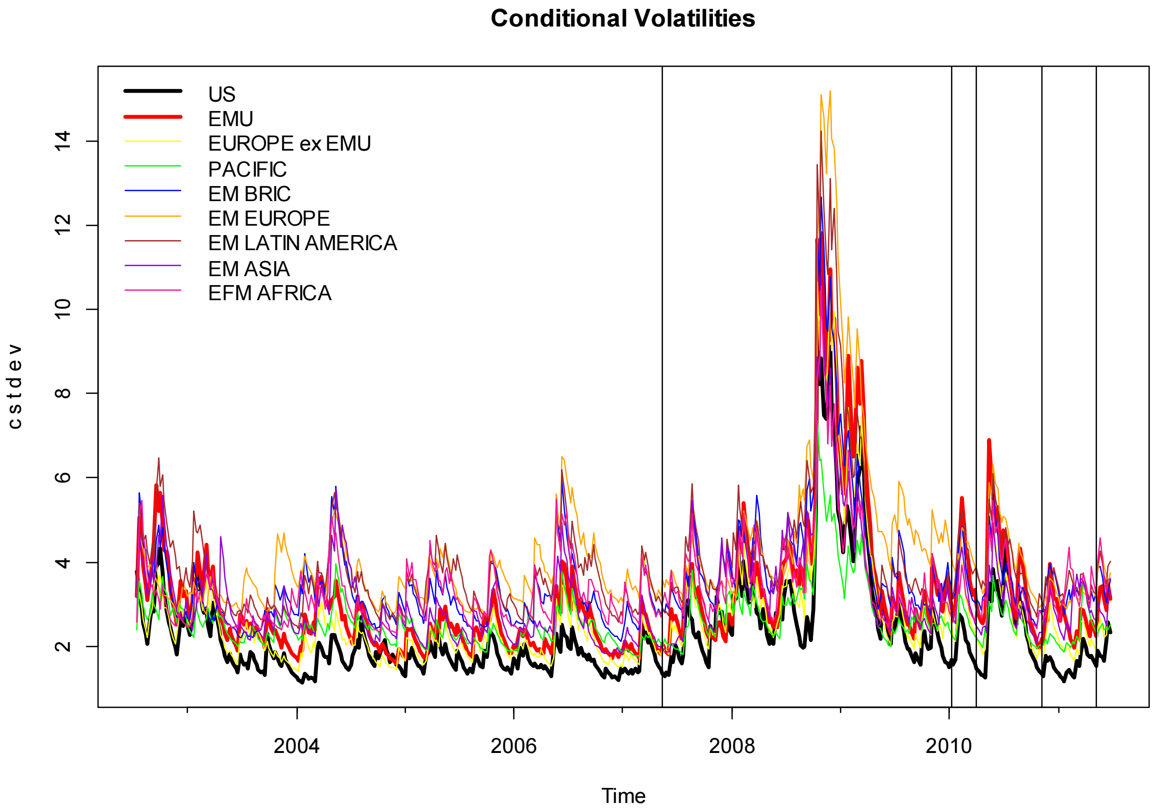
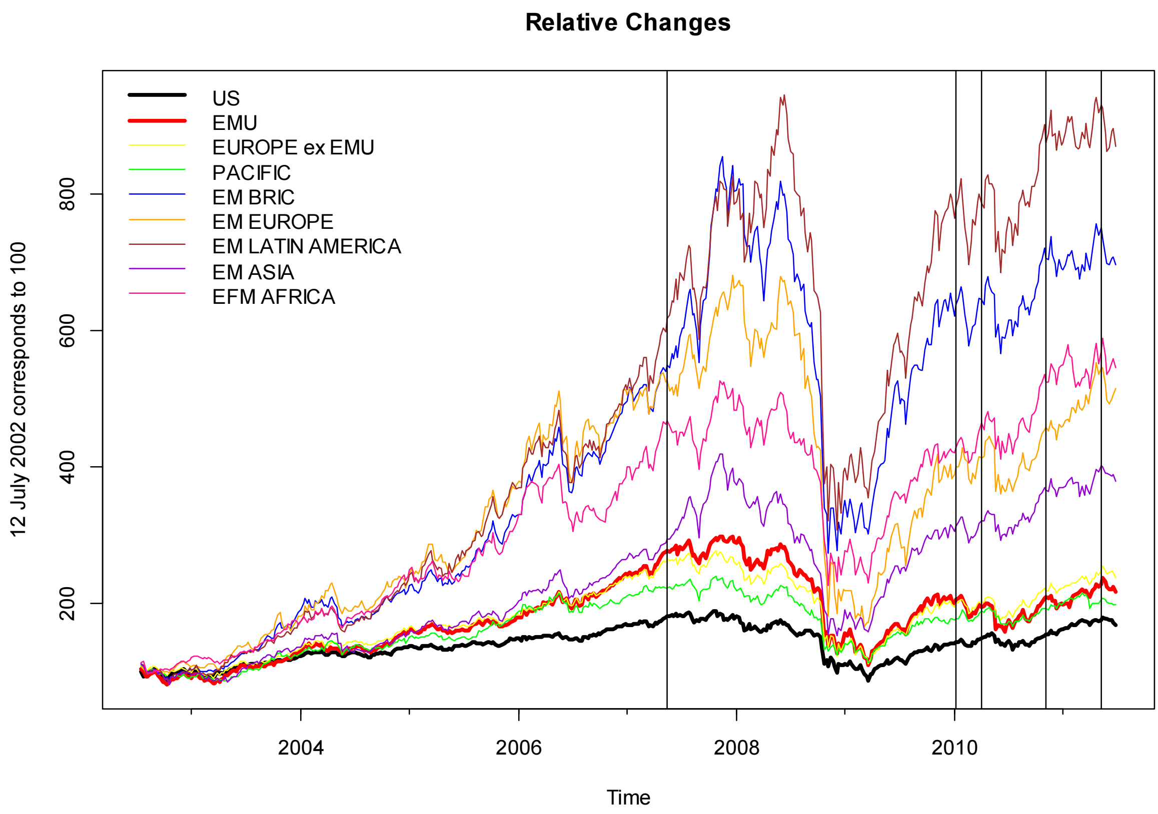


Figure 4.2 Relative changes of US, developed and emerging/frontier region stock indices

Notes: The graph shows the relative changes of the US and respective indices over the period 12 July 2002 to 1 July 2011. The five vertical lines represent: the start of global financial crisis (11 May 2007), the end of global financial crisis (1 January 2010), Euro crisis related events (April 2010, November 2010 and May 2011).



On the basis of the evidence presented in Sections 4.2.2.1 and 4.2.2.2 I conclude that my dataset does allow me to distinguish between the long-term or permanent changes in the extent of changes in market linkages resulting in from the 2007 crisis and the subsequent relatively small and short-term changes in market linkages associated with the Euro crisis. However, in order to maintain the robustness of my analysis in the discussion of my results I will add the caveat that care should be taken in interpreting the US-EMU relationship and also US-EM EUROPE relationship.

On the basis of the above arguments I test the following hypotheses:

H1. There has been a long-term post-2007-crisis structural change in the strength of conditional correlations between the US equity market and other developed regional markets.

H2. There has been a long-term post-2007-crisis structural change *of a different magnitude* in the strength of conditional correlations between the US equity market and emerging/frontier regional markets.

H3. The strength of conditional correlations between US and regional markets have been affected by long-term post-crisis structural changes in the relative conditional volatilities of these US and regional markets.

4.3 Data and Methodology

The data used is discussed in the Chapter 3. This chapter measures correlations by applying the dynamic conditional correlation multivariate GARCH model (DCC) proposed by Engle (2002).

Different ARMA specifications of the mean equation were tested through the examination of the significance of the coefficients, information criteria and the Ljung-Box (1978) test for autocorrelation in the standardised residuals. The simplest form of the mean equation (which includes only a constant) was found to be the most appropriate and ARMA (0,0) is used on the basis that it was the most parsimonious of the models found as acceptable in the tests undertaken.

As well as testing the specification of the mean equation, specifications of different forms of the variance equation were also examined. Different orders and specifications of the GARCH model were explored using significance tests of the coefficients and also using the Ljung-Box (1978) and ARCH LM (Engle 1982) tests of the squared standardised residuals.

Alternative asymmetric GARCH specifications were tested: GJR GARCH (Glosten *et al.* 1993), EGARCH (Nelson 1991) and TGARCH (Zakoian 1994). A specification of TGARCH (1,1) was found to be the most appropriate way of dealing with asymmetries in the data.

The multivariate specification of the DCC element of the model was identified as being (1,1) through an examination of the significance of the coefficients and also through the use of information criteria.

The univariate specifications reject the null hypothesis of normality in the series of standardised residuals using the Jarque-Bera (1980) and Shapiro-Wilk (1965) tests.

The full model used in the chapter is expressed as follows.

Mean equation:

$$\mathrm{r}_{\mathrm{i,t}} = \mu_{\mathrm{i}} + \varepsilon_{\mathrm{i,t}} \tag{4.1}$$

where the residuals are assumed to be conditionally multivariate-normal.[3]

Variance equation:

$$\sqrt{h_{i,t}} = \omega_i + \alpha_i\left|\varepsilon_{\mathrm{i,t-1}}\right| + \gamma_{\mathrm{i}}\left|\varepsilon_{\mathrm{i,t-1}}\right| I\left(\varepsilon_{\mathrm{i,t-1}} < 0\right) + \beta_i\sqrt{h_{i,t-1}} \tag{4.2}$$

DCC equation :

$$\mathrm{Q}_{\mathrm{t}} = (1 - \alpha - \beta)\overline{\mathrm{Q}} + \alpha \nu_{\mathrm{t-1}} \nu'_{\mathrm{t-1}} + \beta \mathrm{Q}_{\mathrm{t-1}} \tag{4.3}$$

where ν_{t} represents the residuals standardised by their conditional standard deviation.

[3] The assumption of multivariate normality is not required for consistency and asymptotic normality of the estimated parameters (Engle and Sheppard 2001).

The estimated model is presented in Table 4.4 in the appendix. All the coefficients were found to be positive but not all were found to be statistically significant. The insignificant parameters were mainly found in relation to the developed markets; their insignificance could possibly reflect non-normality in conditional distribution.

The impact of the financial crisis on the conditional correlation is examined using two tests; this is done for comparative purposes and also in order to add to the robustness of the results. The tests applied are the Welch (1938) t test and the Wilcoxon (1945) rank sum test (also known as the Mann-Whitney-Wilcoxon test). The former compares the difference between sample means and the latter compares difference between sample location parameters. It can be noted that the Welch test takes the non-equality of variances into account and the Wilcoxon test is robust to non-normality in the distribution, non-equality in the variance and also for small sample sizes (Sawilowsky 2005). The tests are used to compare the values of the conditional correlation and volatilities in the pre-crisis period of 10 March 2006–11 May 2007 (62 observations) against the values in the post-crisis period of 1 January 2010–4 March 2011 (62 observations). A similar approach can be found in Celık (2012). For robustness, additional tests were undertaken for comparative purposes using longer pre-crisis and post-crisis periods: 31 December 2004–11 May 2007 (124 observations) against 1 January 2010–11 May 2012 (124 observations). A further series of tests producing similar results are not reported in the chapter (using 176 observations for 2 January 2004–11 May 2007 against 124 observations for 1 January 2010–11 May 2012).

4.4 Results and Discussion

4.4.1 Conditional correlation between US and developed region markets

The conditional correlations between the US and developed region weekly returns are shown in Figure 4.3. The reaction of these correlations to the financial crisis appears to be similar across all three developed regions, although there was some variation in timings. An initial fall in correlation with EMU countries was observed in the period immediately after May 2007. This is consistent with the findings of Syllignakis and Kouretas (2011) who studied correlation between US/Germany and Central Easter European markets. This can be interpreted as indicating that stock prices in this region responded relatively slowly to the initial declines in the US market. Non-EMU European countries, however, appeared to track the US market more closely. A large proportion of this index relates to the UK and Swiss markets and therefore the tendency for this index to track the US closely possibly reflects the relatively high importance of the financial services sectors in these countries.

As noted in Section 4.2.2 care needs to be taken in interpretation of the US-EMU relationship because of possible contamination of the data associate with the Euro crisis. In respect to this dataset it may therefore be more appropriate to see these results not so much in terms of the persistence or permanence in the change in correlation relationship but more in terms of identifying changes of financial linkage between the markets at time of financial crisis. I found that the mean correlation rose from 0.771 before the crisis to 0.782 after crisis (see Table 4.1). This shows a clear linkage associated with financial crisis, however, whether this was associated purely with the 2007 crisis or was a `mongrel` effect which was partly associated with this crisis and partly associated with the Euro crisis is difficult to tell.

The crisis appears to have had a positive impact on conditional correlations and volatilities across all three developed regions towards the end of 2008. This is in line with findings of Cheung *et al.* (2008) who studied correlation between the US and Asian-based EMEAP markets. From Figure 4.3 a spike in correlation can be identified as occurring in late 2010 between the US and Europe ex EMU and also between the US and Pacific. At the same time, there were pronounced increases in the conditional volatilities across all developed regions. This is consistent with Nauoi *et al.* (2010) who found that during the crisis period the returns of developed markets were highly volatile. In addition, higher correlations are associated with higher volatility as indicated by Cai *et al.* (2009). Interestingly, however, the ratio of the conditional volatilities did not change substantially; in effect, market volatilities were moving very much in step as might be expected during a contagion event.

As the crisis subsided the conditional volatilities fell in all regions and in the post-crisis period (when the VIX index mean-reverted to approximately pre-crisis levels at the start of January 2010) and conditional correlation levels stabilised.

Table 4.1 identifies changes in the mean correlation and volatility levels between the pre- and post-crisis periods. It can be noted that the estimates appear largely robust to changes in the sample length; however, the longer sample period's mean correlation and mean ratio of volatilities values are generally a little lower for both pre- and post-crisis periods. A third set of results using a 176-week pre-crisis period and a 124-week post-crisis period are not reported given that they produced very similar results.

The mean comparison tests indicate that, with the possible exception of EMU, mean correlation levels were higher in the post-crisis period. This is indicative of a long-term increase in post-crisis conditional correlations. The average post-crisis increase in mean correlations across all samples is 3.39%. The 124-week period sample test shows a statistically significant increase in correlations between the US and all three developed regions. There were, however, regional differences; for example, there is an increase of about 6.3% (from 0.749 to 0.796) in respect to non-EMU Europe, which can be compared to an increase of about 1.43% in respect to EMU.

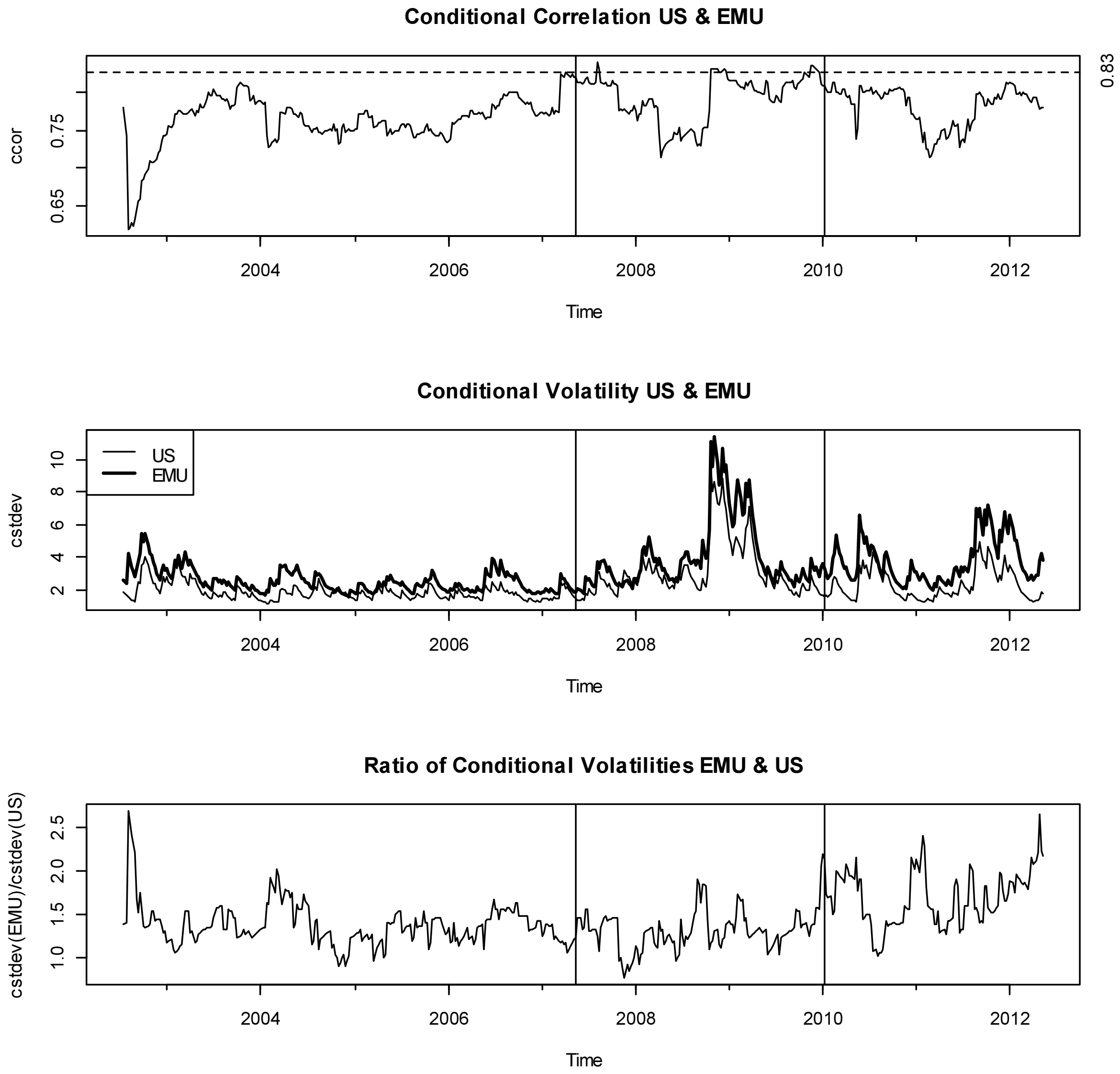
The effect of the crisis on the correlations can be contrasted with the impact that it had on the volatilities. Table 4.1 identifies that all the developed markets in the sample showed higher volatility than the US, both pre-crisis and post-crisis. It is also interesting to note that in two out of the three cases, the volatility of US markets fell relative to its developed country counterparts subsequent to the crisis ending. The possible implications that this had for correlation levels will be discussed in a latter section.

I argue that the results from these tests give support for Hypothesis 1. I contend that the finding of statistically significant increases in the long-term conditional correlations between the US and other developed region markets means that the 2007 crisis has to be seen as being more than just a transitory contagion event. Similar findings are presented by Chaing *et al.* (2007) with respect to post-Asian-crisis correlations between Thailand and developed markets. They found that correlations with Korea and Hong Kong increased significantly. My findings are consistent with the argument by Whalen (2008)[4] that the financial crisis resulted in permanent changes to the world's financial architecture. The increase in the conditional correlation can possibly be explained as being a result of the worldwide structural changes in the banking and regulatory framework that occurred in response to the crisis. As was identified by Moshirian (2011), responses to the financial crisis by governments in the developed world have been highly coordinated and we have also seen significant levels of deleveraging and a rolling back of the investment banking activities throughout the developed economies (Geithner 2008). I would argue that the findings from my study lend support to that argument; that the increase in the coordination of the global regulatory framework, and the constraints this has placed on trading activities, have had a positive long-term impact on the correlation of stock market price movements between developed regions.

[4] It is a paper based on the use of theoretical models and analysis of historical precedents.

Figure 4.3 Relationship between weekly logarithmic returns of US and developed region stock indices

Notes: The graphs show the conditional correlation, conditional volatility and the ratio of conditional volatilities between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period 12 July 2002 to 11 May 2012. The ratio of conditional volatilities is calculated as conditional volatility of the developed region divided by conditional volatility of the US.



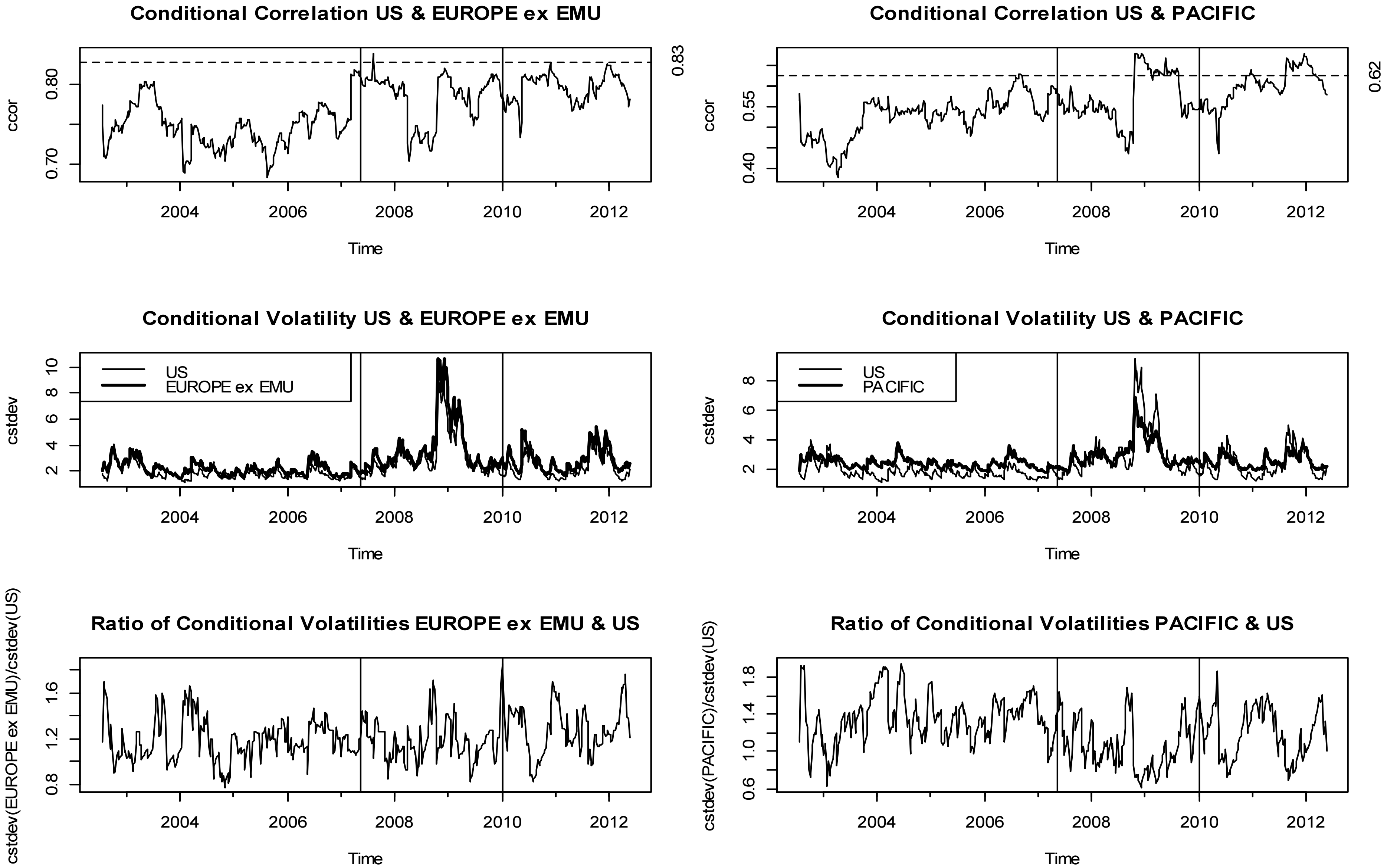

Conditional Correlation US & EUROPE ex EMU
ccor
0.70
0.80
0.83
2004
2006
2008
2010
2012
Time
Conditional Correlation US & PACIFIC
ccor
0.40
0.55
0.62
Conditional Volatility US & EUROPE ex EMU
cstdev
US
EUROPE ex EMU
Conditional Volatility US & PACIFIC
US
PACIFIC
Ratio of Conditional Volatilities EUROPE ex EMU & US
cstdev(EUROPE ex EMU)/cstdev(US)
Ratio of Conditional Volatilities PACIFIC & US
cstdev(PACIFIC)/cstdev(US)

Table 4.1 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations, conditional volatilities and ratio of conditional volatilities (US and developed region stock markets)

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean ratio of volatilities with US pre-crisis period[a]	Mean ratio of volatilities with US post-crisis period[b]	Percentage change in mean ratio of volatilities	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	1.720	2.140	24.42%	0.000***	0.020**	-	-	-	-	-
	124/124	-	-	-	-	-	1.734	2.304	32.872%	0.000***	0.000***	-	-	-	-	-
EMU	62/62	0.788	0.786	-0.254%	0.790	0.099*	2.367	3.397	43.515%	0.000***	0.000***	1.373	1.661	20.976%	0.000***	0.000***
	124/124	0.771	0.782	1.427%	0.000***	0.000***	2.318	3.787	63.374%	0.000***	0.000***	1.339	1.697	26.736%	0.000***	0.000***
EUROPE ex EMU	62/62	0.766	0.797	4.047%	0.000***	0.000***	2.091	2.634	25.968%	0.000***	0.000***	1.210	1.284	6.116%	0.033**	0.020**
	124/124	0.749	0.796	6.275%	0.000***	0.000***	2.068	2.837	37.186%	0.000***	0.000***	1.194	1.279	7.119%	0.000***	0.000***
PACIFIC	62/62	0.571	0.574	0.525%	0.593	0.273	2.373	2.416	1.812%	0.548	0.567	1.403	1.222	-12.901%	0.000***	0.000***
	124/124	0.553	0.599	8.318%	0.000***	0.000***	2.303	2.545	10.508%	0.000***	0.000***	1.350	1.198	-11.259%	0.000***	0.000***

Notes: [a] The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007, [b] the 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all *samples for the mean of conditional correlations, conditional volatilities and ratios of conditional volatilities are 3.390%, 29.957% and 6.131%, respectively. The ratio of conditional volatilities is calculated as conditional volatility of a developed region divided by conditional volatility of US. Note: tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

4.4.2 Conditional correlation between US and emerging/frontier region markets

The impact of the financial crisis appears to have been less severe on the emerging/frontier regional financial markets; it can be argued that this was possibly a result of their lower-leveraged financial sectors and their smaller investment banking sectors. It might be expected that a possible consequence of this could be that changes in the conditional correlations between the emerging/frontier regional markets and the US may be found to be of a different size from the changes in correlations between the US and other developed markets.

From Figure 4.4 it can be identified that the reaction of the conditional correlation to the financial crisis appears to be similar in all the emerging/frontier regions in the sample. As was also found in respect to developed regional markets, there was an initial fall in correlation in May 2007, which indicated that these parts of the world responded relatively slowly to the initial falls in the US market. This was then followed by a spike in correlation that occurred towards the end of 2008. Similar observation was made by Syllignakis and Kouretas (2011) with respect to the correlation between seven Central Easter European markets and US/Germany markets where correlation initially fell and then reached the peak during the second half of 2008. Further evidence (Cheung *et al.* 2008) can be found with respect to the US and Asian-based EMEAP markets where the sharp increase in correlation was observed towards the mid-September 2008.

In the BRIC countries, for example, correlation rose from a low of about 0.548 just prior to the crisis to a peak of about 0.730 during the crisis period. This spike in correlation was accompanied by a spike in the conditional volatility. This is consistent with findings of Kenourgios *et al.* (2011) who studied correlation levels between the US, the UK and BRIC markets during five crises; namely the Brazilian crisis, the Russian default, the Asian crisis, the Technology bust and the second Brazilian crisis. Interestingly, the spikes found in the conditional volatilities across the emerging/frontier markets tended to be higher than the increase experienced in the US; this being despite the fact that the financial crisis was predominantly a developed market phenomenon. It is possible that this was due to the worldwide nature of the crisis prompting developed country investors to withdraw money from emerging markets as identified by Kenourgios *et al.* (2011). Similar behaviour of investors was observed in response to the Asian crisis (Garnaut 1998). It can be observed that, since the 1990s, downturns in developed markets have triggered large underperformance in emerging markets. This may partially reflect the ways in which institutional investors operate. For example, Credit Suisse argues that pension fund investment in emerging markets is problematical given that it is restricted by strict liquidity rules. Funds are required to mark-to-market their assets daily, forcing rapid divestments if assets fall in relation to liability thresholds (Emerging Markets 2010).

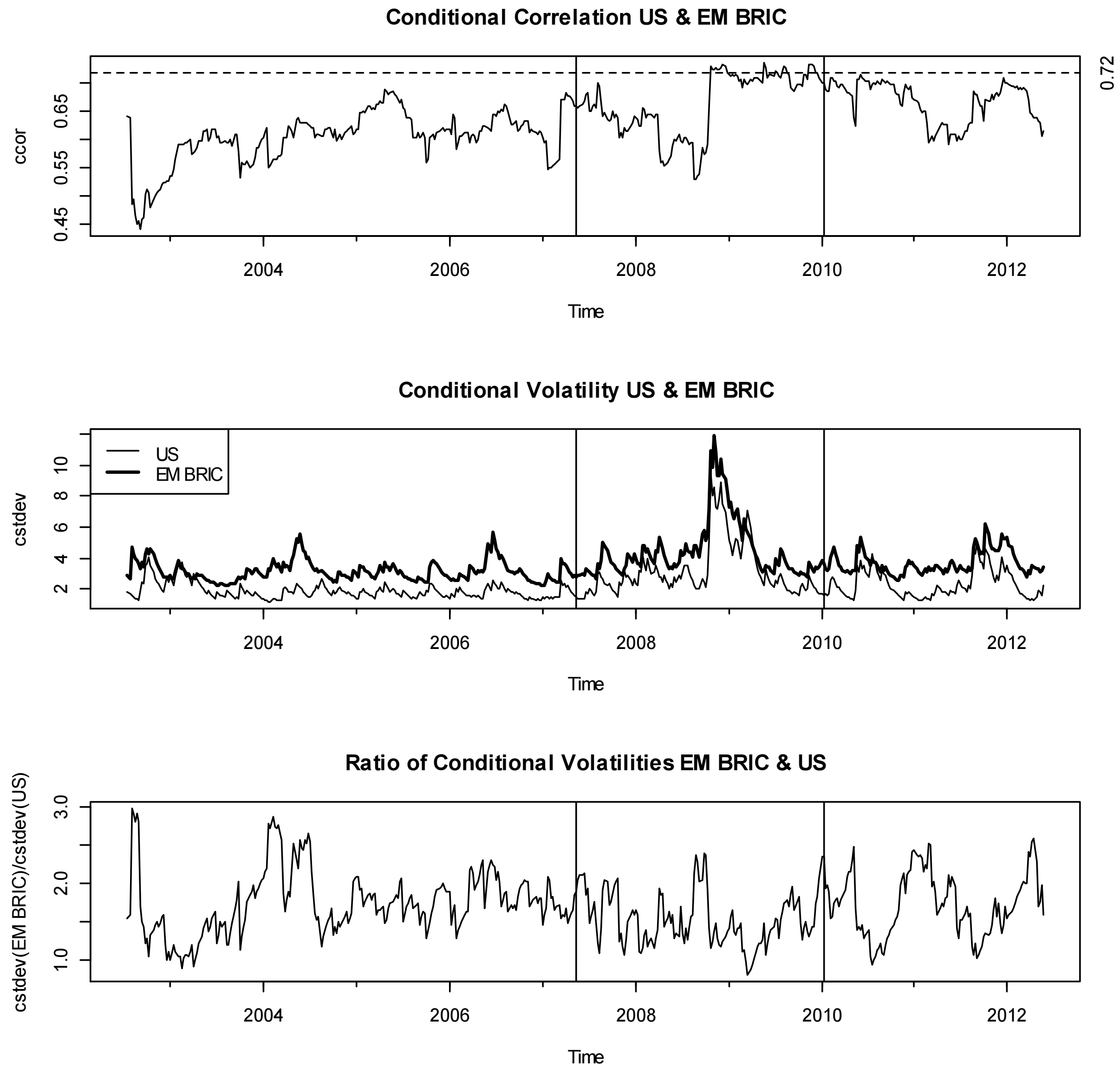
Table 4.2 identifies changes in mean conditional correlation and conditional volatility levels between the pre- and post-crisis periods. It can be noted that, as was the case with the developed market sample, the estimates appear largely robust to changes in the sample length and that the longer sample period mean values are generally a little lower for both the correlations and the ratios of volatilities.

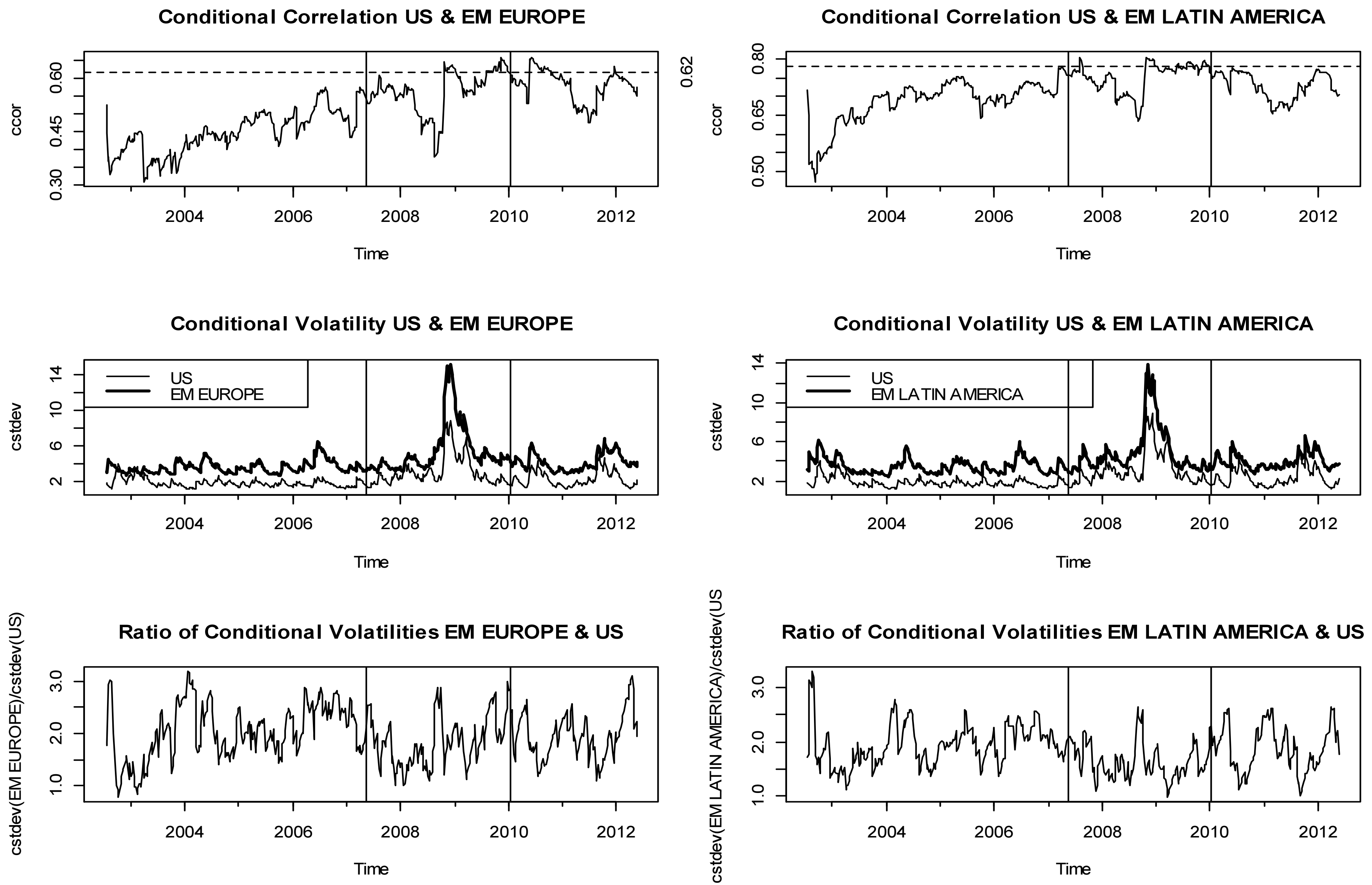
From the 124-week period sample test set it can be identified that subsequent to the end of the crisis in January 2010 mean correlation levels were higher than in the pre-crisis period. In addition, it can be noted that all of these increases were statistically significant. In, for example, the emerging/frontier Africa region correlation increased by about 13% to 0.599 (from 0.530) and for EM ASIA it increased by about 8.2% to 0.618.

These results appear to lend prima facie support to Hypothesis 2. They suggest the correlations between the US and emerging/frontier regional markets have risen by a different magnitude to the increases in correlation between US and developed markets. The mean increase across all samples was found to be 10.1% for emerging/frontier markets compared to the 3.39% mean increase found for the developed markets (Table 4.1). Chiang *et al.* (2007) found that the post-Asian-crisis correlations between Thailand and some developed countries increased significantly but they didn't find significant changes in correlations between Thailand and emerging markets. In the next section I argue that a possible explanation for this difference in size can be found in the differences to which the relative conditional volatilities changed between the two sample groups. The influence of volatility on correlation is well recognised in the literature. For example, both Longin and Solnik (1995) and also Solnik *et al.* (1996) showed there to be a relationship between correlation levels and changes in volatility.

Figure 4.4 Relationship between weekly logarithmic returns of US and emerging/frontier country stock indices

Notes: The graphs show the conditional correlation, conditional volatility and the ratio of conditional volatilities between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period 12 July 2002 to 11 May 2012. The ratio of conditional volatilities is calculated as conditional volatility of the emerging/frontier region divided by conditional volatility of the US.




Conditional Correlation US & EM EUROPE
ccor
0.30
0.45
0.60
0.62
2004
2006
2008
2010
2012
Time
Conditional Correlation US & EM LATIN AMERICA
ccor
0.50
0.65
0.80
0.78
Conditional Volatility US & EM EUROPE
cstdev
US
EM EUROPE
2
6
10
14
Conditional Volatility US & EM LATIN AMERICA
US
EM LATIN AMERICA
Ratio of Conditional Volatilities EM EUROPE & US
cstdev(EM EUROPE)/cstdev(US)
1.0
2.0
3.0
Ratio of Conditional Volatilities EM LATIN AMERICA & US
cstdev(EM LATIN AMERICA)/cstdev(US

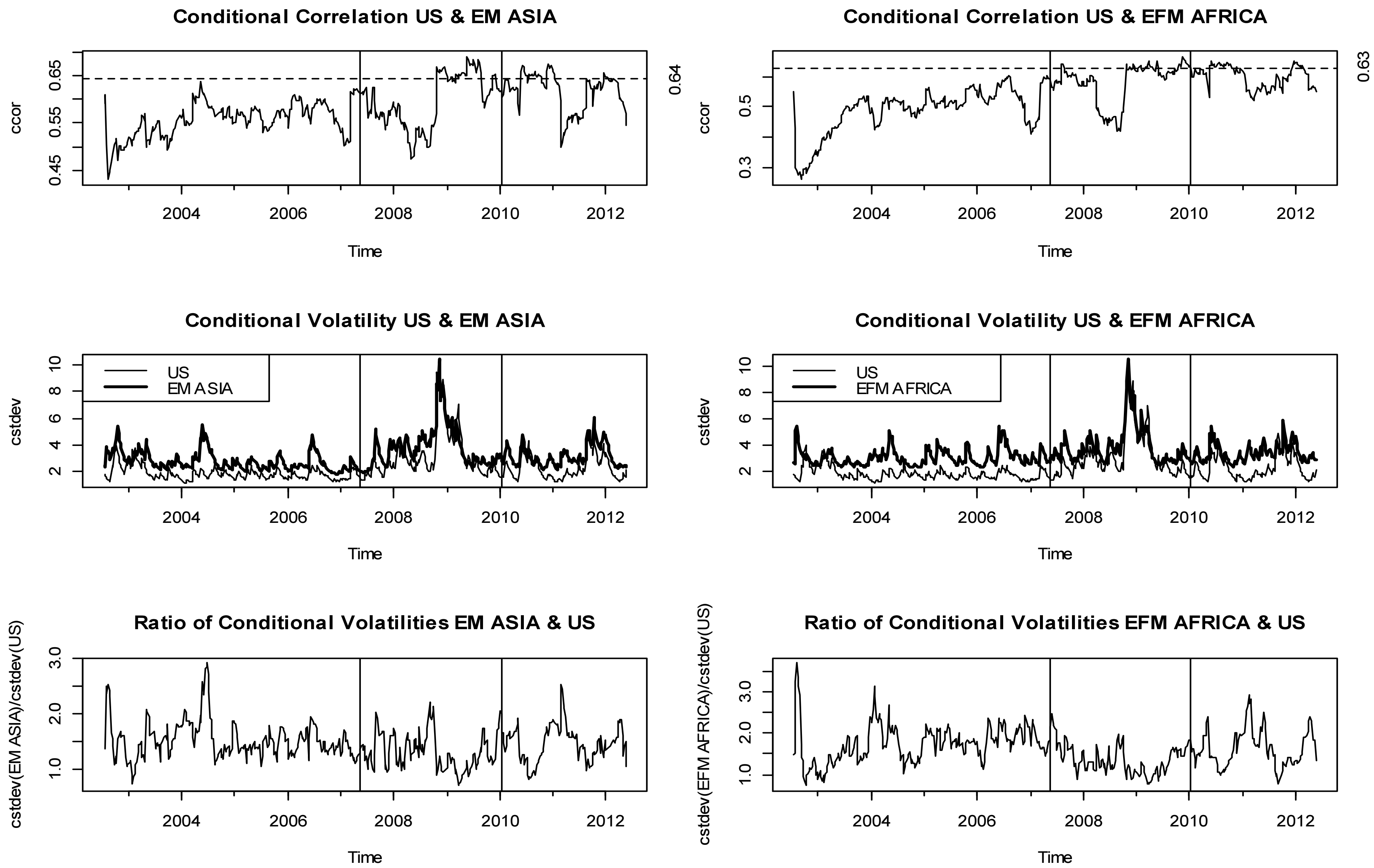

Conditional Correlation US & EM ASIA
ccor
0.45
0.55
0.65
0.64
Conditional Correlation US & EFM AFRICA
ccor
0.3
0.5
0.63
Conditional Volatility US & EM ASIA
cstdev
US
EM ASIA
2
4
6
8
10
Conditional Volatility US & EFM AFRICA
cstdev
US
EFM AFRICA
Ratio of Conditional Volatilities EM ASIA & US
cstdev(EM ASIA)/cstdev(US)
1.0
2.0
3.0
Ratio of Conditional Volatilities EFM AFRICA & US
cstdev(EFM AFRICA)/cstdev(US)
2004
2006
2008
2010
2012
Time

Table 4.2 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations, conditional volatilities and ratio of conditional volatilities (US and emerging/frontier region stock markets)

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean ratio of volatilities with US pre-crisis period[a]	Mean ratio of volatilities with US post-crisis period[b]	Percentage change in mean ratio of volatilities	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	1.720	2.140	24.419%	0.000***	0.020**	-	-	-	-	-
	124/124	-	-	-	-	-	1.734	2.304	32.872%	0.000***	0.000***	-	-	-	-	-
BRIC	62/62	0.624	0.683	9.455%	0.000***	0.000***	3.206	3.473	8.328%	0.030**	0.003***	1.868	1.774	-5.032%	0.157	0.334
	124/124	0.629	0.668	6.200%	0.000***	0.000***	3.096	3.688	19.121%	0.000***	0.000***	1.796	1.735	-3.396%	0.151	0.142
EM EUROPE	62/62	0.514	0.606	17.899%	0.000***	0.000***	4.058	3.931	-3.130%	0.416	0.349	2.381	1.963	-17.556%	0.000***	0.000***
	124/124	0.496	0.582	17.339%	0.000***	0.000***	3.748	4.197	11.980%	0.000***	0.000***	2.185	1.956	-10.481%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.724	0.739	2.072%	0.005***	0.004***	3.664	3.851	5.104%	0.162	0.112	2.141	1.949	-8.968%	0.005***	0.026**
	124/124	0.719	0.729	1.391%	0.014**	0.008***	3.511	4.003	14.013%	0.000***	0.000***	2.039	1.880	-7.798%	0.001***	0.001***
EM ASIA	62/62	0.575	0.634	10.261%	0.000***	0.000***	2.533	2.933	15.792%	0.001***	0.000***	1.471	1.490	1.292%	0.739	0.581
	124/124	0.571	0.618	8.231%	0.000***	0.000***	2.516	3.164	25.755%	0.000***	0.000***	1.456	1.467	0.755%	0.765	0.632
EMF	62/62	0.532	0.613	15.226%	0.000***	0.000***	3.326	3.300	-0.782%	0.840	0.962	1.946	1.680	-13.669%	0.000***	0.000***

AFRICA	124/124	0.530	0.599	13.019%	0.000***	0.000***	3.218	3.440	6.899%	0.010***	0.003***	1.867	1.633	-12.533%	0.000***	0.000***

*Notes: [a] [b] Samples as described in Table 4.1. The average percentage changes across all samples for the mean of conditional correlations, conditional volatilities and ratios of conditional volatilities are: 10.109%, 13.364% and -7.739%, respectively. The ratio of conditional volatilities is calculated as conditional volatility of an emerging/frontier region divided by conditional volatility of the US. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

4.4.3 CONDITIONAL CORRELATIONS AND THE RATIO OF CONDITIONAL VOLATILITIES: WHY DO DEVELOPED AND EMERGING/FRONTIER MARKET CORRELATIONS DIFFER?

It was noted above that the mean increase across all samples was found to be 10.1% for emerging/frontier markets (Table 4.2) compared to the 3.39% mean increase found for the developed markets (Table 4.1). I now discuss potential reasons for this large difference.

One possible explanation for the apparent long-term increases in market correlation is that they are the consequence of changes to the financial architecture, resulting in greater financial regulation and significant deleveraging in developed markets. This would not, however, account for the differences found in the sizes of the increases in correlation in the emerging/frontier market and developed market sample data sets. A possible explanation of this difference lies in the different ways in which the conditional volatilities responded to the crisis.

I argue in this chapter that the differences in correlation found between developed and emerging/frontier markets may reflect the impact of two separate factors: firstly, the effect of changes to the financial architecture[5] that have a positive impact on correlation; secondly, the effect of changes in the ratio of volatilities between the second (regional) market and the US market. I find evidence to suggest that that the effect on correlations of the second factor works in *opposite* directions in developed and emerging/frontier regional markets.

The importance of volatility on correlation was identified, for example, by Cai *et al.* (2009), Gupta and Mollik (2008), Knif and Pynnonen (2007) and also Jithendranathan (2005). My study found that the volatilities of developed and emerging/frontier markets relative to the US

[5] Minsky (1975, 1992) identified that financial crisis resulted in significant changes within financial institutions and financial practices. This was described as changes in financial architecture. For example, in response to 2007 crisis Basel III has recommended increases in the Tier I capital ratios of banks. Other changes include a substantial reduction in some derivatives products such as CDOs and also substantial reductions in leverage ratios in the investment banking sector.

market responded differently to the 2007 crisis. From Table 4.1 and Table 4.2 it can be identified that in most instances the ratio of the conditional volatility with the US *increased* in respect to developed markets but *decreased* in respect to emerging/frontier markets.

I argue in this chapter that developed markets showed a relatively small increase in their correlation with the US because the positive impact on correlations associated with the change in the world's financial architectures was partially offset by the *increase* in their conditional volatility relative to the US. This can be contrasted with emerging/frontier markets where the larger increases in the conditional correlation can be explained in terms of the positive impact associated with financial architecture effects being augmented by the impact of the *fall* in the volatility of emerging markets relative to the US (which has an additional positive impact on correlation levels).

I use the following regression model to examine this relationship in more detail:

$$\rho_{i,t} = \alpha_i + \beta_{1i}\frac{Volatility_{market,t}}{Volatility_{US,t}} + \beta_{2i} dummy\ variable_t + \varepsilon_t \tag{4.4}$$

Where $\rho_{i,t}$ is the conditional correlation between the regional and the US indices, $\frac{Volatility_{market,t}}{Volatility_{US,t}}$ is the ratio of conditional volatility between the regional market and the US market, $dummy\ variable_t$ is an intercept dummy variable that equals 0 (1) for observation before (after) crisis, *i* refers to the index and *t* to time.

The impact of the crisis on the financial architecture is identified through the intercept dummy variable which distinguishes between the pre- and post-crisis periods. The parameter values presented in Table 4.3 are found to be mainly positive for both the developed and emerging markets. They are also largely significant, especially in respect to emerging markets (providing additional support for our Hypothesis 1).

The regression shown in Equation 4.4 was run with the same three sample observation periods used in Table 4.1 and Table 4.2; for consistency I report the results for the same 62- and 124-observation periods in Table 4.3. The sign of the ratio of volatilities variable is negative for both groups. This provides support to our Hypothesis 3: that market conditional correlations are partly determined by relative conditional volatilities. I only find statistical significance in respect to the emerging/frontier markets for this variable, which may possibly reflect the fact that the size of the change in the ratio of volatilities was generally smaller in respect to the developed countries.

I would argue that although these results are not unequivocal, they do provide significant support to the third hypothesis. They are also consistent with the literature; Gupta and Mollik (2008), for example, also found changes in the relative volatilities of developed and emerging markets influenced their correlation.

Table 4.3 Regression results of factors affecting the conditional correlations (US and developed/emerging/frontier region stock markets)

Index	Sample length before[a]/after[b]	Constant	Ratio of conditional volatilities with US	Intercept dummy	Adj. R^2	F test p-value
EMU	62/62	0.822 (0.000***)	-0.025 (0.242)	0.006 (0.786)	0.062	0.008***
	124/124	0.773 (0.000***)	-0.001 (0.948)	0.012 (0.496)	0.044	0.001***
EUROPE ex EMU	62/62	0.800 (0.000***)	-0.028 (0.167)	0.033 (0.007***)	0.374	0.000***
	124/124	0.771 (0.000***)	-0.019 (0.165)	0.049 (0.000***)	0.519	0.000***
PACIFIC	62/62	0.563 (0.000***)	0.006 (0.774)	0.005 (0.869)	-0.013	0.793
	124/124	0.570 (0.000***)	-0.012 (0.581)	0.044 (0.039**)	0.264	0.000***
BRIC	62/62	0.692 (0.000***)	-0.037 (0.029**)	0.056 (0.003***)	0.570	0.000***
	124/124	0.668 (0.000***)	-0.022 (0.077*)	0.037 (0.037**)	0.268	0.000***
EM EUROPE	62/62	0.614 (0.000***)	-0.042 (0.000***)	0.074 (0.000***)	0.702	0.000***
	124/124	0.482 (0.000***)	0.006 (0.710)	0.088 (0.000***)	0.527	0.000***
EM LATIN AMERICA	62/62	0.830 (0.000***)	-0.050 (0.041**)	0.006 (0.766)	0.399	0.000***
	124/124	0.753 (0.000***)	-0.017 (0.292)	0.007 (0.696)	0.051	0.001***
EM ASIA	62/62	0.645 (0.000***)	-0.047 (0.364)	0.060 (0.003***)	0.522	0.000***
	124/124	0.632 (0.000***)	-0.042 (0.123)	0.048 (0.003***)	0.392	0.000***
EMF AFRICA	62/62	0.643 (0.000***)	-0.057 (0.000***)	0.066 (0.053*)	0.543	0.000***
	124/124	0.600 (0.000***)	-0.037 (0.014**)	0.060 (0.001***)	0.485	0.000***

Notes: [a b] *Sample as described in Table 4.1. The ratio of conditional volatilities is calculated as* *conditional volatility of a developed/emerging/frontier region divided by conditional volatility of the US. P-values are presented in the brackets below the coefficients. Standard errors have been corrected for autocorrelation and heteroskedasticity using the Newey-West correction. The intercept dummy variable equals 0 (1) for observation before (after) the crisis. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Regression equation: $\rho_{i,t} = \alpha_i + \beta_{1i}\frac{Volatility_{market,t}}{Volatility_{US,t}} + \beta_{2i} dummy\ variable + \varepsilon_t$

4.5 CONCLUSIONS

This chapter asks the question of whether or not the 2007 financial crisis resulted in a long-term structural change in the conditional correlation relationship between returns in the US equity market and the returns in international equity markets. This is important from the perspective of optimal portfolio selection as increases in correlation reduce the benefits associated with international portfolio diversification. Previous researchers such as Longin and Solnik (2001) identified short-term correlation increases during bear market phases and others, such as You and Daigler (2010), argued that there was a short-term reduction in portfolio diversification benefits during these periods. I believe, however, that this chapter produces evidence to suggest that the 2007 financial crisis-related increases in conditional correlations are *permanent*. If this is the case it will have major implications for the ways in which US investors use international diversification in their portfolio selection.

I find prima facie evidence to support the hypothesis that economic structural adjustment has resulted in long-term increases in the correlation between the US and developed markets and also between the US and emerging/frontier markets.

The second key finding is that the *magnitude* of the increase in correlation appears to be greater in respect to emerging/frontier markets. For example, from pre-crisis to post-crisis the correlation between BRIC countries and the US rose by 6.2% to 0.668. It also increased between the US and EM ASIA by 8.2% to 0.618 and between the US and emerging frontier Africa by 13% to 0.599. I argue in this chapter that there is a prima face case for the argument that the increases in correlation found are possibly a consequence of two interrelated factors: first, the global tightening of regulations and the deleveraging effects seen across much of the world financial sector in response to the crisis; and, second, the impact of the crisis on relative market conditional volatilities. It was found that in most instances post-crisis volatility *rose* in other developed markets relative to the US and that post-crisis volatility *fell* in emerging/frontier markets relative to the US. I would argue that this difference possibly explains why I found greater increases in the correlation with the US in respect to emerging/frontier markets that in respect to developed economy markets.

4.6 APPENDICES

Table 4.4 DCC(1,1)-TGARCH(1,1) model for the logarithmic returns for the nine MSCI indices

Parameter	Estimate	Std. error	t value	Pr(>|t|)
US				
μ	0.112375	0.060353	1.861970	0.062608*
ω	0.176424	0.121118	1.456630	0.145218
α	0.125609	0.076503	1.641900	0.100612
γ	1.000000	0.391318	2.555460	0.010605**
β	0.826713	0.105525	7.834290	0.000000***
EMU				
μ	0.165232	0.081702	2.022370	0.043138**
ω	0.231389	0.120612	1.918460	0.055053*
α	0.113870	0.052256	2.179080	0.029326**
γ	1.000000	0.240486	4.158250	0.000032***
β	0.838841	0.070210	11.947600	0.000000***
Europe ex EMU				
μ	0.201190	0.109583	1.835960	0.066363*
ω	0.219127	0.118019	1.856700	0.063353*
α	0.117188	0.060649	1.932220	0.053332*
γ	1.000000	0.285764	3.499390	0.000466***
β	0.827790	0.080246	10.315620	0.000000***
Pacific				
μ	0.109969	0.113864	0.965790	0.334149
ω	0.247988	0.170572	1.453860	0.145984
α	0.075309	0.039314	1.915590	0.055418*
γ	0.921783	0.405580	2.272750	0.023041**
β	0.847973	0.081597	10.392260	0.000000***
EM BRIC				
μ	0.466896	0.158356	2.948400	0.003194***
ω	0.331698	0.201699	1.644520	0.100069
α	0.101471	0.034261	2.961710	0.003059***
γ	0.685051	0.267757	2.558480	0.010513**
β	0.827542	0.073186	11.307330	0.000000***
EM Europe				
μ	0.307575	0.138342	2.223290	0.026197**
ω	0.253707	0.111582	2.273720	0.022983**
α	0.090235	0.027841	3.241050	0.001191***
γ	0.655310	0.274521	2.387100	0.016982**
β	0.871520	0.037822	23.042940	0.000000***

EM Latin America				
μ	0.434562	0.167056	2.601300	0.009287***
ω	0.320633	0.160301	2.000190	0.045479**
α	0.084149	0.024202	3.476890	0.000507***
γ	1.000000	0.298997	3.344520	0.000824***
β	0.853897	0.052929	16.132740	0.000000***
EM Asia				
μ	0.327047	0.084670	3.862620	0.000112***
ω	0.324017	0.127986	2.531660	0.011352**
α	0.112531	0.032175	3.497470	0.000470***
γ	0.810159	0.264753	3.060060	0.002213***
β	0.806754	0.054841	14.710700	0.000000***
EFM Africa				
μ	0.344854	0.155949	2.211330	0.027013**
ω	0.552053	0.283479	1.947420	0.051484*
α	0.100831	0.031708	3.179960	0.001473***
γ	1.000000	0.318689	3.137860	0.001702***
β	0.757527	0.099462	7.616230	0.000000***
DCC				
α	0.023365	0.003143	7.433910	0.000000***
β	0.937110	0.010067	93.085660	0.000000***

Notes: Mean equation: $r_{i,t} = \mu_i + \varepsilon_{i,t}$ (4.5)

Variance equation: $\sqrt{h_{i,t}} = \omega_i + \alpha_i|\varepsilon_{i,t-1}| + \gamma_i|\varepsilon_{i,t-1}|I(\varepsilon_{i,t-1} < 0) + \beta_i\sqrt{h_{i,t-1}}$ (4.6)

DCC equation: $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha v_{t-1}v'_{t-1} + \beta Q_{t-1}$ (4.7)

Where v_t *represents standardised residuals by their conditional standard deviation.*

** Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

P-values of Ljung-Box Q statistic for the null hypothesis of no serial correlation up to order 10 in the levels and squares of the standardised residuals are given below.

Q(10) p-values: 0.884 (US), 0.138 (EMU), 0.392 (Europe ex EMU), 0.927 (Pacific), 0.184 (EM BRIC), 0.367 (EM Europe), 0.188 (EM Latin America), 0.288 (EM Asia), 0.407 (EMF Africa).

Q^2(10) p-values: 0.216 (US), 0.927 (EMU), 0.284 (Europe ex EMU), 0.764 (Pacific), 0.938 (EM BRIC), 0.822 (EM Europe), 0.929 (EM Latin America), 0.696 (EM Asia), 0.972 (EMF Africa).

Estimation based on 513 observations (from 19 July 2002 to 11 May 2012) using R (2012) and rgarch package (Ghalanos 2011).

5 A COMPARISON OF CONDITIONAL CORRELATION AND CONDITIONAL VOLATILITY MODELS: COPULA DCC, GO-GARCH ML, NLS, ICA, MM, SMA AND EWMA

5.1 INTRODUCTION, AIMS, OBJECTIVES AND CONTRIBUTION

It was argued more than 20 years ago by French and Poterba (1991) that behavioural factors, such as biases in investor expectations, can lead to under-diversification in the international dimension. Portfolio managers wanting to optimise their stock selection can now be seen to face another important issue; namely, whether or not a financial crisis results in significant long-term permanent changes in between-market correlation levels.

In the previous chapter I identified that the correlations and volatilities for developed as well as emerging regions vary over time. Moreover, the impact of the financial crisis had a significant positive impact on the correlations, which can be seen in Table 4.1, Table 4.2 and Table 4.3 in Chapter 4. These changes in the correlations and volatilities are of key importance from the efficient portfolio perspective. According to the Markowitz formula (1952):

$$\sigma_P^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j>i}^{n} w_i w_j \sigma_{ij} = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j>i}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{5.1}$$

Where σ_P^2 is variance of portfolio returns, w_i weight of asset i in the portfolio, σ_i^2 is variance of asset i returns, σ_{ij} is covariance between asset i and j returns, σ_i is standard deviation of asset i returns, ρ_{ij} is correlation between asset i and j returns; we see that the important factors that will influence the efficient portfolio are the correlation and volatility levels.

In the literature there are many different models for estimating correlation as well as the volatilities. The literature suggests that different methodologies will provide different estimates for correlations and volatilities (Bauwens *et al.* 2006, Silvennoinen and Teräsvirta 2008). In this chapter I examine the extent to which different models produce statistically different estimates of correlations as well as volatilities. If statistically significant differences are found, in the following chapter I will analyse which of the considered models will be the best from the efficient portfolio perspective.

In this chapter I consider some of those models: in particular, I look at some of the most recent methods such as GO-GARCH (van der Weide 2002), DCC (Engle 2002) and the extension of the DCC model, copula DCC (Patton 2006) model. There are four main different estimation methods for the GO-GARCH model, such as ML (van der Weide 2002), NLS (Boswijk and van der Weide 2006), ICA (Broda and Paolella 2009) and MM (Boswijk and van der Weide 2011). For comparison purposes, I use the following models as benchmarks: unconditional (time-invariant, constant), SMA and EWMA because of their popularity in the literature. This gives nine methods in total.

There are a number of novel contributions made in this chapter. Whilst most studies in the literature that have examined the relative performance of different conditional covariance models, for example, Boswijk and van der Weide (2006), Caporin and McAleer (2014) and Engle (2002), I can find no examples of papers which make the comparison between the specific group of models that I have chosen in this thesis. What is more, my Hypothesis 1 (below) explores the long-term impact of a crisis period on *relative* model performance. I have not found this elsewhere in the literature.

An additional contribution made is that in Hypothesis 2 (below) I extend my work from Chapter 4 by examining how the estimates made by each individual models in respect to correlations and volatilities are influence by the financial crisis. There are a number of studies that examine the contagion (short-term) effect based on one methodology, for example, Celık (2012), Kazi *et al.* (2014) and Syllignakis and Kouretas (2011). I, however, focus on the long-term impact of the 2007 financial crisis on correlation and volatility estimates using several alternative models. This is of significance from the development portfolio perspective as it will help in determining the most efficient methodology in respect to correlation and volatility estimation.

A further novel contribution to the chapter is found in the discussion of the model-specific differences found in respect to developed and emerging/frontier markets. I feel that this issue will become increasingly important in the portfolio literature given the globalisation of investment portfolios (Goetzmann *et al*. 2005, You and Daigler 2010) and the fact that at the moment this issue has a relatively limited coverage.

The chapter is structured as follows. First, the hypotheses for Chapter 5 are presented in Section 5.2. Next, the Section 5.3 describes the data and methodology used. Further on the results are presented in terms of temporal analysis, as well as testing Hypotheses 1 and 2 in Section 5.4. It is then followed by discussion and implication of the results in Section 5.5. Lastly, the conclusions are drawn in Section 5.6.

5.2 HYPOTHESES DEVELOPMENT

Evidence found in the literature suggests that there will be differences in correlation and volatility estimates using different methods; for example, Bauwens *et al.* (2006), Boswijk and van der Weide (2006), Caporin and McAleer (2011), Engle (2002) and Silvennoinen and Teräsvirta (2008). Engle (2002) in his paper compares the performance of: SMA, DCC, OGARCH, BEKK and EWMA in terms of mean absolute error (goodness-of-fit statistics), test for autocorrelation of squared standardised residuals (multivariate GARCH diagnostic tests) and value at risk (portfolio context). Slightly different approach is taken by Boswijk and van der Weide (2006). They compare covariance models, namely GO-GARCH NLS with O-GARCH and DCC in terms of analysis of volatility and correlation plots based on these different methodologies. In addition, they also examine GO-GARCH ML, O-GARCH and GO-GARCH NLS in higher-variate context with respect to convergence of numerical optimisation procedure and robustness to misspecification. They do this by assessing the standardised residuals. For further details on how alternative covariance models can be compared please refer back to Section 2.5.

In my Hypothesis 1, below, I compare the performance of the models identified above in Section 5.1. My work will contribute in the literature in this area because it is comparing the relative performances of these models before and after 2007 financial crisis (for robustness I also examine the full period of my dataset). My expectation is that differences in performance will be found because of differences in the estimation methodologies. For example, GO-GARCH is based on linear combinations of univariate GARCH models and uses a constant mixing matrix. This approach cannot take in to consideration structural changes in relationships pre- and post-crisis period. The copula DCC will potentially outperform as it is able to take account of any changes in the underlying data distribution that occurred in this period.

Hypothesis 2 (as specified below) extends the work undertaken in Chapter 4. Unlike Hypothesis 1, where I'm comparing the relative performances of different models, here, I examine the performance of the models on an individual basis. In Hypothesis 2 I test the impact of temporal factors for the nine different methodologies. This is a novel contribution to the literature as elsewhere studies focus exclusively on a single methodology rather than comparing the different methodologies.

I argue that correlations and volatilities can vary over time as a result of the observed trend of increases of correlation over time (associated with increasing globalisation) (Barari 2004, Bekaert *et al*. 2002, Kearney and Lucey 2004, Swanson, 2003) and also differences associated with different phases of the market cycle, i.e. bull and bear phases (Bekaer and Wu 2000, Longin and Solnik 2001), particularly in times of crisis, e.g. Forbes and Rigobon (2002) contagion theory. Correlations and volatilities can also vary due to the changes in banking regulations (Basel III) as well as the deleverage effect. More details are given in Chapter 4. Given that correlations and volatilities are estimated in different ways I would expect that we will observe differences between the different methodologies in respect to pre- and post-crisis periods.

I test the following hypotheses:

H1. There will be statistically significant differences in the estimated correlations and volatilities between the different methodologies for:

H1a. the full period;

H1b. the pre-crisis period;

H1c. the post-crisis period.

H2. There will be statistically significant differences between the pre- and post-crisis correlations and volatilities for the individual methodologies.

If both Hypotheses 1 and 2 are found to hold, I would anticipate that the combined effect of the methodology used and time will have an important influence on the efficient portfolio.

I test three groups of methodologies: DCC, GO-GARCH and non-multivariate GARCH-based benchmarks, which consist of the SMA, EWMA and unconditional models.

An interesting feature of my data is that I can identify two different groupings, specifically developed markets and emerging/frontier markets. I therefore discuss the results from Hypothesis 1 and 2 within this context. Difference between these two groups would not be unexpected given that in Chapter 4 I found that the impact of the financial crisis on correlation changes differed considerably and also there were considerable differences in the volatility.

5.3 DATA AND METHODOLOGY

Data is discussed in the Chapter 3. By referring back to that chapter we observe negative skewness (the third moment of the distribution) for all the regions, ranging from -1.50 to -0.44. An additional feature of the data set is the high kurtosis (the fourth moment of the distribution) for all the regions, ranging from 3.21 to 12.16. This suggests that the empirical distributions have longer left-hand tails but also much fatter tails than the normal distribution.

Further issues that can be identified from the data in Figure 3.2 are the impacts of the financial crisis. It can be noted here that volatility seems to be rising significantly during this crisis period. These aspects have implications for the structure of the models developed.

5.3.1 MODEL SPECIFICATION: GO-GARCH

The aim is to identify the most appropriate model. I follow a similar approach to that presented in Chapter 4. First, different ARMA specifications of the mean equation are tested through the examination of the significance of the coefficients and the Ljung-Box (1978) test for autocorrelation in the standardised residuals. The simplest form of the mean equation (which includes only a constant) is found to be the most appropriate and ARMA (0,0) is used on the basis that it is the most parsimonious of the models found as acceptable in the tests undertaken.

As well as testing the specification of the mean equation, specifications of different forms of the variance equation is also examined. Different orders and specifications of the GARCH model are explored using significance tests of the coefficients and also using the Ljung-Box (1978), Li-McLeod (1981) and ARCH LM (Engle 1982) tests of the squared standardised residuals. Refer to Chapter 4 for details.

Babikir *et al*. (2012) suggest that simple GARCH (1,1), i.e. based on the assumption that the positive and negative shocks are treated evenly, seems to be performing well in the context of the financial crisis in South Africa. However, in my case the simple symmetric GARCH (1,1) specification for the components is found not to be adequate. The data suggest that their distributions are non-symmetric due to the cyclical nature of the price movements in financial markets and the specific issue of the 2007 financial crisis. Therefore, alternative asymmetric GARCH specifications are tested: GJR GARCH (Glosten *et al.* 1993), TGARCH (Zakoian 1994) and APARCH (Ding *et al.* 1993). A specification of GJR GARCH (1,1) is found to be the most appropriate way of dealing with asymmetries in the data; this is similar to Babikir *et al*. (2012), who find that GJR GARCH (1,1) is performing better in some cases than simple GARCH (1,1). However, GJR GARCH (1,1) is not the perfect model, as for some of the series the portmanteau test statistics suggest that not all autoregressive heteroskedasticity is picked up by the model (e.g. the US market in the MM model). A similar issue has been found by Boswijk and van der Weide (2009), where both the ML and MM models are found to be misspecified in their empirical part but they keep continuing with their analysis. This aspect will be considered during the discussion of the results. A possible explanation of that fact could be the existence of the structural break caused by the financial crisis. My test results, not presented here, suggest that the misspecification issue disappears when the data exclude the financial crisis period, i.e. the data period ending at 2007 (e.g. the previously mentioned US market in MM model).

5.3.2 MODEL SPECIFICATION: COPULA DCC

Weekly returns reject the null hypothesis of normal distribution, as can be seen in Chapter 3, Table 3.2. The univariate as well as the multivariate specifications reject the null hypothesis of normality in the series of standardised residuals using the Jarque-Bera (1980) and Shapiro-Wilk (1965) tests.[6] These results suggest that the possible misspecification of the model can be caused by the assumptions of Gaussian factors.

The non-normality of the residuals is taken into account by the extension of the DCC model called copula DCC. This model allows us to incorporate the non-normality found in the data. Copula is a function that connects disparate marginal distributions together to obtain a joint multivariate distribution. The copula approach allows us to use different marginal distributions for different series in order to obtain a better fit in the data. Given a non-zero skewness and heavy tails, I use Student copula with standardised skewed Student margins to account for those facts found in the data (Table 3.1, Chapter 3). There exist other copulas, for instance Frank or Clayton-Gumbel, but they are not directly applicable in the context of the DCC model because there is no one-to-one relationship between correlation and Kendall's τ (Manner and Reznikova 2012, Rodriguez 2007).

I find that the standardised skewed Student distribution fits the data better than the normal one (see Appendix Figure 5.11–Figure 5.28).

[6] Not presented here but available upon request.

5.3.3 Model specification: EWMA and SMA

SMA has been chosen to act as one of the benchmarks. It is a simple and therefore popular method of estimating correlation and volatility. A major problem with SMA is that all observations are equally important whether it was yesterday or a long time ago (Alexander 1998). Having one unusual observation will keep the SMA estimate on an abnormal level for a long time until it returns to a normal level. The shorter the estimation window for SMA, the more abnormal levels in its absolute values but for a shorter period of time. The SMA estimates appear to be more stable for a longer averaging period (Alexander 1998). I have decided to balance out the advantages and disadvantages of different estimation windows and I use 100 observations in my SMA estimation.

To overcome the main drawback of the SMA that all observations have a similar impact on an SMA estimate, an EWMA is proposed in the literature. This model puts more weight on the current observation than on past observations. Weights change in an exponential manner. JP Morgan's RiskMetrics^{TM} (1994) suggests that the smoothing factor λ of 0.97 should be used for weekly data (Allen and Singh 2010, Harris and Nguyen 2011, Härdle and Mungo 2008). The larger the λ the more smoothed the series becomes as more weight is placed on past observations (Alexander 1998).

5.3.4 Testing procedure for hypotheses

For robustness of our analysis, two statistical tests are used for testing Hypotheses 1 and 2. Parametric Welch (1938) t (non-parametric Wilcoxon (1945) rank sum) tests the difference in means (location parameter) between two samples. For details please see Chapter 4. Volatility and correlation estimates for all models are considered.

On the one hand, Hypothesis 1 is tested by comparing means and location parameters between one model estimates in a particular time period with another model estimates in the same time period for all models considered. In this way I am able to compare differences between estimates based on different models.

On the other hand, for Hypothesis 2, means and location parameters are compared between model estimates in the pre-crisis period against those in the post-crisis period. This allows us to test differences from a time perspective for a particular model.

5.4 Results

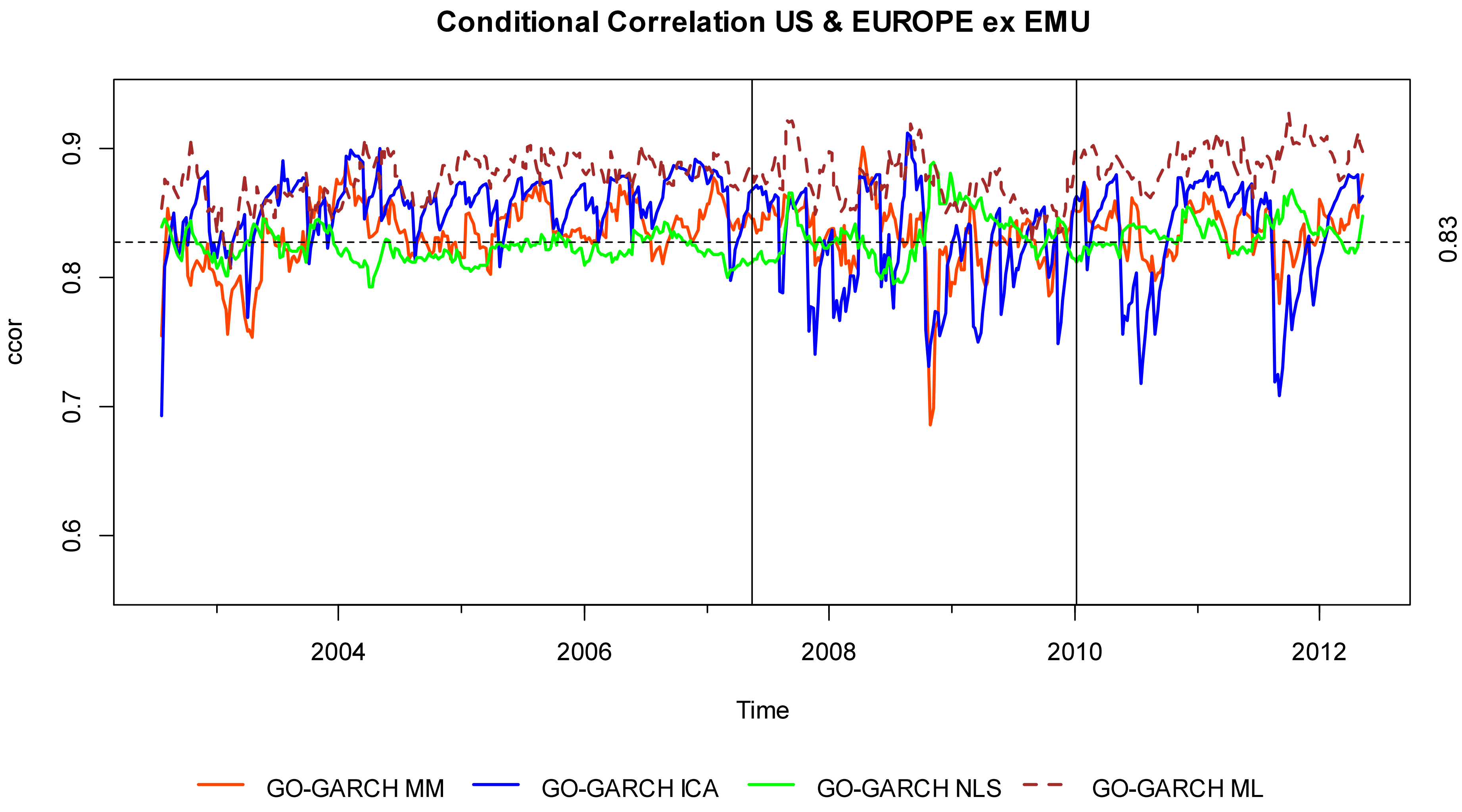
All the results are obtained using R (2012) and its packages, mainly rmgarch (Ghalanos 2012) or gogarch (Pfaff 2009).

5.4.1 Descriptive temporal analysis

This section presents the values of the conditional correlations and volatilities over the whole examined time period (from 12 July 2002 to 11 May 2012) for all nine markets based on nine methodologies. Figure 5.1 presents the correlation of the US against Europe ex EMU as well as the volatility of Europe ex EMU market. To be precise the first graph represents the conditional correlation based on the four GO-GARCH models in comparison to the unconditional correlation depicted by the dashed line with the value on the right-hand side. The second graph shows the conditional correlation but based on the other four methods employed. Beneath the correlation plots the volatility graphs are presented respectively. Similar figures for all other markets are presented in the Appendix in Figure 5.29–Figure 5.43. In the appendix, Figure 5.3–Figure 5.10 also provide correlation and volatility plots with respect to one method only. This could be useful when more detailed information is needed. Similar to the plots in Chapter 4, the two vertical lines represent the beginning (11 May 2007) and the end (1 January 2010) of the financial crisis.

Summary statistics for the estimated correlations and volatilities can be found in Table 5.17, Table 5.19, Table 5.21, Table 5.23, Table 5.25, Table 5.27, Table 5.29, Table 5.31, and Table 5.33 in the appendix.

Figure 5.1 Conditional correlation plots of US & Europe ex EMU based on nine models



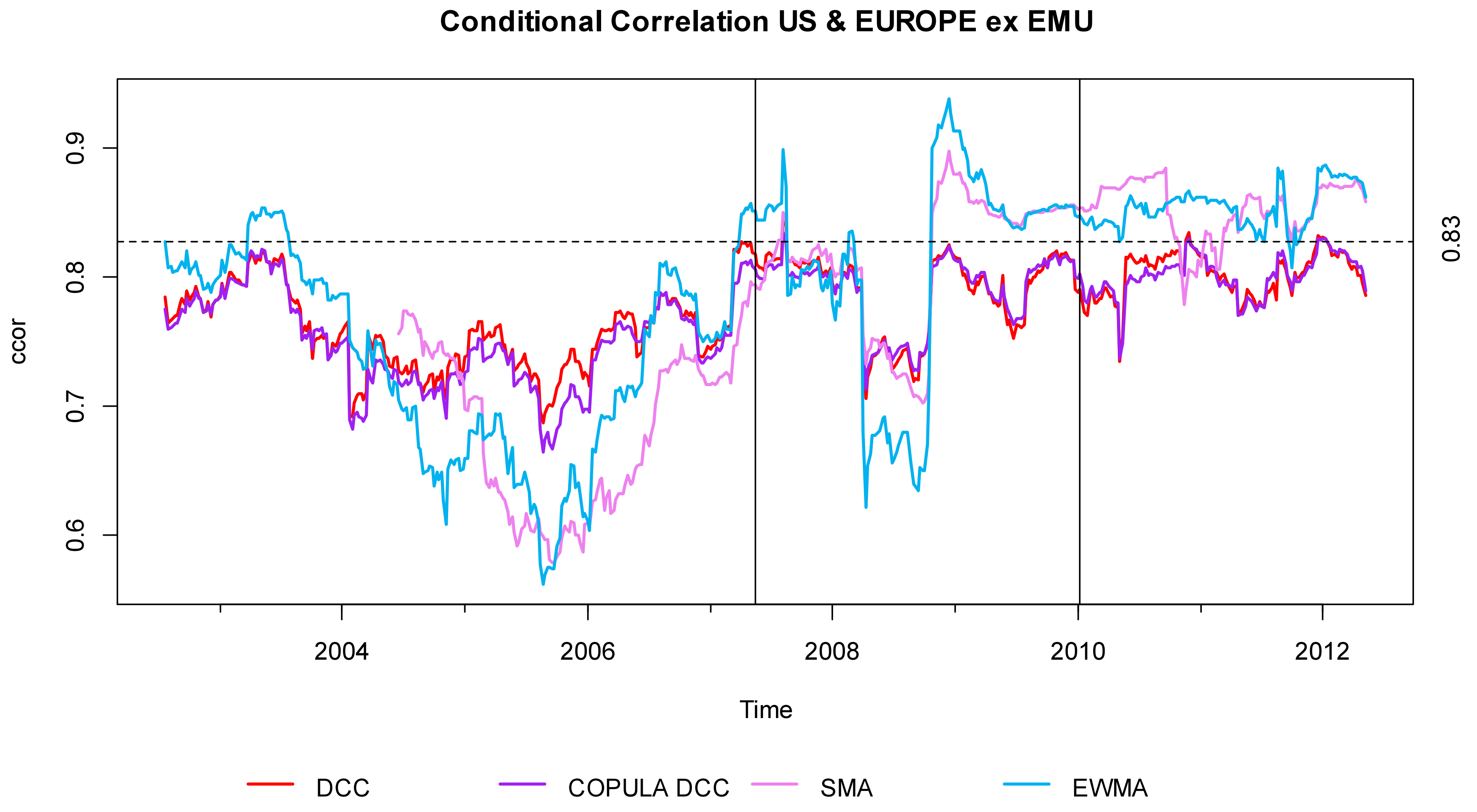
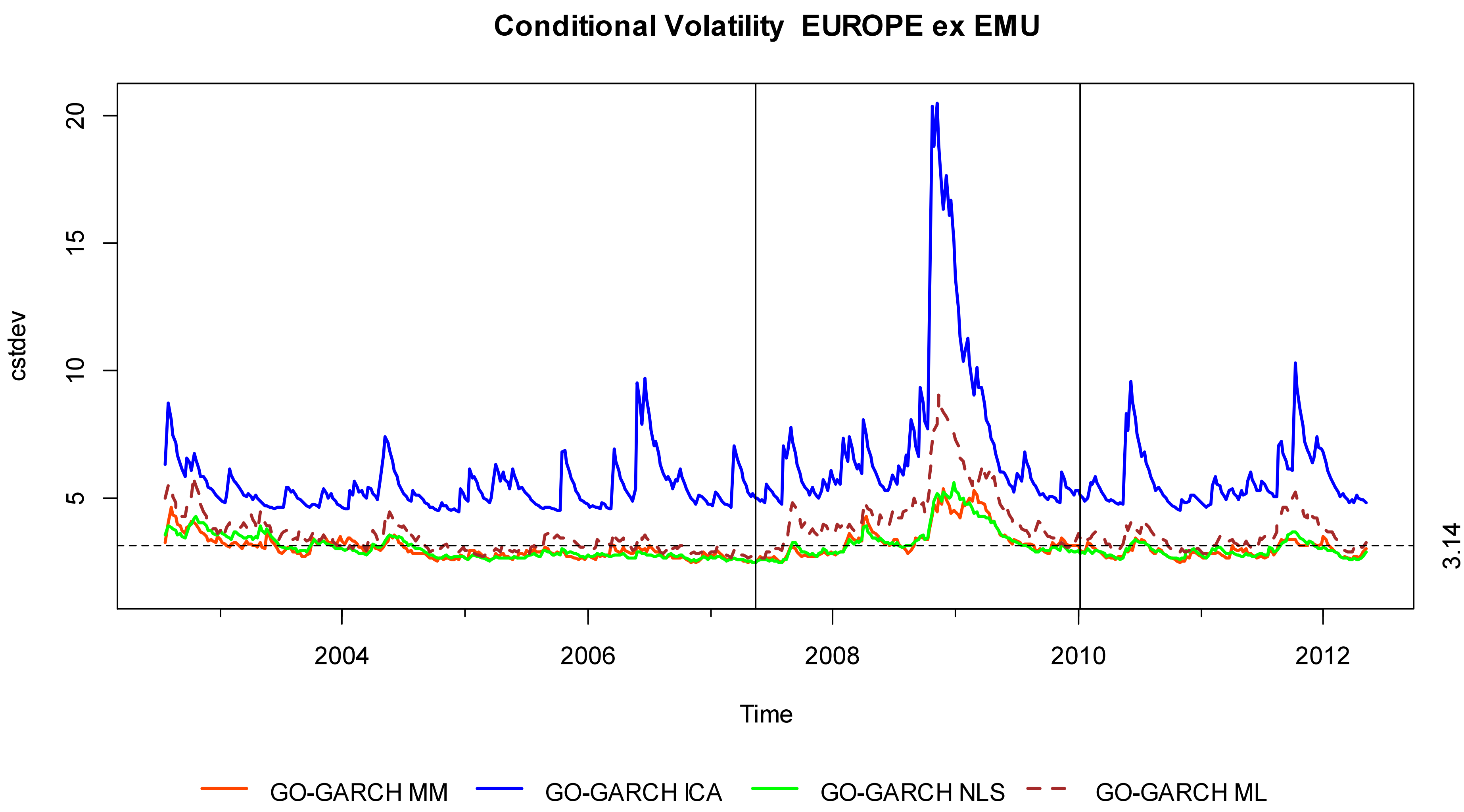
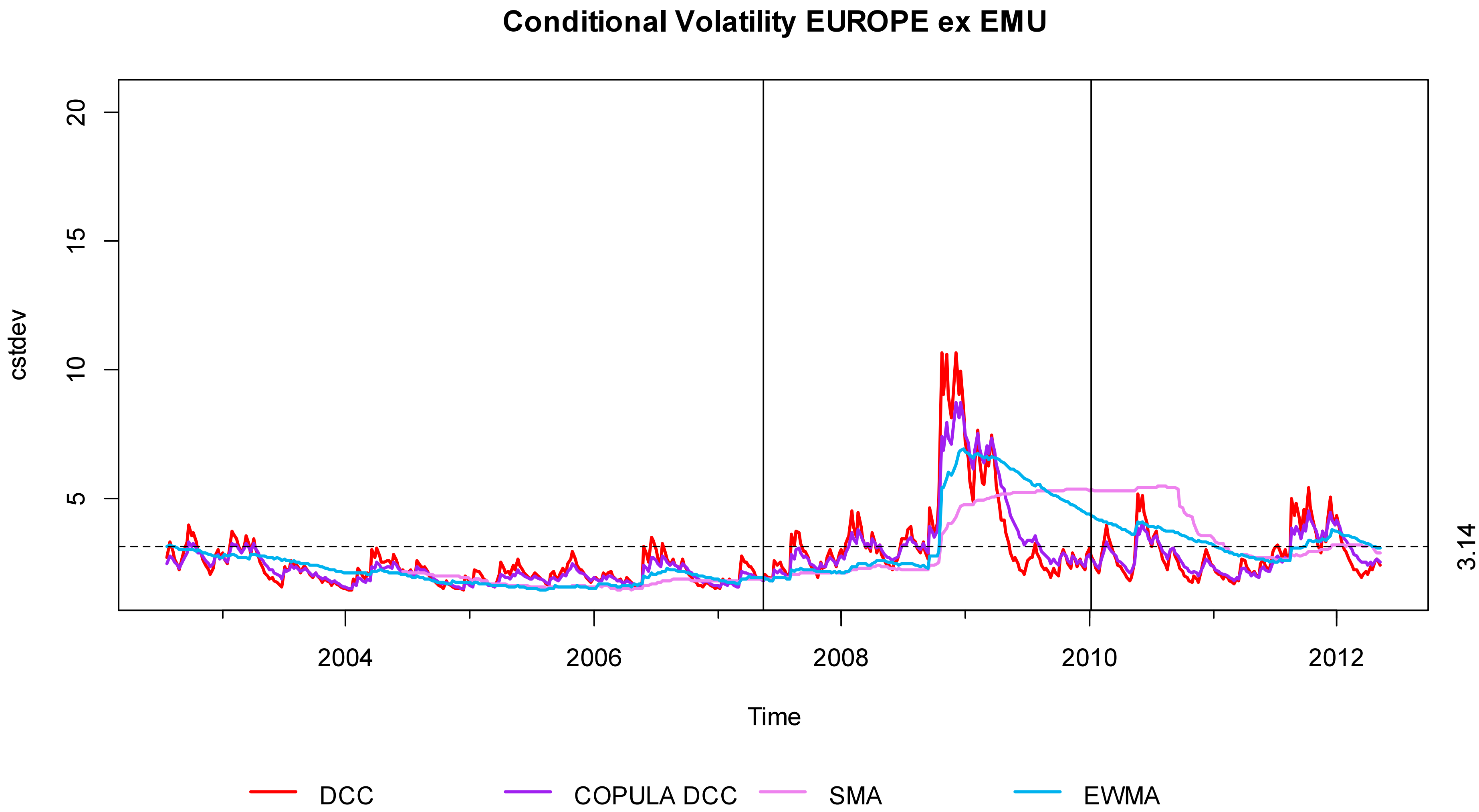

Conditional Correlation US & EUROPE ex EMU
ccor
0.6
0.7
0.8
0.9
0.83
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.2 Conditional volatility plots of Europe ex EMU based on nine models




Conditional Volatility EUROPE ex EMU
cstdev
20
15
10
5
3.14
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Conditional volatility plots for all methods reveal similar pattern. This is consistent with Biswijk and van der Weide (2006), and Biswijk and van der Weide (2011) who analysed conditional volatility estimates of different models and found that they revealed a similar pattern over time. The difference lies in the value and variation levels of the volatilities. GO-GARCH MM and NLS as well as the SMA and EWMA produce quite smooth lines with relatively low values. However, relatively greater variation as well as the values can, in general, be observed in the GO-GARCH ML, DCC and COPULA DCC volatilities, whereas the highest variation and values are obtained via the GO-GARCH ICA methodology. For all models the peak in volatility around 2009 can be identified. However, the height and length of that peak varies between models; for instance, the maximum volatility ranges from 5.381% for MM to 20.510% for ICA for Europe ex EMU (Table 5.21). The speed of mean reversion differs too and it is quite slow, especially for EWMA, and even slower for SMA. This fact has been seen in the literature before (Alexander 1998). A similar finding was presented by Boswijk and van der Weide (2006) who argued that the main difference between volatility plots based on different models is with respect to the height of the volatility during peaks and the speed of mean reversion afterwards.

When it comes to the correlation plots the situation is more diverse. Similar point was made by Boswijk and van der Weide (2006), and Engle (2002). At first glance, there seem to be more discrepancies than similarities, especially when it comes to the GO-GARCH models. Their patterns are rather different. In terms of the trend, all four models, in general, oscillate more or less around the dashed line without any firm upward or downward tendency.

However, the situation within DCC, COPULA DCC, SMA and EWMA is slightly less complicated. The common shape can be identified, although there are differences in variation of those plots; for instance, the correlation for US & Europe ex EMU ranges from 0.562 to

0.938 for EWMA and from 0.687 to 0.848 for DCC. Unsurprisingly, the COPULA DCC and DCC models produce similar shapes as the main differences between these two methodologies lie within the distributions applied. Generally speaking we can observe that DCC conditional correlation is above that of COPULA DCC. Some sort of similar behaviour can also be seen between SMA and EWMA, which is also not a surprise as the differences between the models corresponds to the weighting applied to past observations (Alexander 1998).

In terms of the reaction of the correlation to the peaking volatility around 2009, we get a slightly mixed picture. A similar conclusion was reached by Engle (2002) with respect to the episode in 2000. It is especially useful to look at Figure 5.3–Figure 5.10 in the appendix for a more detailed view. In general, the majority of models show an increase in correlation around 2009 when the volatility is rising rapidly (e.g. DCC, COPULA DCC, SMA, EWMA and NLS) but some of the models, such as MM, ICA and ML, show otherwise.

I can identify that there are differences in correlations and volatilities based on the methodologies applied and therefore I am going to test them by means of the Welch t and Wilcoxon rank sum tests in the next section.

5.4.2 TESTING HYPOTHESIS 1

In this section I test Hypothesis 1:

There will be statistically significant differences in the estimated correlations and volatilities between the different methodologies for:

H1a. the full period;

H1b. the pre-crisis period;

H1c. the post-crisis period.

The statistical testing results are presented in Table 5.1–Table 5.5. Table 5.1 corresponds to the testing of Hypothesis 1a, where the whole period (from 11 June 2004 to 11 May 2012) is considered, which represents 414 estimates. The first 99 estimates are dropped because the first 99 SMA estimates are not available, as the length of the estimation window for SMA is 100 observations. Table 5.2 and Table 5.3 relate to Hypothesis 1b, where 62 and 124 estimates are used respectively for the robustness of our analysis. Likewise, Table 5.4 and Table 5.5 test Hypothesis 1c, where two sample sizes are also used: 62 and 124 respectively. Those tables show the number of insignificant Welch t and Wilcoxon test statistics for all nine methods for the whole, pre- and post-crisis periods. Table 5.1 is a summary of Table 5.18, Table 5.20, Table 5.22, Table 5.24, Table 5.26, Table 5.28, Table 5.30, Table 5.32 and Table 5.34, which can be found in the appendix. Similarly, Table 5.2 (Table 5.3) is based on Table 5.44–Table 5.52 (Table 5.53–Table 5.61) (see appendix). Similarly, Table 5.62–Table 5.70 (Table 5.71–Table 5.79), which can be seen in the appendix, are summarised in Table 5.4 (Table 5.5).

Table 5.1 Statistical insignificance of conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	**-**	**1**	0	0	0	0	**2**	**2**	**2**	**-**	0	**3**	0	0	**1**	**1**	**2**	0
GO-GARCH ICA	414	0	**-**	0	0	0	0	0	0	**3**	0	**-**	0	0	0	0	0	0	0
GO-GARCH NLS	414	**1**	**1**	**-**	0	0	0	**3**	**3**	0	**9**	0	**-**	0	0	**1**	**1**	**2**	0
GO-GARCH ML	414	0	0	0	**-**	**4**	0	**2**	0	0	0	0	0	**-**	0	0	0	0	**2**
DCC	414	0	0	0	**1**	**-**	**2**	**1**	0	0	**4**	0	**5**	0	**-**	**9**	**7**	**5**	0
COPULA DCC	414	0	0	0	0	0	**-**	0	0	0	**4**	0	**5**	0	**9**	**-**	**7**	**5**	0
SMA (100)	414	**1**	0	**1**	**1**	**2**	**1**	**-**	**8**	0	**6**	0	**6**	0	**5**	**4**	**-**	**8**	0
EWMA (0.03, 0.97)	414	**1**	0	**2**	0	**1**	0	**7**	**-**	0	**7**	0	**8**	0	**5**	**5**	**9**	**-**	0
UNCONDITIONAL	414	**1**	**1**	0	0	0	0	0	0	**-**	0	0	0	**2**	0	0	0	0	**-**

*Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available, as it is based on 100 observations. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*8=) 576 correlation and (72*9=) 648 volatility test results, 55 and 147 respectively are insignificant, which corresponds to 9.55% and 22.69%.*

Table 5.2 Statistical insignificance of conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	0	**1**	0	0	0	0	0	**1**	-	0	**2**	**3**	**2**	**2**	**1**	**1**	0
GO-GARCH ICA	62	0	-	**1**	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	62	**1**	**1**	-	0	0	0	0	0	**1**	**2**	0	-	**2**	**2**	**3**	**1**	**1**	0
GO-GARCH ML	62	0	0	0	-	0	0	0	**2**	0	0	0	**2**	-	0	0	0	**1**	0
DCC	62	0	0	0	0	-	**4**	**4**	**5**	0	**3**	0	**3**	**2**	-	**9**	**2**	**8**	**1**
COPULA DCC	62	0	0	0	0	**4**	-	**4**	**1**	0	**3**	0	**3**	**2**	**9**	-	**3**	**7**	**2**
SMA (100)	62	0	0	0	0	**3**	**4**	-	**1**	0	0	0	0	0	0	0	-	**2**	**1**
EWMA (0.03, 0.97)	62	0	0	0	**2**	**4**	**1**	**2**	-	0	**2**	0	**2**	**1**	**3**	**4**	**1**	-	0
UNCONDITIONAL	62	**1**	0	**1**	0	0	0	0	0	-	0	0	0	0	**5**	**5**	**1**	**1**	-

*Notes: The period runs from 10 March 2006 to 11 May 2007. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*8=) 576 correlation and (72*9=) 648 volatility test results, 49 and 110 respectively are insignificant, which corresponds to 8.51% and 16.98%.*

Table 5.3 Statistical insignificance of conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	0	**3**	0	0	0	0	0	0	-	0	**3**	**1**	0	**1**	0	0	0
GO-GARCH ICA	124	0	-	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	124	**3**	0	-	0	0	0	0	0	0	**3**	0	-	0	0	**1**	0	0	0
GO-GARCH ML	124	0	0	0	-	0	**1**	0	**1**	**1**	0	0	**1**	-	0	0	0	0	0
DCC	124	0	0	0	0	-	0	**1**	**2**	0	**1**	0	**2**	0	-	**8**	**1**	**1**	**2**
COPULA DCC	124	0	0	0	0	0	-	**1**	**3**	0	**1**	0	**2**	0	**8**	-	**1**	**2**	**3**
SMA (100)	124	0	0	0	0	**1**	**2**	-	**4**	0	0	0	0	0	**1**	**1**	-	**2**	0
EWMA (0.03, 0.97)	124	0	0	0	**1**	**2**	**3**	0	-	0	0	0	0	0	0	0	**2**	-	0
UNCONDITIONAL	124	0	0	0	0	0	0	0	0	-	0	0	0	0	**2**	**2**	0	**2**	-

*Notes: The period runs from 31 December 2004 to 11 May 2007. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*8=) 576 correlation and (72*9=) 648 volatility test results, 29 and 54 respectively are insignificant, which corresponds to 5.03% and 8.33%.*

Table 5.4 Statistical insignificance of conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	0	**3**	0	0	0	0	0	0	-	0	**3**	**1**	0	**1**	0	0	0
GO-GARCH ICA	62	0	-	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	62	**3**	0	-	0	0	0	0	0	0	**3**	0	-	0	0	**1**	0	0	0
GO-GARCH ML	62	0	0	0	-	0	**1**	0	**1**	**1**	0	0	**1**	-	0	0	0	0	0
DCC	62	0	0	0	0	-	0	**1**	**2**	0	**1**	0	**2**	0	-	**8**	**1**	**1**	**2**
COPULA DCC	62	0	0	0	0	0	-	**1**	**3**	0	**1**	0	**2**	0	**8**	-	**1**	**2**	**3**
SMA (100)	62	0	0	0	0	**1**	**2**	-	**4**	0	0	0	0	0	**1**	**1**	-	**2**	0
EWMA (0.03, 0.97)	62	0	0	0	**1**	**2**	**3**	0	-	0	0	0	0	0	0	0	**2**	-	0
UNCONDITIONAL	62	0	0	0	0	0	0	0	0	-	0	0	0	0	**2**	**2**	0	**2**	-

*Notes: The period runs from 1 January 2010 to 4 March 2011. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*8=) 576 correlation and (72*9=) 648 volatility test results, 46 and 77 respectively are insignificant, which corresponds to 7.99% and 11.88%.*

Table 5.5 Statistical insignificance of conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**2**	**1**	0	0	0	0	0	0	-	0	**3**	**1**	**1**	**1**	**3**	**4**	**1**
GO-GARCH ICA	124	**3**	-	**1**	0	0	0	0	**1**	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	124	**2**	**2**	-	**1**	**1**	**1**	0	0	0	**3**	0	-	**1**	**2**	**2**	**1**	0	**1**
GO-GARCH ML	124	**1**	0	**1**	-	0	**2**	0	0	0	**1**	0	**1**	-	0	0	**2**	**2**	**2**
DCC	124	0	0	**2**	0	-	**3**	0	0	0	**4**	0	**7**	**2**	-	**9**	0	0	**4**
COPULA DCC	124	0	0	**1**	**2**	**4**	-	0	0	0	**3**	0	**5**	**1**	**9**	-	0	0	**3**
SMA (100)	124	0	0	0	0	0	0	-	**4**	**3**	0	0	0	**1**	0	0	-	**9**	0
EWMA (0.03, 0.97)	124	**1**	**1**	**1**	0	0	0	**2**	-	**1**	**2**	0	0	**1**	0	0	0	-	0
UNCONDITIONAL	124	0	**2**	0	0	0	0	**1**	**1**	-	0	0	0	0	**2**	**2**	0	0	-

*Notes: The period runs from 1 January 2010 to 11 May 2012. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*8=) 576 correlation and (72*9=) 648 volatility test results, 48 and 96 respectively are insignificant, which corresponds to 8.33% and 14.81%.*

Each of the five tables above (Table 5.1–Table 5.5) corresponds to (72*8=) 576 correlations and (72*9=) 648 volatilities. For the robustness of our analysis, the differences in mean (and location parameter) between estimated correlations and volatilities between nine models are tested by means of the Welch t and (Wilcoxon rank sum) test.

By looking at Table 5.1, which corresponds to the whole period, I can conclude that most of the correlations (576-55=521) and volatilities (648-147=501), which are 90.45% and 77.31% respectively, are statistically different. There are 33 (22) insignificant differences between models for correlations based on the Wilcoxon rank sum (Welch t) test, whereas slightly more insignificant differences can be found with respect to volatilities 54 (93). Those results support my Hypothesis 1a.

The answer for Hypothesis 1b can be found in Table 5.2 and Table 5.3. I look at two (shorter and longer) pre-crisis periods for the robustness of my analysis. There are 49 (8.51%) correlation and 110 (16.98%) volatility differences, which are insignificant for the shorter sample, whereas there are 29 (5.03%) and 54 (8.33%), respectively, for the longer period. It can be noted that out of the insignificant differences in correlations in Table 5.2, 25 (24), and in Table 5.3, 17 (12) relate to the Wilcoxon (Welch t) test. However, in terms of the volatility differences, the splits between the aforementioned tables looks to be 56 (54) and 26 (28) respectively. Most of those differences are statistically significant, which supports my Hypothesis 1b.

In terms of Hypothesis 1c, Table 5.4 and Table 5.5 are analysed. The number of statistically significant differences for the shorter sample is (576-46=) 530 for correlations and (648-77=) 571 for volatilities, which is 92.01% and 88.12% respectively. However, the number of significant differences is slightly smaller for the longer samples, which is (576-48=) 528 (91.67%) for correlations and (648-96=) 552 (85.19%) for volatilities. The split between insignificant differences between the Wilcoxon rank sum test (and Welch t test) looks to be as follows: 22 (24) and 35 (42) for the short pre-crisis period for correlations and volatilities, respectively, and likewise 21 (27) and 52 (44) for the post-crisis period. Hypothesis 1c is supported by these results.

Therefore in the next section I am testing Hypothesis 2, which looks at the differences between correlation and volatilities in the pre- and post-crisis periods.

5.4.3 TESTING HYPOTHESIS 2

This section tries to verify my Hypothesis 2.

There will be statistically significant differences in the pre- and post-crisis correlations and volatilities for the individual methodologies.

Table 5.6 is constructed using information from Table 5.35 to Table 5.42 in the appendix. It contains a number of statistical significant pre- and post-crisis differences in terms of correlations and volatilities for all regions based on nine models. The Welch t test for an unconditional model is not available as the standard deviation of the mean value is zero. For the robustness of our analysis, two different samples are considered (62 and 124 observations).

Table 5.6 Statistical significance of differences between pre-crisis and post-crisis mean: correlations and volatilities (US and developed/emerging/frontier region stock markets) based on all models

Index	Sample length before[a]/after[b]	Welch two sample t test	Wilcoxon rank sum test	Welch two sample t test	Wilcoxon rank sum test
US	62/62	-	-	**6 (0) 6**	**7 (0) 7**
	124/124	-	-	**8 (0) 8**	**8 (0) 8**
EMU	62/62	**3 (3) 6**	**3 (5) 8**	**7 (1) 8**	**8 (1) 9**
	124/124	**5 (3) 8**	**6 (3) 9**	**7 (0) 7**	**8 (0) 8**
EUROPE ex EMU	62/62	**6 (2) 8**	**7 (2) 9**	**7 (0) 7**	**8 (1) 9**
	124/124	**6 (2) 8**	**7 (2) 9**	**7 (0) 7**	**8 (0) 8**
PACIFIC	62/62	**3 (2) 5**	**4 (2) 6**	**5 (0) 5**	**6 (0) 6**
	124/124	**5 (2) 7**	**6 (2) 8**	**8 (0) 8**	**9 (0) 9**
BRIC	62/62	**5 (3) 8**	**6 (3) 9**	**7 (0) 7**	**7 (2) 9**
	124/124	**5 (3) 8**	**6 (3) 9**	**8 (0) 8**	**8 (0) 8**
EM EUROPE	62/62	**5 (1) 6**	**6 (1) 7**	**5 (0) 5**	**5 (2) 7**
	124/124	**4 (2) 6**	**5 (2) 7**	**7 (0) 7**	**8 (0) 8**
EM LATIN AMERICA	62/62	**5 (2) 7**	**4 (2) 6**	**4 (0) 4**	**5 (1) 6**

	124/124	**4 (2) 6**	**6 (3) 9**	**8 (0) 8**	**9 (0) 9**
EM ASIA	62/62	**4 (2) 6**	**5 (1) 6**	**7 (0) 7**	**8 (0) 8**
	124/124	**4 (2) 6**	**6 (1) 7**	**8 (0) 8**	**9 (0) 9**
EMF AFRICA	62/62	**3 (2) 5**	**4 (2) 6**	**4 (1) 5**	**4 (2) 6**
	124/124	**5 (2) 7**	**6 (2) 8**	**7 (0) 7**	**8 (0) 8**
TOTAL	62/62	**34 (17) 51** 53% (27%) 80%	**39 (18) 57** 54% (25%) 79%	**52 (2) 54** 72% (3%) 75%	**58 (9) 67** 72% (11%) 83%
	124/124	**38 (18) 56** 59% (28%) 88%	**48 (18) 66** 67% (25%) 92%	**68 (0) 68** 94% (0%) 94%	**75 (0) 75** 93% (0%) 93%

Notes: [a] The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007, [b] the 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The values indicate the number of statistically significant ***positive (negative) positive*** *+* ***negative*** *pre- and post-crisis changes in correlation and volatilities based on nine models. Percentages for correlation are calculated out of (8*8=) 64 and (9*8=) 72 for Welch t and Wilcoxon rank sum tests, respectively. Percentages for volatility are calculated out of (8*9=) 72 and (9*9=) 81 for Welch t and Wilcoxon rank sum tests, respectively. The Welch t test cannot be performed for an unconditional model.*

The impact of the financial crisis is significant as the volatility and correlations show significant differences of 75–94% between pre- and post-crisis levels. Similar findings can be found in the work of Chiang *et al.* (2007) and Kenourgios (2014). This is also consistent with the theory that the crisis results in significant change in correlation and volatilities. The argument can be made that the impact of a financial crisis may be permanent rather than short-term contagion. Minsky (1992), among others, suggested that a crisis can have a major impact on the architecture of financial markets. Whalen (2008) described the 2007 crisis as a Minsky moment and argued that the crisis has resulted in wide-ranging structural changes across global financial markets. In such circumstances it may be expected that we would expect consistency in the direction of the relationship. This is, however, not the case in respect to all of the models. Around quarter (25–28%) of the changes are statistically negative in terms of correlations. These are predominantly produced by GO-GARCH models. Given that an increase in volatility would be expected to be associated with increases in correlation (for example, Karolyi and Stulz (1996), Rachand and Susmel (1998)), I would possibly question the reliability of such results. One possible explanation is that we have a constant mixing matrix in GO-GARCH methodology. The second possibility is that the fit of the GO-GARCH models is not that great, as discussed previously. This may mean that GO-GARCH methods are less reliable during a period of financial crisis than DCC and COPULA DCC.

Even though the results are not unequivocal, I believe there is strong support for Hypothesis 2.

5.4.4 DIFFERENCES BETWEEN DEVELOPED AND EMERGING/FRONTIER MARKETS

In this section I focus on the results from regional perspective, namely developed versus emerging/frontier markets. I will refer back to the results of temporal analysis as well as testing Hypothesis 1 and 2.

For this reason I have divided the results from Table 5.1–Table 5.5, referring to testing Hypothesis 1, into developed (US, EMU, Europe ex EMU and Pacific) and emerging/frontier (EM BRIC, EM Europe, EM Latin America, EM Asia and EMF Africa) markets. These can be found in Table 5.7–Table 5.16. Table 5.7 (Table 5.8) is based on Table 5.18, Table 5.20, Table 5.22 and Table 5.24 (Table 5.26, Table 5.28, Table 5.30, Table 5.32 and Table 5.34) and corresponds to developed (emerging/frontier) regions for the whole period. Similarly, Table 5.9 (Table 5.10) is constructed for the short pre-crisis period using Table 5.44–Table 5.47 (Table 5.48–Table 5.52). The number of insignificant conditional correlations and volatilities between models for the long pre-crisis period is given in Table 5.11 (Table 5.12). This is based on the results presented in Table 5.53–Table 5.56 (Table 5.57–Table 5.61) respectively. Following similar approach, tables for post-crisis period are constructed. Table 5.13 (Table 5.14) refers to the short period and is based on Table 5.62–Table 5.65 (Table 5.66–Table 5.70). For the long period I have created Table 5.15 and Table 5.16 which are formed from Table 5.71–Table 5.74 and Table 5.75–Table 5.79 respectively.

Table 5.7 Statistical insignificance of conditional correlations and conditional volatilities between models for the whole period for developed markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	-	**1**	0	0	0	0	0	0	**2**	-	0	**2**	0	0	**1**	0	**1**	0
GO-GARCH ICA	414	0	-	0	0	0	0	0	0	**1**	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	414	0	**1**	-	0	0	0	0	**1**	0	**4**	0	-	0	0	**1**	0	**1**	0
GO-GARCH ML	414	0	0	0	-	**1**	0	0	0	0	0	0	0	-	0	0	0	0	**1**
DCC	414	0	0	0	0	-	**1**	0	0	0	**2**	0	**2**	0	-	**4**	**4**	**4**	0
COPULA DCC	414	0	0	0	0	0	-	0	0	0	**2**	0	**2**	0	**4**	-	**4**	**4**	0
SMA (100)	414	0	0	0	0	**1**	**1**	-	**3**	0	**2**	0	**2**	0	**4**	**3**	-	**4**	0
EWMA (0.03, 0.97)	414	0	0	0	0	**1**	0	**3**	-	0	**3**	0	**4**	0	**4**	**4**	**4**	-	0
UNCONDITIONAL	414	**1**	**1**	0	0	0	0	0	0	-	0	0	0	**0**	0	0	0	0	-

*Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available, as it is based on 100 observations. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*3=) 216 correlation and (72*4=) 288 volatility test results, 19 and 77 respectively are insignificant, which corresponds to 8.80% and 26.74%.*

Table 5.8 Statistical insignificance of conditional correlations and conditional volatilities between models for the whole period for emerging/frontier markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	-	0	0	0	0	0	**2**	**2**	0	-	0	**1**	0	0	0	**1**	**1**	0
GO-GARCH ICA	414	0	-	0	0	0	0	0	0	**2**	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	414	**1**	0	-	0	0	0	**3**	**2**	0	**5**	0	-	0	0	0	**1**	**1**	0
GO-GARCH ML	414	0	0	0	-	**3**	0	**2**	0	0	0	0	0	-	0	0	0	0	**1**
DCC	414	0	0	0	**1**	-	**1**	**1**	0	0	**2**	0	**3**	0	-	**5**	**3**	**1**	0
COPULA DCC	414	0	0	0	0	0	-	0	0	0	**2**	0	**3**	0	**5**	-	**3**	**1**	0
SMA (100)	414	**1**	0	**1**	**1**	**1**	**0**	-	**5**	0	**4**	0	**4**	0	**1**	**1**	-	**4**	0
EWMA (0.03, 0.97)	414	**1**	0	**2**	0	0	0	**4**	-	0	**4**	0	**4**	0	**1**	**1**	**5**	-	0
UNCONDITIONAL	414	0	0	0	0	0	0	0	0	-	0	0	0	**2**	0	0	0	0	-

*Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available, as it is based on 100 observations. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*5=) 360 correlation and (72*5=) 360 volatility test results, 36 and 70 respectively are insignificant, which corresponds to 10.00% and 19.44%.*

Table 5.9 Statistical insignificance of conditional correlations and conditional volatilities between models for the short pre-crisis period for developed markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	0	**1**	0	0	0	0	0	**1**	-	0	**1**	**1**	**1**	**1**	0	0	0
GO-GARCH ICA	62	0	-	**1**	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	62	**1**	**1**	-	0	0	0	0	0	0	**1**	0	-	0	**1**	**1**	0	0	0
GO-GARCH ML	62	0	0	0	-	0	0	0	**1**	0	0	0	0	-	0	0	0	0	0
DCC	62	0	0	0	0	-	**1**	**1**	**1**	0	**1**	0	**1**	0	-	**4**	0	**3**	0
COPULA DCC	62	0	0	0	0	**1**	-	**1**	**1**	0	**1**	0	**1**	0	**4**	-	0	**2**	0
SMA (100)	62	0	0	0	0	**1**	**1**	-	0	0	0	0	0	0	0	0	-	**1**	**1**
EWMA (0.03, 0.97)	62	0	0	0	**1**	**1**	**1**	0	-	0	0	0	0	0	0	**1**	**1**	-	0
UNCONDITIONAL	62	**1**	0	0	0	0	0	0	0	-	0	0	0	0	**2**	**2**	**1**	0	-

*Notes: The period runs from 10 March 2006 to 11 May 2007. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*3=) 216 correlation and (72*4=) 288 volatility test results, 18 and 33 respectively are insignificant, which corresponds to 8.33% and 11.46%.*

Table 5.10 Statistical insignificance of conditional correlations and conditional volatilities between models for the short pre-crisis period for emerging/frontier markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	0	0	0	0	0	0	0	0	-	0	**1**	**2**	**1**	**1**	**1**	**1**	0
GO-GARCH ICA	62	0	-	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	62	0	0	-	0	0	0	0	0	**1**	**1**	0	-	**2**	**1**	**2**	**1**	**1**	0
GO-GARCH ML	62	0	0	0	-	0	0	0	**1**	0	0	0	**2**	-	0	0	0	**1**	0
DCC	62	0	0	0	0	-	**3**	**3**	**4**	0	**2**	0	**2**	**2**	-	**5**	**2**	**5**	**1**
COPULA DCC	62	0	0	0	0	**3**	-	**3**	0	0	**2**	0	**2**	**2**	**5**	-	**3**	**5**	**2**
SMA (100)	62	0	0	0	0	**2**	**3**	-	**1**	0	0	0	0	0	0	0	-	**1**	0
EWMA (0.03, 0.97)	62	0	0	0	**1**	**3**	0	**2**	-	0	**2**	0	**2**	**1**	**3**	**3**	0	-	0
UNCONDITIONAL	62	0	0	**1**	0	0	0	0	0	-	0	0	0	0	**3**	**3**	0	**1**	-

*Notes: The period runs from 10 March 2006 to 11 May 2007. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*5=) 360 correlation and (72*5=) 360 volatility test results, 31 and 77 respectively are insignificant, which corresponds to 8.61% and 21.39%.*

Table 5.11 Statistical insignificance of conditional correlations and conditional volatilities between models for the long pre-crisis period for developed markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	0	**2**	0	0	0	0	0	0	-	0	**2**	0	0	0	0	0	0
GO-GARCH ICA	124	0	-	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	124	**2**	0	-	0	0	0	0	0	0	**2**	0	-	0	0	0	0	0	0
GO-GARCH ML	124	0	0	0	-	0	0	0	0	**1**	0	0	0	-	0	0	0	0	0
DCC	124	0	0	0	0	-	0	0	0	0	0	0	**1**	0	-	**3**	0	0	0
COPULA DCC	124	0	0	0	0	0	-	0	**1**	0	0	0	**1**	0	**3**	-	0	0	0
SMA (100)	124	0	0	0	0	0	0	-	**1**	0	0	0	0	0	0	0	-	**1**	0
EWMA (0.03, 0.97)	124	0	0	0	0	0	**1**	0	-	0	0	0	0	0	0	0	**1**	-	0
UNCONDITIONAL	124	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	**1**	-

*Notes: The period runs from 31 December 2004 to 11 May 2007. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*3=) 216 correlation and (72*4=) 288 volatility test results, 8 and 15 respectively are insignificant, which corresponds to 3.70% and 5.21%.*

Table 5.12 Statistical insignificance of conditional correlations and conditional volatilities between models for the long pre-crisis period for emerging/frontier markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	0	**1**	0	0	0	0	0	0	-	0	**1**	**1**	0	**1**	0	0	0
GO-GARCH ICA	124	0	-	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	124	**1**	0	-	0	0	0	0	0	0	**1**	0	-	0	0	**1**	0	0	0
GO-GARCH ML	124	0	0	0	-	0	**1**	0	**1**	0	0	0	**1**	-	0	0	0	0	0
DCC	124	0	0	0	0	-	0	**1**	**2**	0	**1**	0	**1**	0	-	**5**	**1**	**1**	**2**
COPULA DCC	124	0	0	0	0	0	-	**1**	**2**	0	**1**	0	**1**	0	**5**	-	**1**	**2**	**3**
SMA (100)	124	0	0	0	0	**1**	**2**	-	**3**	0	0	0	0	0	**1**	**1**	-	**1**	0
EWMA (0.03, 0.97)	124	0	0	0	**1**	**2**	**2**	0	-	0	0	0	0	0	0	0	**1**	-	0
UNCONDITIONAL	124	0	0	0	0	0	0	0	0	-	0	0	0	0	**2**	**2**	0	**1**	-

*Notes: The period runs from 31 December 2004 to 11 May 2007. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*5=) 360 correlation and (72*5=) 360 volatility test results, 21 and 39 respectively are insignificant, which corresponds to 5.83% and 10.83%.*

Table 5.13 Statistical insignificance of conditional correlations and conditional volatilities between models for the short post-crisis period for developed markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	**3**	**1**	0	0	0	0	0	0	-	0	**4**	0	**1**	**2**	0	0	**1**
GO-GARCH ICA	62	**3**	-	0	0	0	0	**1**	**1**	**1**	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	62	**1**	**2**	-	0	0	0	0	0	0	**3**	0	-	0	**1**	**1**	0	0	**1**
GO-GARCH ML	62	0	0	0	-	**1**	0	0	0	0	0	0	0	-	0	0	0	0	0
DCC	62	0	0	0	**1**	-	**1**	0	0	0	**3**	0	**2**	0	-	**4**	0	0	**1**
COPULA DCC	62	0	0	0	0	**2**	-	0	0	0	**3**	0	**3**	0	**4**	-	0	0	0
SMA (100)	62	0	0	0	0	0	0	-	**1**	**1**	0	0	0	0	0	0	-	0	0
EWMA (0.03, 0.97)	62	0	0	0	0	0	0	**1**	-	**1**	0	0	0	0	0	0	0	-	0
UNCONDITIONAL	62	0	0	0	0	**1**	**1**	0	0	-	**1**	0	**1**	0	**3**	**2**	0	0	-

*Notes: The period runs from 1 January 2010 to 4 March 2011. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*3=) 216 correlation and (72*4=) 288 volatility test results, 24 and 41 respectively are insignificant, which corresponds to 11.11% and 14.24%.*

Table 5.14 Statistical insignificance of conditional correlations and conditional volatilities between models for the short post-crisis period for emerging/frontier markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	**1**	**1**	0	0	0	0	0	0	-	0	**1**	**1**	0	0	0	0	0
GO-GARCH ICA	62	**2**	-	0	0	0	0	0	0	**1**	0	-	0	0	0	0	**3**	0	0
GO-GARCH NLS	62	**1**	**1**	-	**2**	0	0	0	0	0	**1**	0	-	**1**	**1**	**1**	0	0	0
GO-GARCH ML	62	**1**	0	0	-	0	0	0	0	0	**1**	0	0	-	0	0	0	**2**	0
DCC	62	0	0	0	0	-	**3**	0	0	0	0	0	**3**	0	-	**5**	0	0	**2**
COPULA DCC	62	0	0	0	0	**5**	-	0	0	0	0	0	**3**	0	**5**	-	0	0	**2**
SMA (100)	62	0	0	0	0	0	0	-	**1**	0	0	0	0	0	0	0	-	0	0
EWMA (0.03, 0.97)	62	0	0	0	0	0	0	**1**	-	**1**	0	0	0	**1**	0	0	0	-	0
UNCONDITIONAL	62	0	**1**	0	0	0	0	0	0	-	0	0	0	0	**1**	**2**	0	0	-

*Notes: The period runs from 1 January 2010 to 4 March 2011. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*5=) 360 correlation and (72*5=) 360 volatility test results, 22 and 36 respectively are insignificant, which corresponds to 6.11% and 10.00%.*

Table 5.15 Statistical insignificance of conditional correlations and conditional volatilities between models for the long post-crisis period for developed markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**1**	**1**	0	0	0	0	0	0	-	0	**3**	0	**1**	**1**	0	0	0
GO-GARCH ICA	124	**2**	-	**1**	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	124	**1**	**2**	-	0	0	0	0	0	0	**2**	0	-	0	**1**	**1**	0	0	0
GO-GARCH ML	124	0	0	0	-	0	0	0	0	0	0	0	0	-	0	0	**1**	**1**	**1**
DCC	124	0	0	0	0	-	**2**	0	0	0	**3**	0	**3**	**1**	-	**4**	0	0	**1**
COPULA DCC	124	0	0	0	0	**2**	-	0	0	0	**2**	0	**2**	0	**4**	-	0	0	**1**
SMA (100)	124	0	0	0	0	0	0	-	**3**	**2**	0	0	0	0	0	0	-	**4**	0
EWMA (0.03, 0.97)	124	**1**	0	**1**	0	0	0	**2**	-	0	0	0	0	0	0	0	0	-	0
UNCONDITIONAL	124	0	0	0	0	0	0	0	**1**	-	0	0	0	0	0	0	0	0	-

*Notes: The period runs from 1 January 2010 to 11 May 2012. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*3=) 216 correlation and (72*4=) 288 volatility test results, 22 and 37 respectively are insignificant, which corresponds to 10.19% and 12.85%.*

Table 5.16 Statistical insignificance of conditional correlations and conditional volatilities between models for the long post-crisis period for emerging/frontier markets

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**1**	0	0	0	0	0	0	0	-	0	0	**1**	0	0	**3**	**4**	**1**
GO-GARCH ICA	124	**1**	-	0	0	0	0	0	**1**	0	0	-	0	0	0	0	0	0	0
GO-GARCH NLS	124	**1**	0	-	**1**	**1**	**1**	0	0	0	**1**	0	-	**1**	**1**	**1**	**1**	0	**1**
GO-GARCH ML	124	**1**	0	**1**	-	0	**2**	0	0	0	**1**	0	**1**	-	0	0	**1**	**1**	**1**
DCC	124	0	0	**2**	0	-	**1**	0	0	0	**1**	0	**4**	**1**	-	**5**	0	0	**3**
COPULA DCC	124	0	0	**1**	**2**	**2**	-	0	0	0	**1**	0	**3**	**1**	**5**	-	0	0	**2**
SMA (100)	124	0	0	0	0	0	0	-	**1**	**1**	0	0	0	**1**	0	0	-	**5**	0
EWMA (0.03, 0.97)	124	0	**1**	0	0	0	0	0	-	**1**	**2**	0	0	**1**	0	0	0	-	0
UNCONDITIONAL	124	0	**2**	0	0	0	0	**1**	0	-	0	0	0	0	**2**	**2**	0	0	-

*Notes: The period runs from 1 January 2010 to 11 May 2012. The values represent the number of insignificant test statistics. The upper (lower) triangle corresponds to the Wilcoxon rank sum (Welch t) test. Out of (72*5=) 360 correlation and (72*5=) 360 volatility test results, 26 and 59 respectively are insignificant, which corresponds to 7.22% and 16.39%.*

We can examine the differences between developed and emerging/frontier markets in terms of (i) temporal analysis, (ii) mean comparison tests in respect to Hypothesis 1 and (iii) mean comparison tests in respect to Hypothesis 2.

The temporal analysis in Figure 5.1–Figure 5.2 and Figure 5.29–Figure 5.43 in the Appendix can be used to examine the differences between developed and emerging/frontier markets. It can be identified that the spikes in volatility associated with the financial crisis are generally higher in emerging/frontier markets than developed markets. This can also be seen in the mean values in Table 5.19, Table 5.21, Table 5.23, Table 5.25, Table 5.27, Table 5.29, Table 5.31 and Table 5.33. This is, perhaps, not surprising given that volatility tends to generally higher in emerging/frontier markets (see, for example, Aggarwal *et al.* 1999, Domowitz *et al.* 2001).

Examination of Table 5.19, Table 5.21, Table 5.23, Table 5.25, Table 5.27, Table 5.29, Table 5.31 and Table 5.33 shows there to be larger spikes in correlations relative to the mean in emerging/frontier markets than in developed markets. This would be consistent with herding behaviour resulting in short-term contagion effects in these markets (see, for example, Forbes and Rigobon 2002).

It can also be seen in Table 5.7–Table 5.16 in respect to correlations that the percentage of insignificant tests were higher in pre-crisis period for emerging/frontier markets than for developed markets (for example, in the long pre-crisis period it rose *marginally* from 3.70% for developed markets to 5.83% for emerging/frontier markets). There is also evidence that this reversed marginally in the post-crisis period (for example, in the long pre-crisis period it rose from 10.19% for developed markets to 7.22% for emerging/frontier markets). The finding of relatively small differences between the performance of models and also the finding that pre- and post-crisis differences are only marginally different is an indication that both the period when the analysis is undertaken, and also types of markets that analysis is undertaken in, makes very little difference in respect to the relative efficiencies of the different models examined. This conclusion is also supported by evidence from Table 5.6. This identifies that for both developed and emerging/frontier markets differences in correlation and volatility are largely statistically significantly different with respect to pre- and post-crisis period. Similar finding with respect to the developed markets was found by Kenourgios (2014) who considered implied volatility indices. In contrast, Chiang *et al.* (2007) did not find significant differences between pre- and post-crisis correlations for emerging markets with respect to the Asian crisis.

I conclude that the main implications of these findings are that there are only limited differences in covariance model performance in respect to the type of market and the phase of the market cycle.

5.5 IMPLICATIONS OF FINDINGS

The main aim of my PhD thesis is to look at the application of different covariance estimates in the portfolio context. I want to compare those different methods from a portfolio performance perspective. In order to do this I will first look in more detail at the key issues. I have identified three principle issues; practical estimation issues, how will they deal with the structural breaks within the data and how they deal with non-normality in statistical distribution within the data.

Practical estimation issues

In terms of speed of estimation, GO-GARCH ML seems to be very slow as it takes roughly 26 minutes for this data set (513 returns per series x 9 series = 4,617 returns in total) to estimate on a quite decent computer (processor Intel i5-2400 3.10GHz with 4GB RAM). The other GO-GARCH models are much quicker as it takes roughly 5.5 seconds for NLS, 1 second for ICA and 1 second for MM to obtain the results. When it comes to the DCC model, it is about 30 seconds and 74 seconds for COPULA DCC. The MA models are also quite fast as well, as it takes circa 0.3 and 0.3 seconds to get SMA and EWMA results, respectively.

From that perspective, the DCC model looks quite good but for a larger data set it can have problems in terms of estimation. To overcome this high-dimensionality issue some other approaches have been proposed in the literature. One of them is the Dynamic Equicorrelation model (DECO) proposed by Engle and Kelly (2012). In that model, all pairs of returns have the same correlation at a given point in time but this correlation varies over time. Another possible approach is to use a factor model. In this model, the observations are generated by underlying univariate GARCH factors that can generate the time-varying correlations while keeping the residuals correlation matrix constant (Engle 2009a, Engle *et al.* 1990 and 1992). GO-GARCH models belong to the factor models group. There are two main differences between the factor models. One of them is the specification of the transformation matrix and the second is because of the number of heteroskedastic factors that could be less or equal to the number of assets (Silvennoinen and Terasvirta 2008).

Another practical aspect that is worth mentioning is that the parameters for MA models are chosen subjectively, whereas parameters for the other models are estimated. Even though MA models are quite easy to implement, they are possibly not as accurate as the other models considered.

Dealing with structural change

Another aspect worth mentioning is the identification of structural breaks as I examine the impact of the financial crisis. GO-GARCH models are based on the constant mixing matrix so they cannot show up the impact of the crisis as they would possibly for a time-varying matrix, as mentioned in the literature (van der Weide 2002). It depends on the data whether the impact of the financial crisis will be shown. If the identified factors are not very different then the GO-GARCH model can struggle (Boswijk and van der Weide 2009, van der Weide 2002). The ML model does not seem to pick out the financial crisis well in my data set in terms of correlations. Moreover, this method is not particularly useful when a portfolio is growing because of convergence problems as well as the estimation time required.

Introducing time variation has been discussed in the literature in terms of the mixing matrix (van der Weide 2002); however, I have not found any evidence as far.

The MA model suffers from ‘ghost features’, as mentioned in Alexander (1998). Extreme events such as, for example, the financial crisis push the MA estimate up for a long period of time, which can induce apparent stability in the MA estimate. The longer the estimation window of the MA model is, the longer the ‘ghost feature’ will last. We can observe this on volatility plots (Figure 5.29, Figure 5.31, Figure 5.33, Figure 5.35, Figure 5.37, Figure 5.39, Figure 5.41, and Figure 5.43 in the appendix). The EWMA places more weight on more recent observation. This helps to reduce the ‘ghost feature’ (Alexander 1998).

My conclusion is that the DCC model would be superior in this particular thesis given that we have substantial change in the conditional correlations for the DCC model. However, there are other issues, which are that all correlations follow the same structure and the dummy variable could also be introduced in the correlation equation (Cappiello *et al.* 2006).

Dealing with non-normality in statistical distribution within the data

What we see from Table 3.1 and Table 3.2 in Chapter 3 is that the data is not normally distributed. The literature confirms that the fat tails can be replicated by the GARCH model (Bolerslev 1986, He and Teräsvirta 1999a, He and Teräsvirta 1999b, Zivot and Wang 2006).

On the one hand, the fat tails and asymmetry found within the data may be explained by time-varying and asymmetric volatility; on the other hand, volatility on its own may not be able to explain all the non-normality observed (Zivot 2013, Zivot and Wang 2006). That is why skew Student t distribution for margins with Student copula, which is used in our COPULA DCC model, is designed to capture the asymmetry and fat tails of the empirical distribution. That is why I would expect that the COPULA DCC would outperform a standard multivariate-normal DCC.

Taking into consideration the issues mentioned above, the conclusion I reach is that all the models have some potential drawbacks associated with them but our preferred model is COPULA DCC.

5.6 Conclusions: Which methods are most likely to identify the most efficient portfolio?

I finish this chapter by considering which models I will take forward to the next stage of the thesis. As I have identified DCC and COPULA DCC as the most potential promising methodologies I will use both in Chapter 6. In respect to which other methodologies to use for comparative purposes, as well as considering the issues identified above I also need to take into consideration a number of other factors; for example, the considerable variation within the estimated correlations that are found using the different approaches.[7] These differences will potentially have a significant influence on the portfolio performance.

[7] There are other factors that may also be of significance. For example, the coefficients of variation of the correlations are highest for MA models and lowest for GO-GARCH models. This implies that the MA portfolios will show greater variation in the constituent elements of the portfolios over time.

If you refer back to the volatility charts (for example, Figure 5.3–Figure 5.10) it can be noted that volatility increased significantly during the financial crisis. This may have implications for how constituents of a portfolio change over time. I would expect to see greater changes appearing during high volatility periods.

From Table 5.17, Table 5.19, Table 5.21, Table 5.23, Table 5.25, Table 5.27, Table 5.29, Table 5.31, and Table 5.33 in appendix we see that GO-GARCH correlations *are higher* than both DCC and MA correlations. The potential implications of these findings are that the diversification benefits *are lower* according to the GO-GARCH methodologies than for the DCC and MA methodologies. On this basis I conclude that although the GO-GARCH methodologies have considerable drawbacks they should still be considered in the next stage of the thesis.

Conditional volatilities of GO-GARCH models (especially ICA and ML) *are generally higher* than those of the DCC and MA models. The implications of these are that the GO-GARCH portfolios will be less efficient because by keeping correlations constant higher asset volatility implies higher portfolio volatility.[8]

In Chapter 6 I make use of the MM and ICA GO-GARCH models. I have decided to drop the GO-GARCH ML, GO-GARCH NLS and SMA models for different reasons. GO-GARCH ML seems to be very impractical as the estimation time required is relatively very long. In terms of the GO-GARCH NLS model, the ICA model is found to be more efficient than NLS (Broda and Paolella 2009).

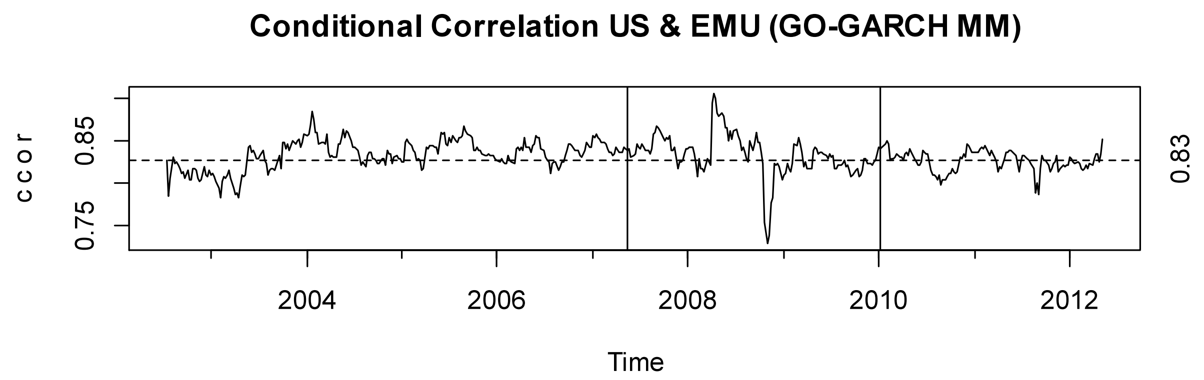
There is insufficient evidence to discount MA-based models. However, I only take EWMA forward to Chapter 6 as I argue that it is superior to the SMA model given the greater weight applied to more recent observations and also relatively the slow speed with which SMA reacts to large (and possibly structural) shocks to the financial system.

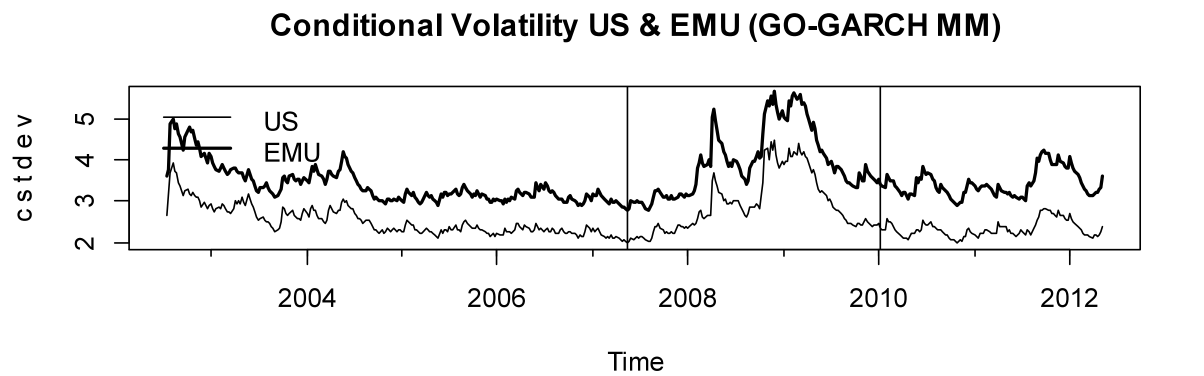
[8] Another issue is that the coefficient of variation of the conditional volatilities of the GO-GARCH models is lower than both the DCC and MA models. This implies that the GO-GARCH portfolios will show lower variation in the constituent elements of the portfolios over time.

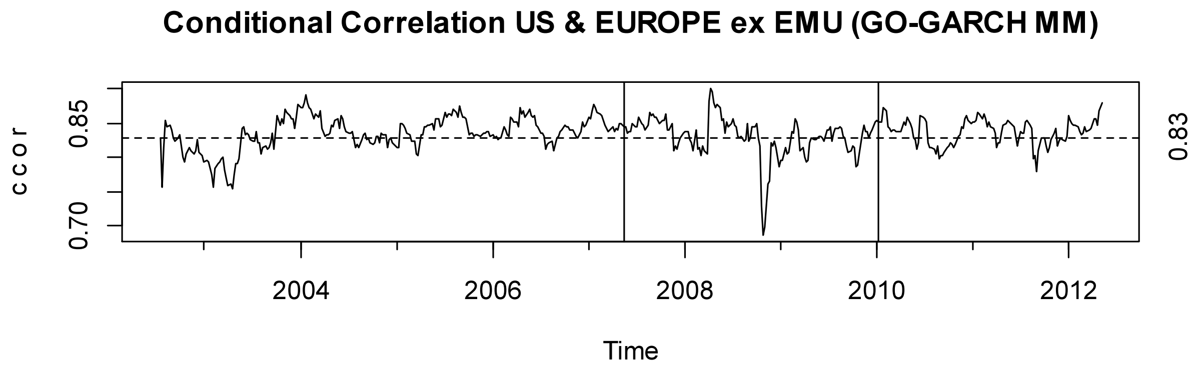
5.7 APPENDICES

Figure 5.3 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on GO-GARCH MM model

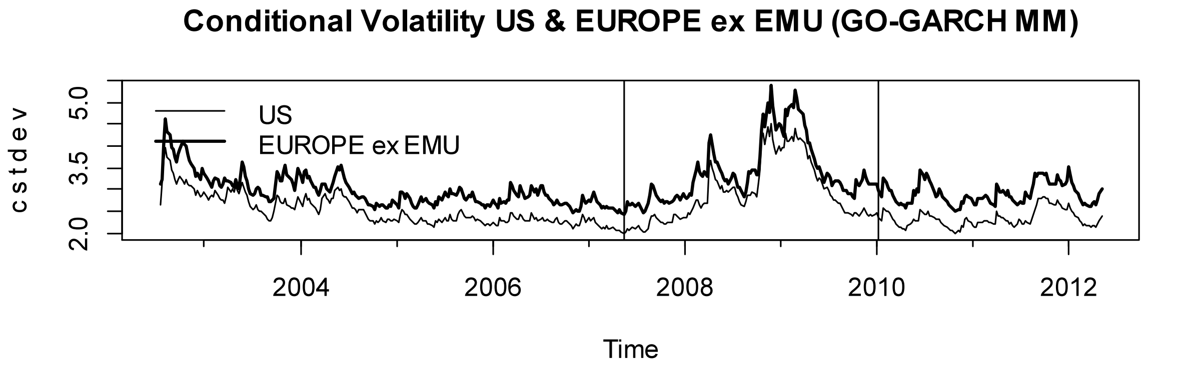
Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.



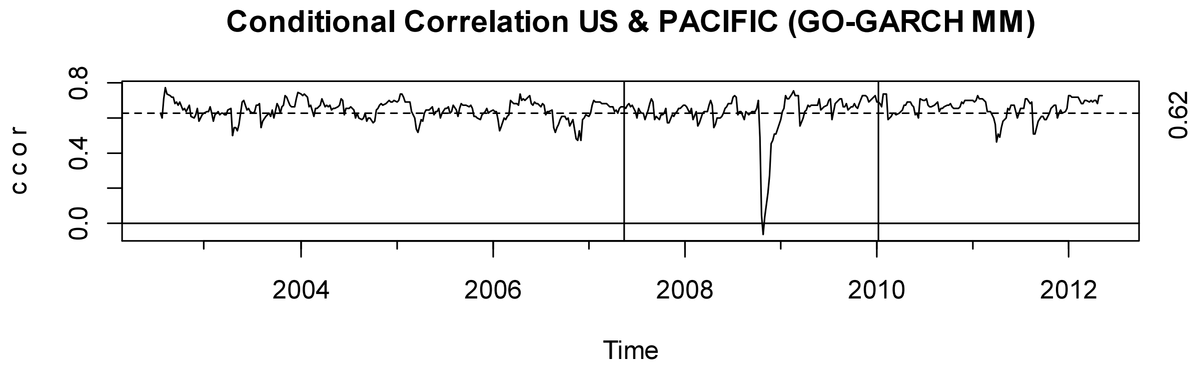




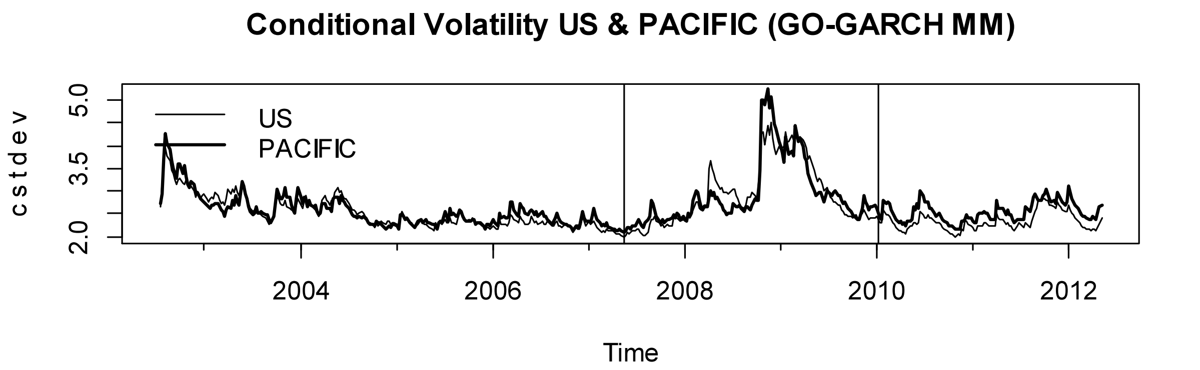
Conditional Correlation US & EUROPE ex EMU (GO-GARCH MM)
ccor
0.70
0.85
0.83
2004
2006
2008
2010
2012
Time



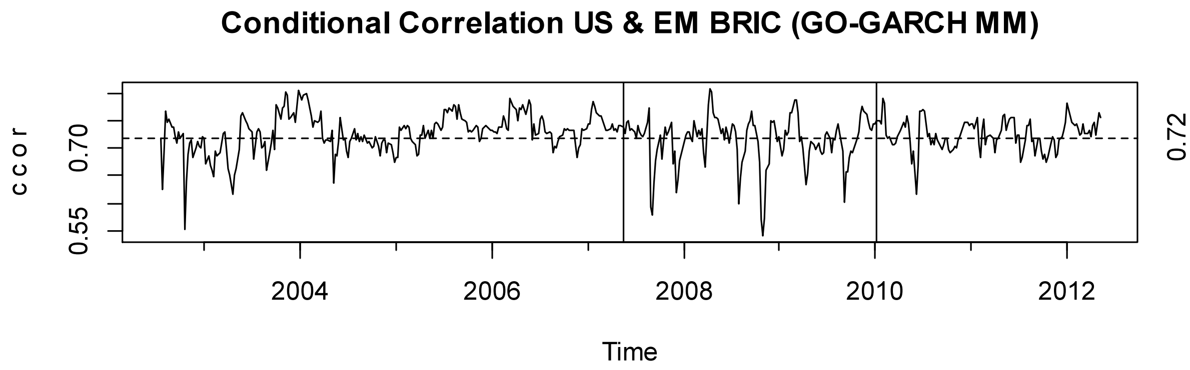
Conditional Volatility US & EUROPE ex EMU (GO-GARCH MM)
cstdev
2.0
3.5
5.0
US
EUROPE ex EMU
2004
2006
2008
2010
2012
Time

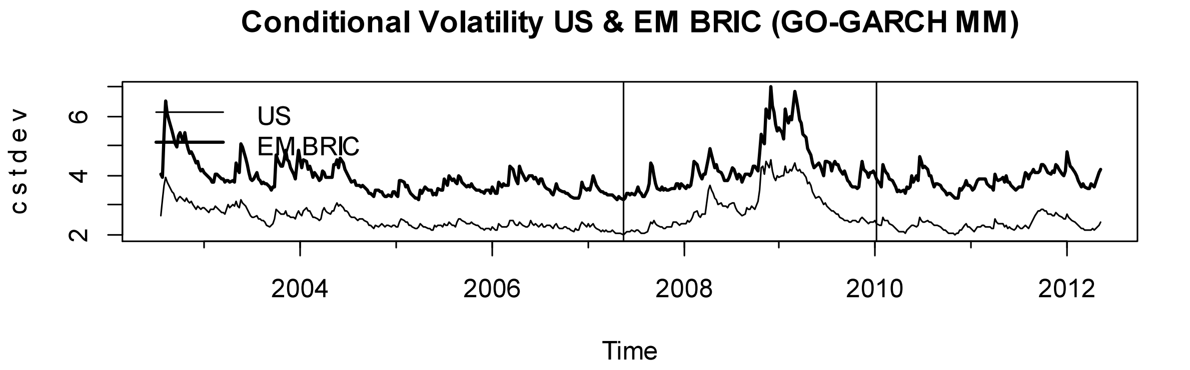


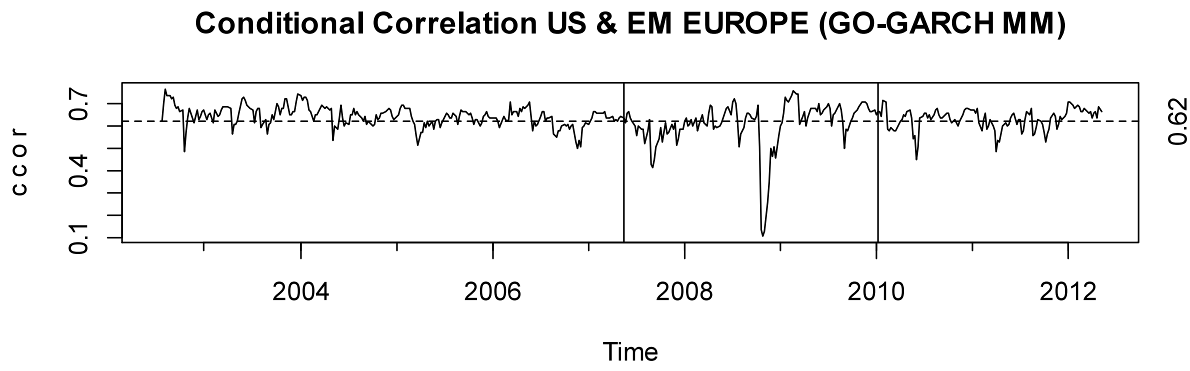
Conditional Correlation US & PACIFIC (GO-GARCH MM)
ccor
0.0
0.4
0.8
0.62
2004
2006
2008
2010
2012
Time

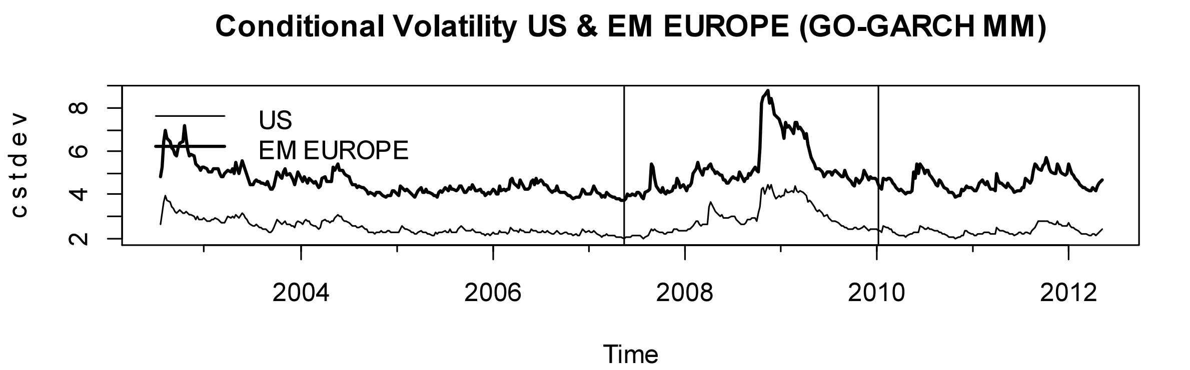


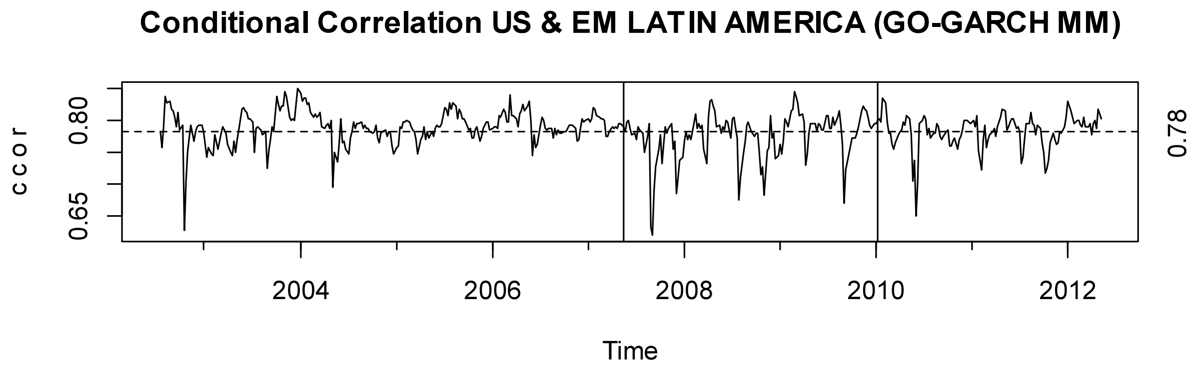
Conditional Volatility US & PACIFIC (GO-GARCH MM)
cstdev
2.0
3.5
5.0
US
PACIFIC
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM BRIC (GO-GARCH MM)
ccor
0.55
0.70
0.72
2004
2006
2008
2010
2012
Time

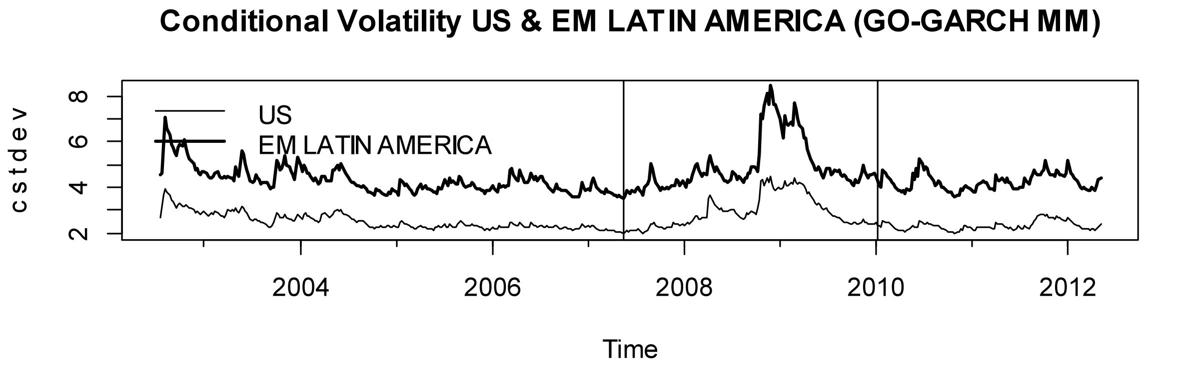

Conditional Volatility US & EM BRIC (GO-GARCH MM)
cstdev
2
4
6
US
EM BRIC
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM EUROPE (GO-GARCH MM)
ccor
0.1
0.4
0.7
0.62
2004
2006
2008
2010
2012
Time

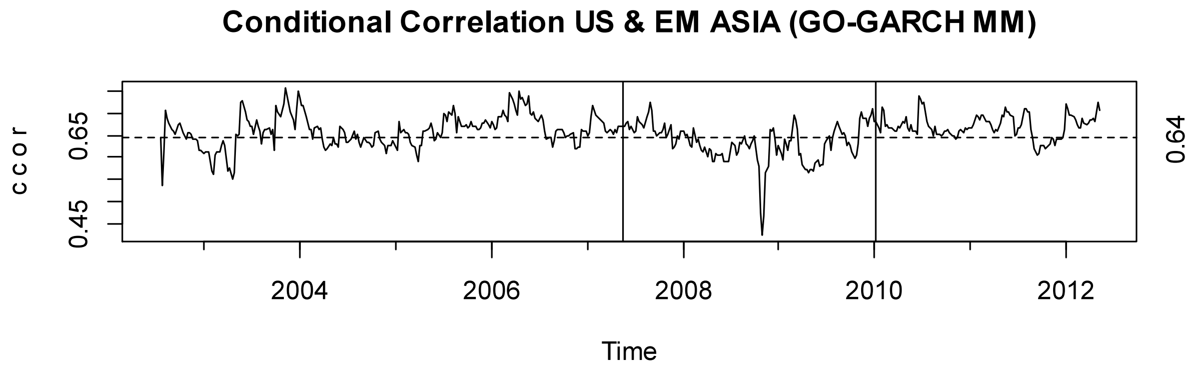

Conditional Volatility US & EM EUROPE (GO-GARCH MM)
cstdev
2
4
6
8
US
EM EUROPE
2004
2006
2008
2010
2012
Time



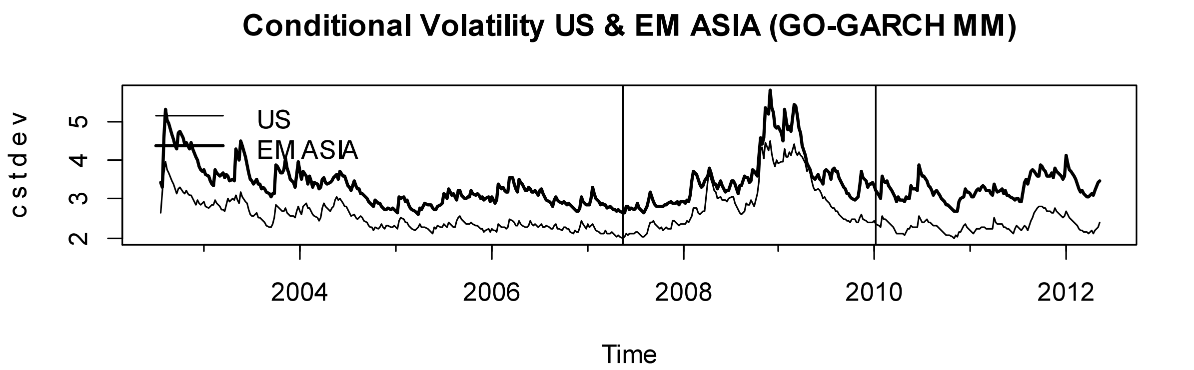
Conditional Correlation US & EM LATIN AMERICA (GO-GARCH MM)
ccor
0.65
0.80
0.78
2004
2006
2008
2010
2012
Time



Conditional Volatility US & EM LATIN AMERICA (GO-GARCH MM)
cstdev
2
4
6
8
US
EM LATIN AMERICA
2004
2006
2008
2010
2012
Time

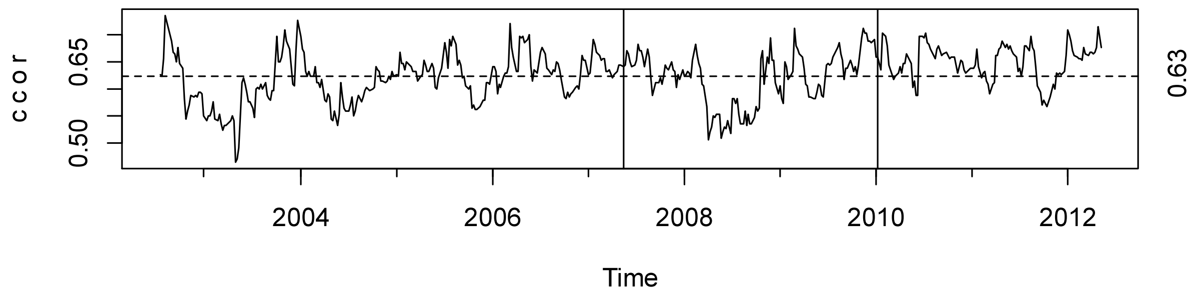


Conditional Correlation US & EM ASIA (GO-GARCH MM)
ccor
0.45
0.65
0.64
2004
2006
2008
2010
2012
Time



Conditional Volatility US & EM ASIA (GO-GARCH MM)
cstdev
2
3
4
5
US
EM ASIA
2004
2006
2008
2010
2012
Time

Conditional Correlation US & EFM AFRICA (GO-GARCH MM)



Conditional Volatility US & EFM AFRICA (GO-GARCH MM)

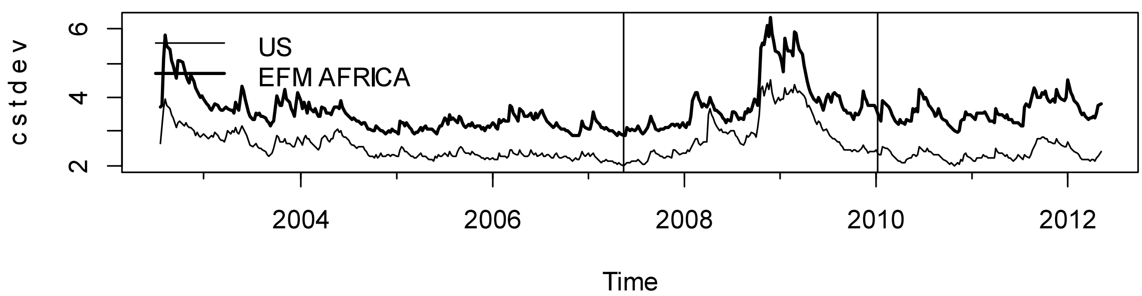
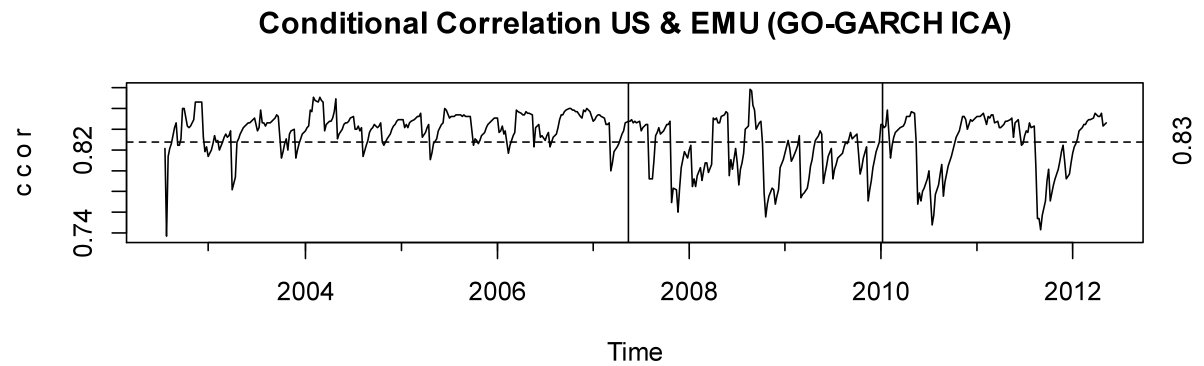
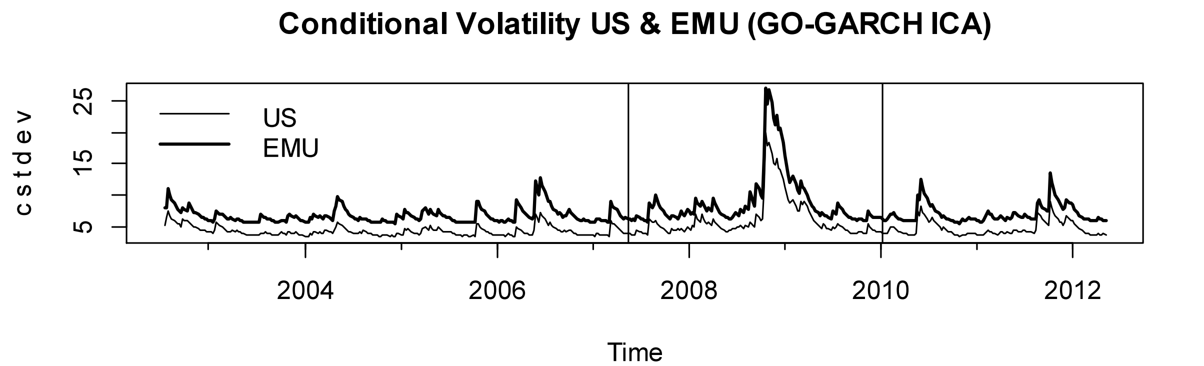
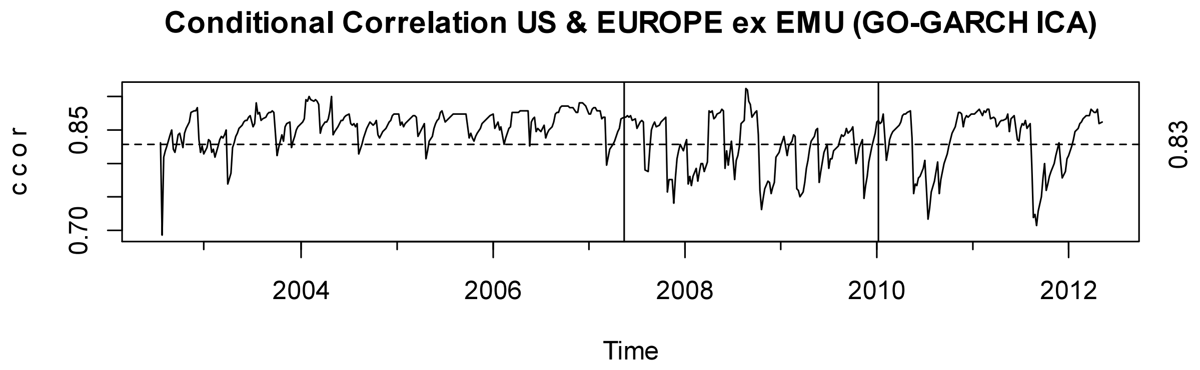


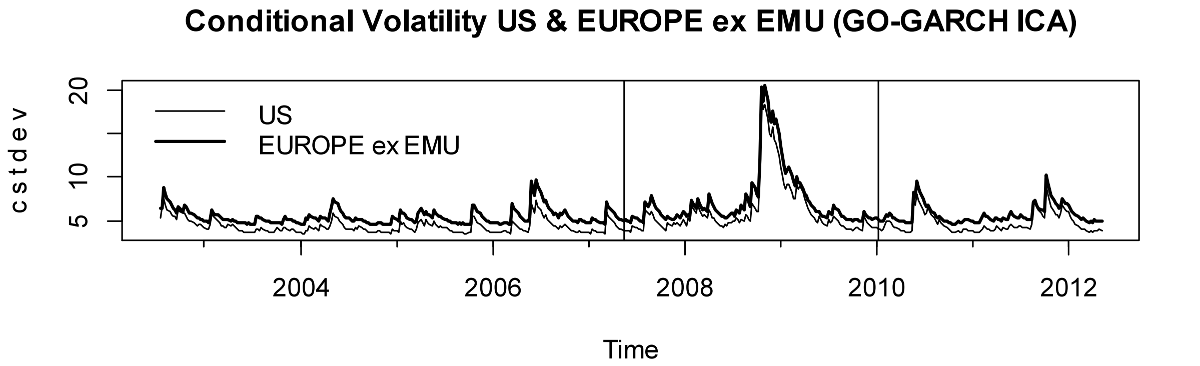
Figure 5.4 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on GO-GARCH ICA model

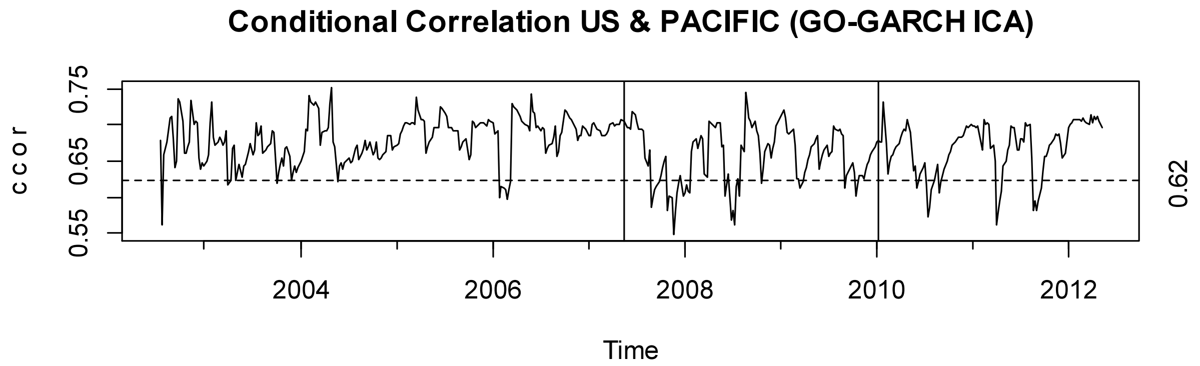
Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.

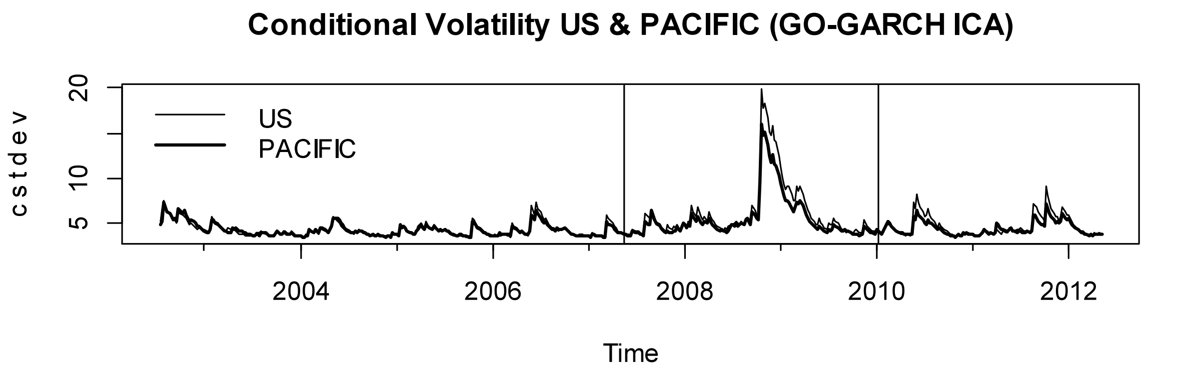


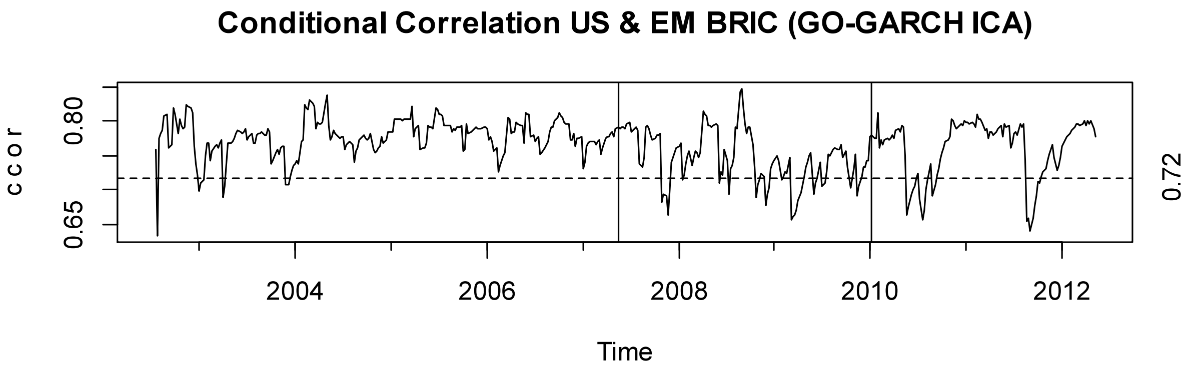


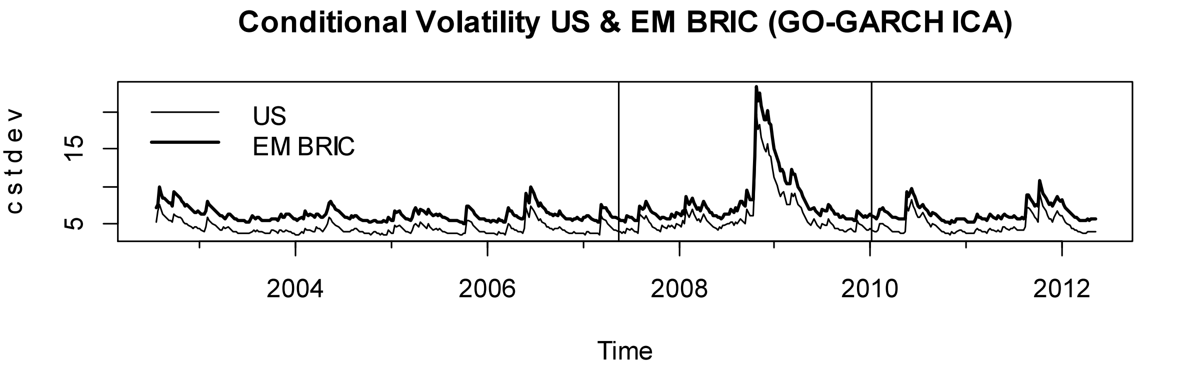

Conditional Correlation US & EUROPE ex EMU (GO-GARCH ICA)
ccor
0.70
0.85
0.83
2004
2006
2008
2010
2012
Time

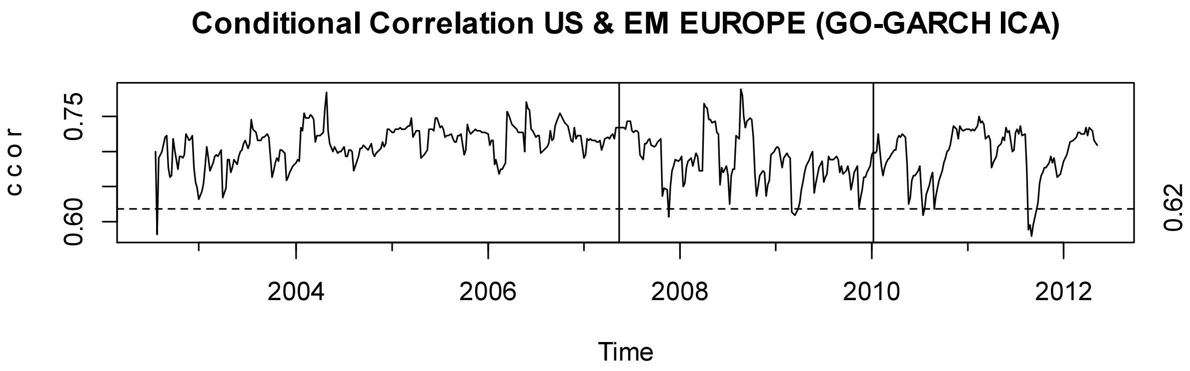

Conditional Volatility US & EUROPE ex EMU (GO-GARCH ICA)
cstdev
5
10
20
US
EUROPE ex EMU
2004
2006
2008
2010
2012
Time

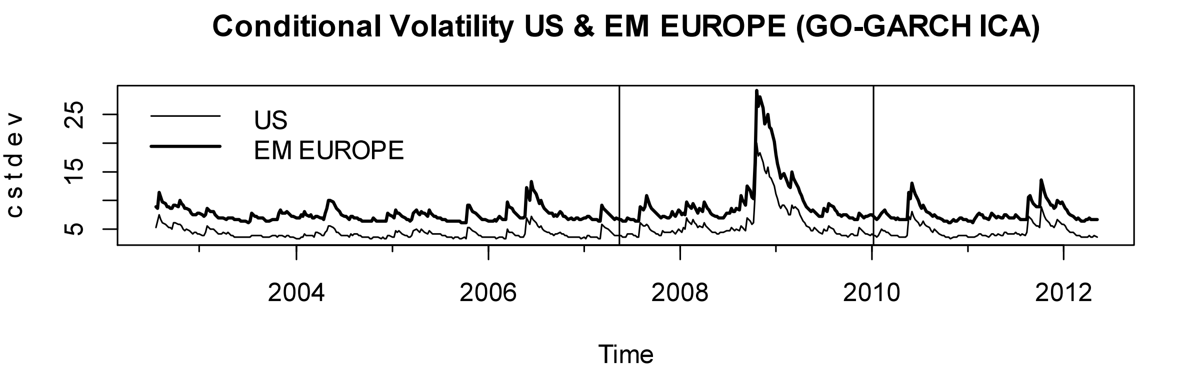

Conditional Correlation US & PACIFIC (GO-GARCH ICA)
ccor
0.55
0.65
0.75
0.62
2004
2006
2008
2010
2012
Time


Conditional Volatility US & PACIFIC (GO-GARCH ICA)
cstdev
5
10
20
US
PACIFIC
2004
2006
2008
2010
2012
Time

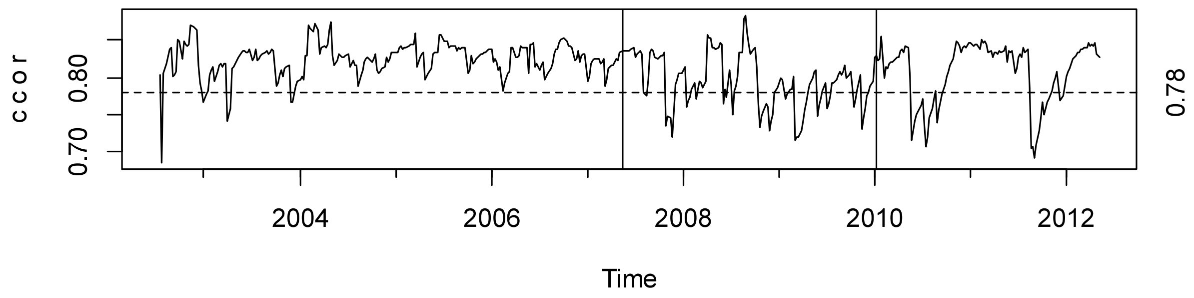

Conditional Correlation US & EM BRIC (GO-GARCH ICA)
ccor
0.65
0.80
0.72
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM BRIC (GO-GARCH ICA)
cstdev
5
15
US
EM BRIC
2004
2006
2008
2010
2012
Time

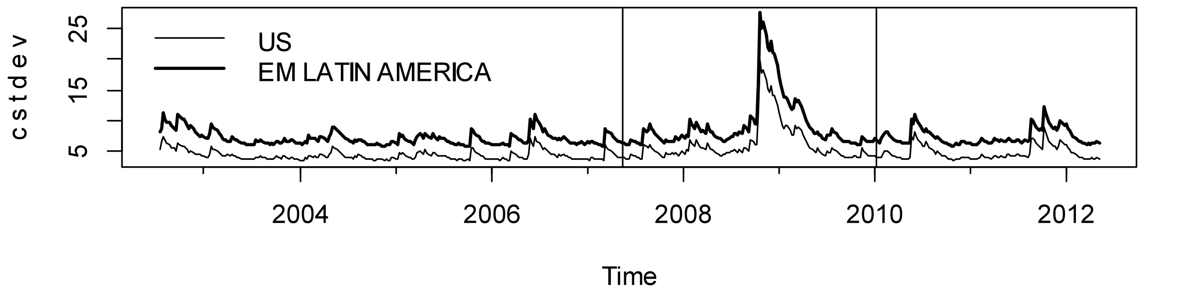

Conditional Correlation US & EM EUROPE (GO-GARCH ICA)
ccor
0.60
0.75
0.62
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM EUROPE (GO-GARCH ICA)
cstdev
5
15
25
US
EM EUROPE
2004
2006
2008
2010
2012
Time

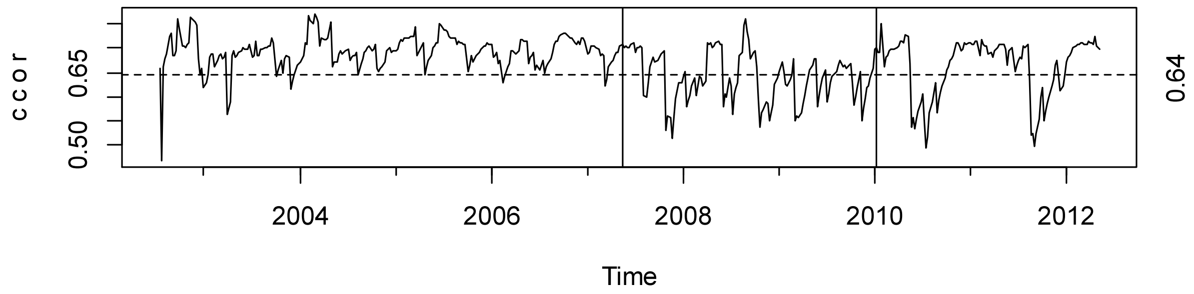
Conditional Correlation US & EM LATIN AMERICA (GO-GARCH ICA)



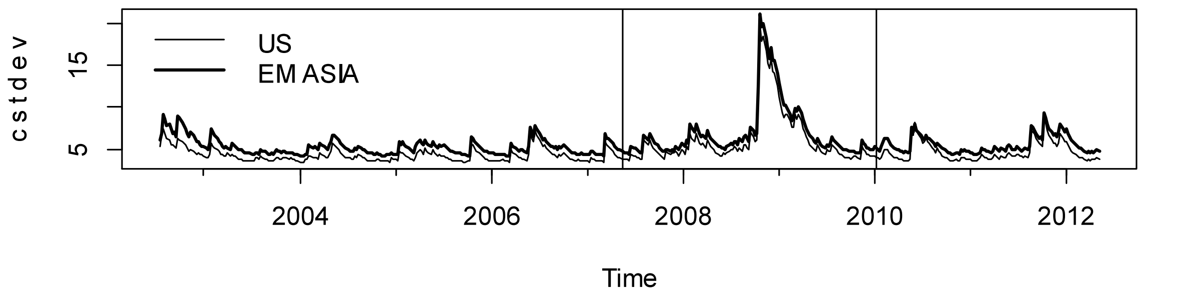
Conditional Volatility US & EM LATIN AMERICA (GO-GARCH ICA)

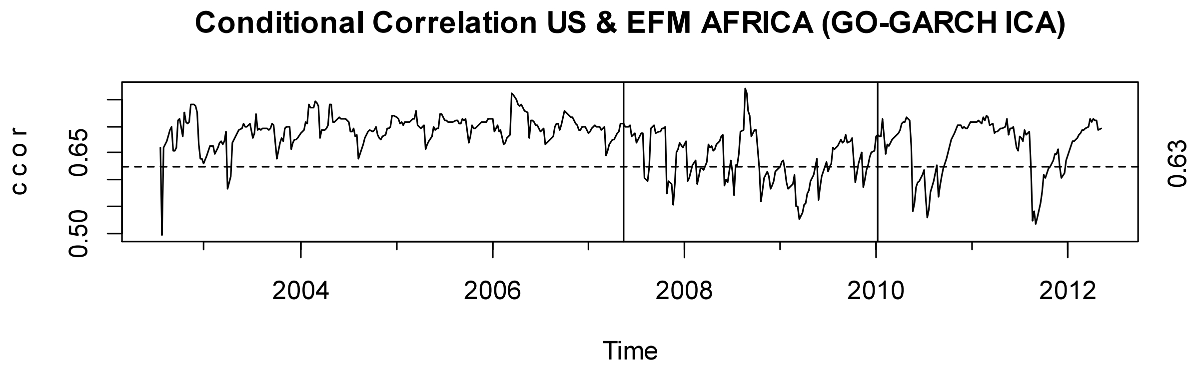


Conditional Correlation US & EM ASIA (GO-GARCH ICA)



Conditional Volatility US & EM ASIA (GO-GARCH ICA)




Conditional Correlation US & EFM AFRICA (GO-GARCH ICA)
ccor
0.50
0.65
0.63
2004
2006
2008
2010
2012
Time

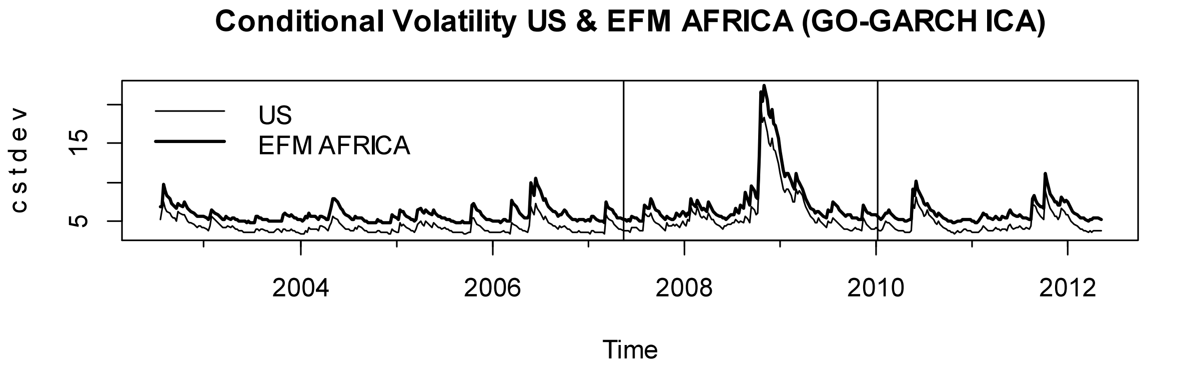
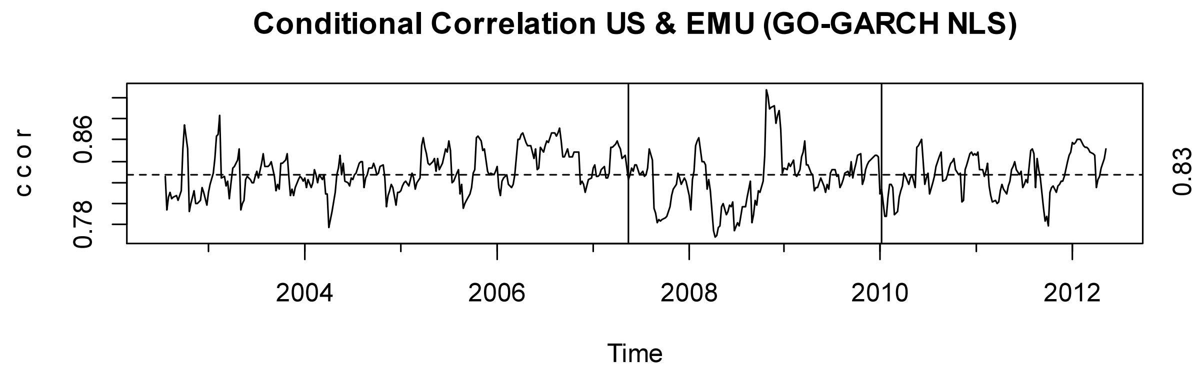
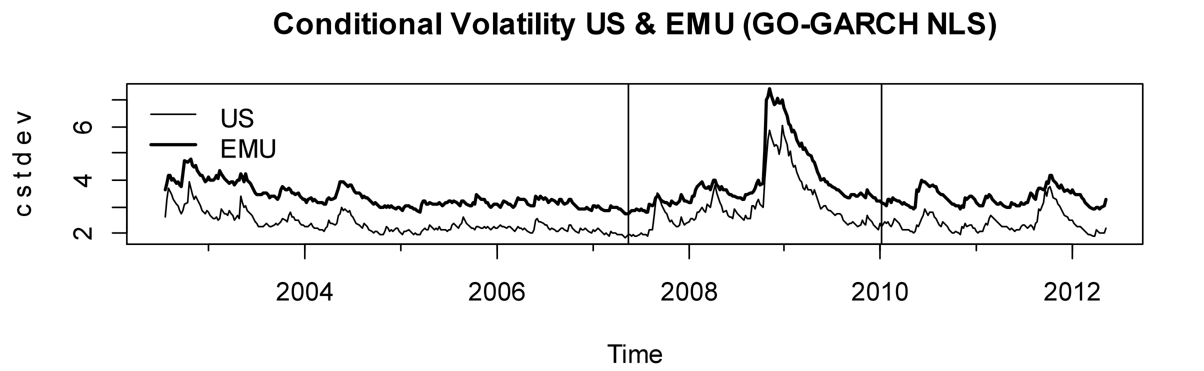

Conditional Volatility US & EFM AFRICA (GO-GARCH ICA)
cstdev
5
15
US
EFM AFRICA
2004
2006
2008
2010
2012
Time

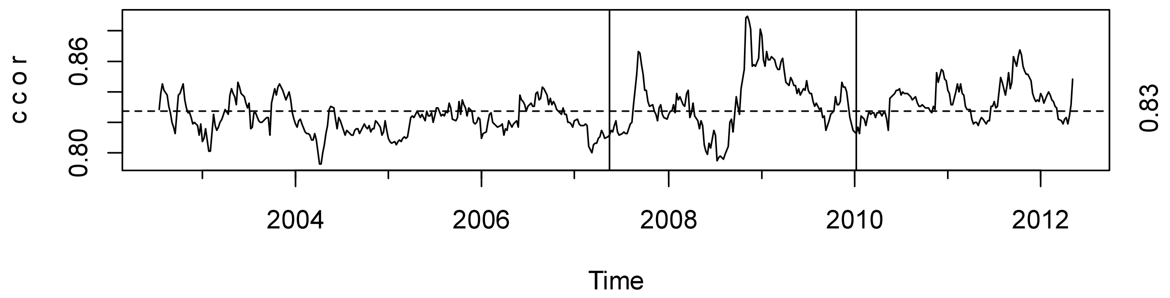
Figure 5.5 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on GO-GARCH NLS model

Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.

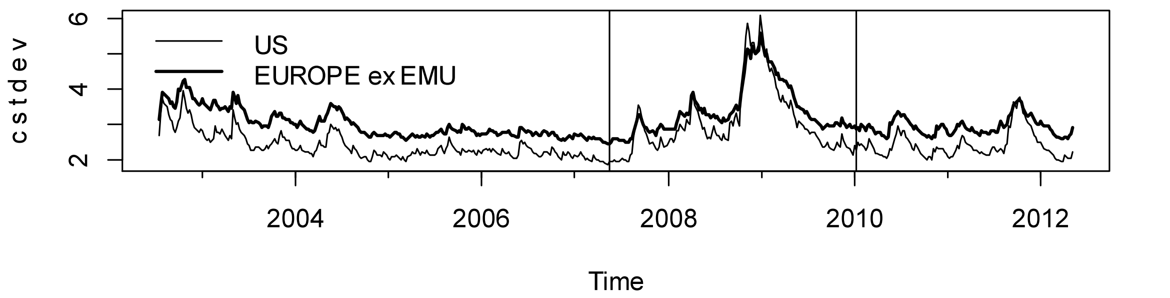




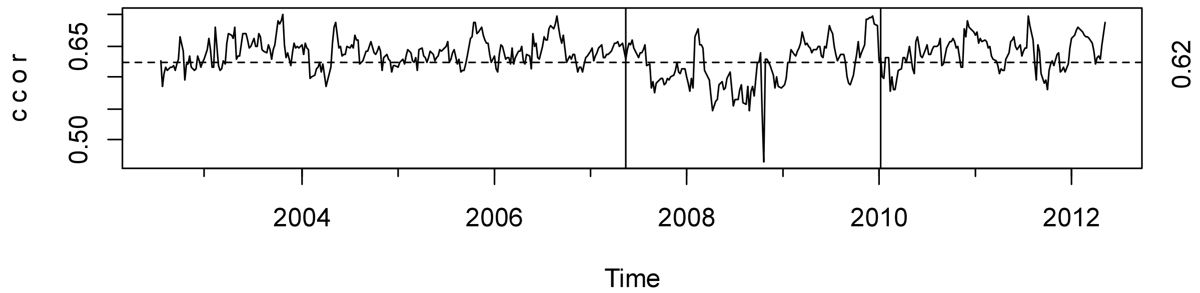
Conditional Correlation US & EUROPE ex EMU (GO-GARCH NLS)



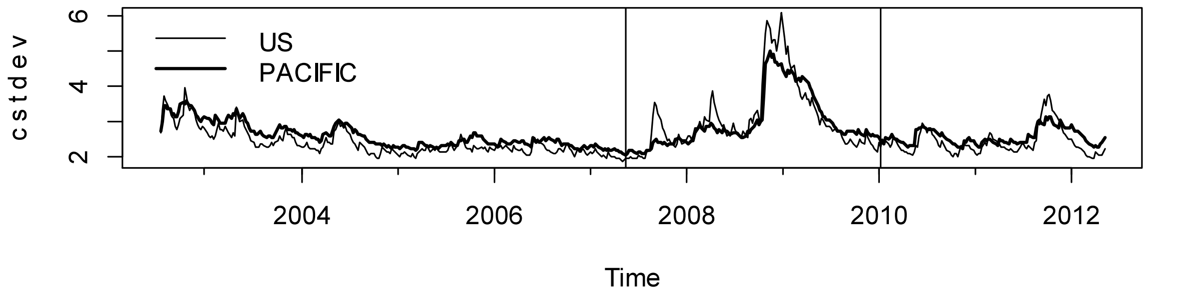
Conditional Volatility US & EUROPE ex EMU (GO-GARCH NLS)

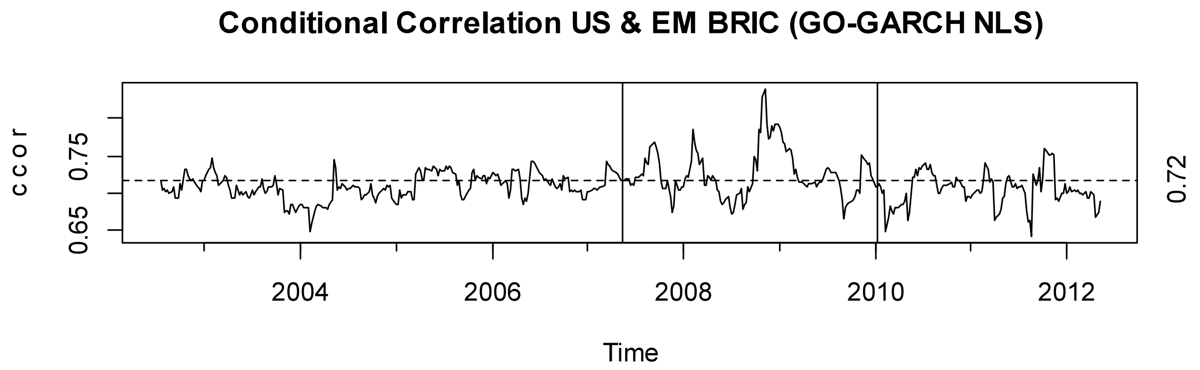


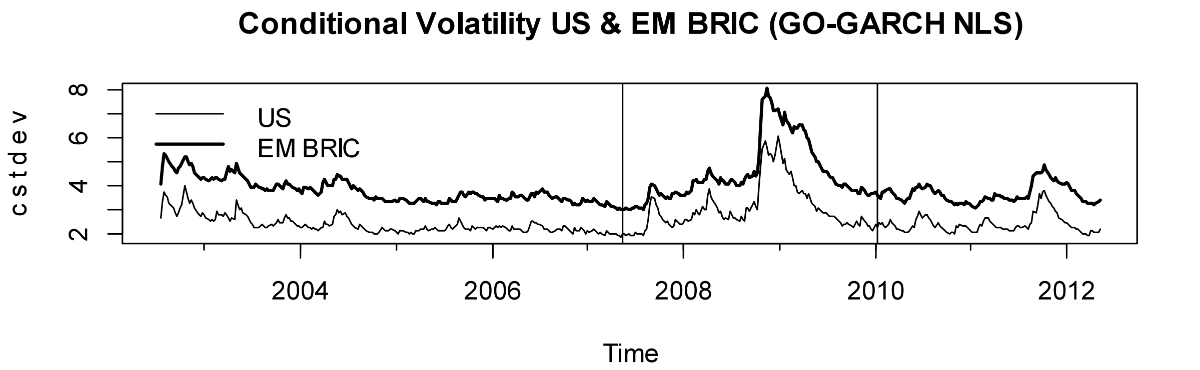
Conditional Correlation US & PACIFIC (GO-GARCH NLS)

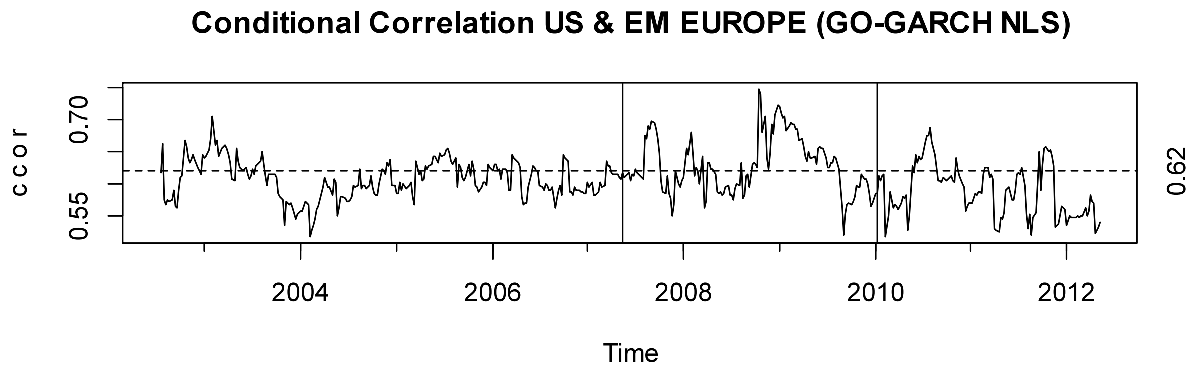


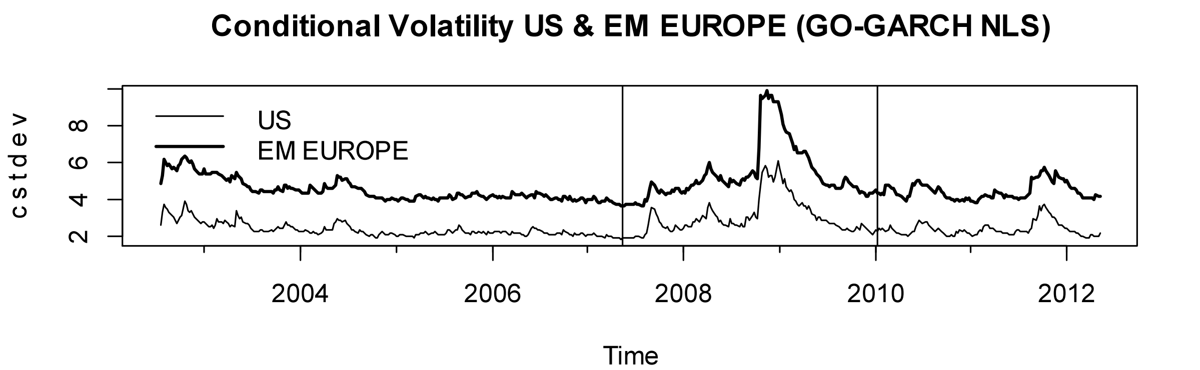
Conditional Volatility US & PACIFIC (GO-GARCH NLS)

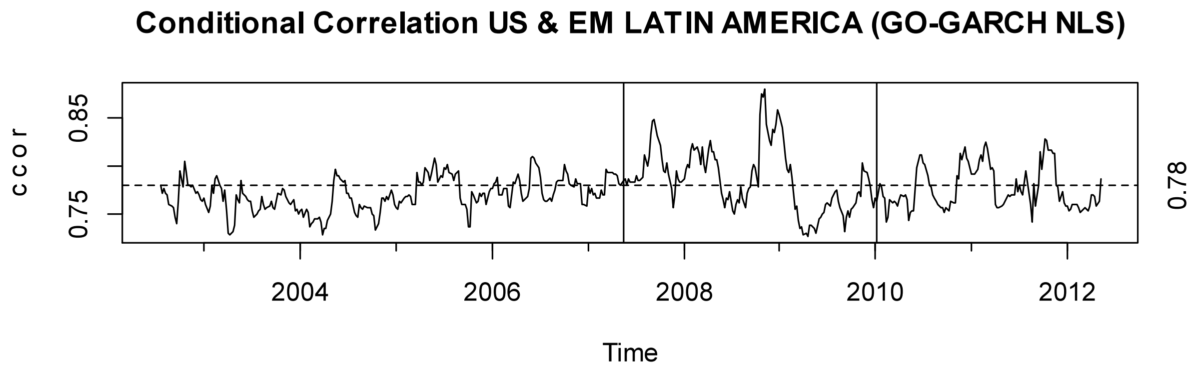


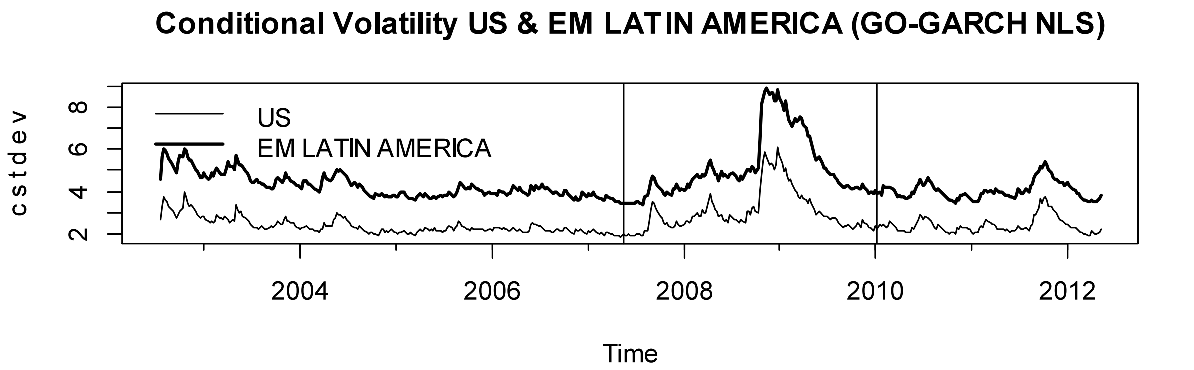

Conditional Correlation US & EM BRIC (GO-GARCH NLS)
ccor
0.65
0.75
0.72
2004
2006
2008
2010
2012
Time

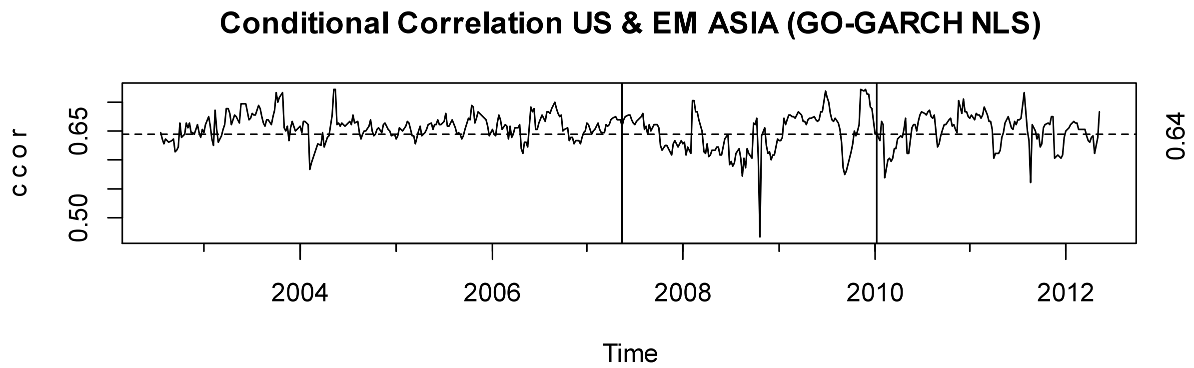

Conditional Volatility US & EM BRIC (GO-GARCH NLS)
cstdev
2
4
6
8
US
EM BRIC
2004
2006
2008
2010
2012
Time

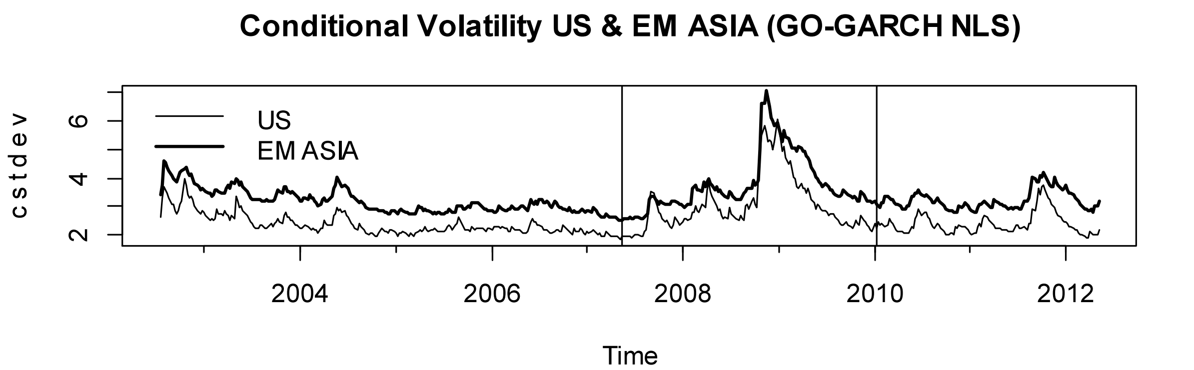

Conditional Correlation US & EM EUROPE (GO-GARCH NLS)
ccor
0.55
0.70
0.62
2004
2006
2008
2010
2012
Time

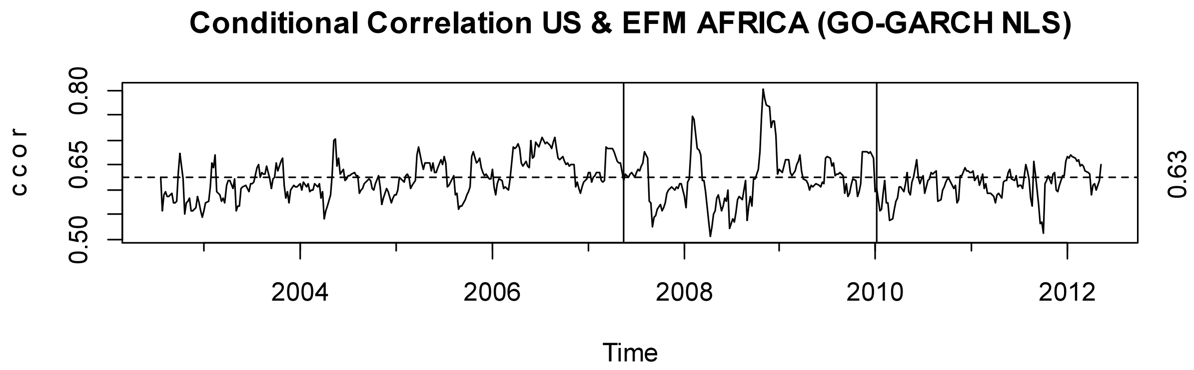

Conditional Volatility US & EM EUROPE (GO-GARCH NLS)
cstdev
2
4
6
8
US
EM EUROPE
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM LATIN AMERICA (GO-GARCH NLS)
ccor
0.75
0.85
0.78
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM LATIN AMERICA (GO-GARCH NLS)
cstdev
2
4
6
8
US
EM LATIN AMERICA
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM ASIA (GO-GARCH NLS)
ccor
0.50
0.65
0.64
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM ASIA (GO-GARCH NLS)
cstdev
2
4
6
US
EM ASIA
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EFM AFRICA (GO-GARCH NLS)
ccor
0.50
0.65
0.80
0.63
2004
2006
2008
2010
2012
Time

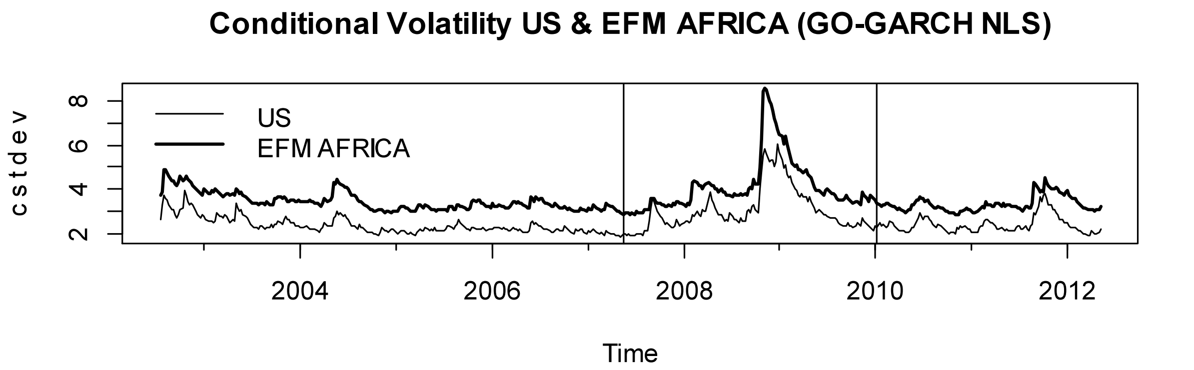
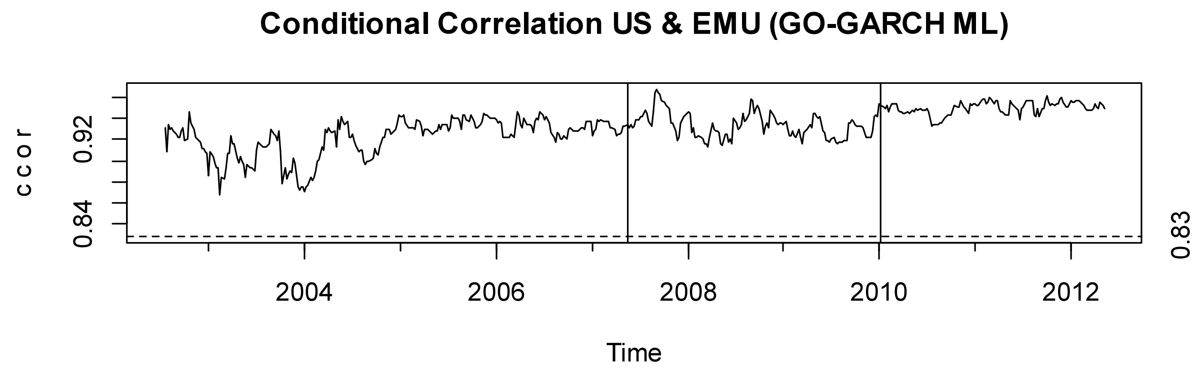
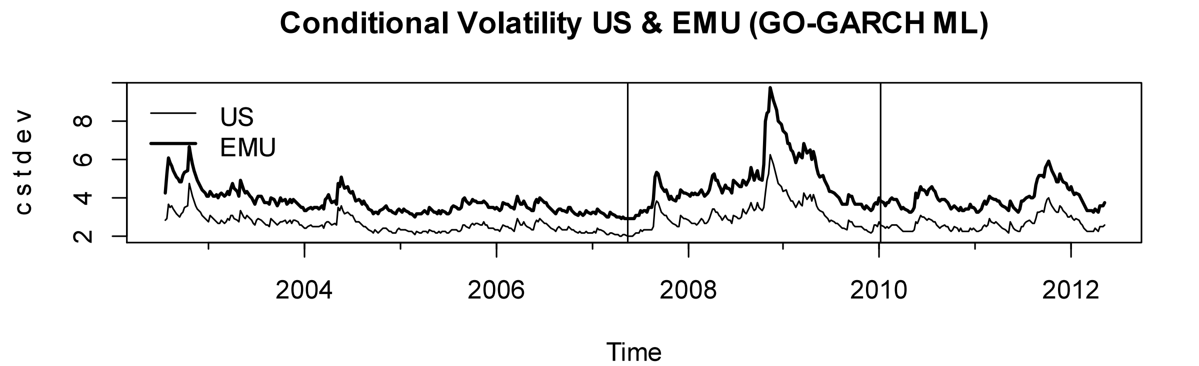
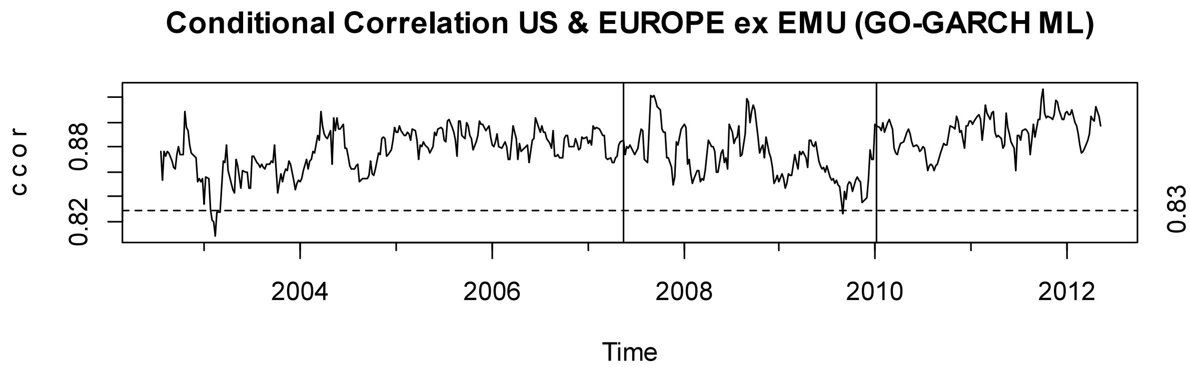

Conditional Volatility US & EFM AFRICA (GO-GARCH NLS)
cstdev
2
4
6
8
US
EFM AFRICA
2004
2006
2008
2010
2012
Time

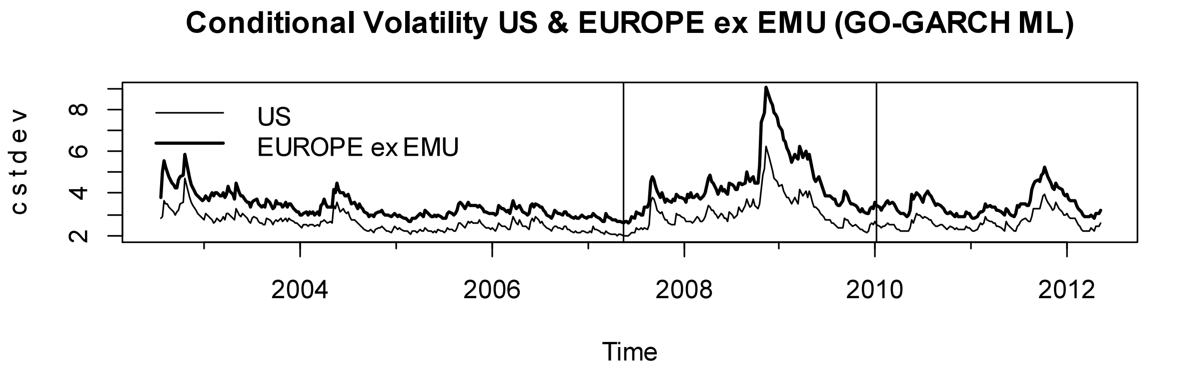
Figure 5.6 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on GO-GARCH ML model

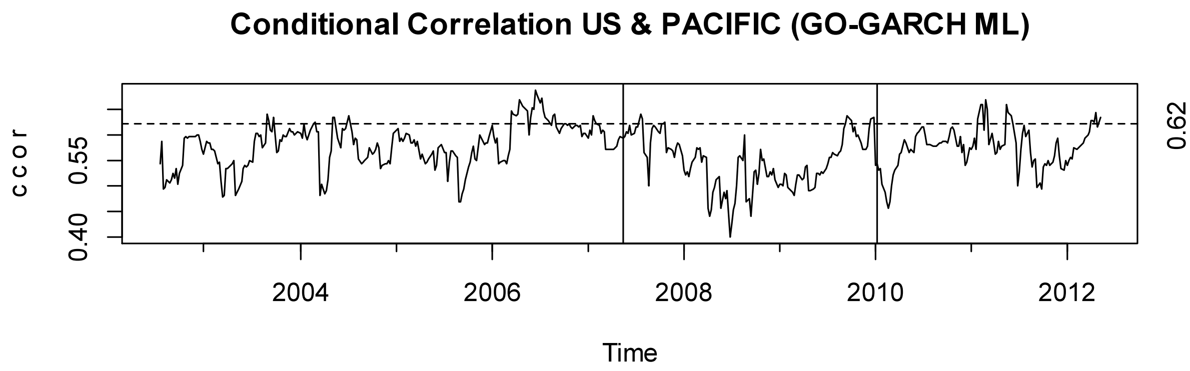
Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.

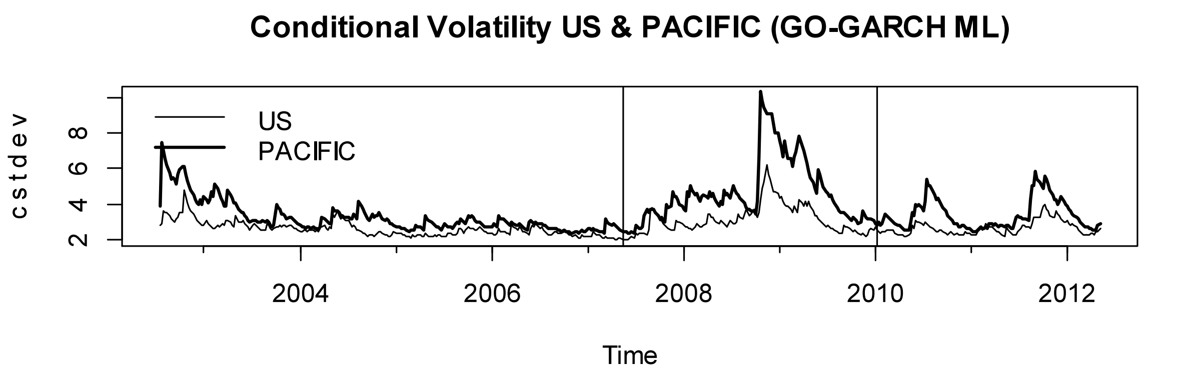


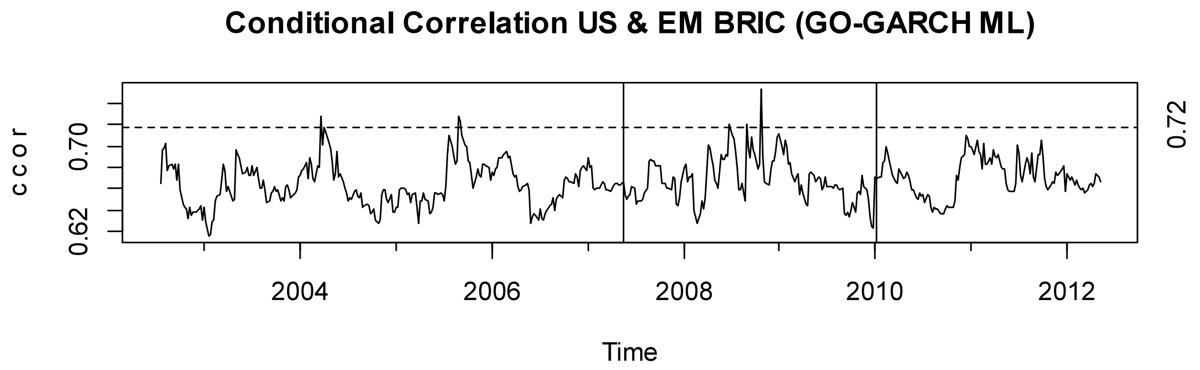


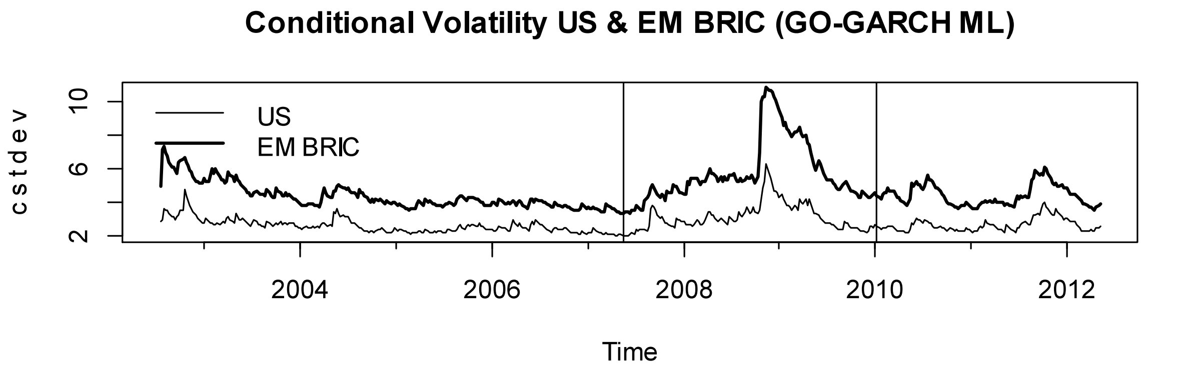

Conditional Correlation US & EUROPE ex EMU (GO-GARCH ML)
ccor
0.82
0.88
0.83
2004
2006
2008
2010
2012
Time

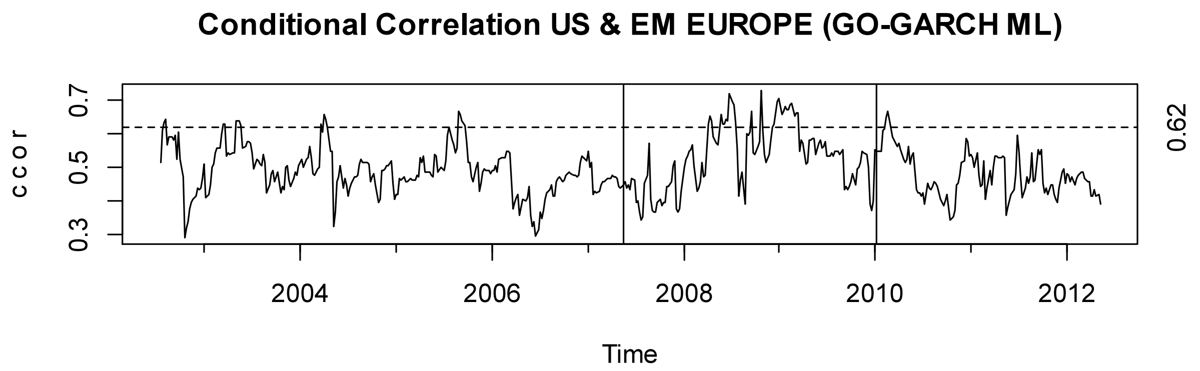

Conditional Volatility US & EUROPE ex EMU (GO-GARCH ML)
cstdev
2
4
6
8
US
EUROPE ex EMU
2004
2006
2008
2010
2012
Time

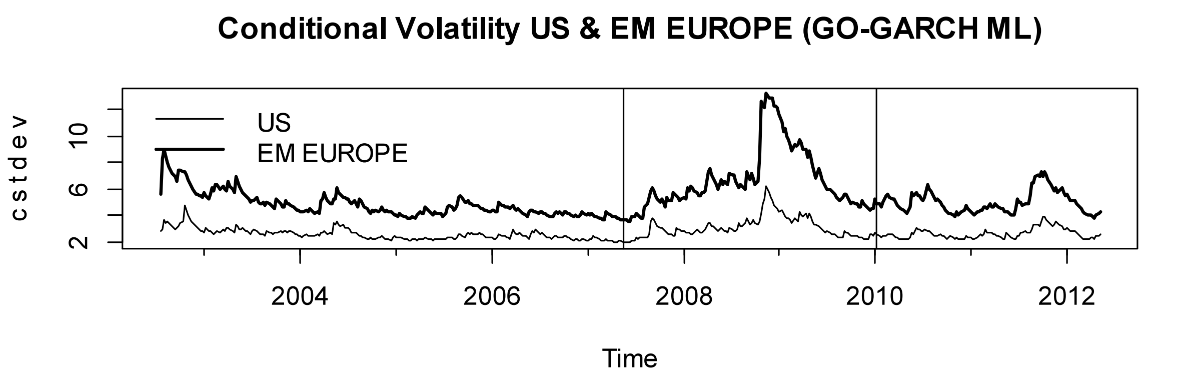

Conditional Correlation US & PACIFIC (GO-GARCH ML)
ccor
0.40
0.55
0.62
2004
2006
2008
2010
2012
Time

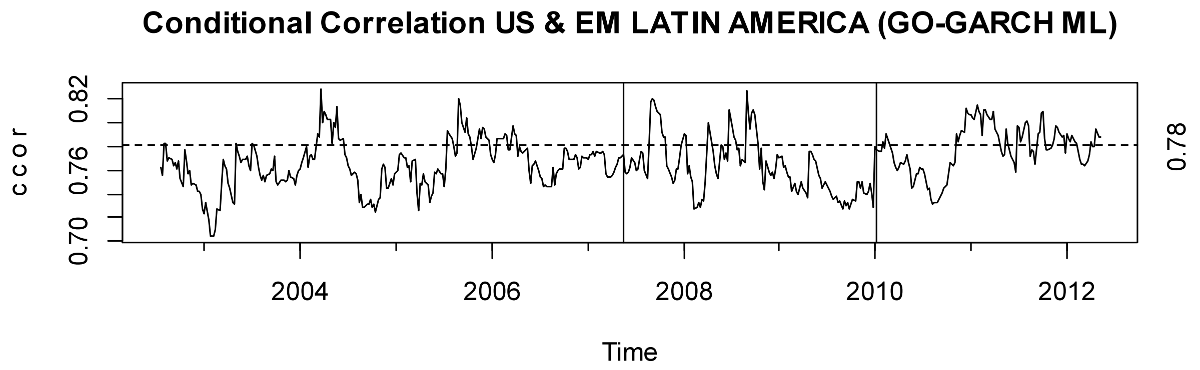

Conditional Volatility US & PACIFIC (GO-GARCH ML)
cstdev
2
4
6
8
US
PACIFIC
2004
2006
2008
2010
2012
Time

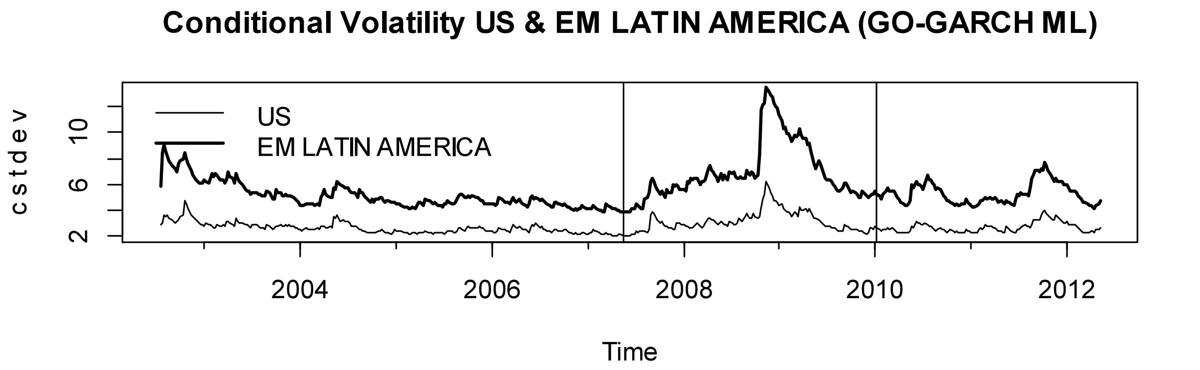

Conditional Correlation US & EM BRIC (GO-GARCH ML)
ccor
0.62
0.70
0.72
2004
2006
2008
2010
2012
Time

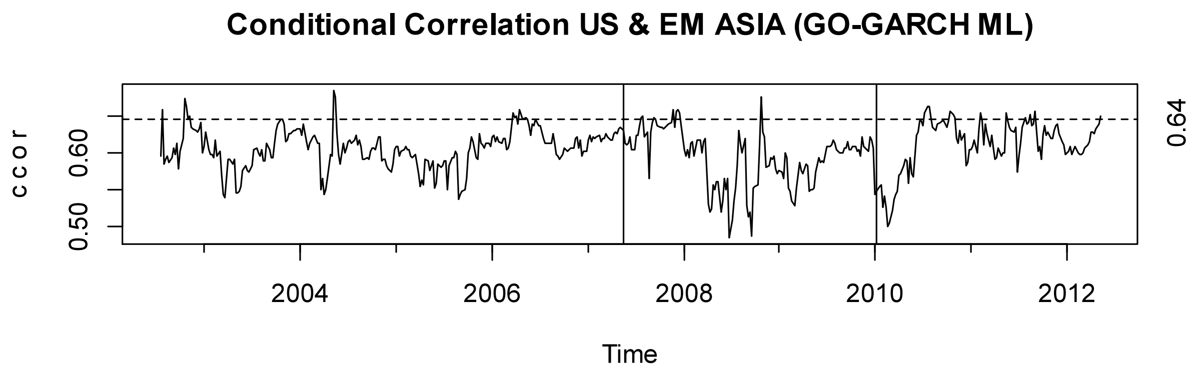

Conditional Volatility US & EM BRIC (GO-GARCH ML)
cstdev
2
6
10
US
EM BRIC
2004
2006
2008
2010
2012
Time

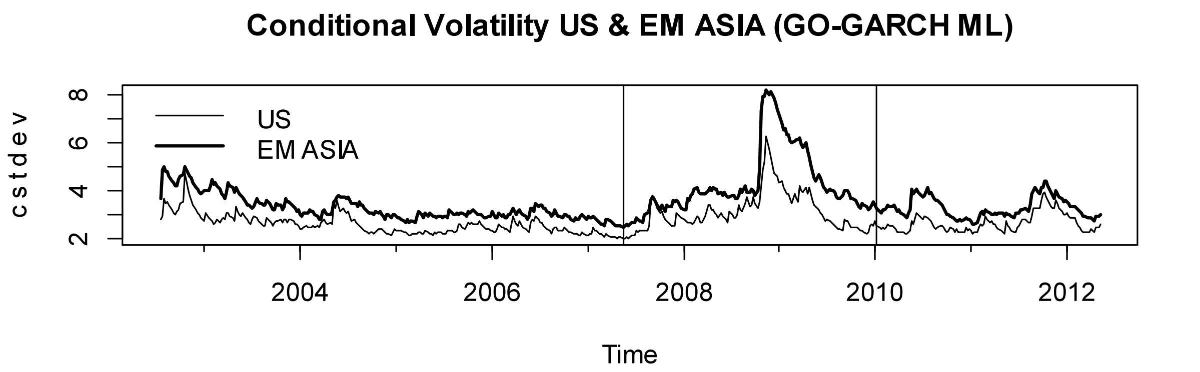

Conditional Correlation US & EM EUROPE (GO-GARCH ML)
ccor
0.3
0.5
0.7
0.62
2004
2006
2008
2010
2012
Time

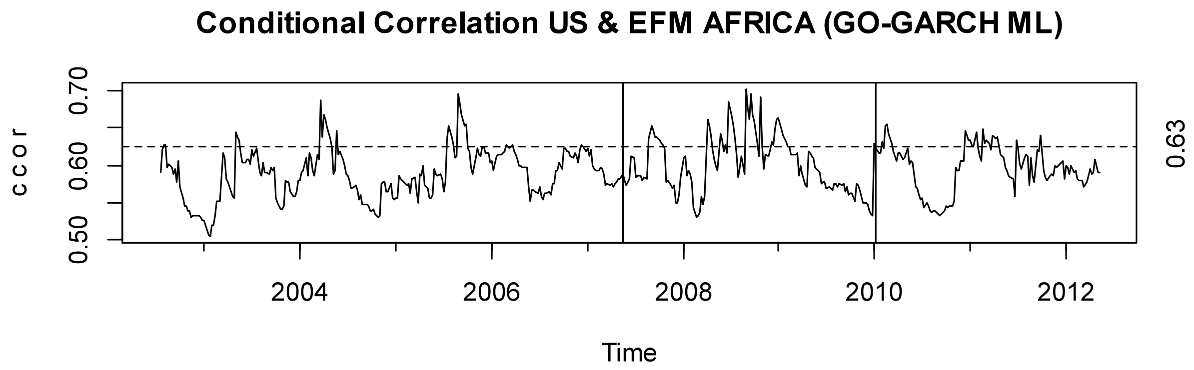

Conditional Volatility US & EM EUROPE (GO-GARCH ML)
cstdev
2
6
10
US
EM EUROPE
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM LATIN AMERICA (GO-GARCH ML)
ccor
0.70
0.76
0.82
0.78
2004
2006
2008
2010
2012
Time

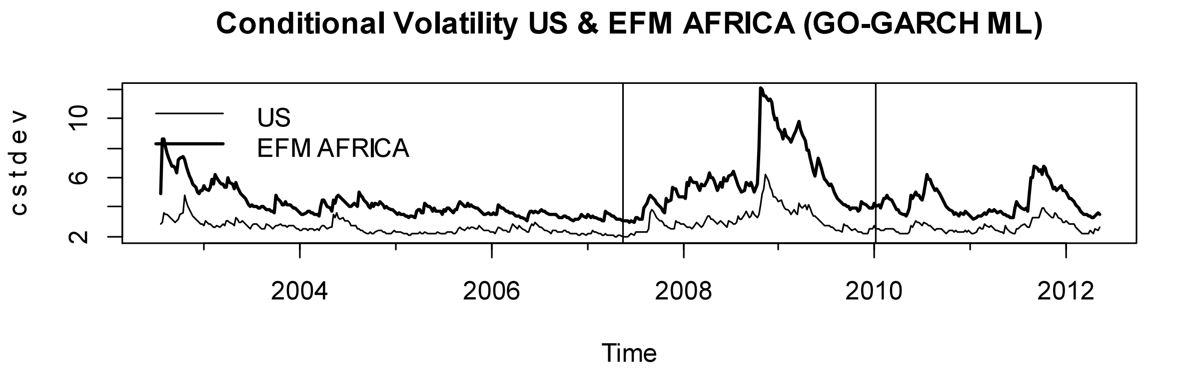

Conditional Volatility US & EM LATIN AMERICA (GO-GARCH ML)
cstdev
2
6
10
US
EM LATIN AMERICA
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM ASIA (GO-GARCH ML)
ccor
0.50
0.60
0.64
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM ASIA (GO-GARCH ML)
cstdev
2
4
6
8
US
EM ASIA
2004
2006
2008
2010
2012
Time



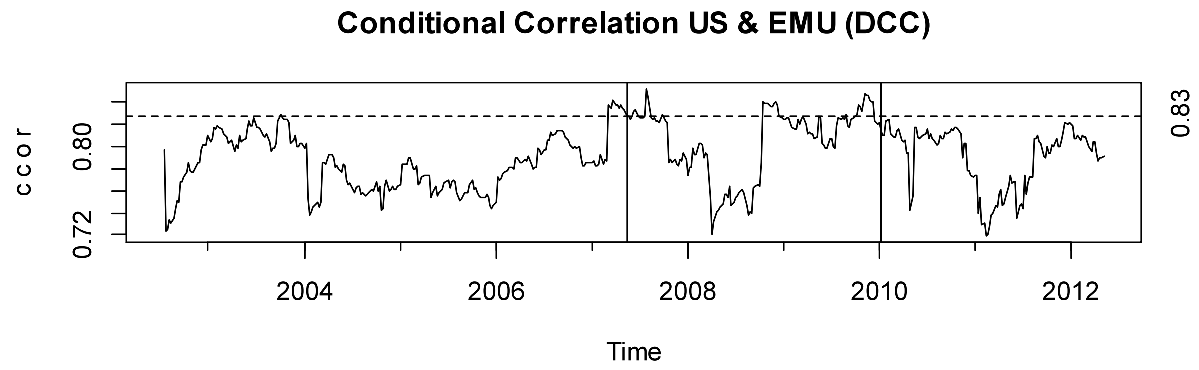
Conditional Correlation US & EFM AFRICA (GO-GARCH ML)
ccor
0.50
0.60
0.70
0.63
2004
2006
2008
2010
2012
Time

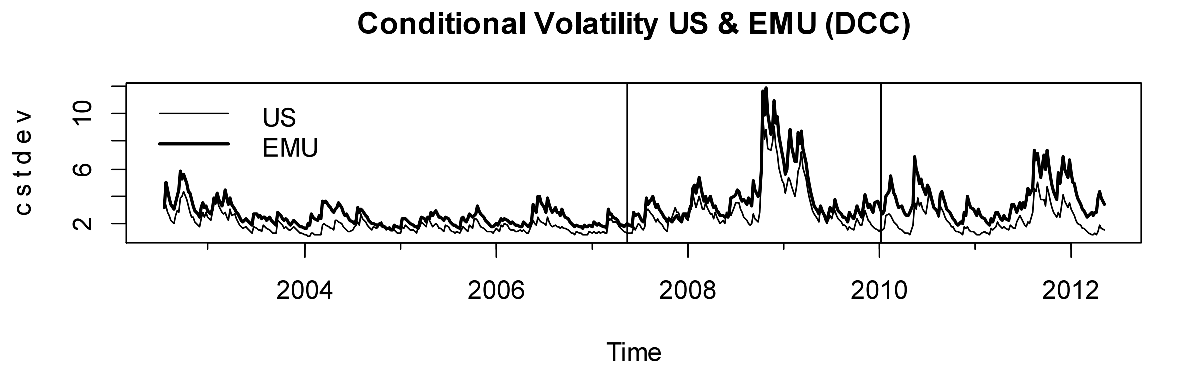


Conditional Volatility US & EFM AFRICA (GO-GARCH ML)
cstdev
2
6
10
US
EFM AFRICA
2004
2006
2008
2010
2012
Time

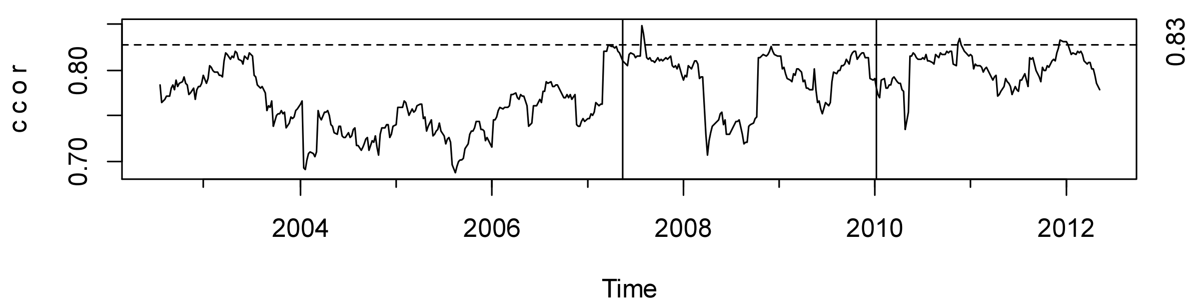
Figure 5.7 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on DCC model

Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.

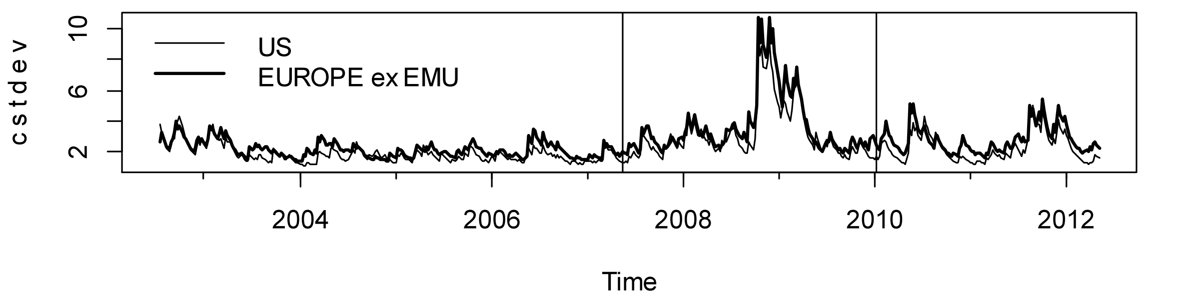




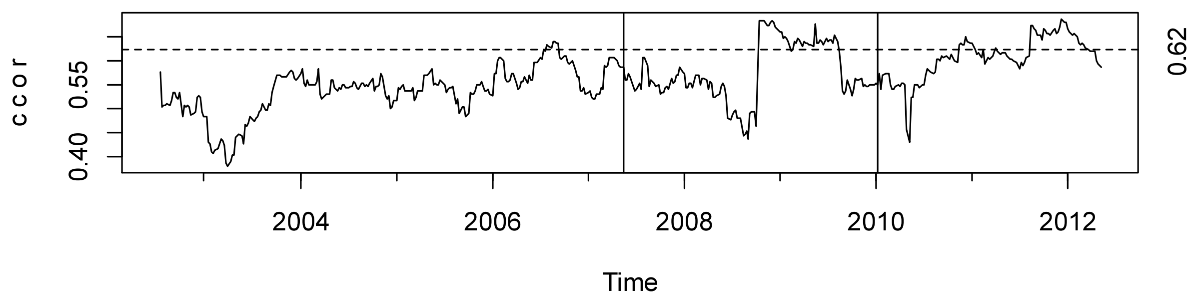
Conditional Correlation US & EUROPE ex EMU (DCC)



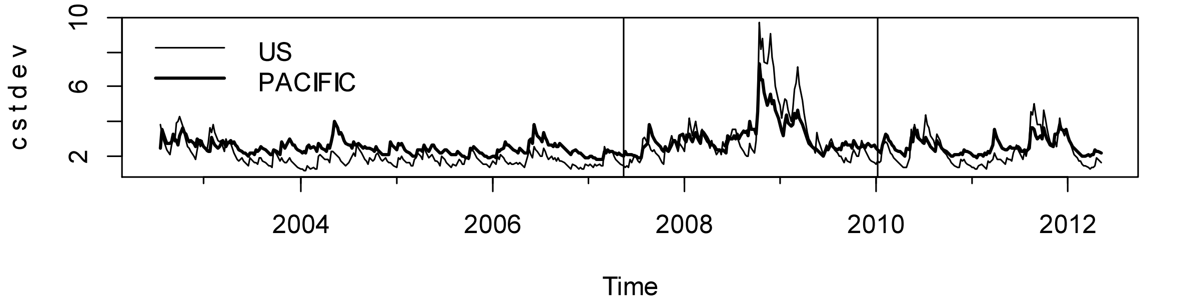
Conditional Volatility US & EUROPE ex EMU (DCC)



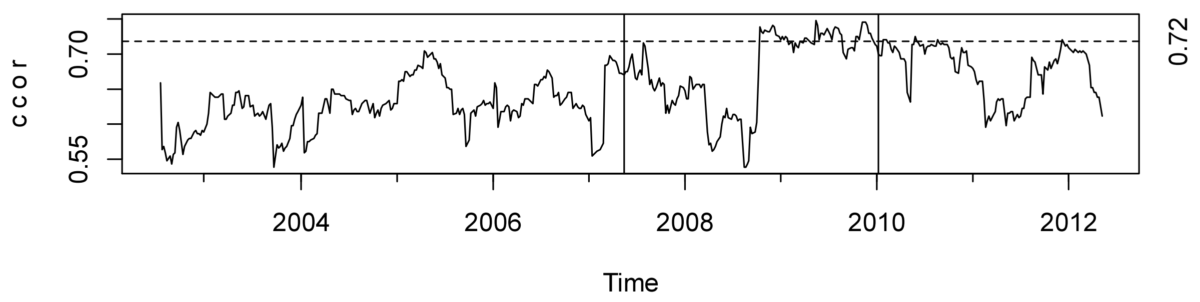
Conditional Correlation US & PACIFIC (DCC)



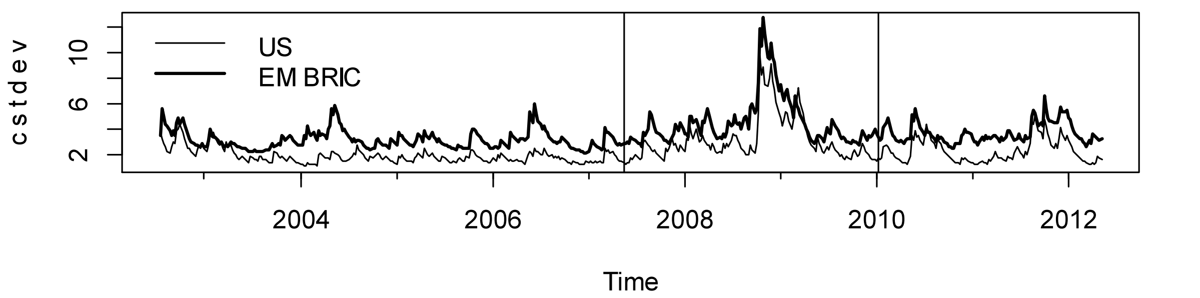
Conditional Volatility US & PACIFIC (DCC)



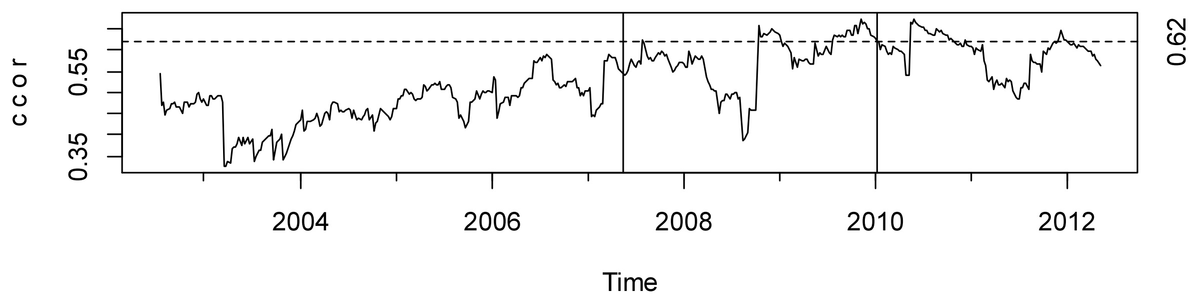
Conditional Correlation US & EM BRIC (DCC)



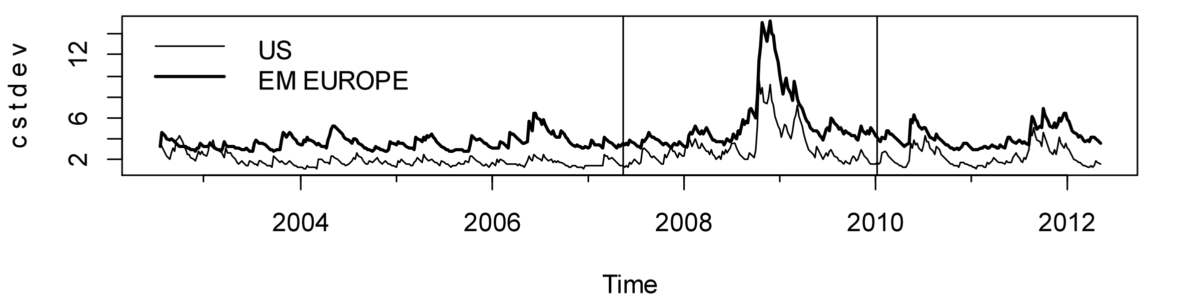
Conditional Volatility US & EM BRIC (DCC)



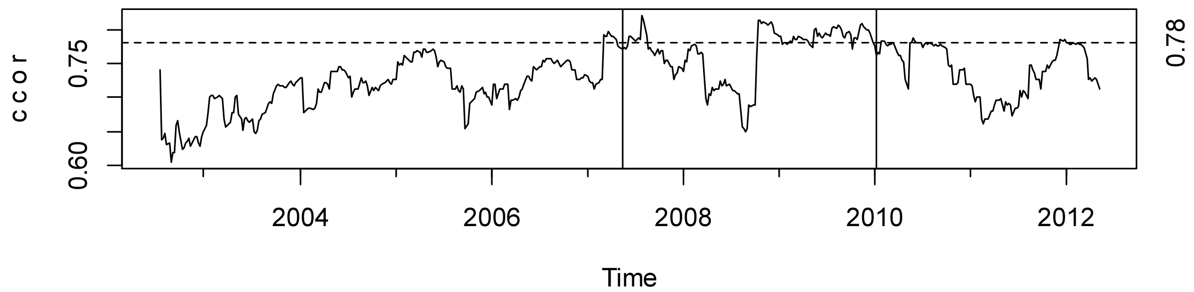
Conditional Correlation US & EM EUROPE (DCC)



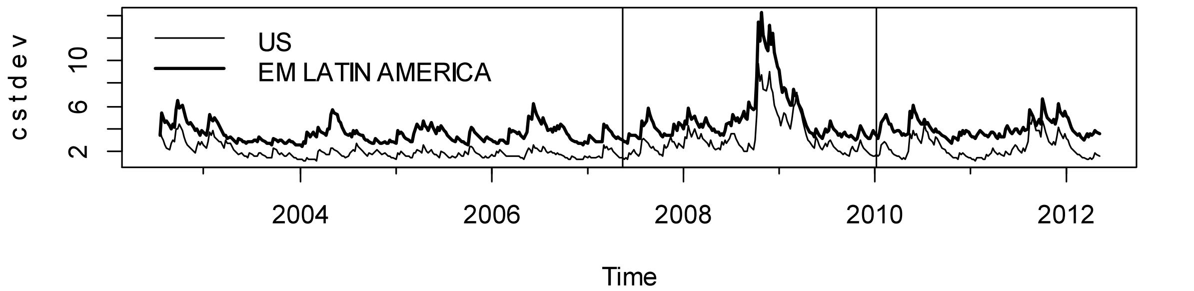
Conditional Volatility US & EM EUROPE (DCC)



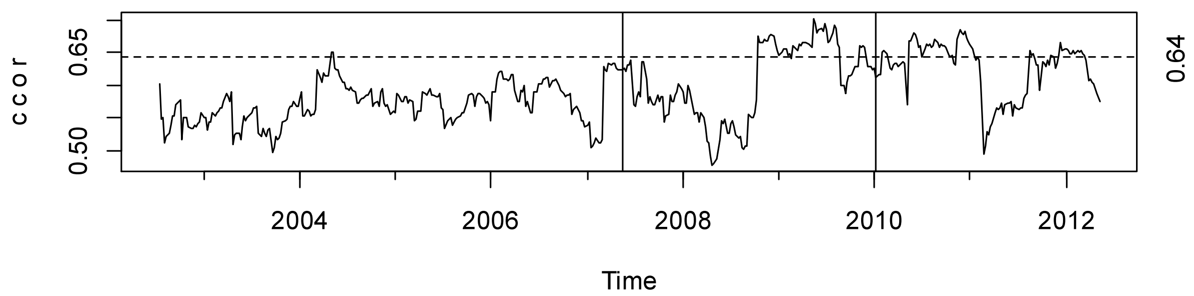
Conditional Correlation US & EM LATIN AMERICA (DCC)



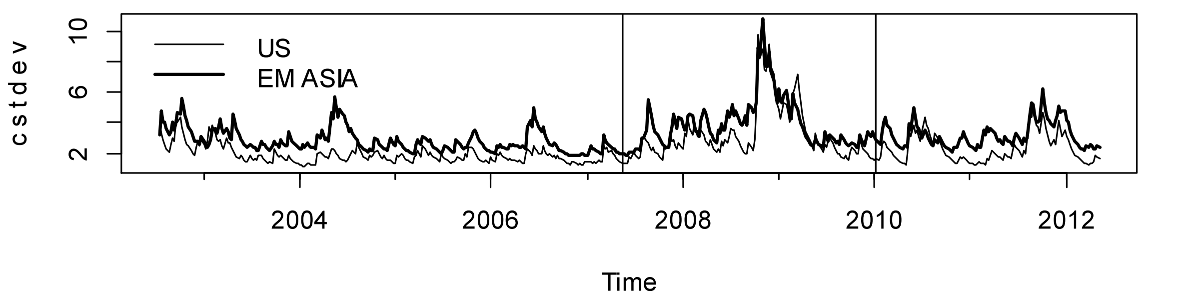
Conditional Volatility US & EM LATIN AMERICA (DCC)

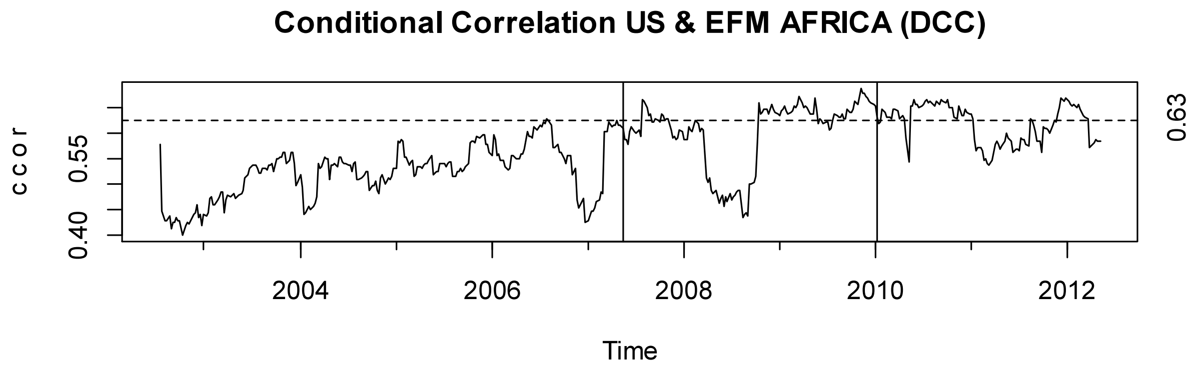


Conditional Correlation US & EM ASIA (DCC)



Conditional Volatility US & EM ASIA (DCC)




Conditional Correlation US & EFM AFRICA (DCC)
ccor
0.40
0.55
0.63
2004
2006
2008
2010
2012
Time

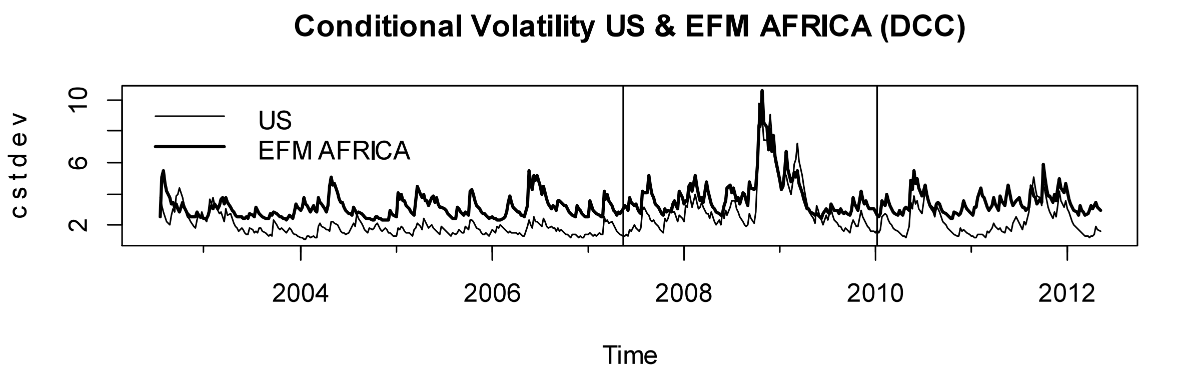
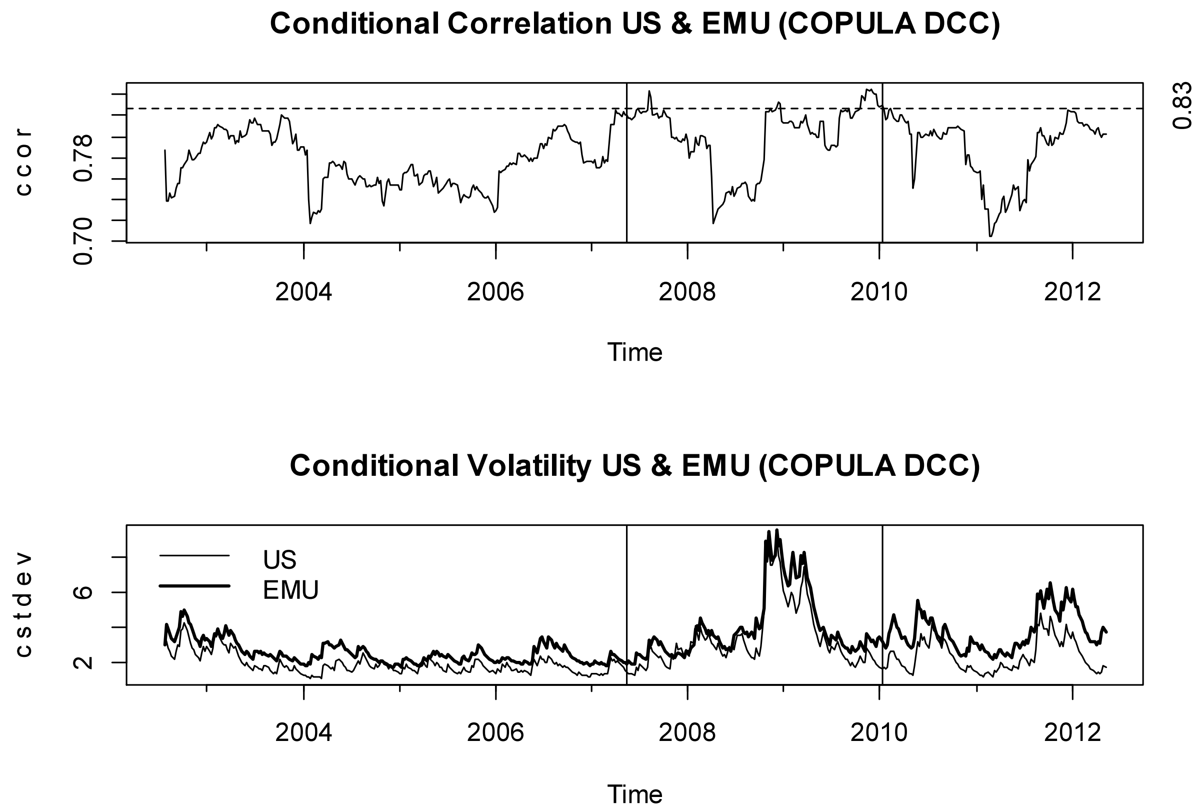
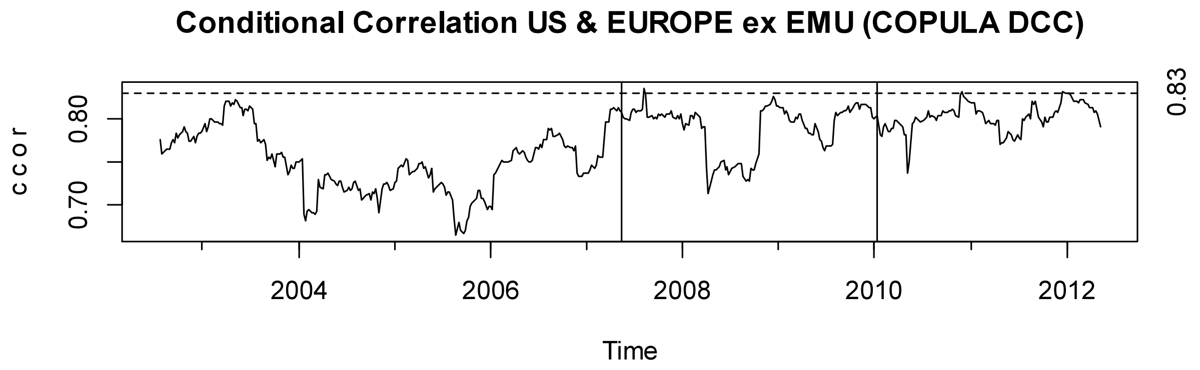
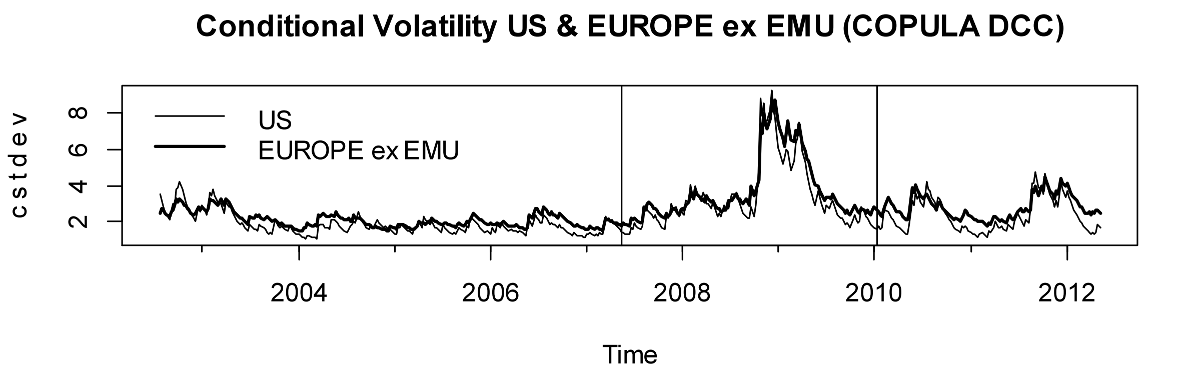

Conditional Volatility US & EFM AFRICA (DCC)
cstdev
2
6
10
US
EFM AFRICA
2004
2006
2008
2010
2012
Time

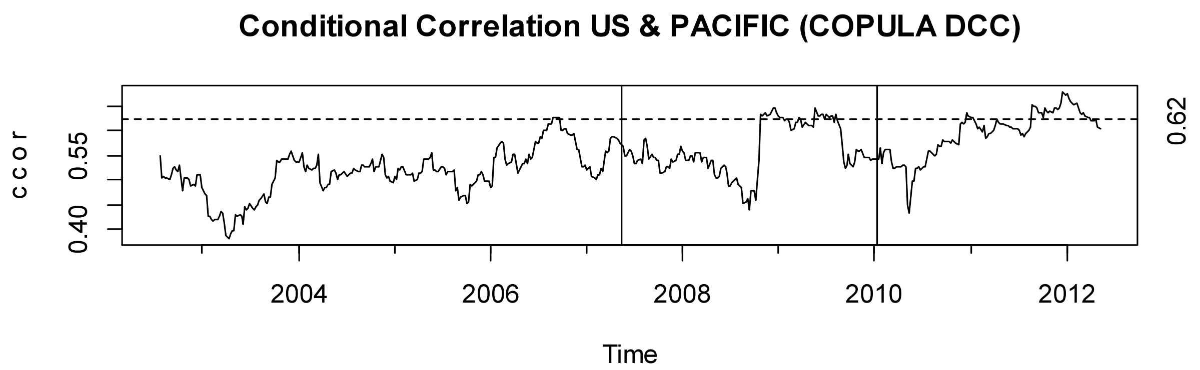
Figure 5.8 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on Copula DCC model

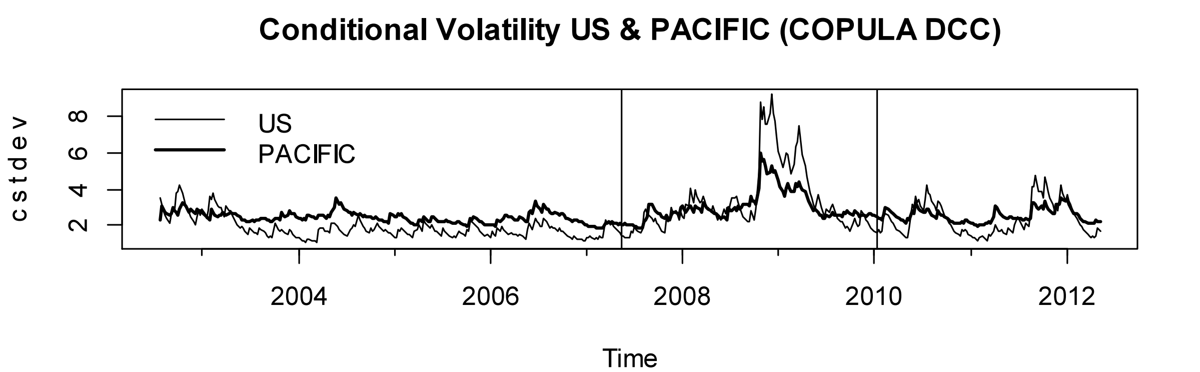
Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.

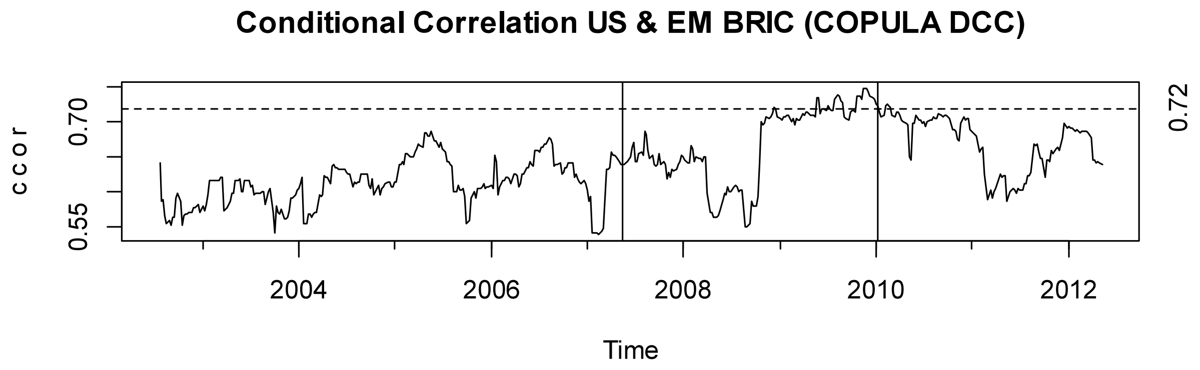


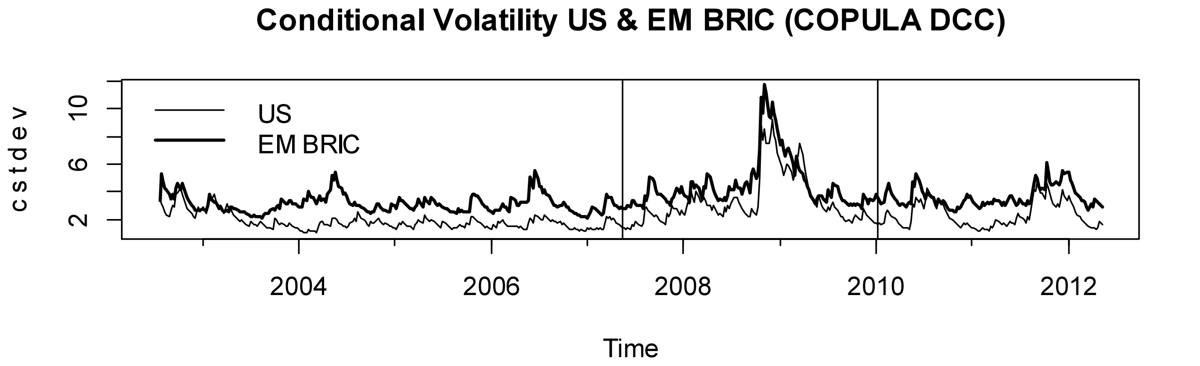

Conditional Correlation US & EUROPE ex EMU (COPULA DCC)
ccor
0.70
0.80
0.83
2004
2006
2008
2010
2012
Time

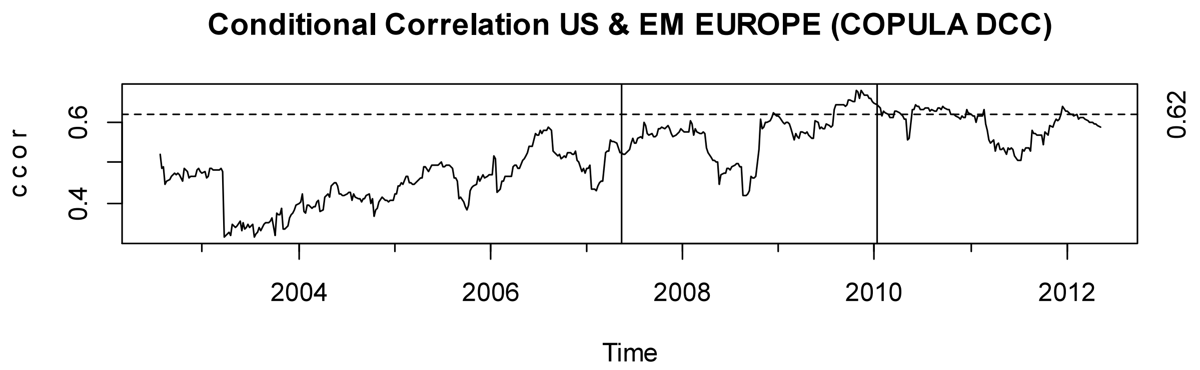

Conditional Volatility US & EUROPE ex EMU (COPULA DCC)
cstdev
2
4
6
8
US
EUROPE ex EMU
2004
2006
2008
2010
2012
Time

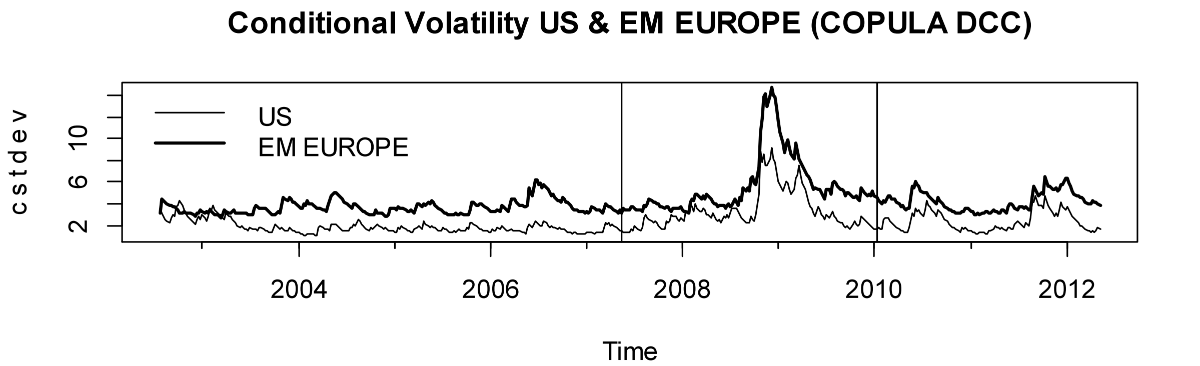

Conditional Correlation US & PACIFIC (COPULA DCC)
ccor
0.40
0.55
0.62
2004
2006
2008
2010
2012
Time


Conditional Volatility US & PACIFIC (COPULA DCC)
cstdev
2
4
6
8
US
PACIFIC
2004
2006
2008
2010
2012
Time

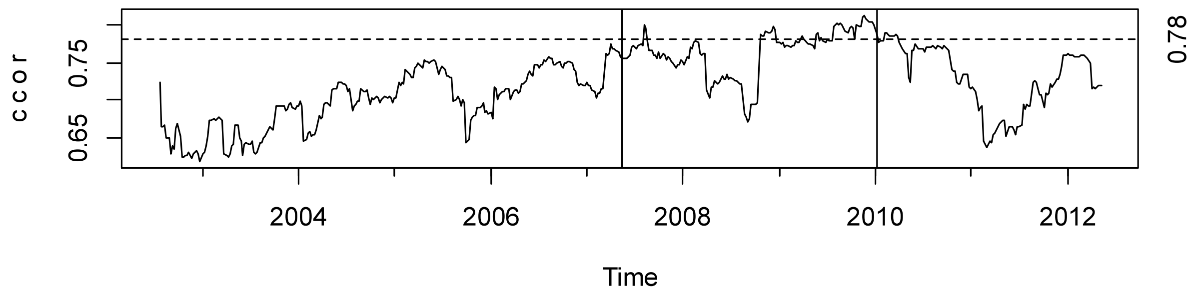

Conditional Correlation US & EM BRIC (COPULA DCC)
ccor
0.55
0.70
0.72
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM BRIC (COPULA DCC)
cstdev
2
6
10
US
EM BRIC
2004
2006
2008
2010
2012
Time

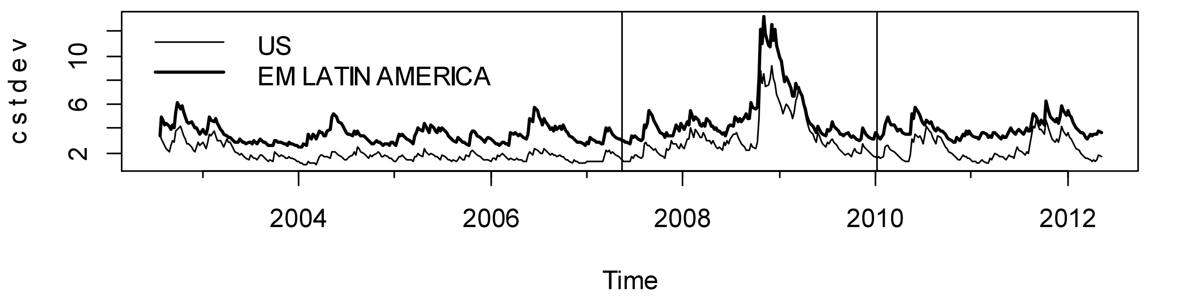

Conditional Correlation US & EM EUROPE (COPULA DCC)
ccor
0.4
0.6
0.62
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM EUROPE (COPULA DCC)
cstdev
2
6
10
US
EM EUROPE
2004
2006
2008
2010
2012
Time

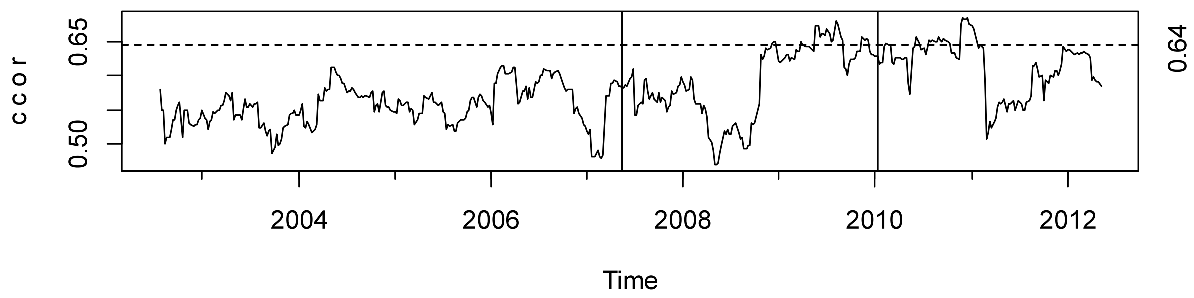
Conditional Correlation US & EM LATIN AMERICA (COPULA DCC)



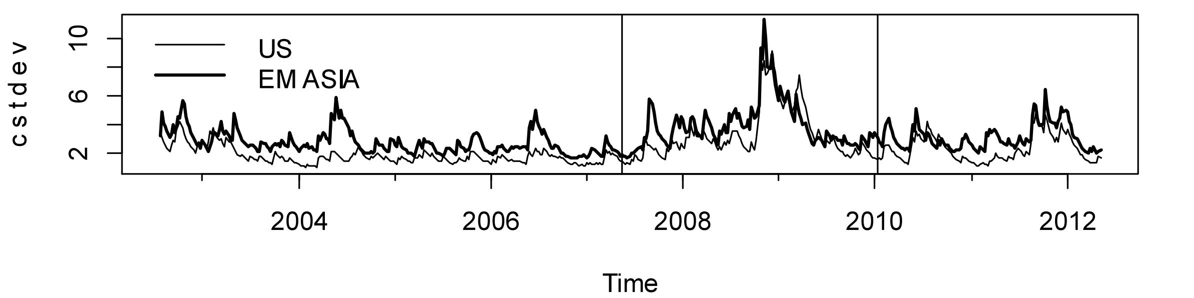
Conditional Volatility US & EM LATIN AMERICA (COPULA DCC)

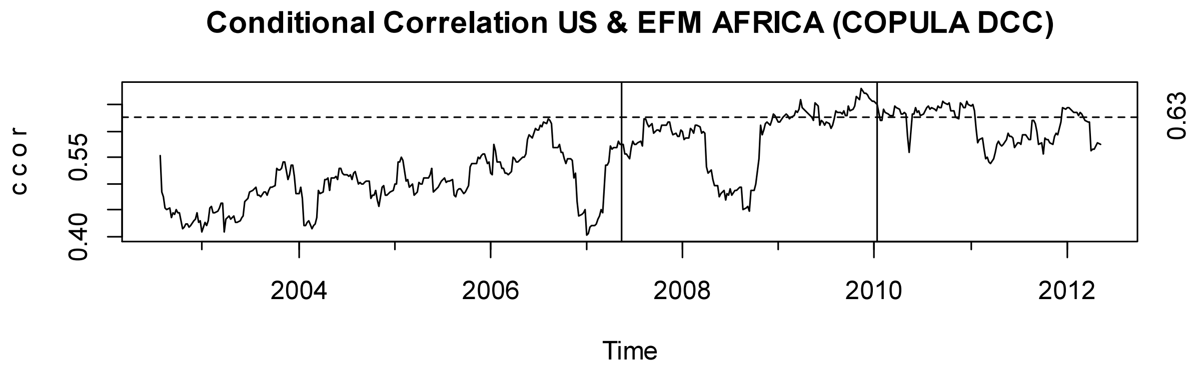


Conditional Correlation US & EM ASIA (COPULA DCC)



Conditional Volatility US & EM ASIA (COPULA DCC)




Conditional Correlation US & EFM AFRICA (COPULA DCC)
ccor
0.40
0.55
0.63
2004
2006
2008
2010
2012
Time

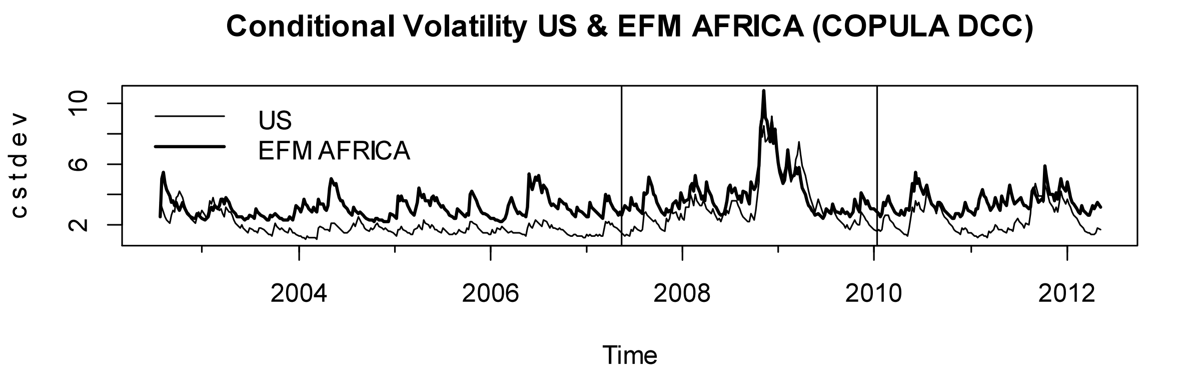
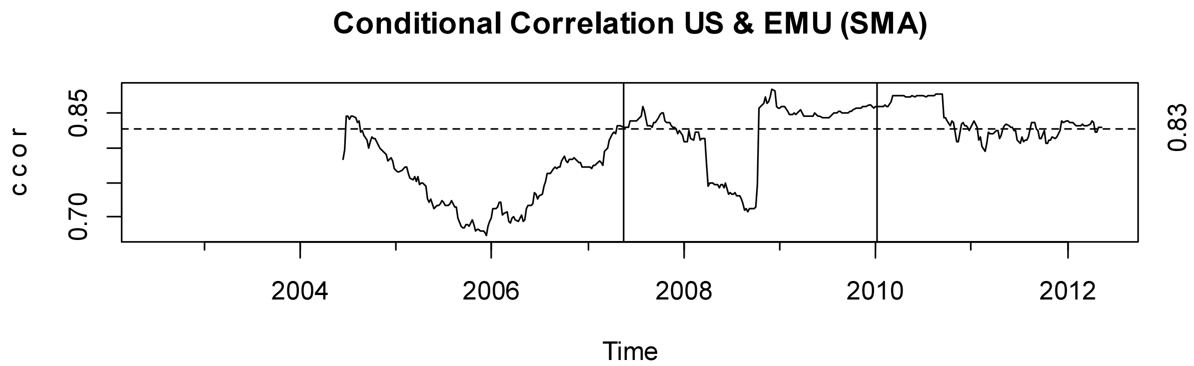
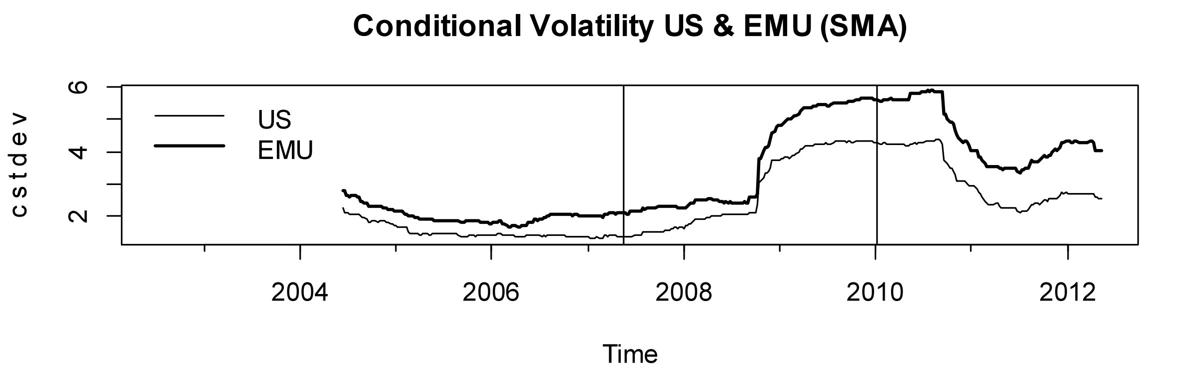

Conditional Volatility US & EFM AFRICA (COPULA DCC)
cstdev
2
6
10
US
EFM AFRICA
2004
2006
2008
2010
2012
Time

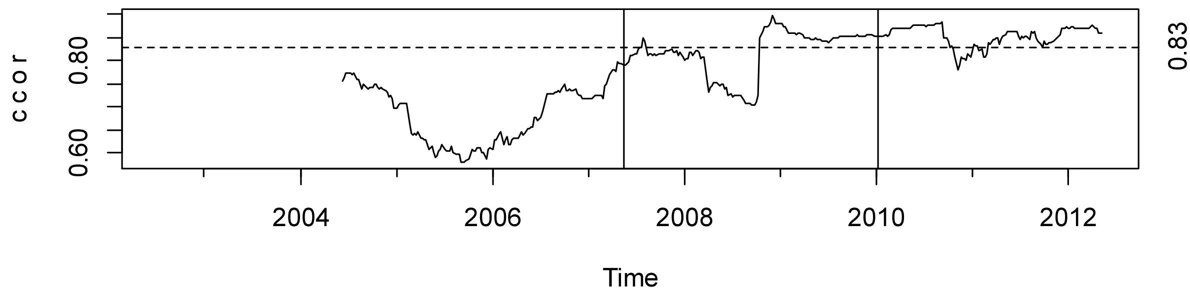
Figure 5.9 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on SMA model

Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.

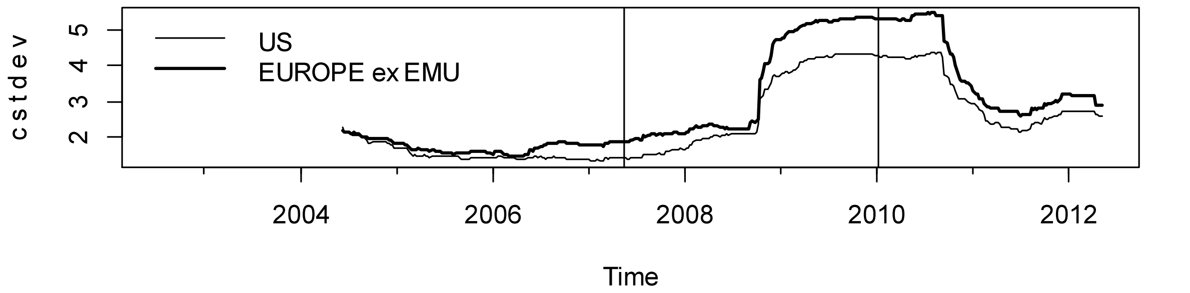




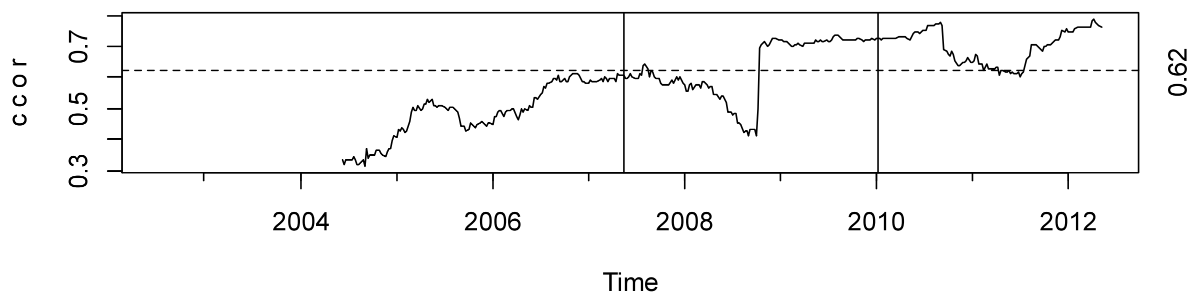
Conditional Correlation US & EUROPE ex EMU (SMA)



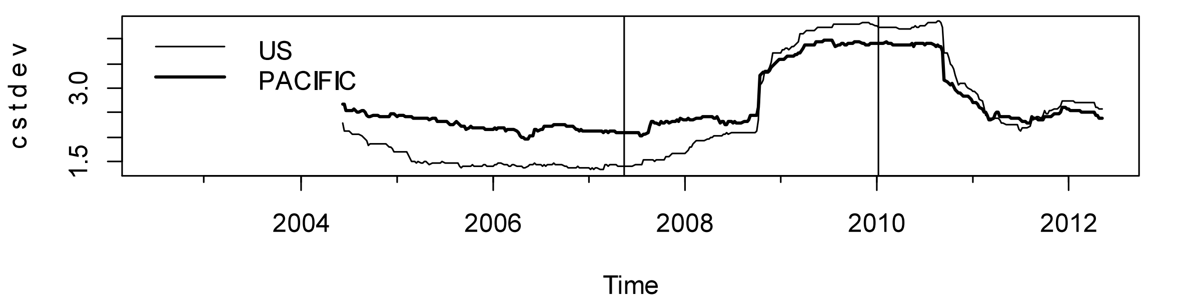
Conditional Volatility US & EUROPE ex EMU (SMA)



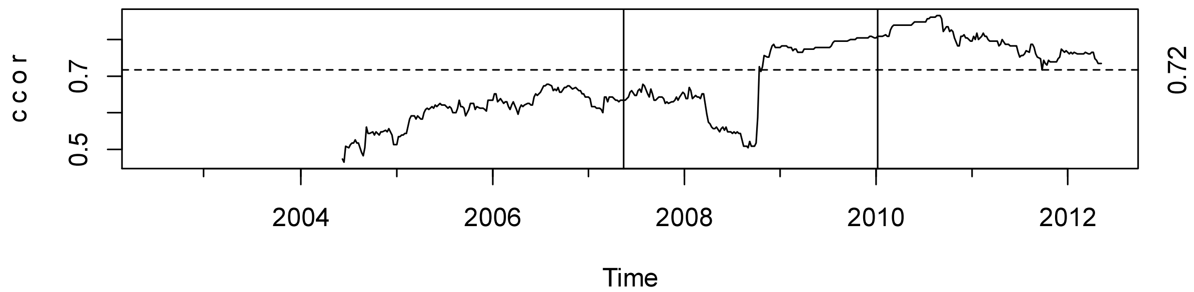
Conditional Correlation US & PACIFIC (SMA)



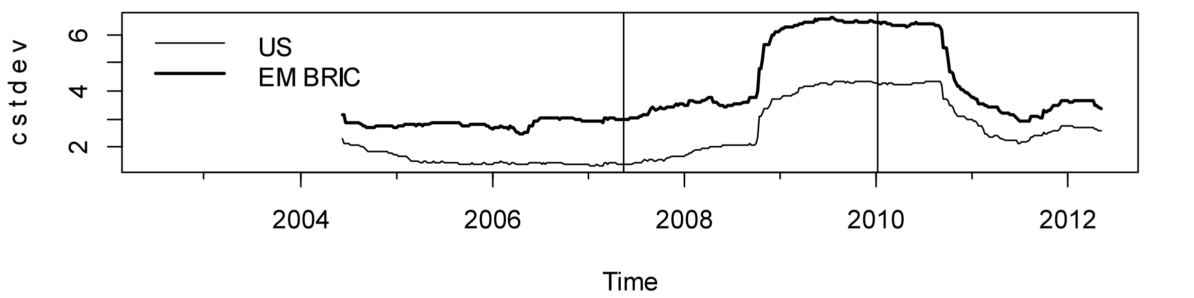
Conditional Volatility US & PACIFIC (SMA)



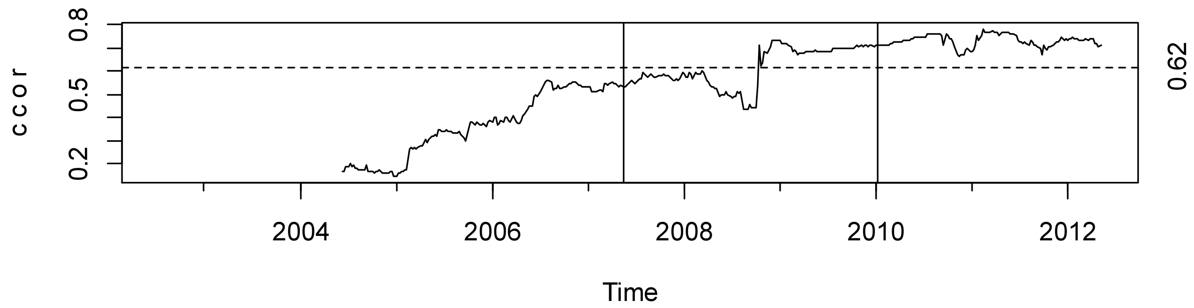
Conditional Correlation US & EM BRIC (SMA)



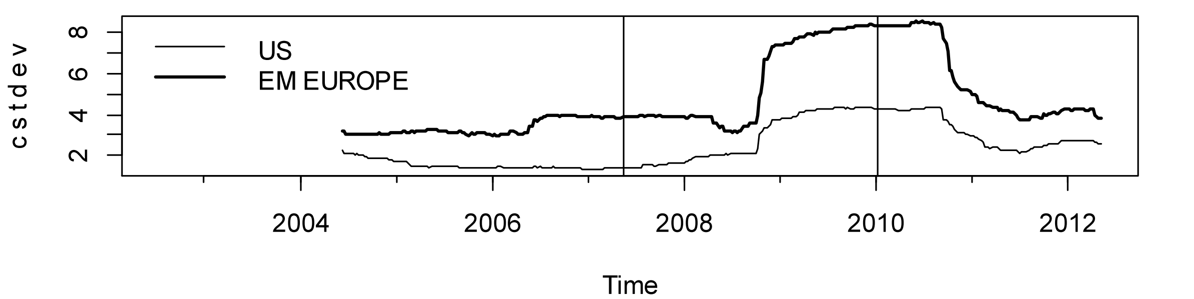
Conditional Volatility US & EM BRIC (SMA)



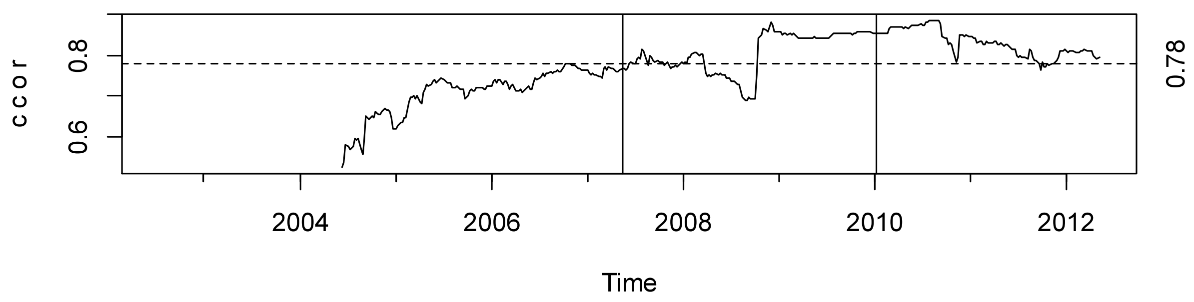
Conditional Correlation US & EM EUROPE (SMA)



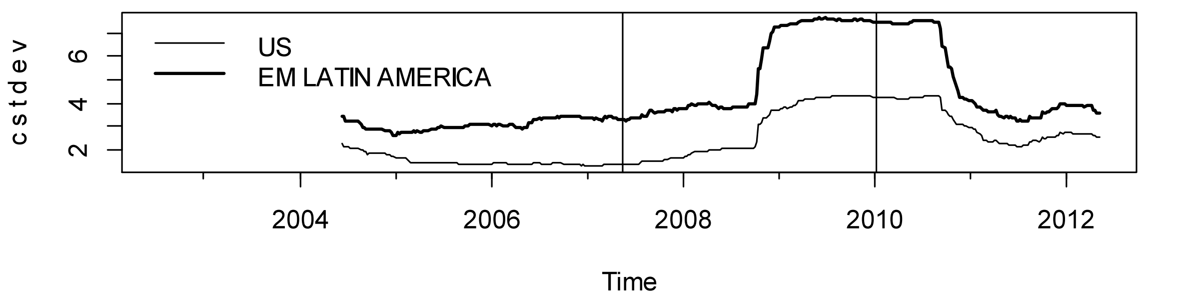
Conditional Volatility US & EM EUROPE (SMA)



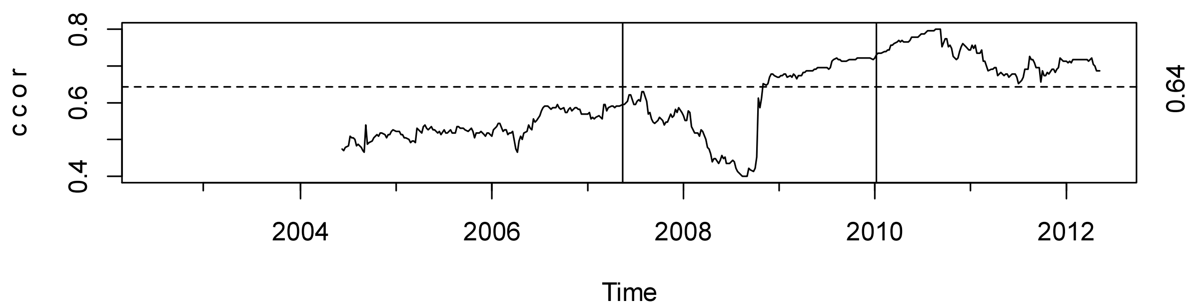
Conditional Correlation US & EM LATIN AMERICA (SMA)



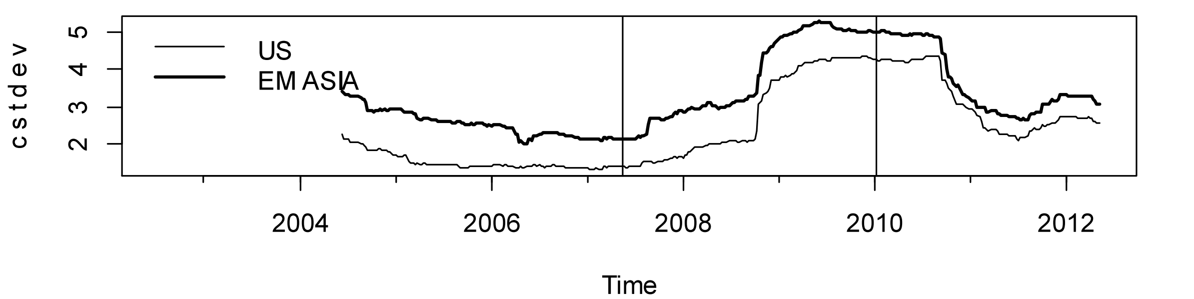
Conditional Volatility US & EM LATIN AMERICA (SMA)

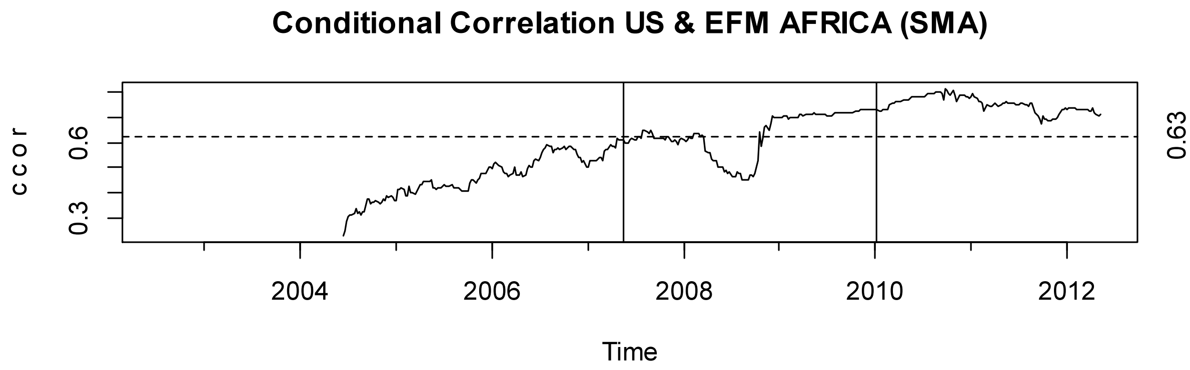


Conditional Correlation US & EM ASIA (SMA)



Conditional Volatility US & EM ASIA (SMA)




Conditional Correlation US & EFM AFRICA (SMA)
ccor
0.3
0.6
0.63
2004
2006
2008
2010
2012
Time

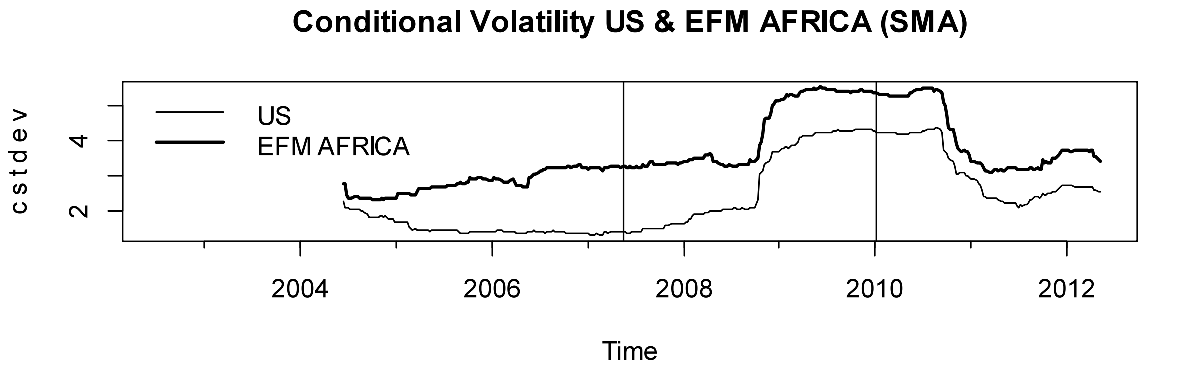
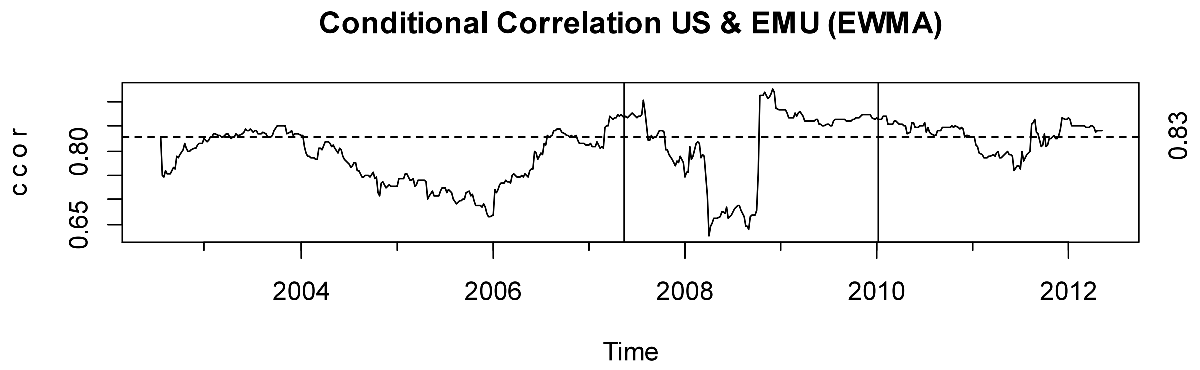
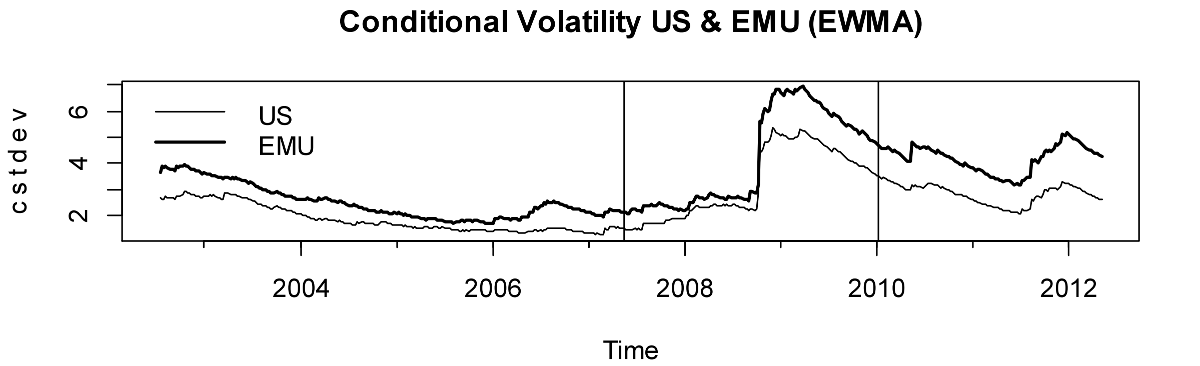
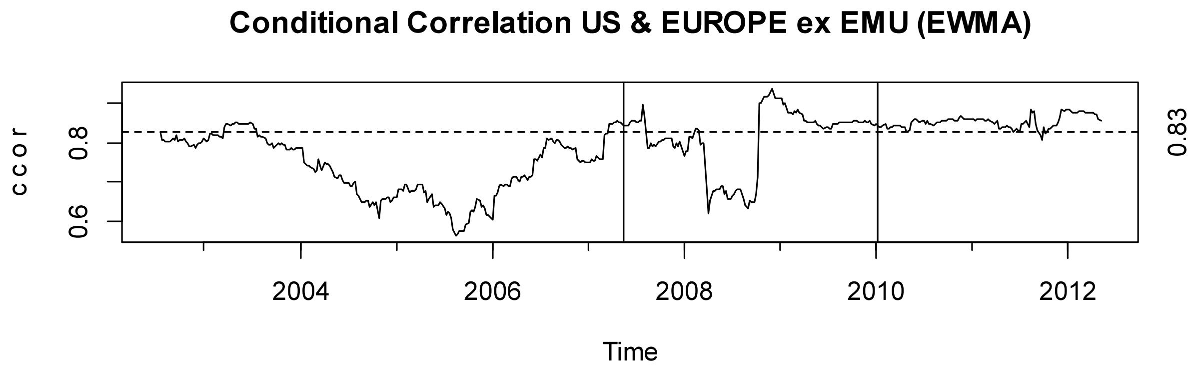

Conditional Volatility US & EFM AFRICA (SMA)
cstdev
2
4
US
EFM AFRICA
2004
2006
2008
2010
2012
Time

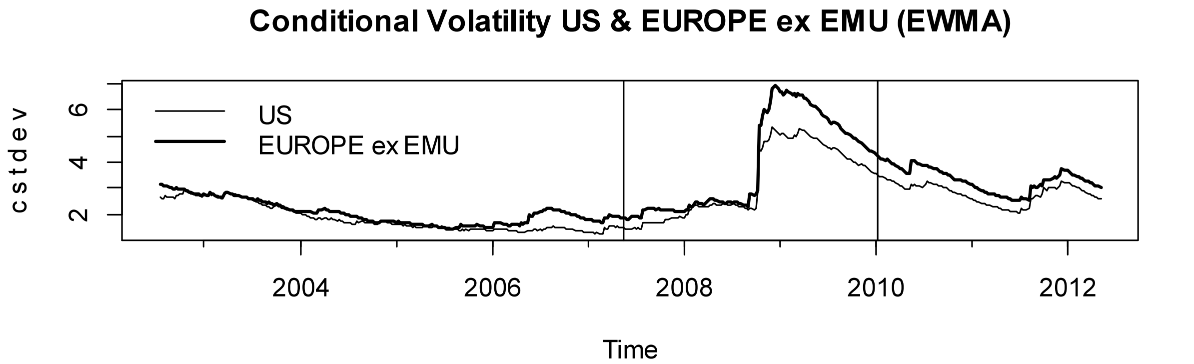
Figure 5.10 Relationship between weekly logarithmic returns of US and developed/emerging/frontier region stock indices based on EWMA model

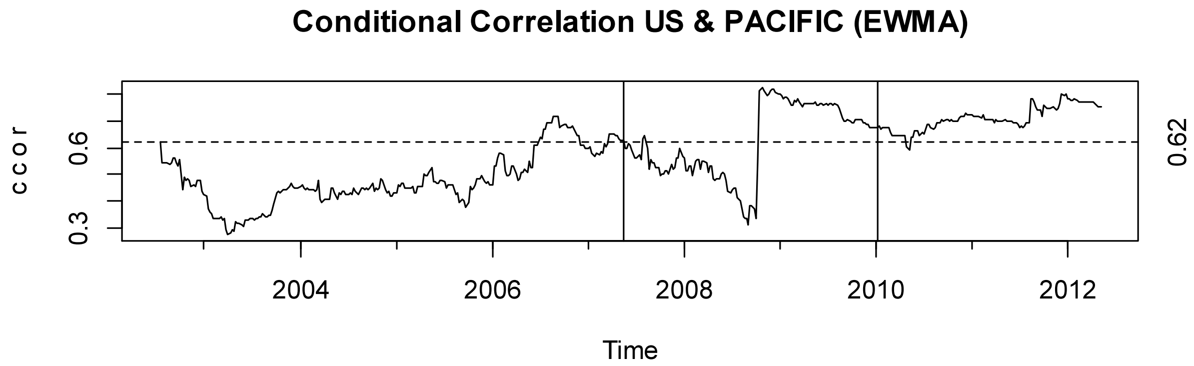
Notes: The graphs show the conditional correlation and conditional volatility between the US and respective indices over the period 12 July 2002 to 11 May 2012. The two vertical lines represent the start (11 May 2007) and the end (1 January 2010) of the crisis. The dashed line represents unconditional correlation over the period from 12 July 2002 to 11 May 2012.

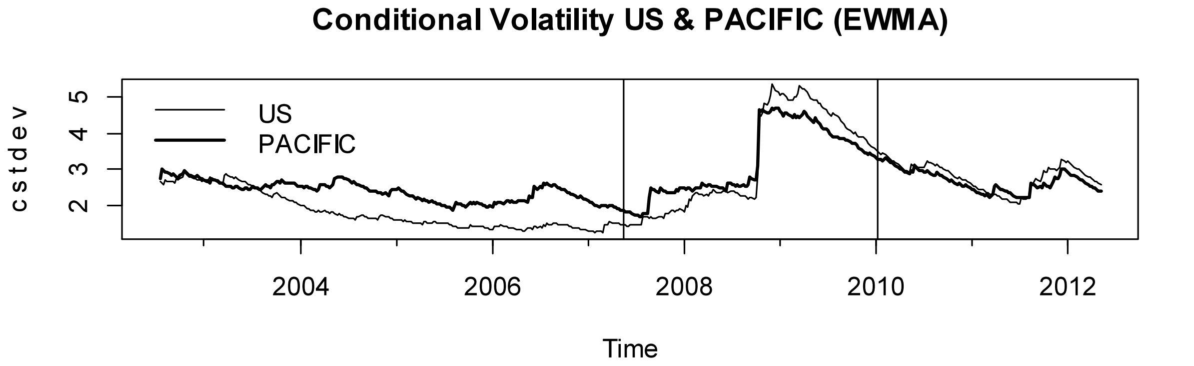


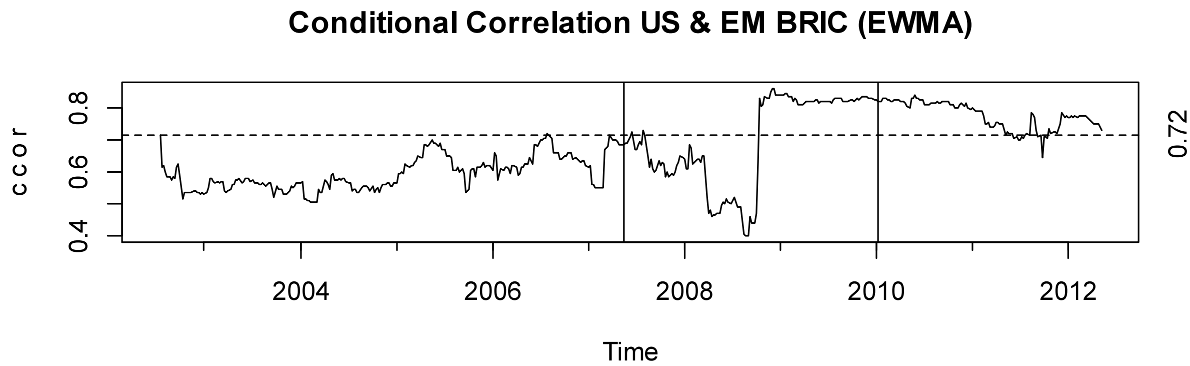


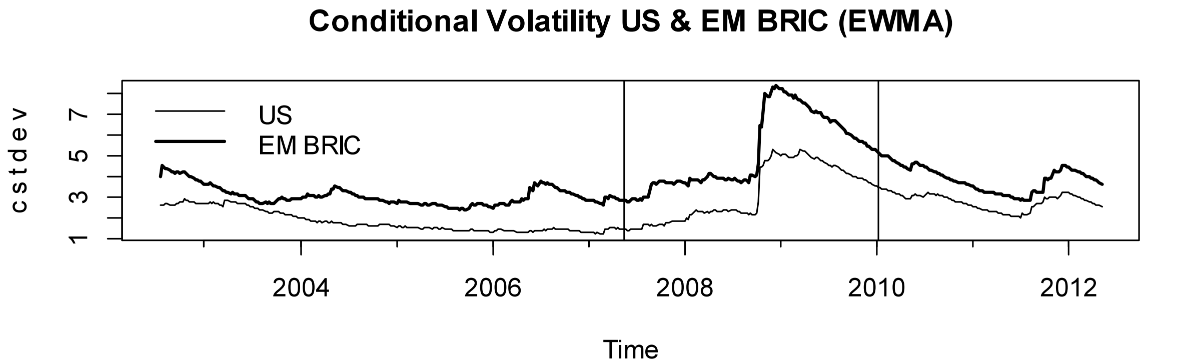

Conditional Correlation US & EUROPE ex EMU (EWMA)
ccor
0.6
0.8
0.83
2004
2006
2008
2010
2012
Time

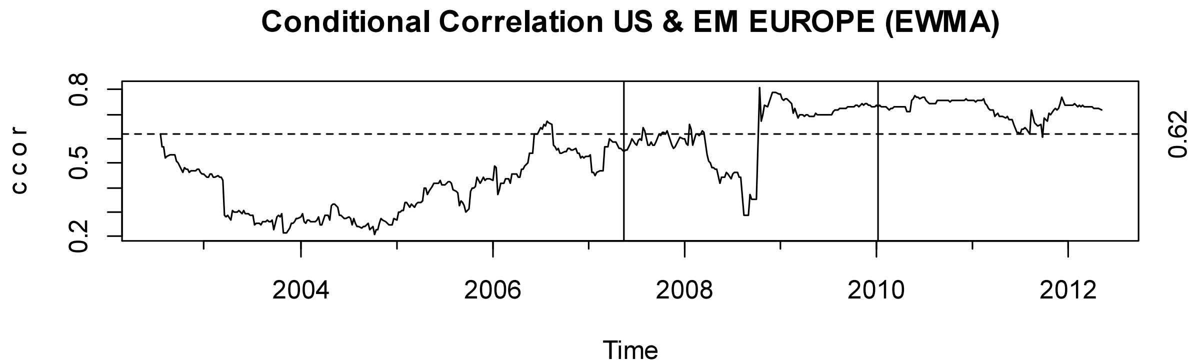

Conditional Volatility US & EUROPE ex EMU (EWMA)
cstdev
2
4
6
US
EUROPE ex EMU
2004
2006
2008
2010
2012
Time

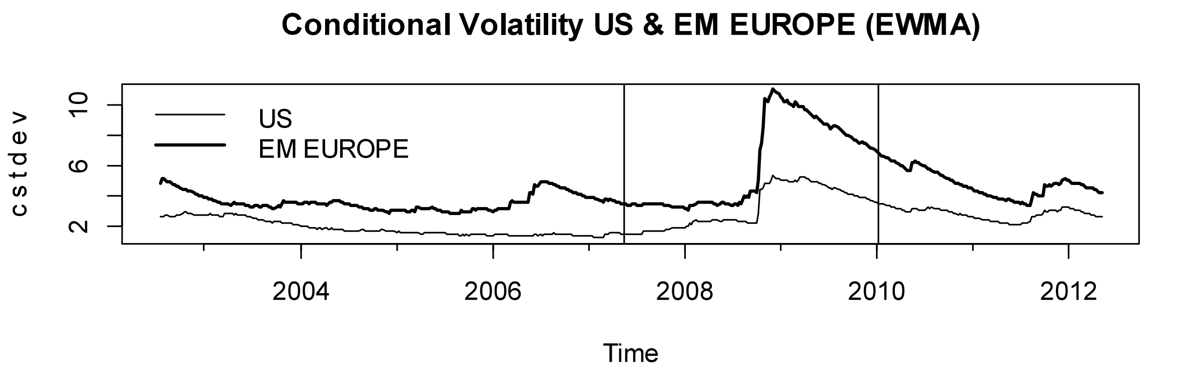

Conditional Correlation US & PACIFIC (EWMA)
ccor
0.3
0.6
0.62
2004
2006
2008
2010
2012
Time

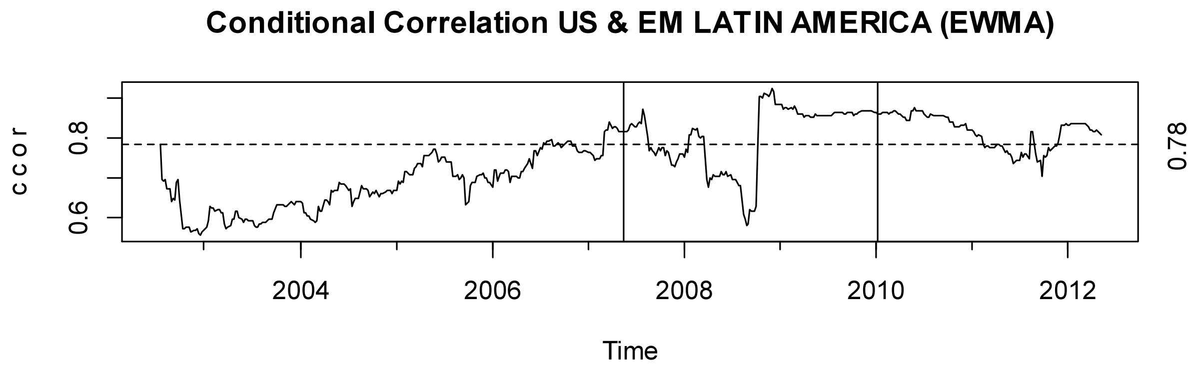

Conditional Volatility US & PACIFIC (EWMA)
cstdev
2
3
4
5
US
PACIFIC
2004
2006
2008
2010
2012
Time

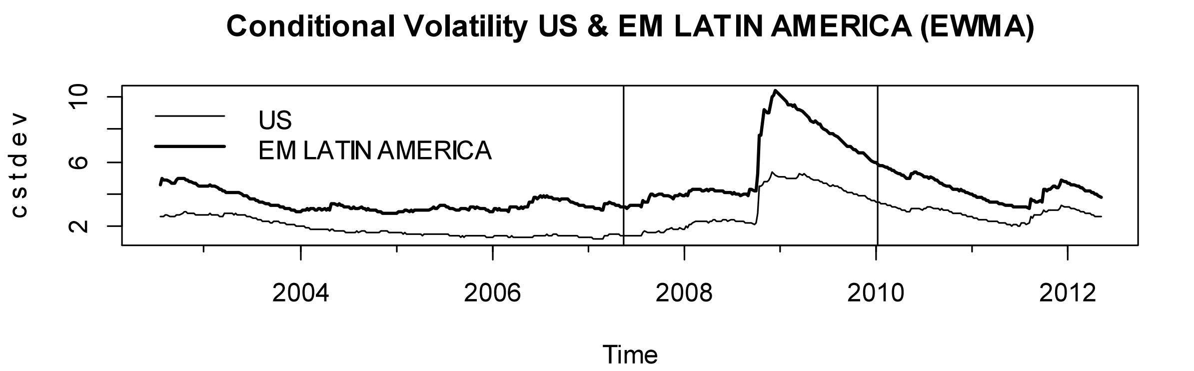

Conditional Correlation US & EM BRIC (EWMA)
ccor
0.4
0.6
0.8
0.72
2004
2006
2008
2010
2012
Time

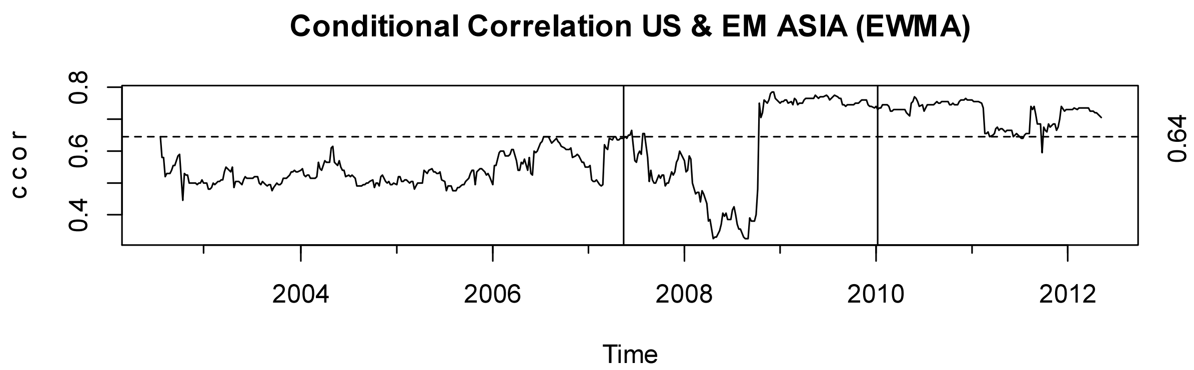

Conditional Volatility US & EM BRIC (EWMA)
cstdev
1
3
5
7
US
EM BRIC
2004
2006
2008
2010
2012
Time

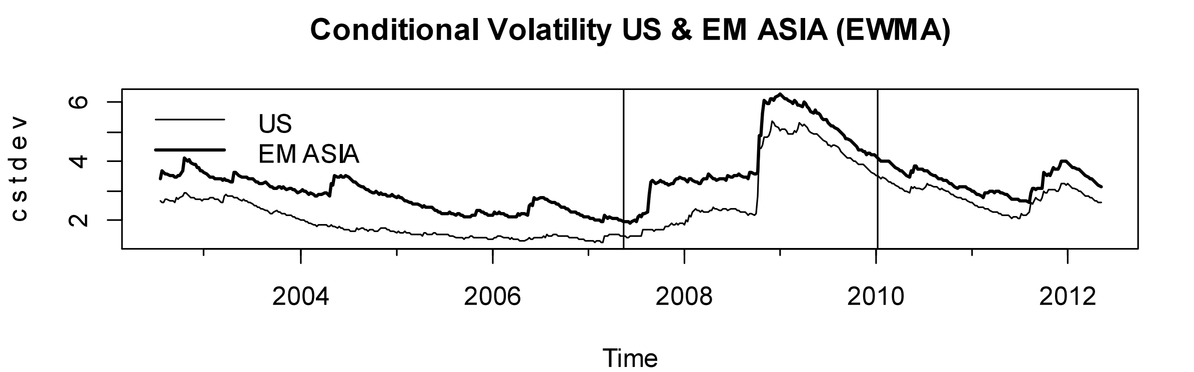

Conditional Correlation US & EM EUROPE (EWMA)
ccor
0.2
0.5
0.8
0.62
2004
2006
2008
2010
2012
Time

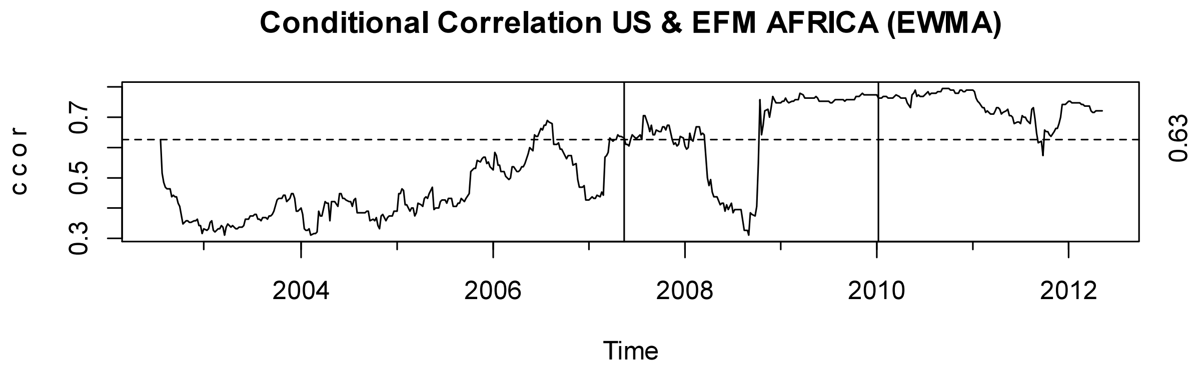

Conditional Volatility US & EM EUROPE (EWMA)
cstdev
2
6
10
US
EM EUROPE
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM LATIN AMERICA (EWMA)
ccor
0.6
0.8
0.78
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM LATIN AMERICA (EWMA)
cstdev
2
6
10
US
EM LATIN AMERICA
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EM ASIA (EWMA)
ccor
0.4
0.6
0.8
0.64
2004
2006
2008
2010
2012
Time


Conditional Volatility US & EM ASIA (EWMA)
cstdev
2
4
6
US
EM ASIA
2004
2006
2008
2010
2012
Time


Conditional Correlation US & EFM AFRICA (EWMA)
ccor
0.3
0.5
0.7
0.63
2004
2006
2008
2010
2012
Time

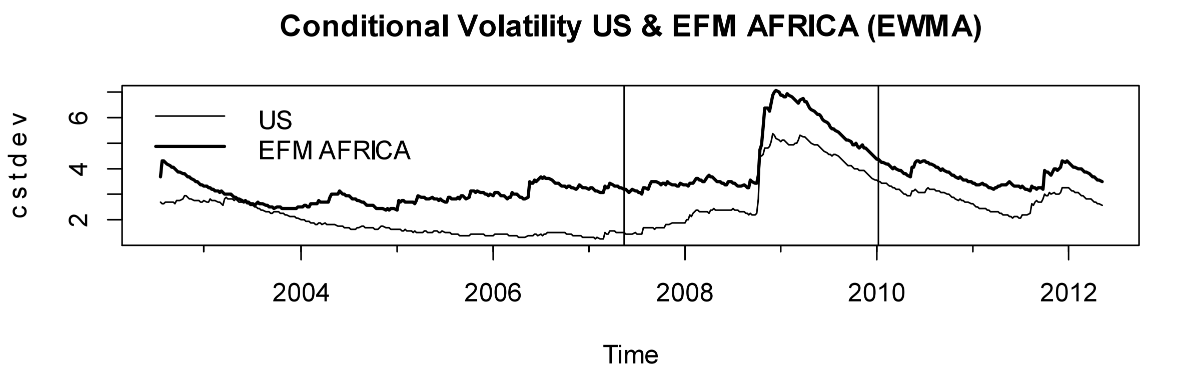

Conditional Volatility US & EFM AFRICA (EWMA)
cstdev
2
4
6
US
EFM AFRICA
2004
2006
2008
2010
2012
Time

Figure 5.11 Skew Student against normal distribution of US standardised residuals based on Copula DCC model

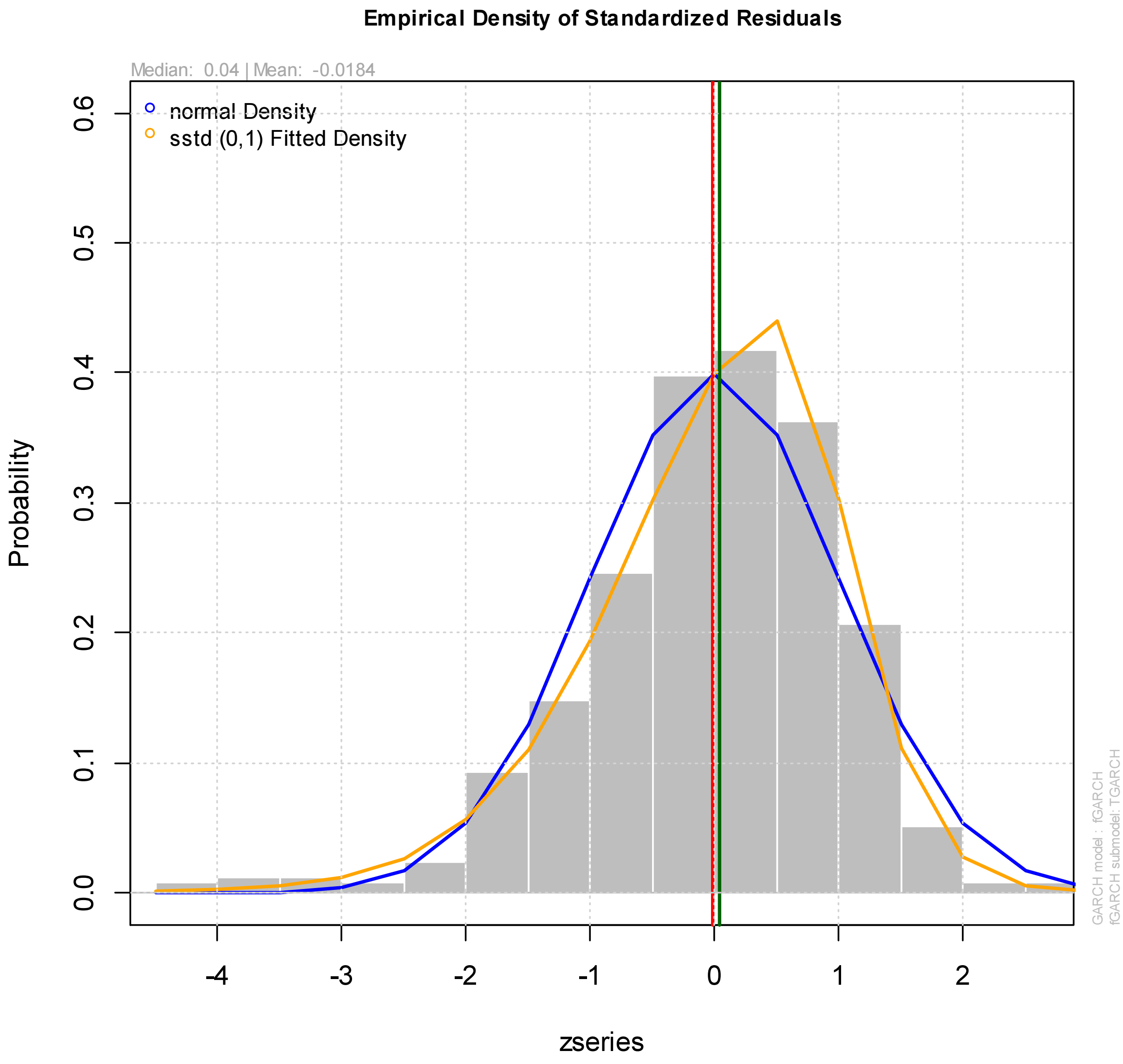


Figure 5.12 QQ plot of US standardised residuals based on Copula DCC model against skew student distribution

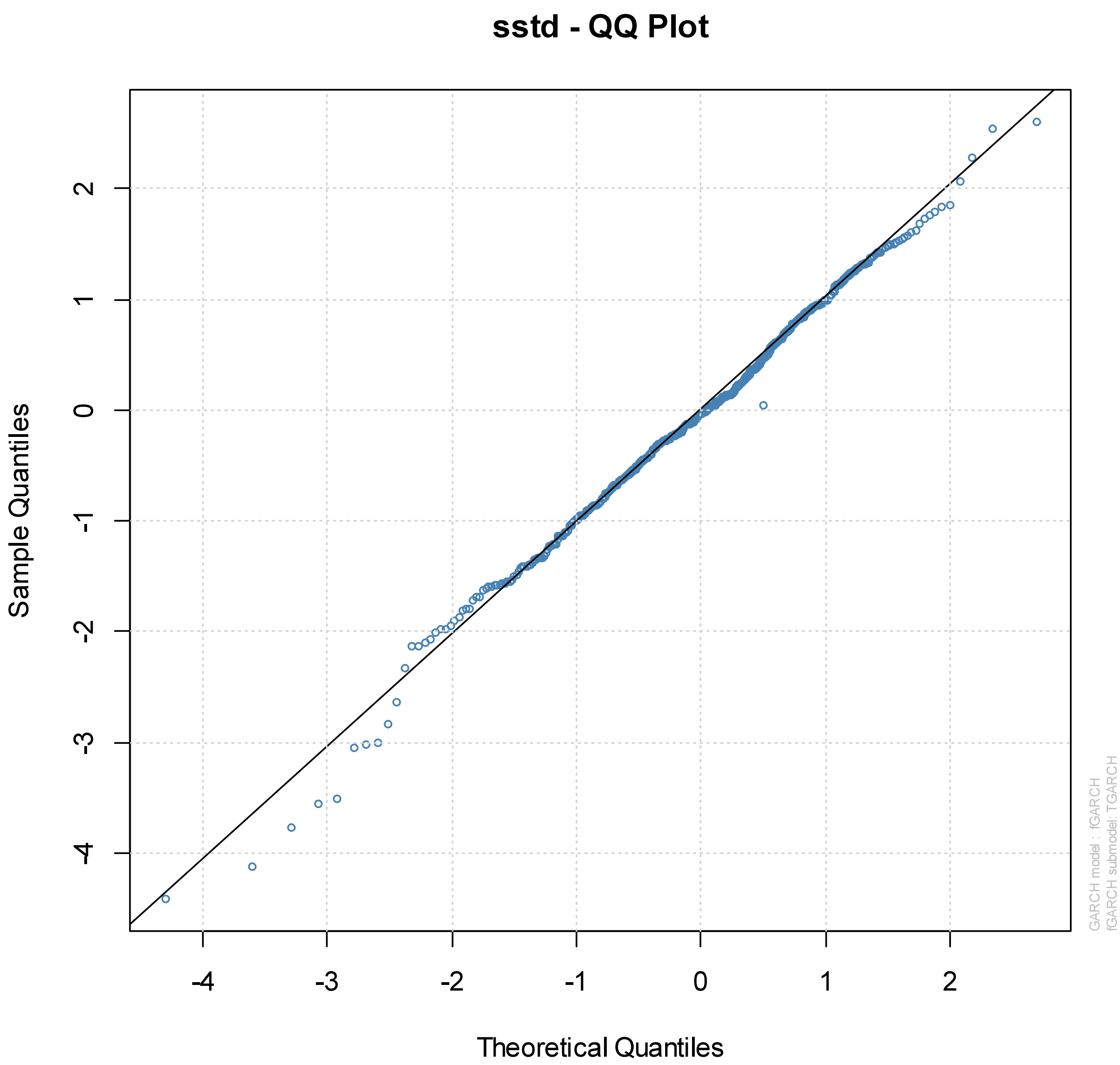


Figure 5.13 Skew Student against normal distribution of EMU standardised residuals based on Copula DCC model

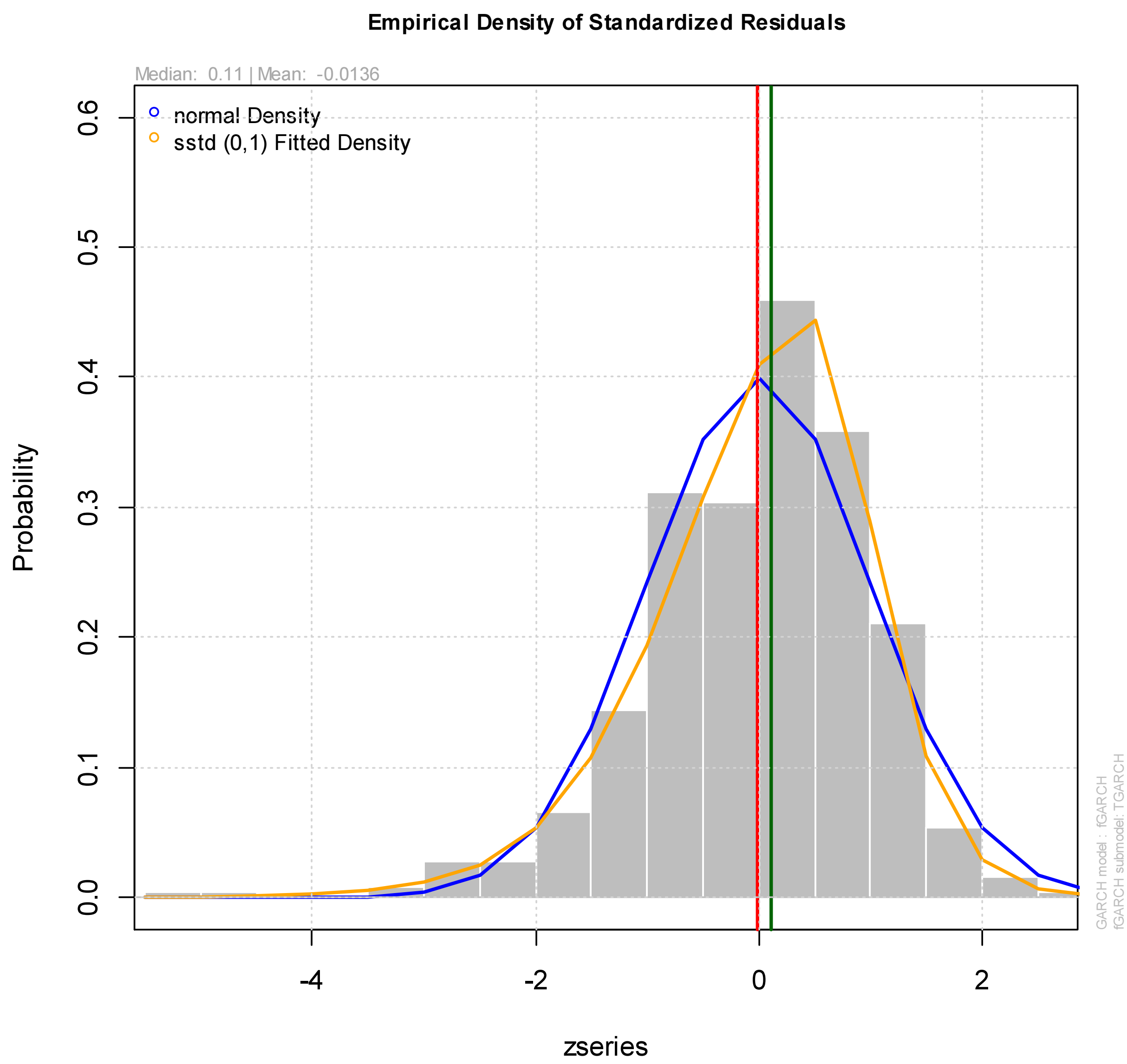


Figure 5.14 QQ plot of EMU standardised residuals based on Copula DCC model against skew student distribution

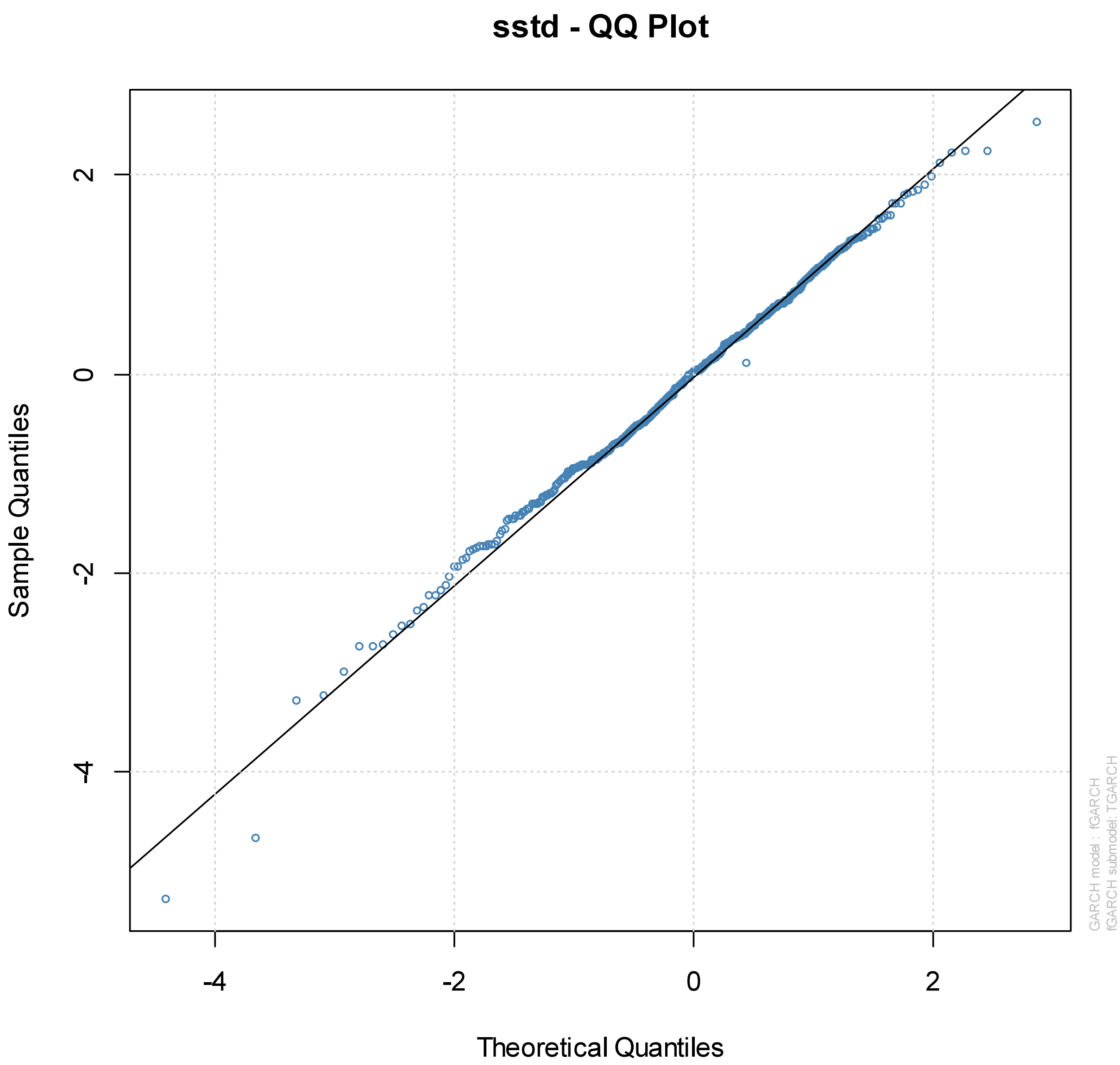


Figure 5.15 Skew Student against normal distribution of Europe ex EMU standardised residuals based on Copula DCC model

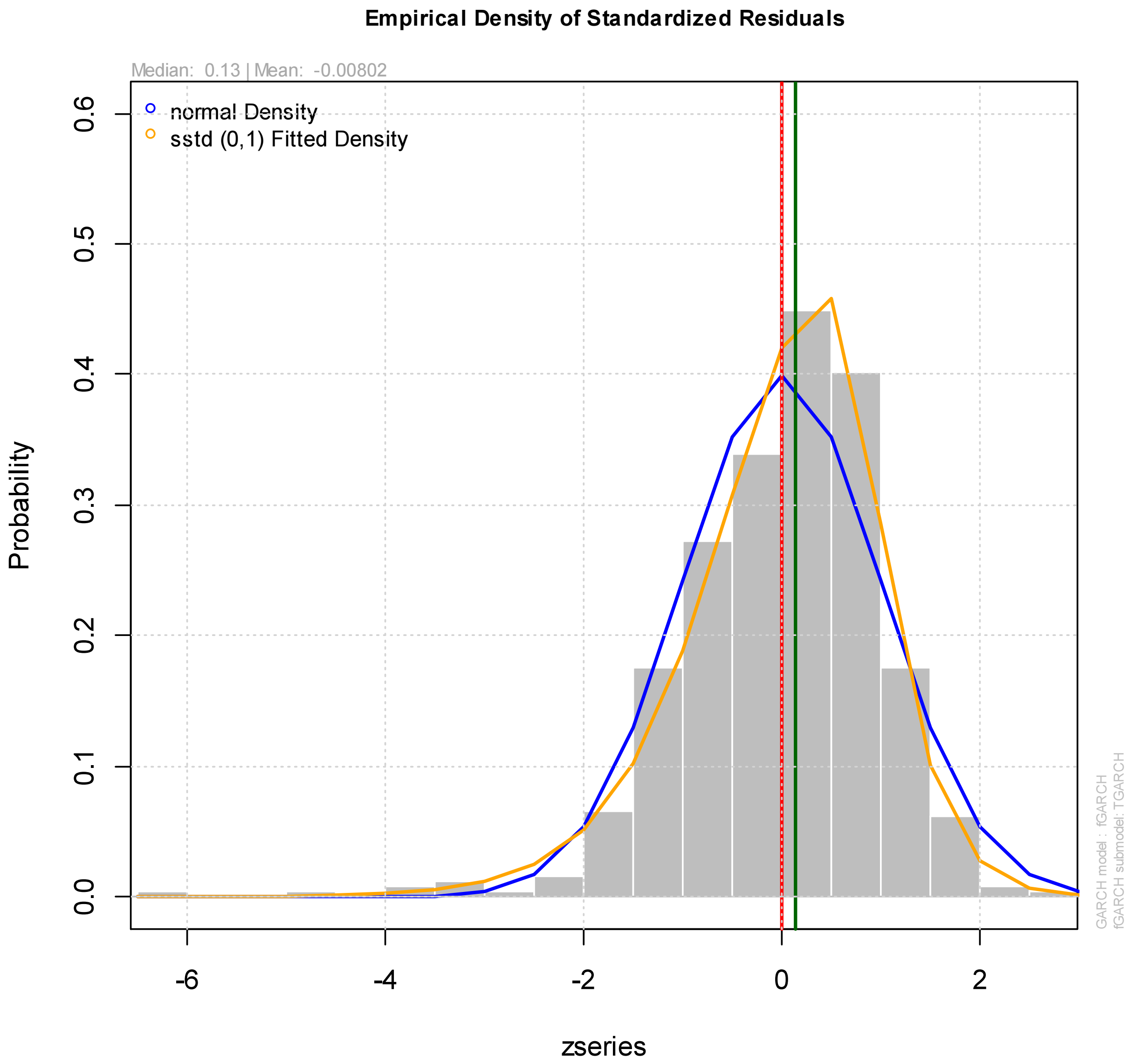


Figure 5.16 QQ plot of Europe ex EMU standardised residuals based on Copula DCC model against skew student distribution

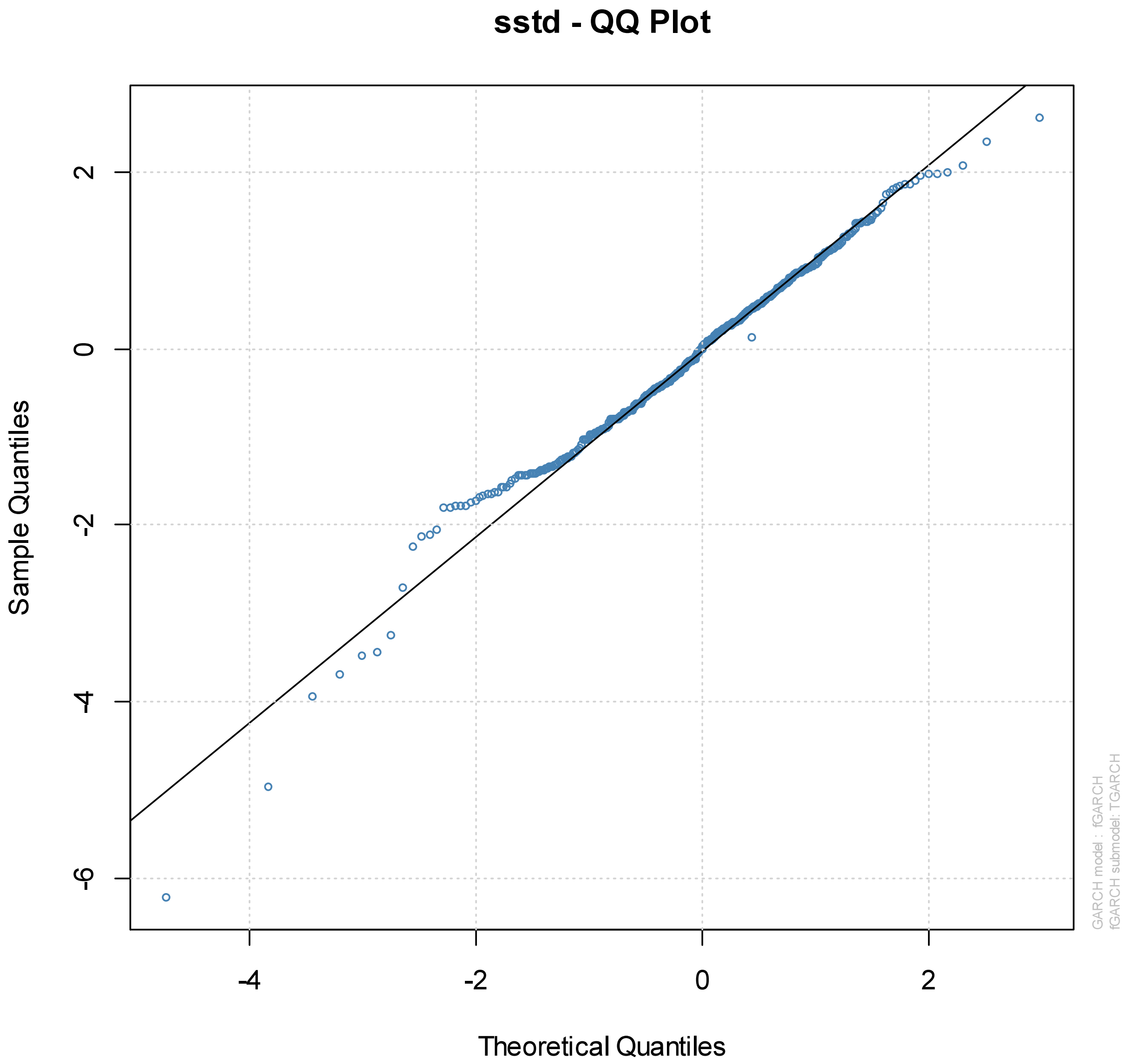


Figure 5.17 Skew Student against normal distribution of Pacific standardised residuals based on Copula DCC model

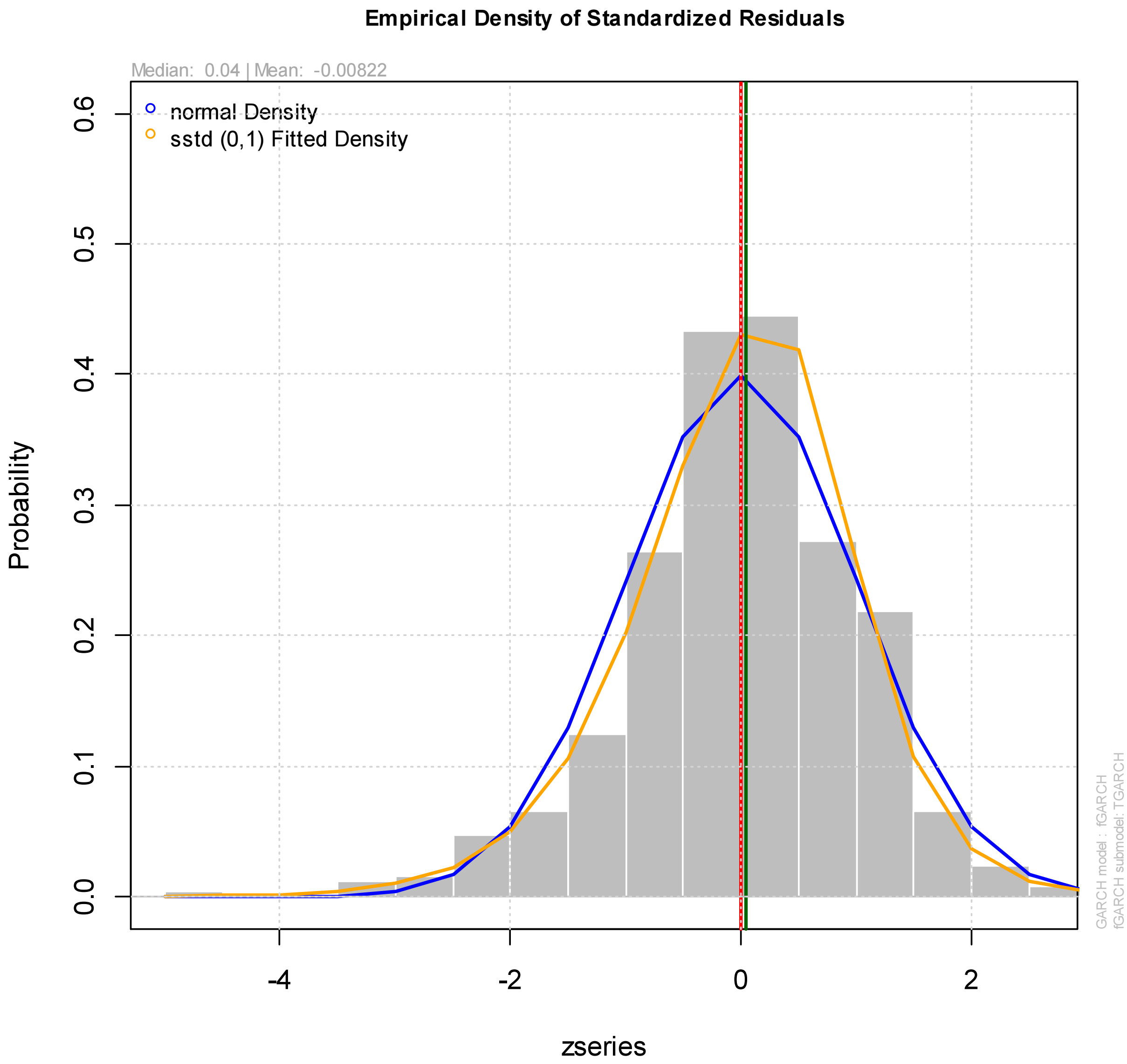


Figure 5.18 QQ plot of Pacific standardised residuals based on Copula DCC model against skew student distribution

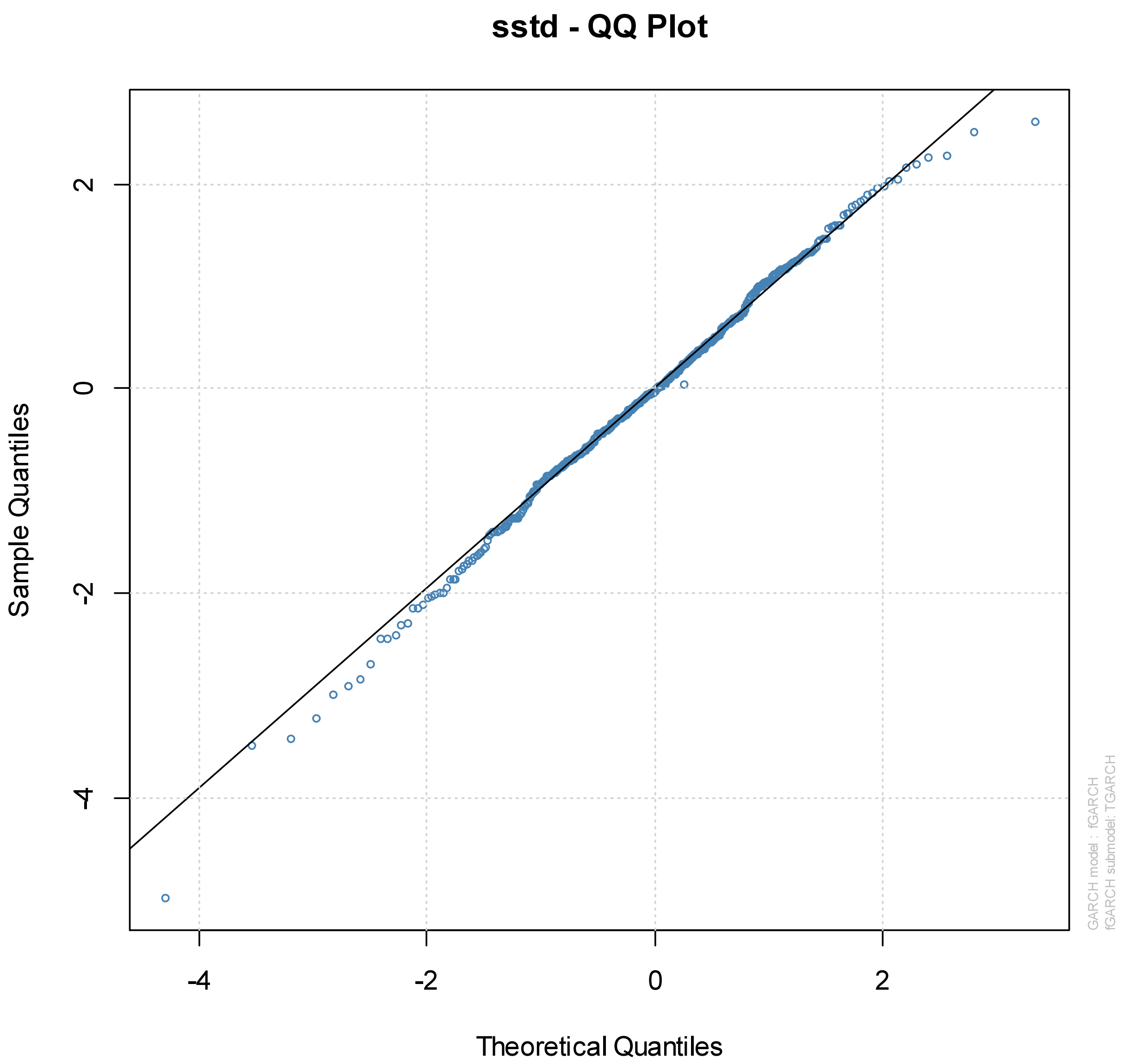


Figure 5.19 Skew Student against normal distribution of EM BRIC standardised residuals based on Copula DCC model

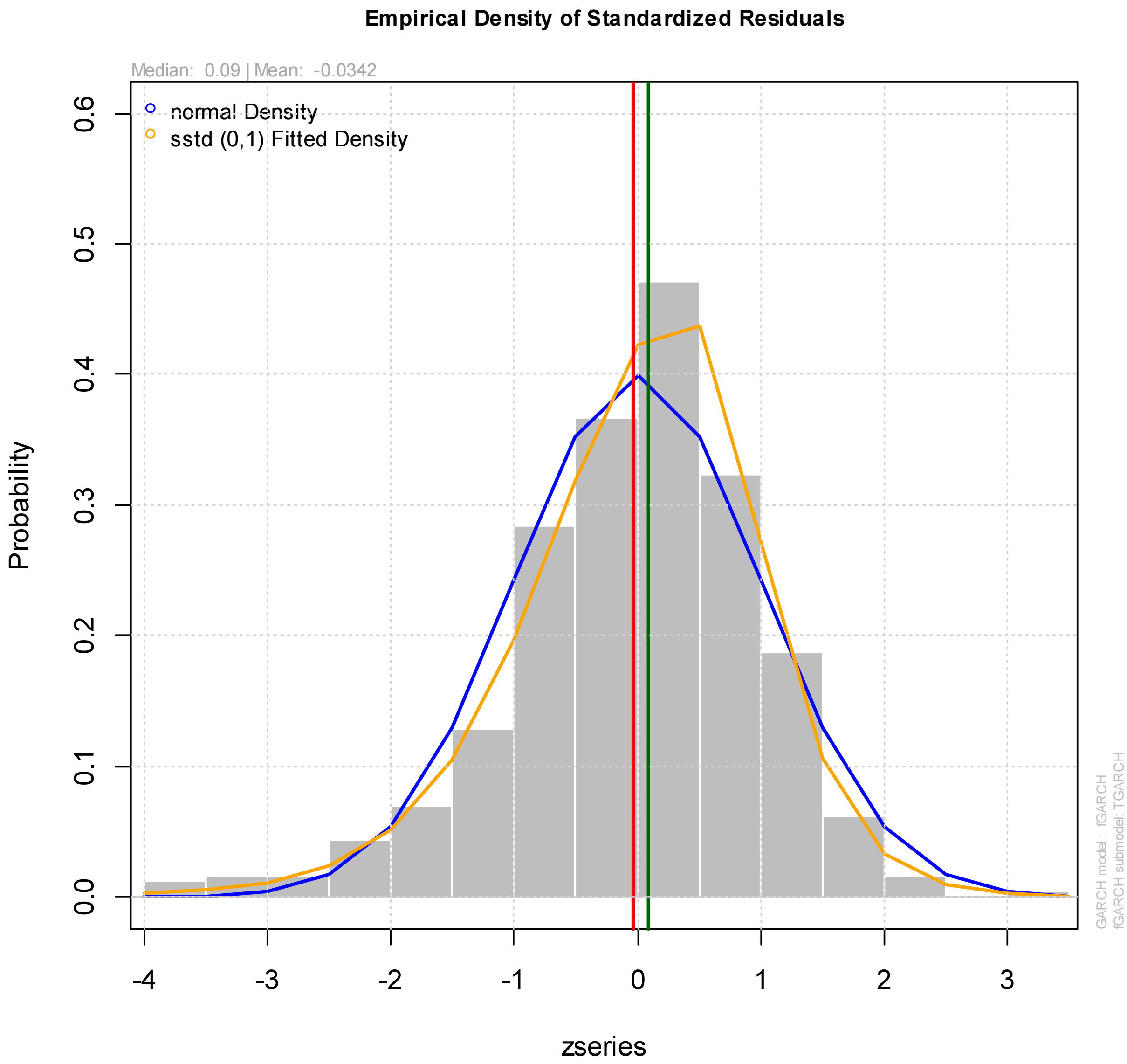


Figure 5.20 QQ plot of EM BRIC standardised residuals based on Copula DCC model against skew student distribution

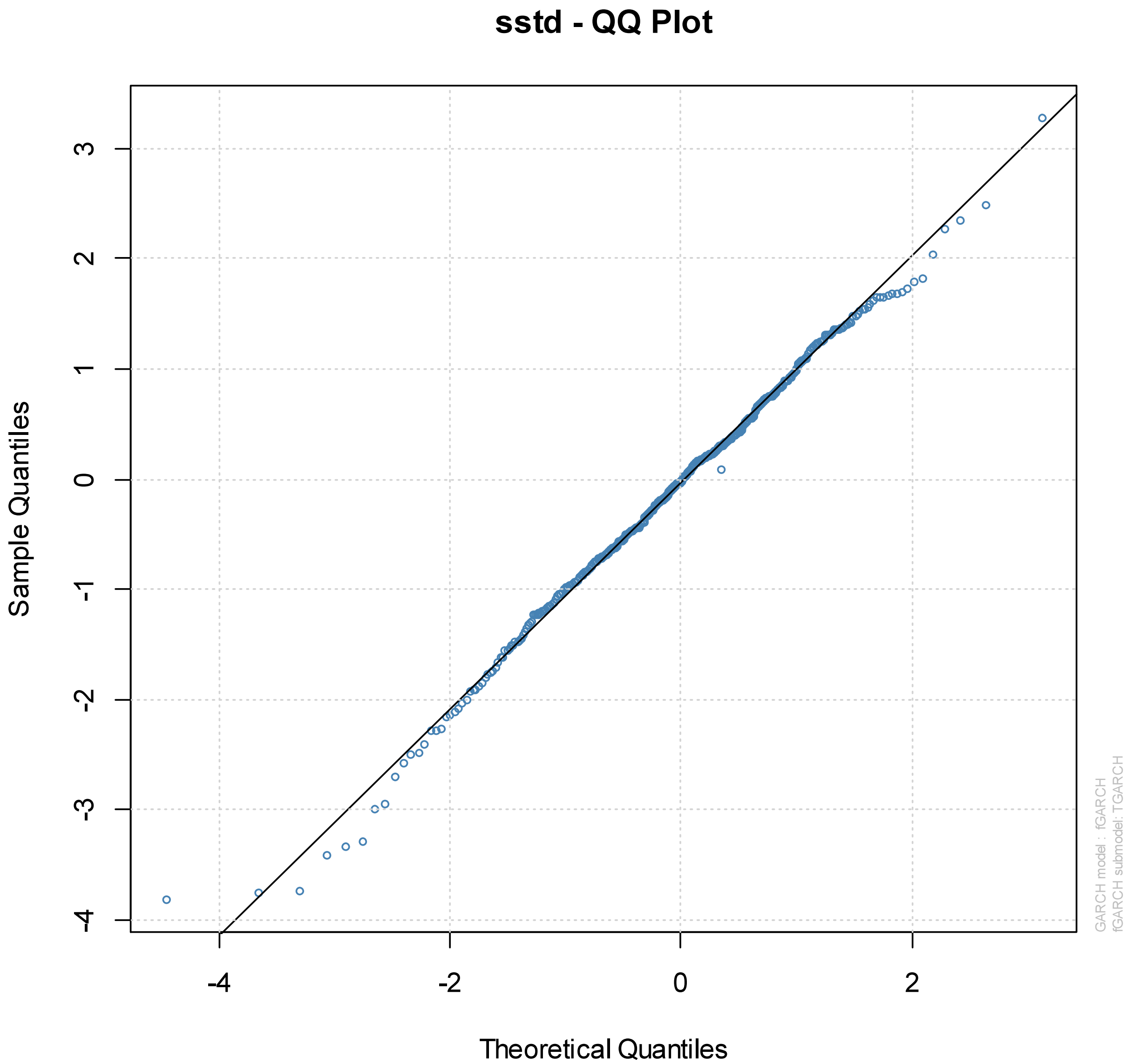


Figure 5.21 Skew Student against normal distribution of EM Europe standardised residuals based on Copula DCC model

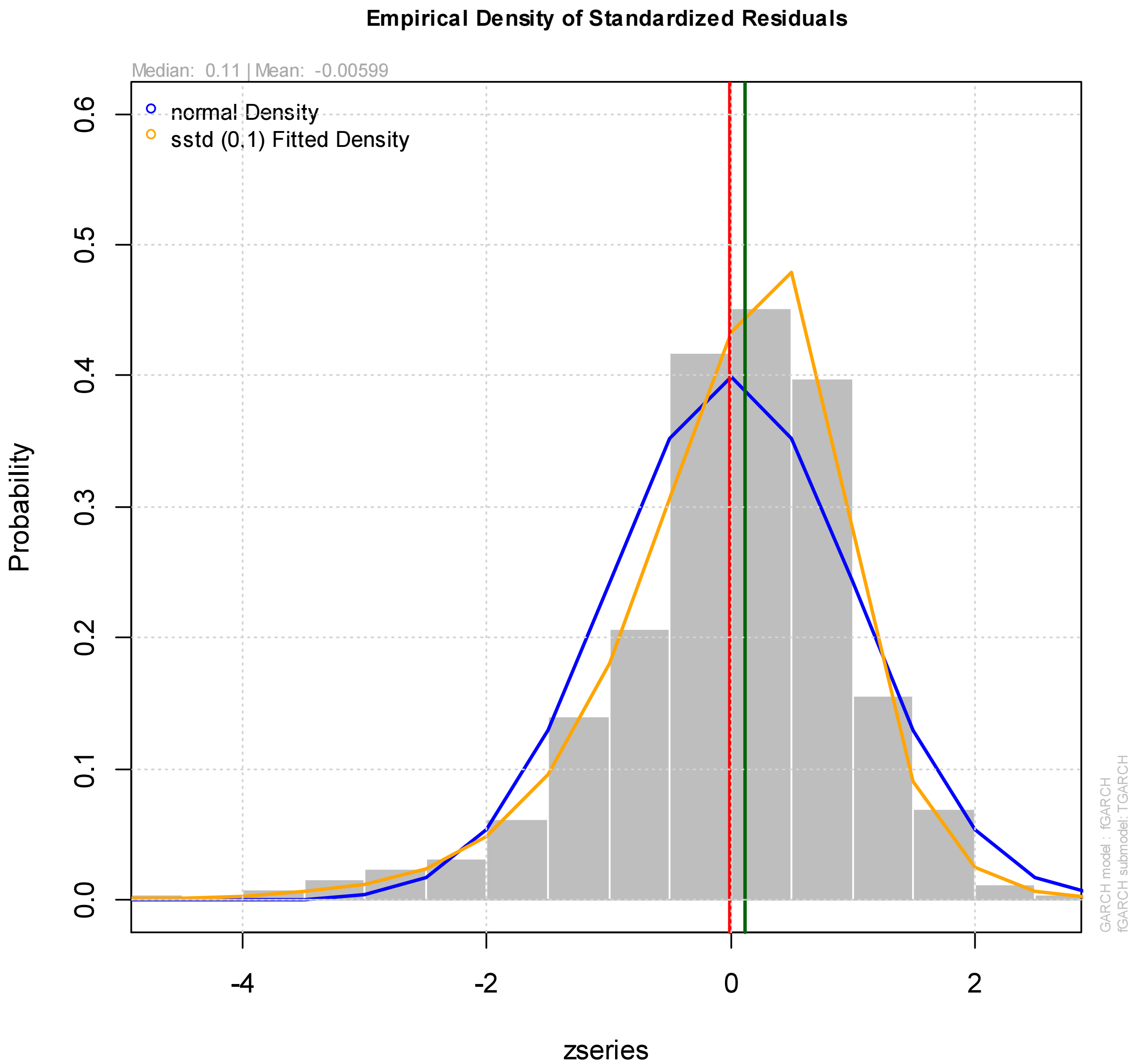


Figure 5.22 QQ plot of EM Europe standardised residuals based on Copula DCC model against skew student distribution

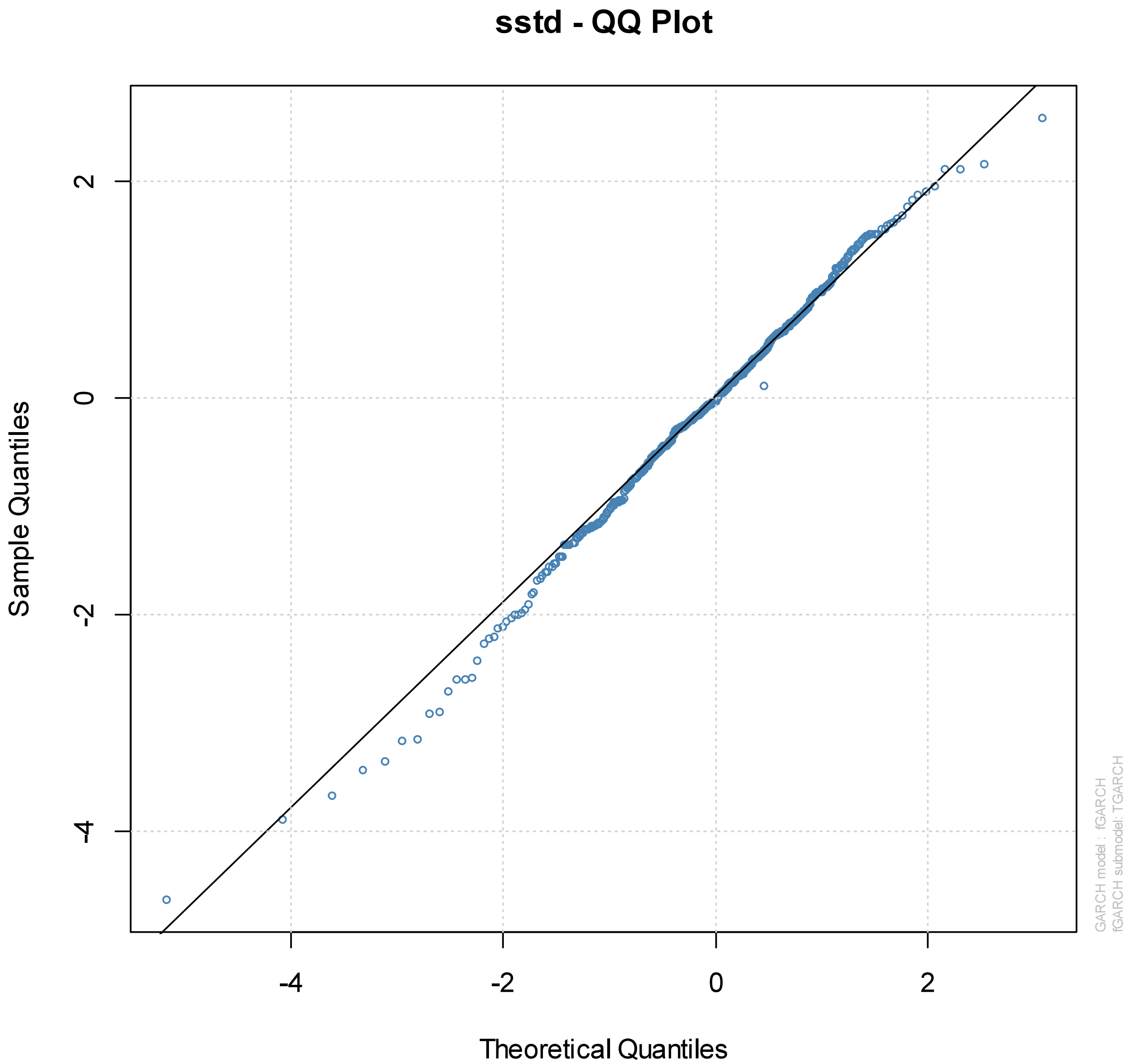


Figure 5.23 Skew Student against normal distribution of EM Latin America standardised residuals based on Copula DCC model

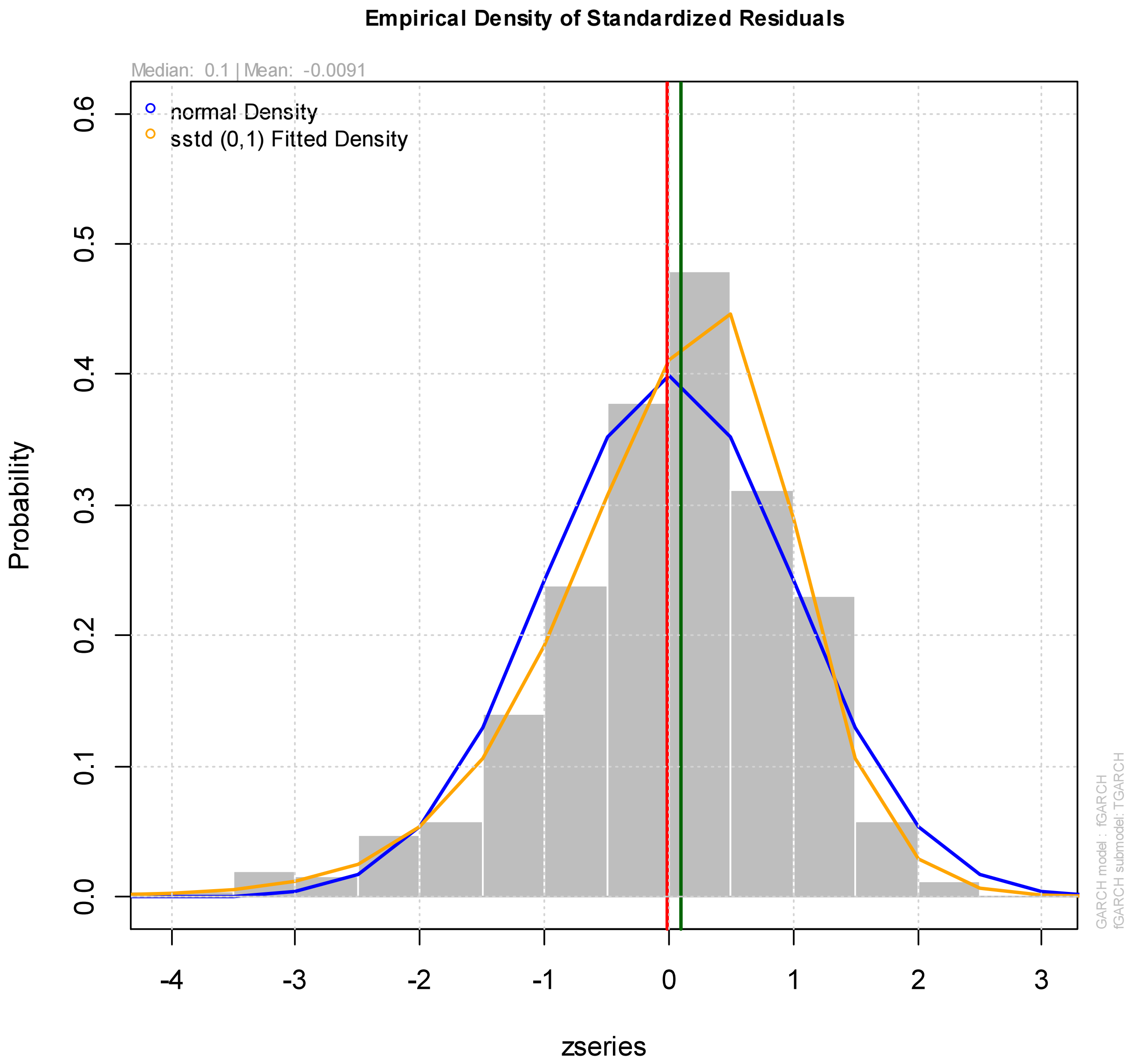


Figure 5.24 QQ plot of EM Latin America standardised residuals based on Copula DCC model against skew student distribution

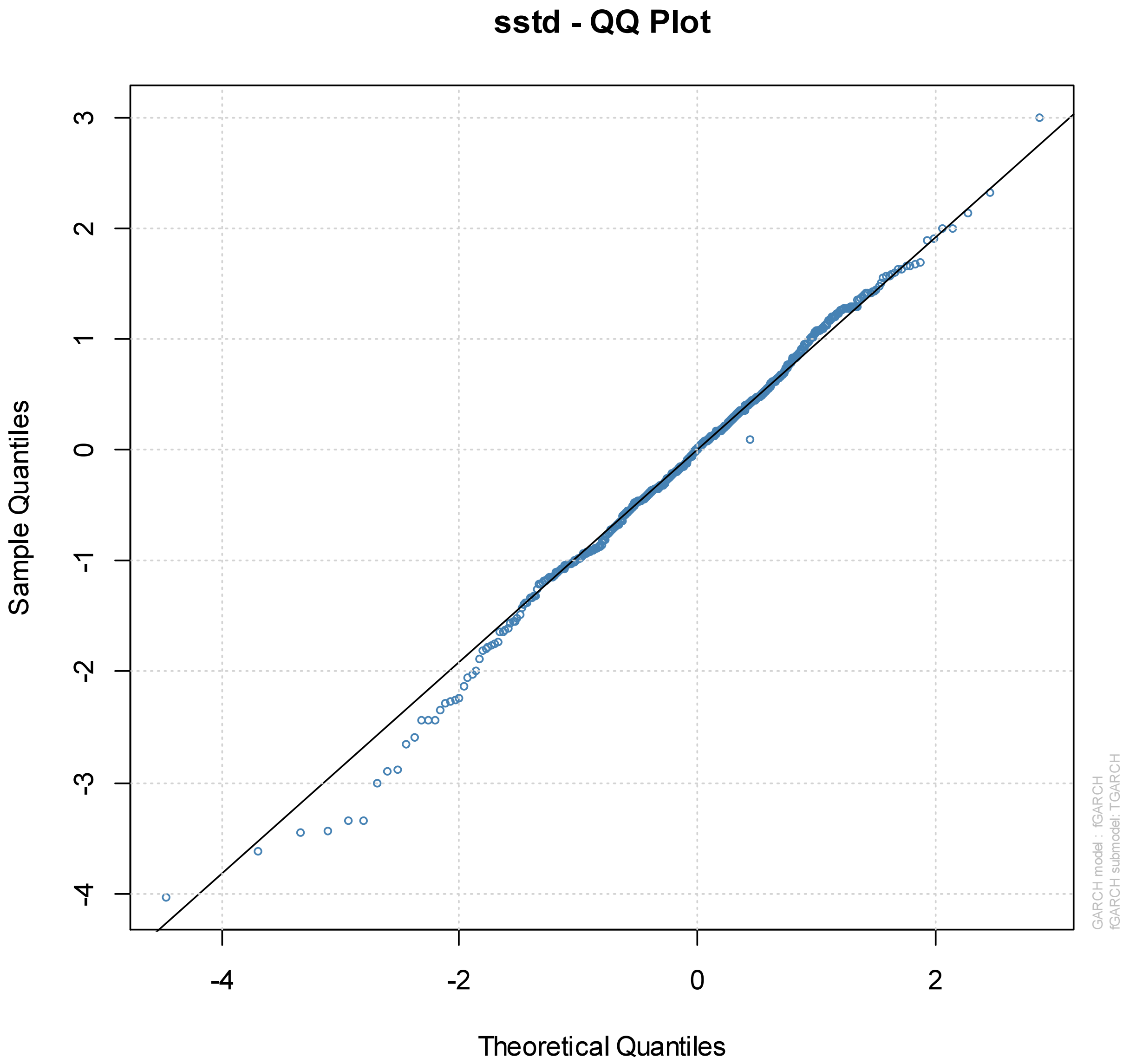


Figure 5.25 Skew Student against normal distribution of EM Asia standardised residuals based on Copula DCC model

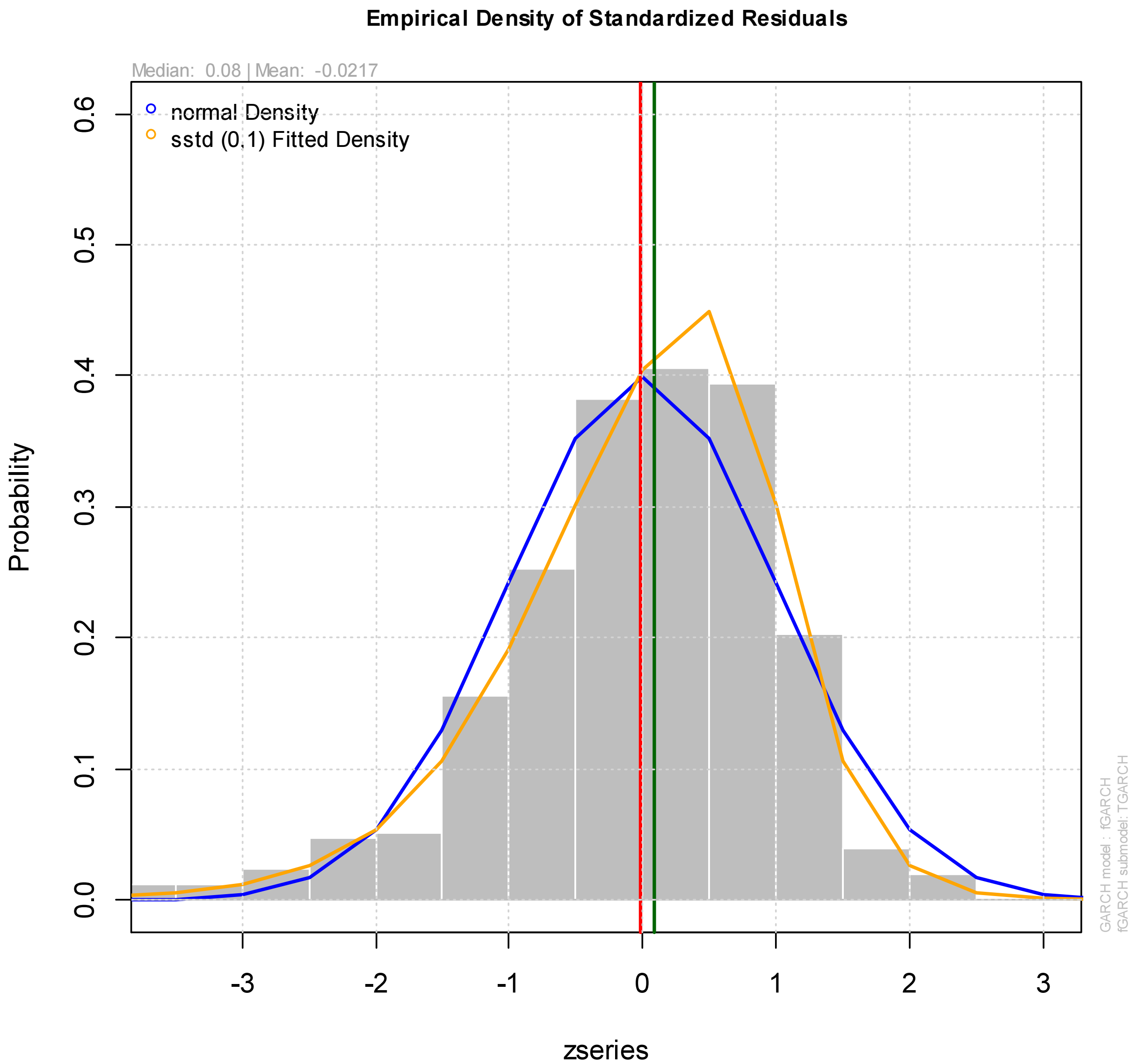


Figure 5.26 QQ plot of EM Asia standardised residuals based on Copula DCC model against skew student distribution

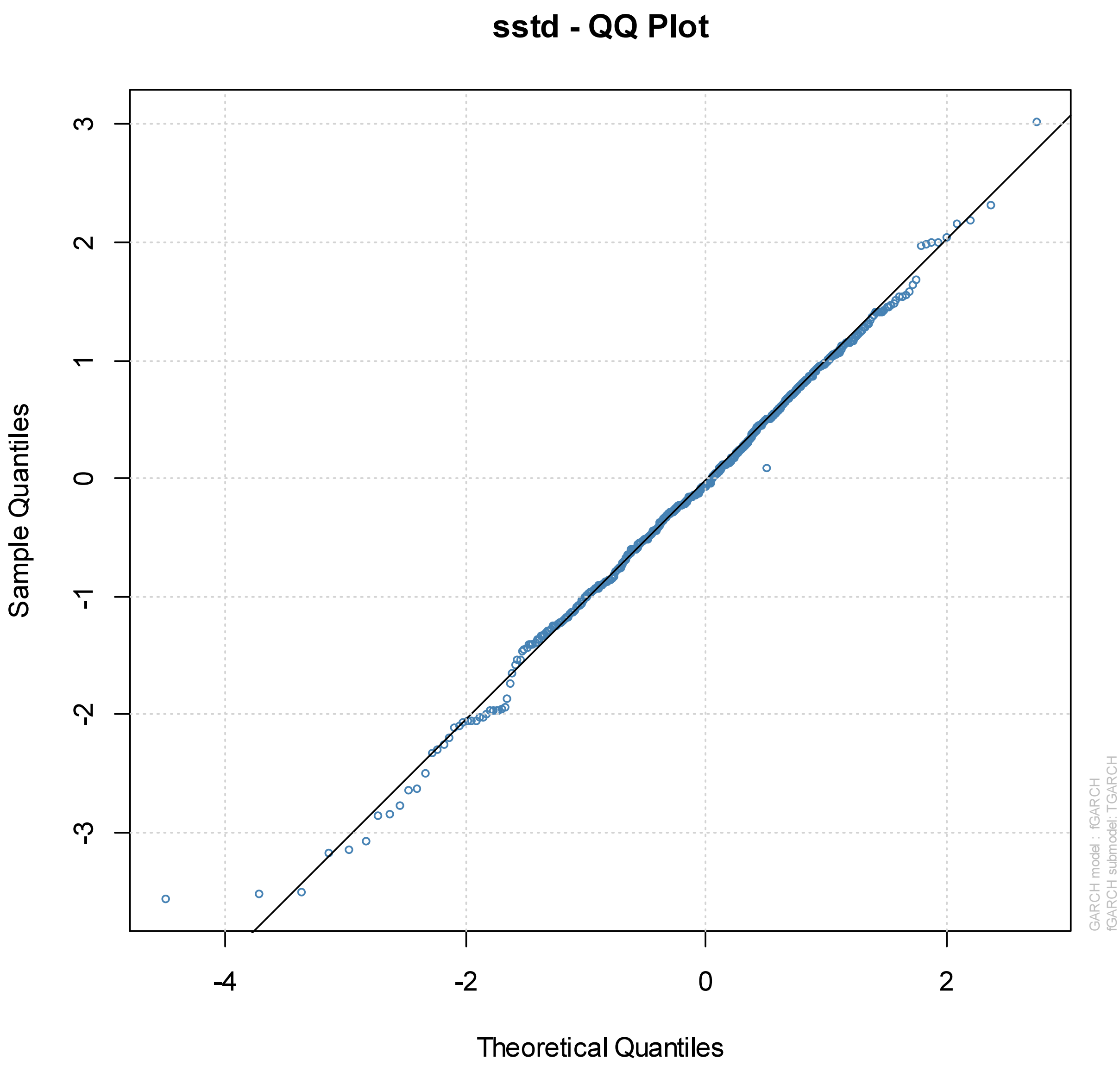


Figure 5.27 Skew Student against normal distribution of EMF Africa standardised residuals based on Copula DCC model

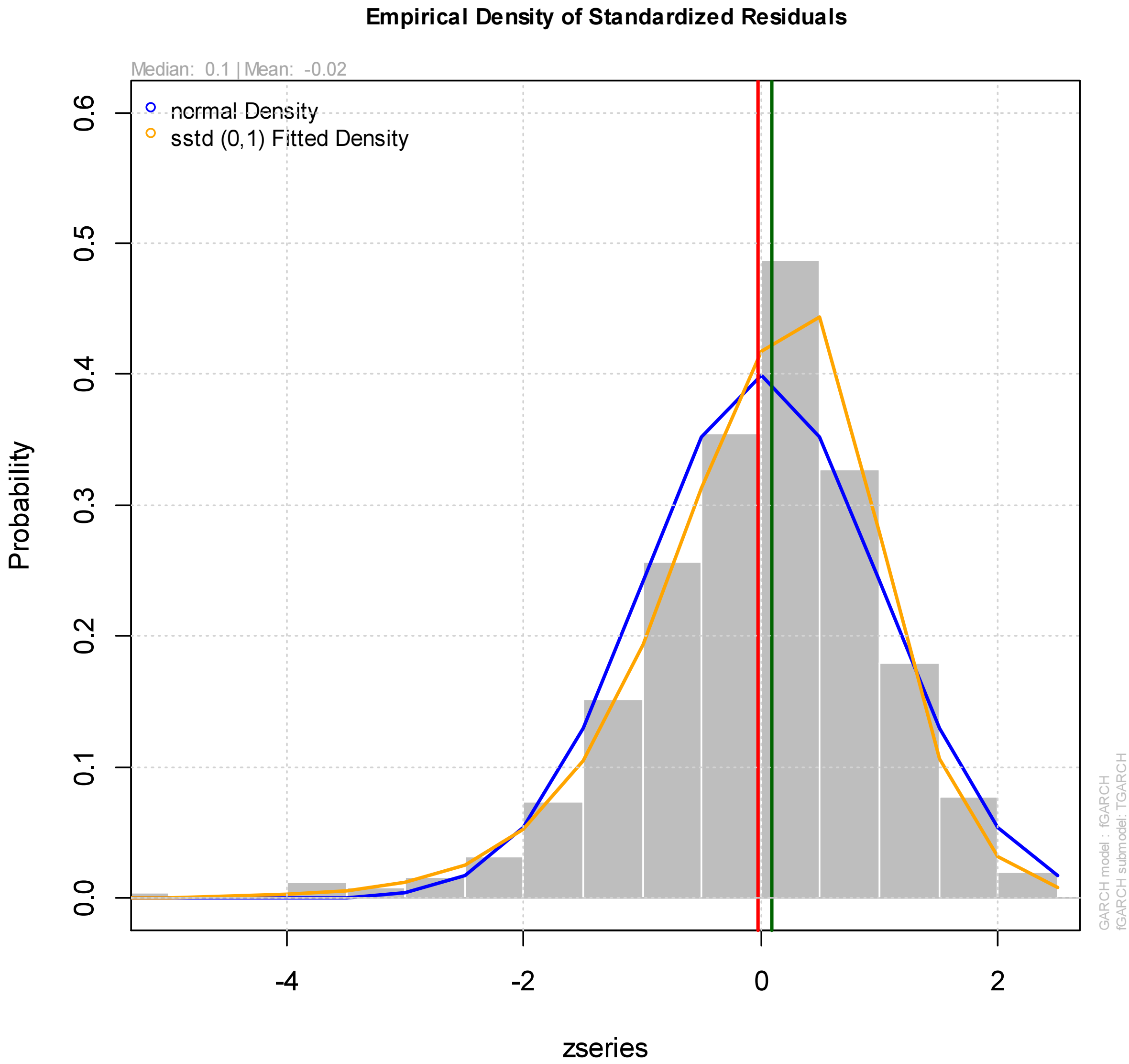


Figure 5.28 QQ plot of EMF Africa standardised residuals based on Copula DCC model against skew student distribution

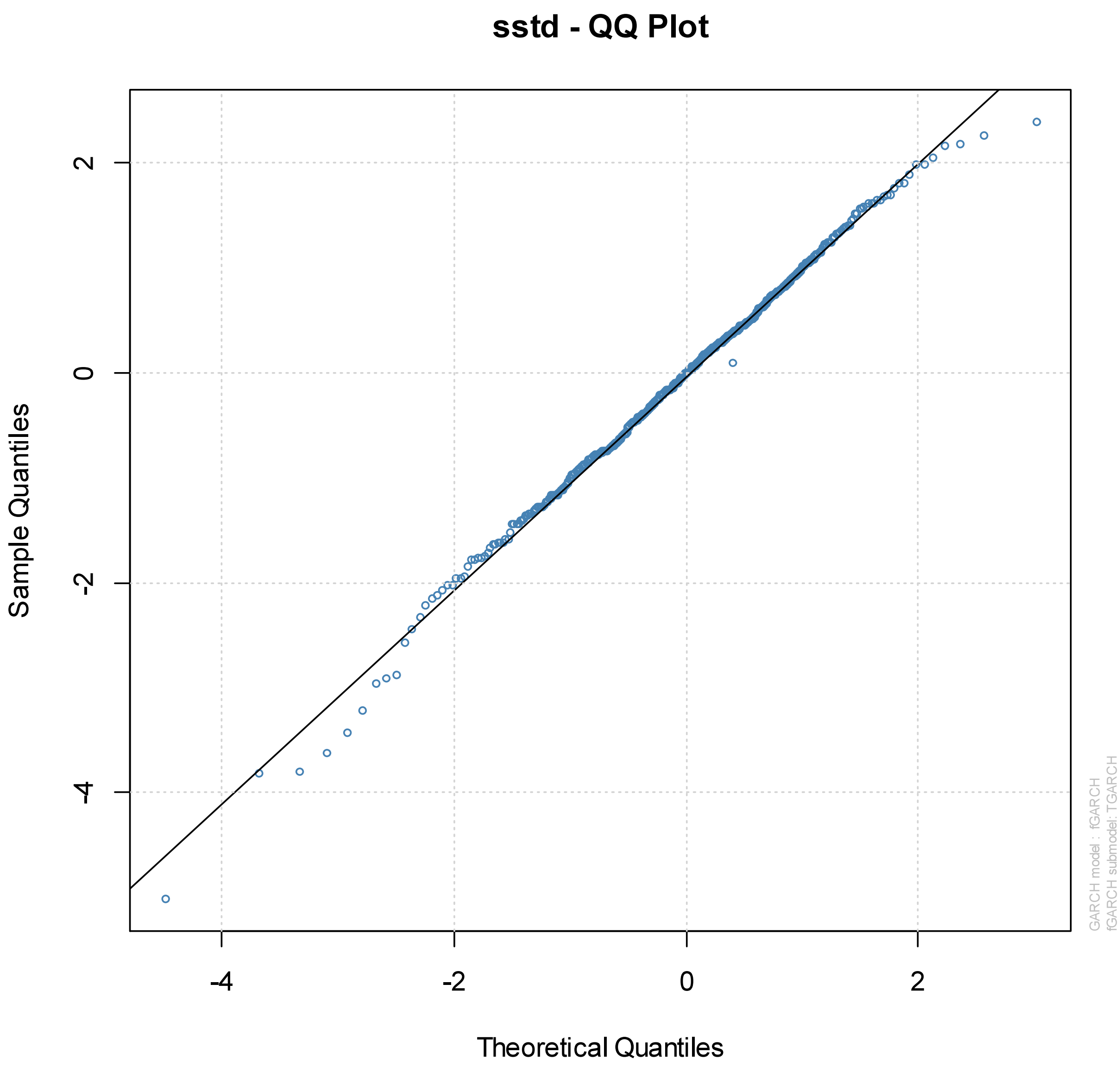
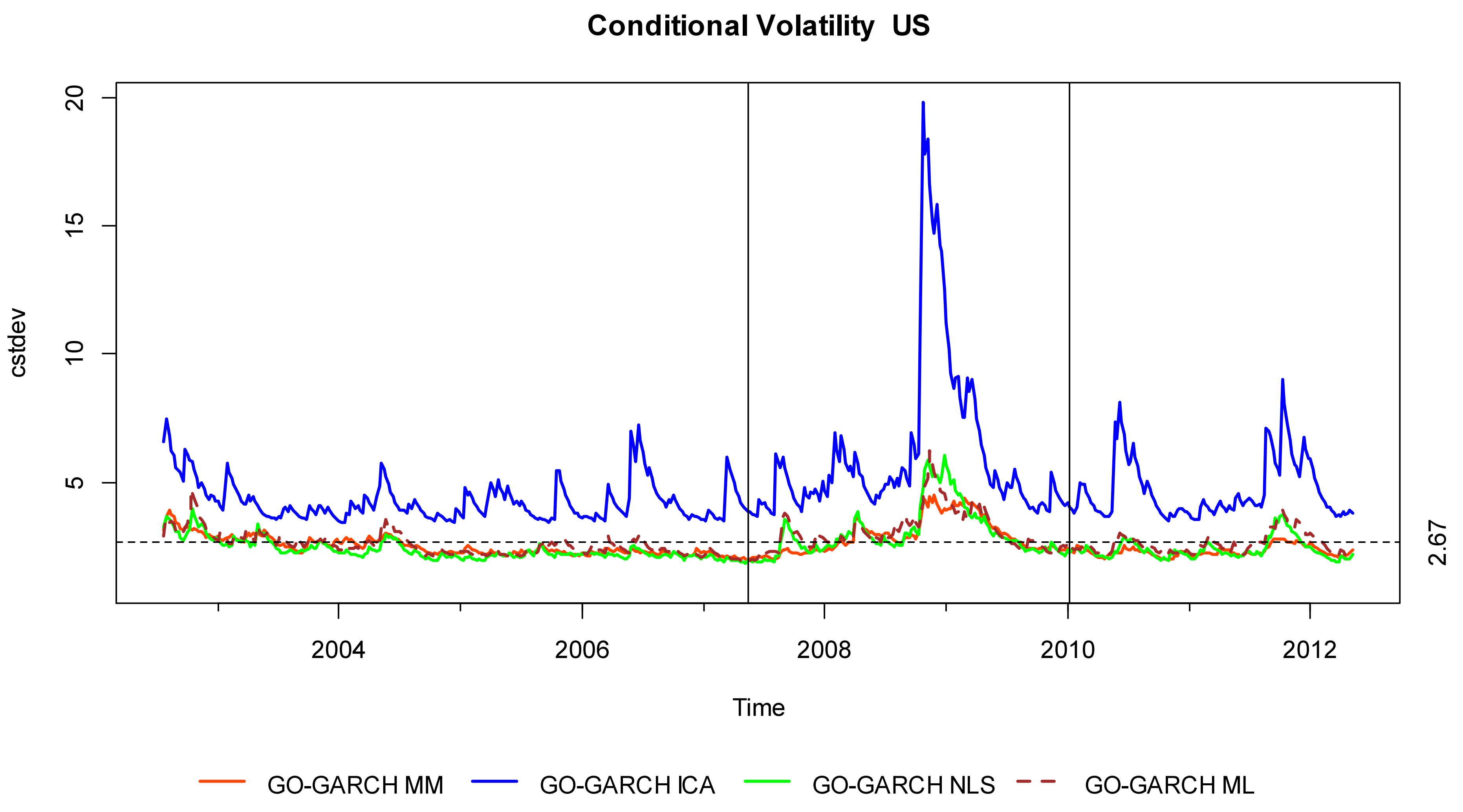
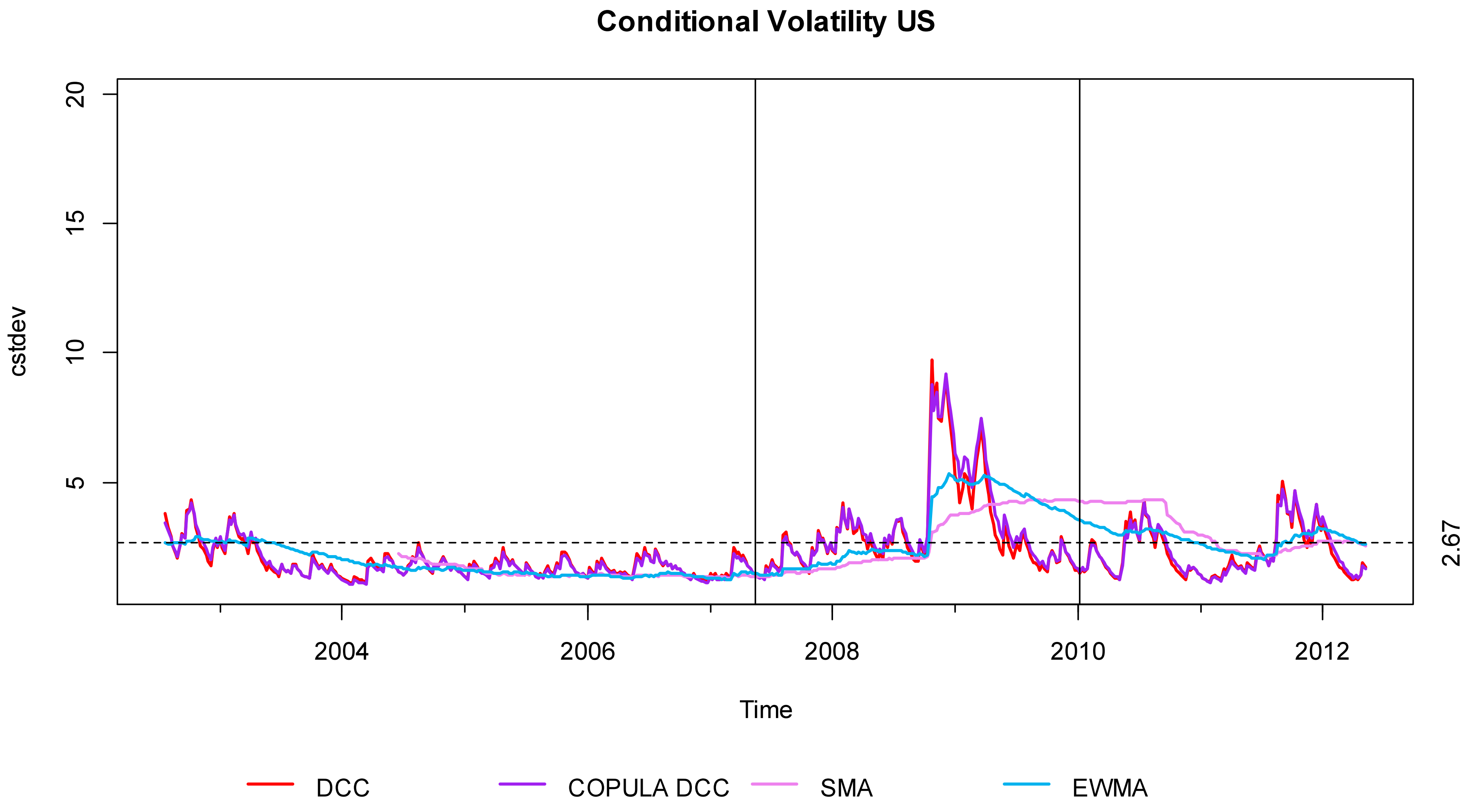


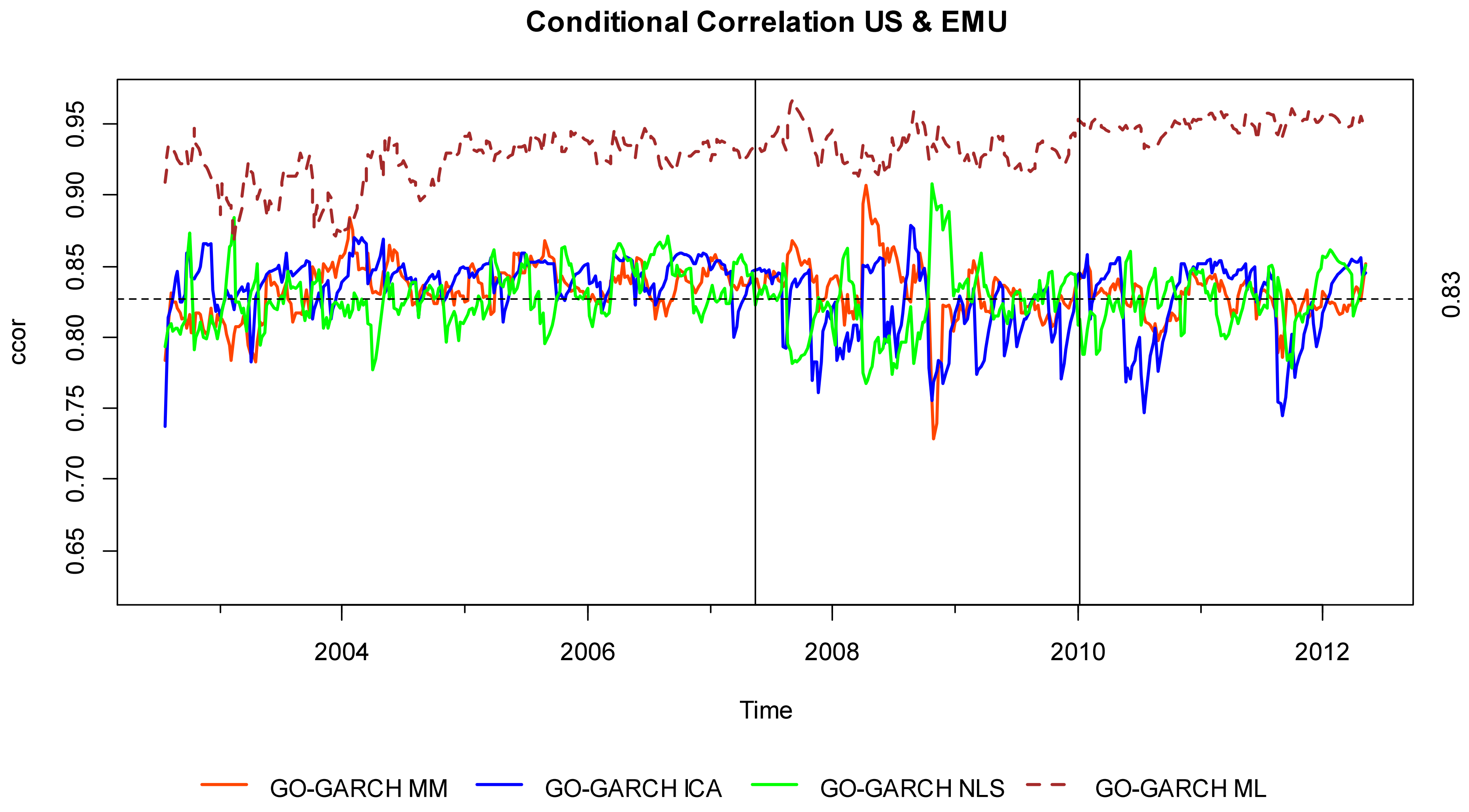
Figure 5.29 Conditional volatility plots of US based on nine models





Conditional Volatility US
cstdev
20
15
10
5
2004
2006
2008
2010
2012
Time
2.67
DCC
COPULA DCC
SMA
EWMA

Figure 5.30 Conditional correlation plots of US & EMU based on nine models



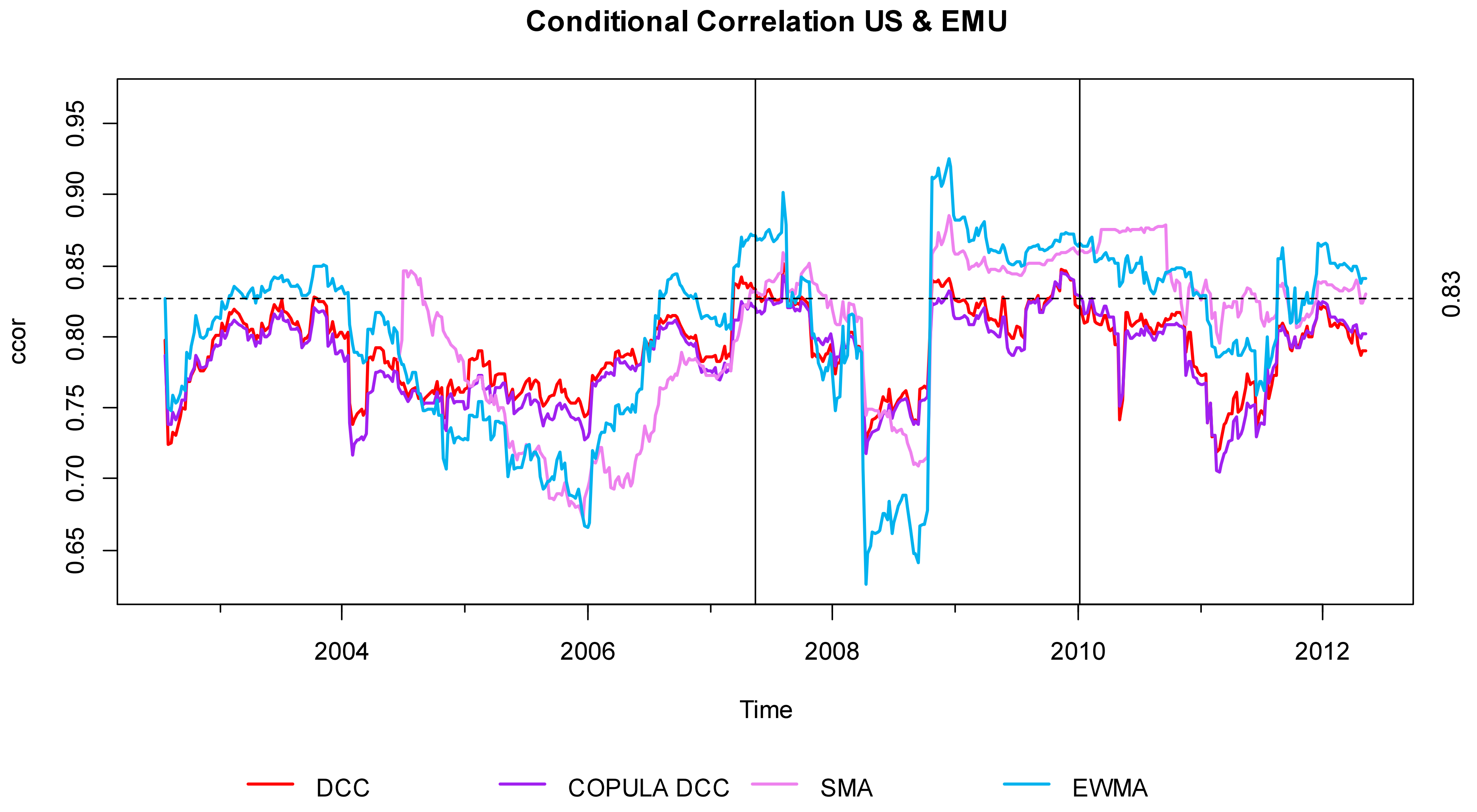
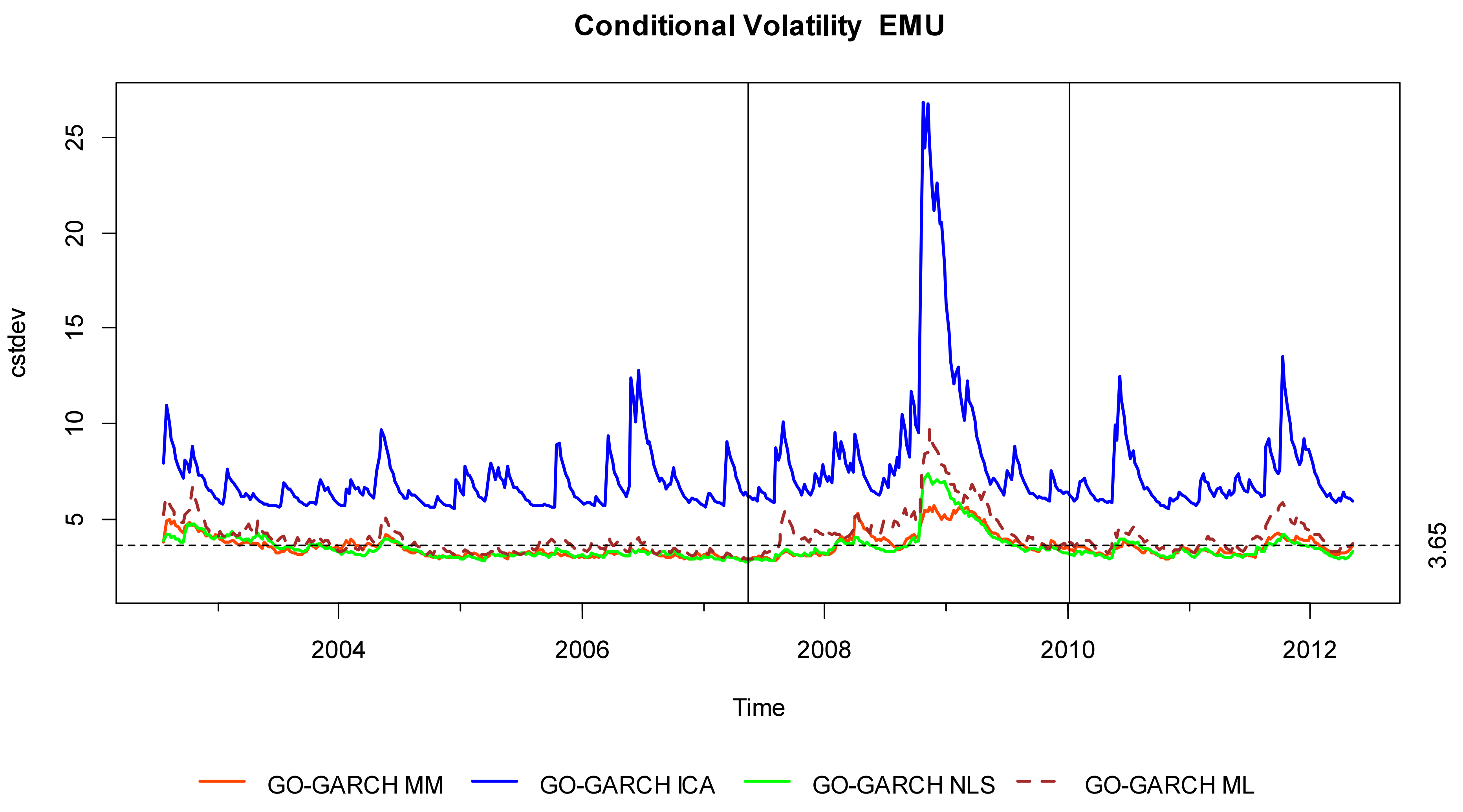

Conditional Correlation US & EMU
ccor
0.65
0.70
0.75
0.80
0.85
0.90
0.95
0.83
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.31 Conditional volatility plots of EMU based on nine models



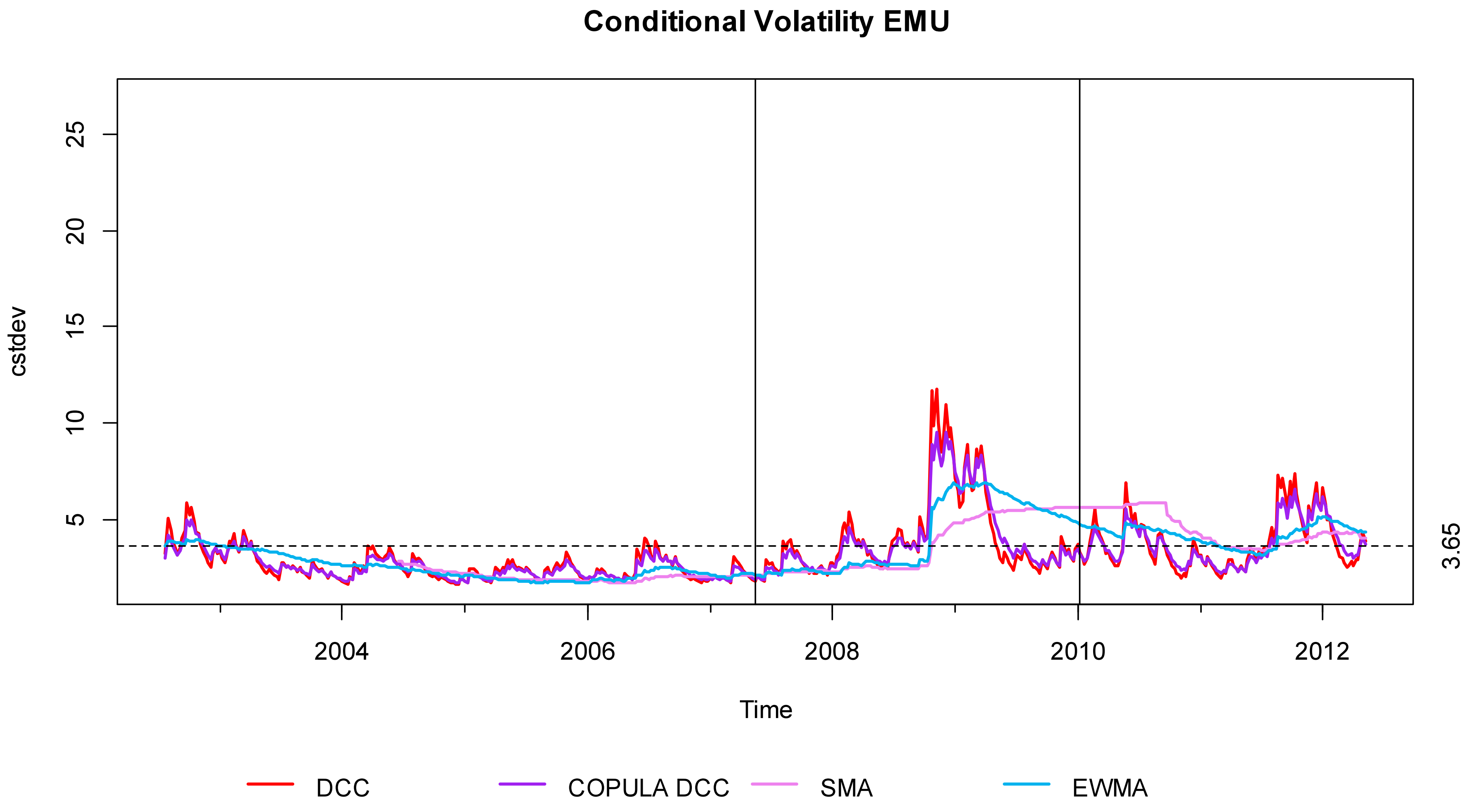
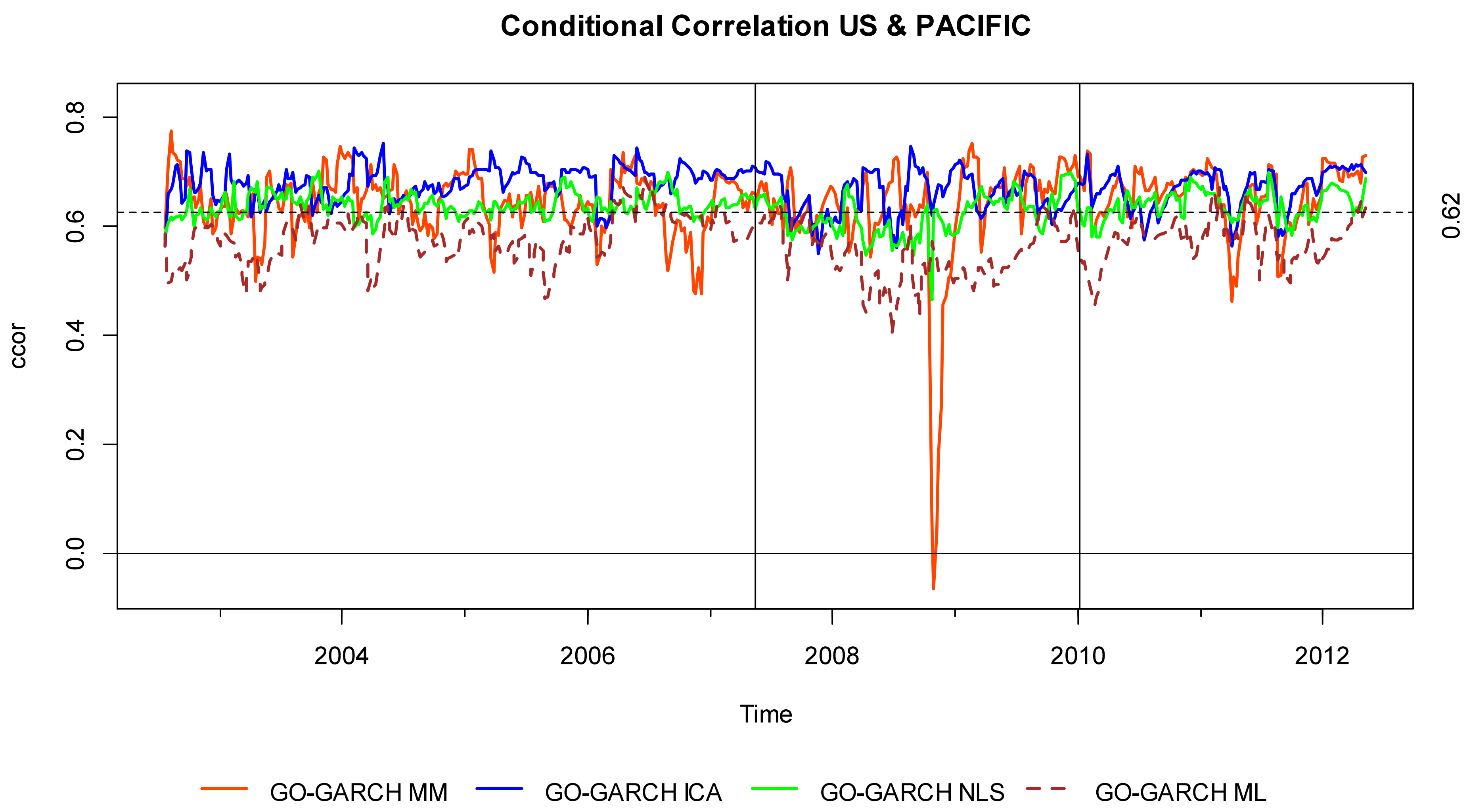

Conditional Volatility EMU
cstdev
25
20
15
10
5
3.65
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.32 Conditional correlation plots of US & Pacific based on nine models



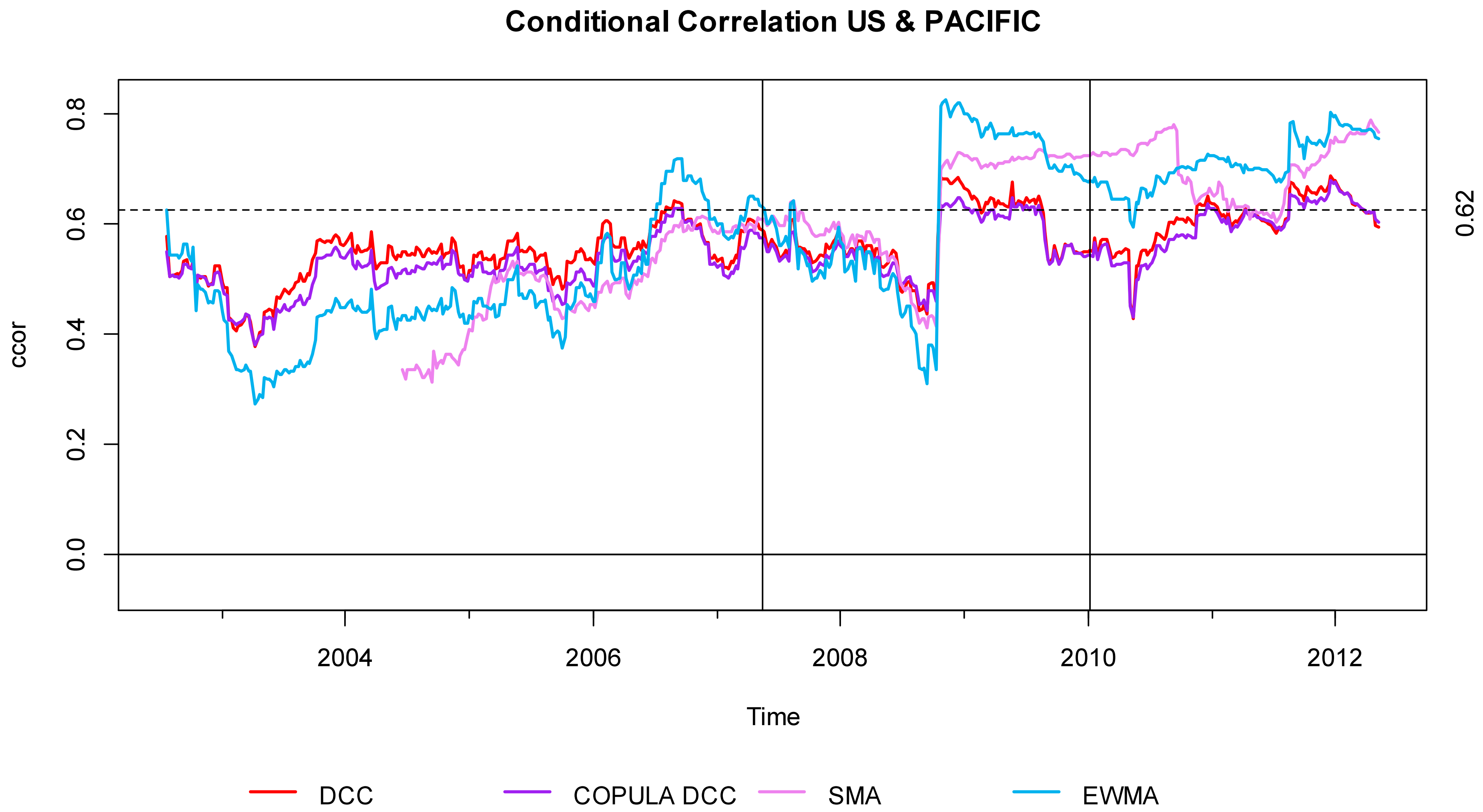
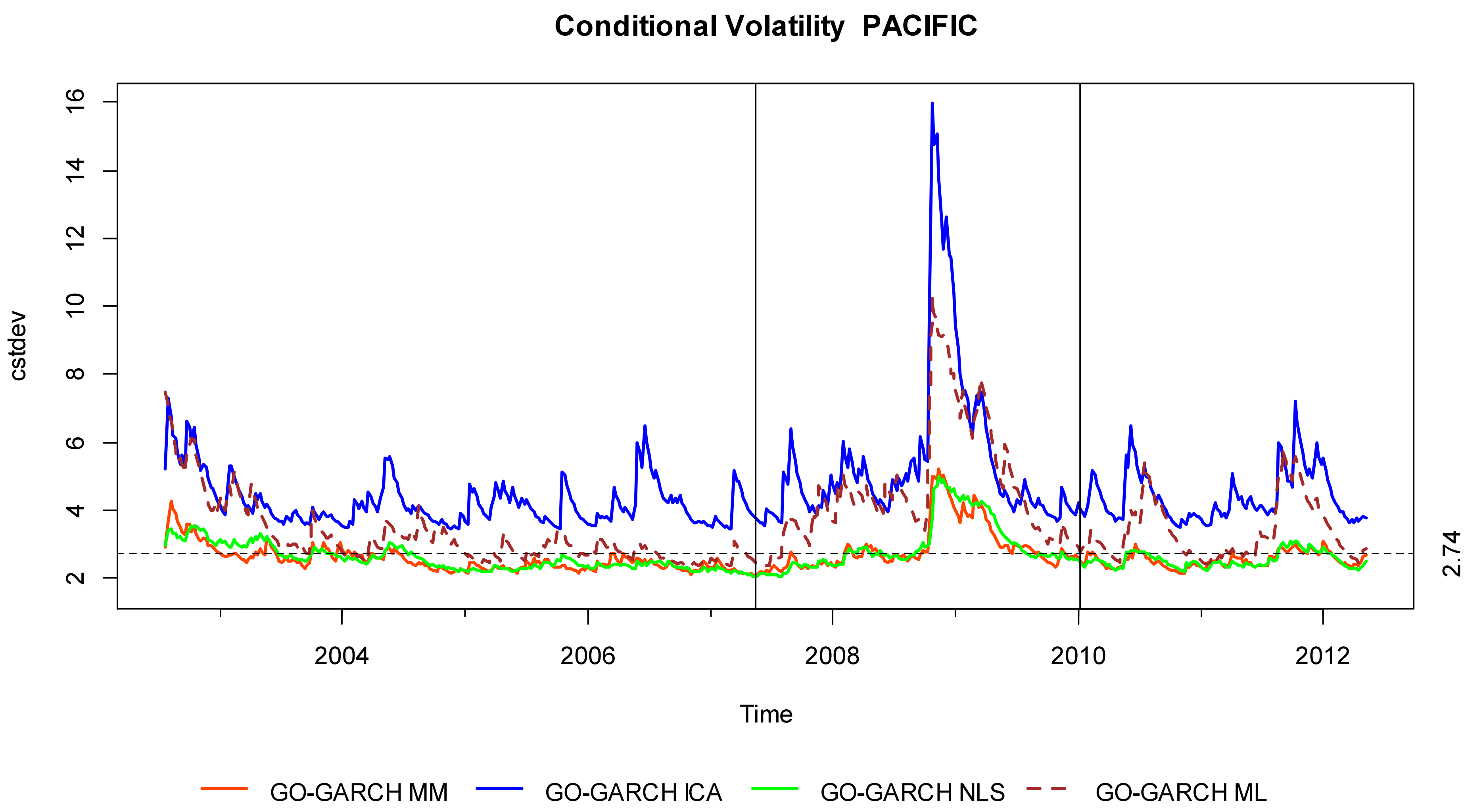

Conditional Correlation US & PACIFIC
ccor
0.0
0.2
0.4
0.6
0.8
0.62
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.33 Conditional volatility plots of Pacific based on nine models



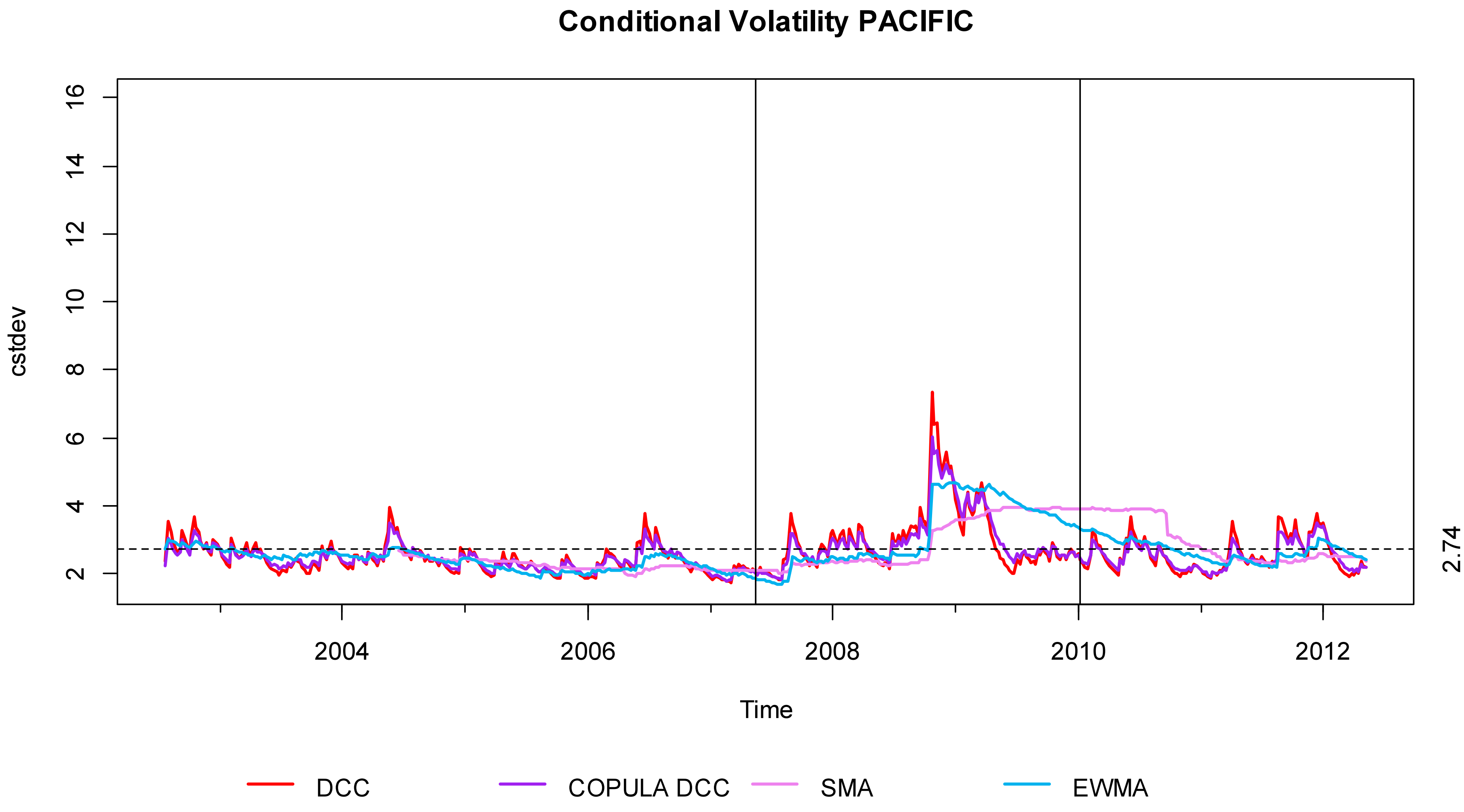
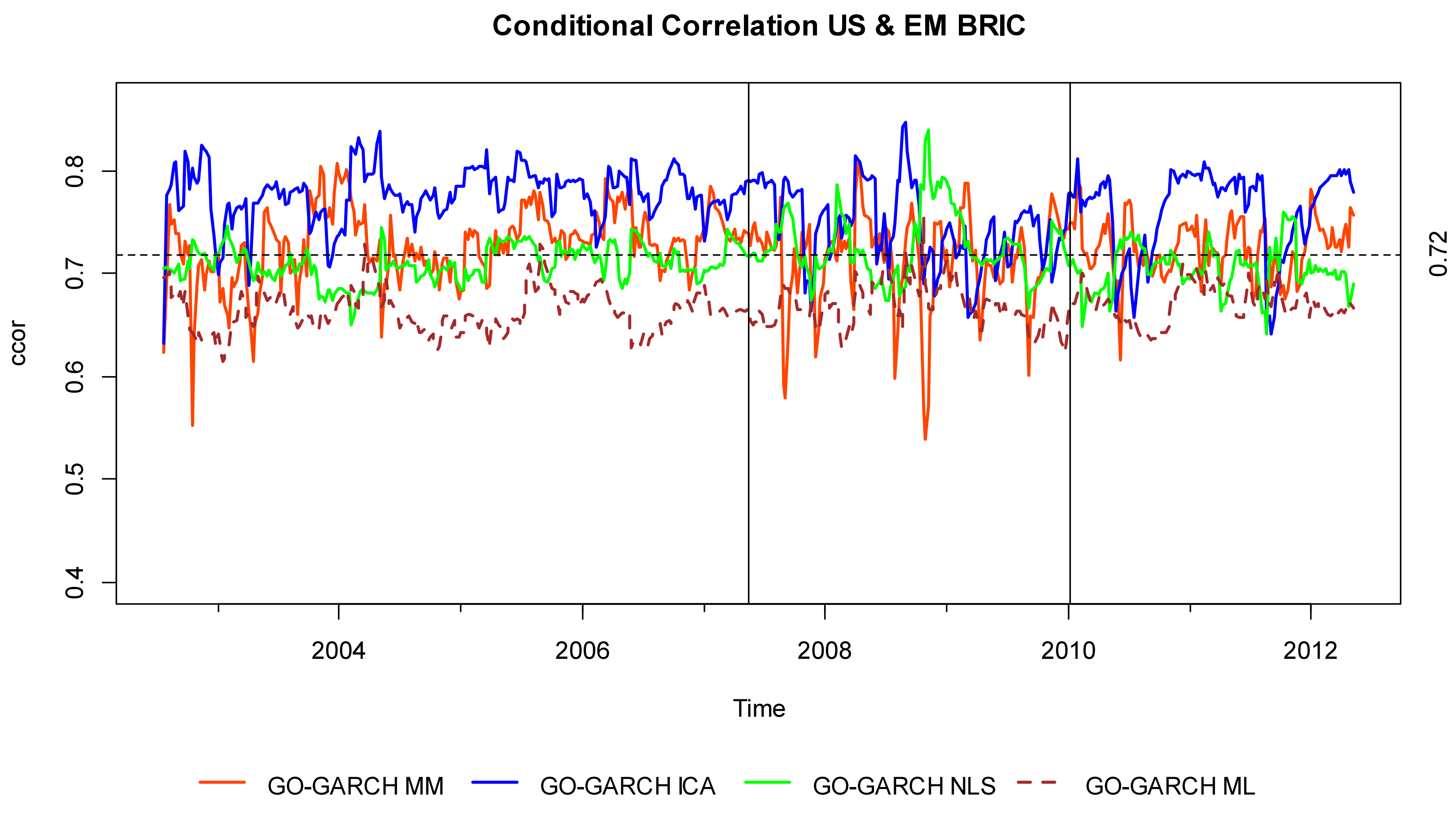

Conditional Volatility PACIFIC
cstdev
16
14
12
10
8
6
4
2
2.74
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.34 Conditional correlation plots of US & EM BRIC based on nine models



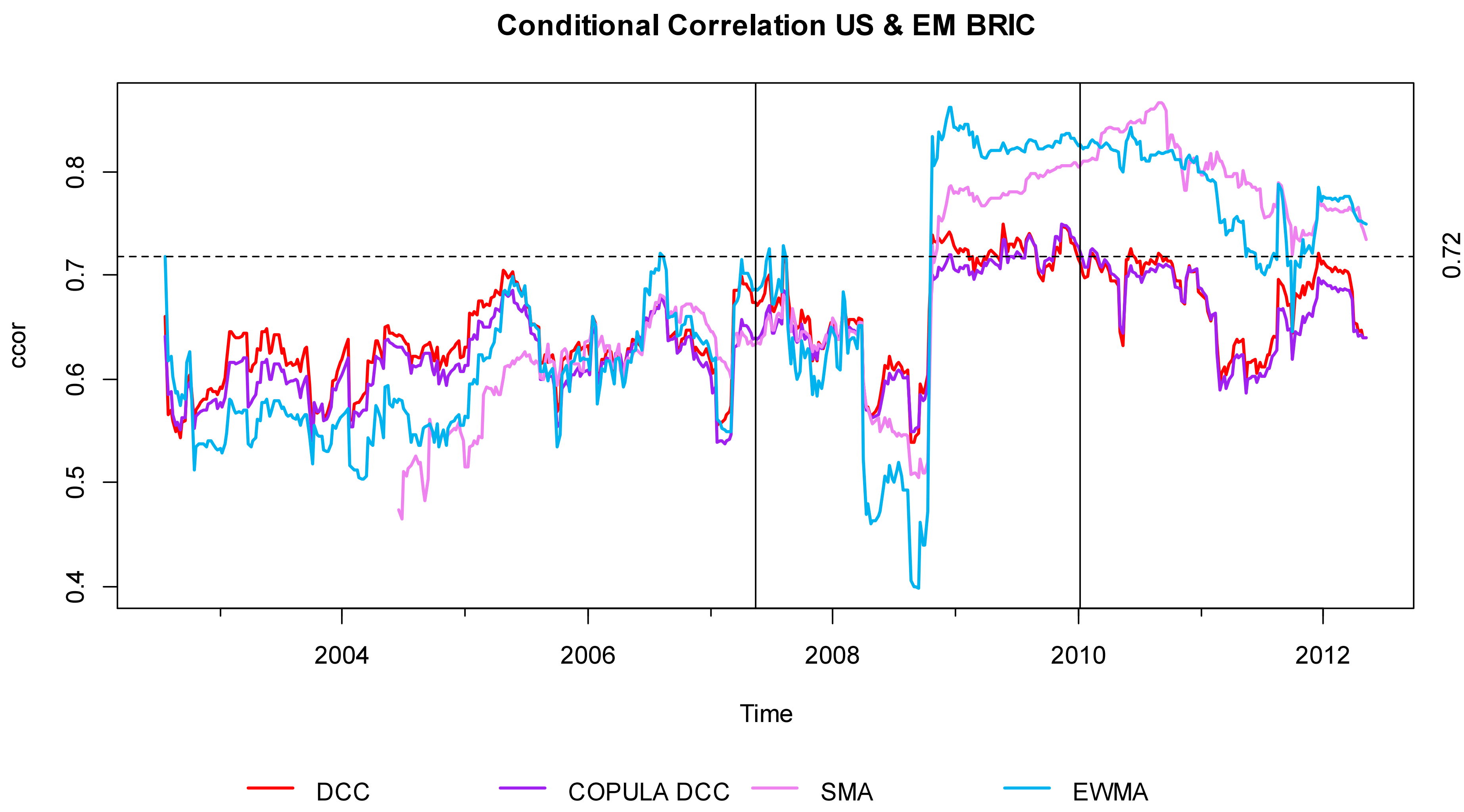
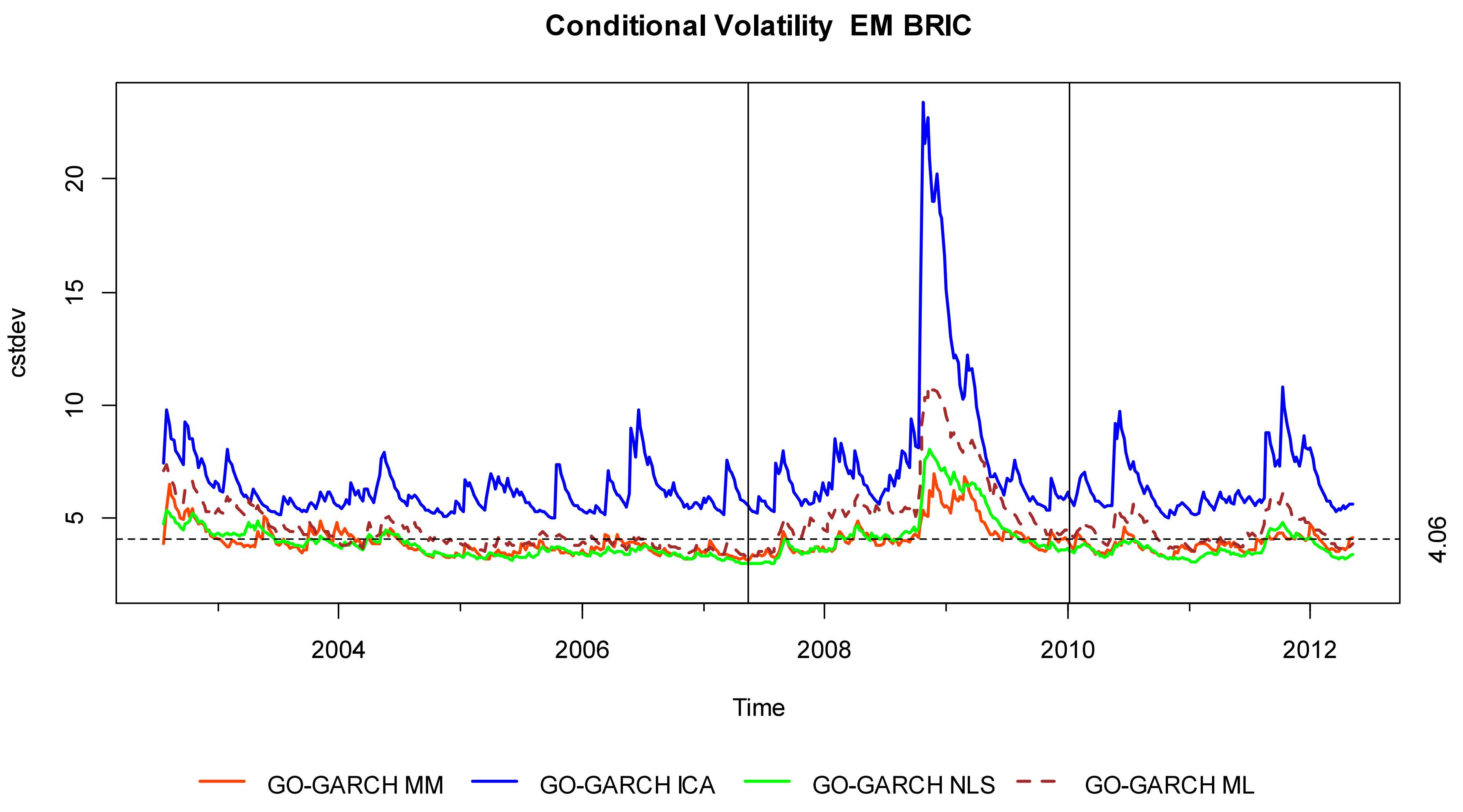

Conditional Correlation US & EM BRIC
ccor
0.4
0.5
0.6
0.7
0.8
0.72
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.35 Conditional volatility plots of EM BRIC based on nine models



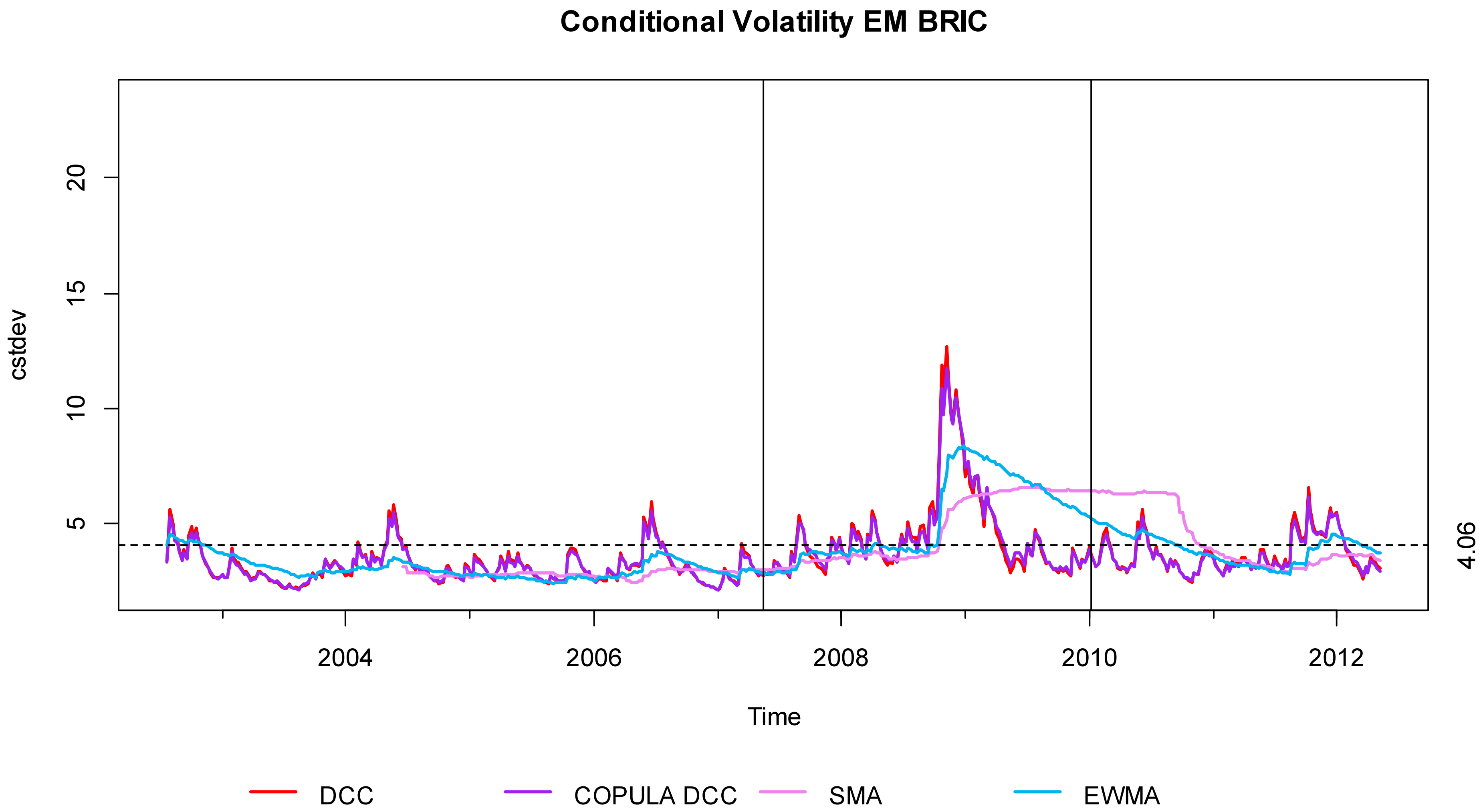
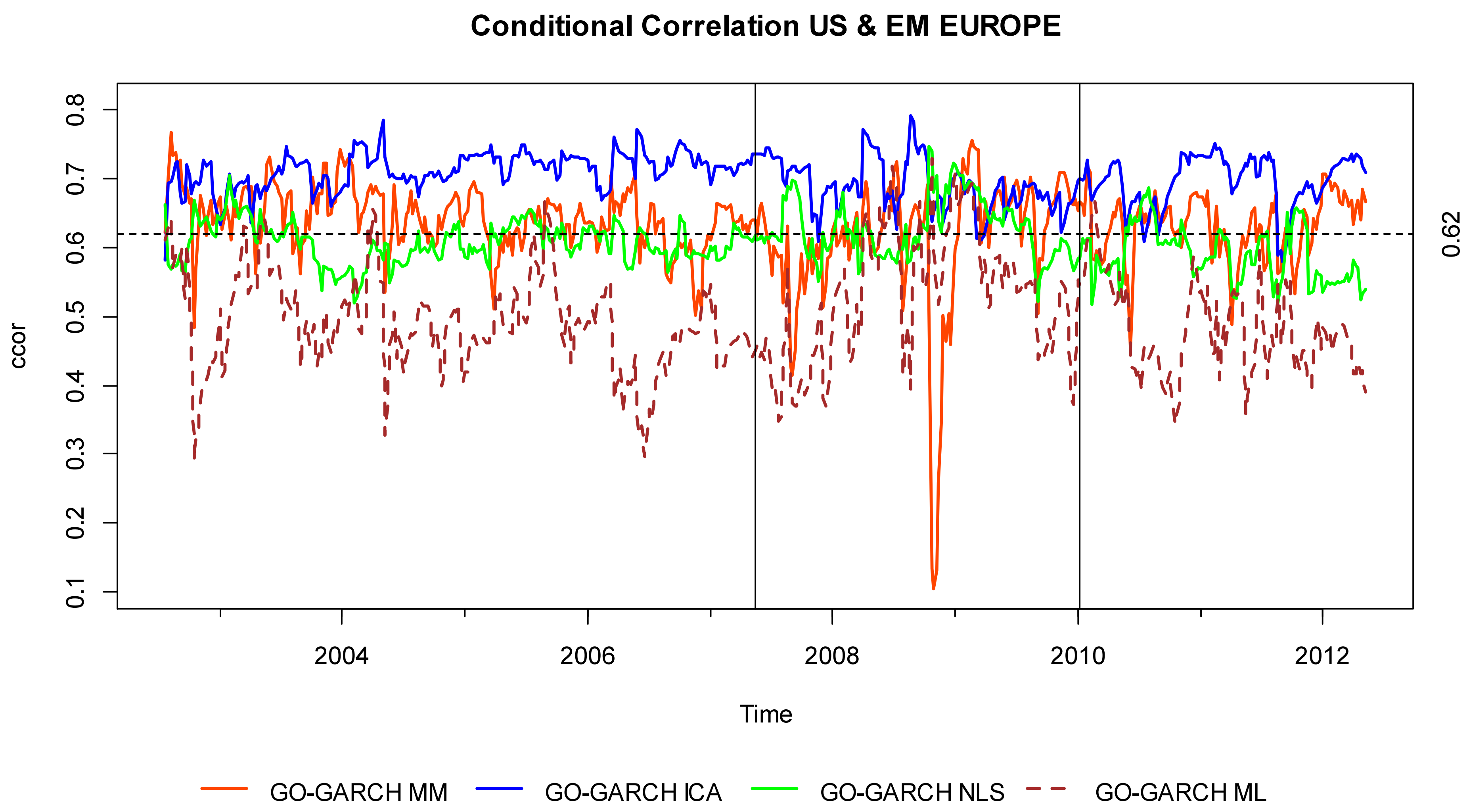

Conditional Volatility EM BRIC
cstdev
20
15
10
5
4.06
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.36 Conditional correlation plots of US & EM Europe based on nine models



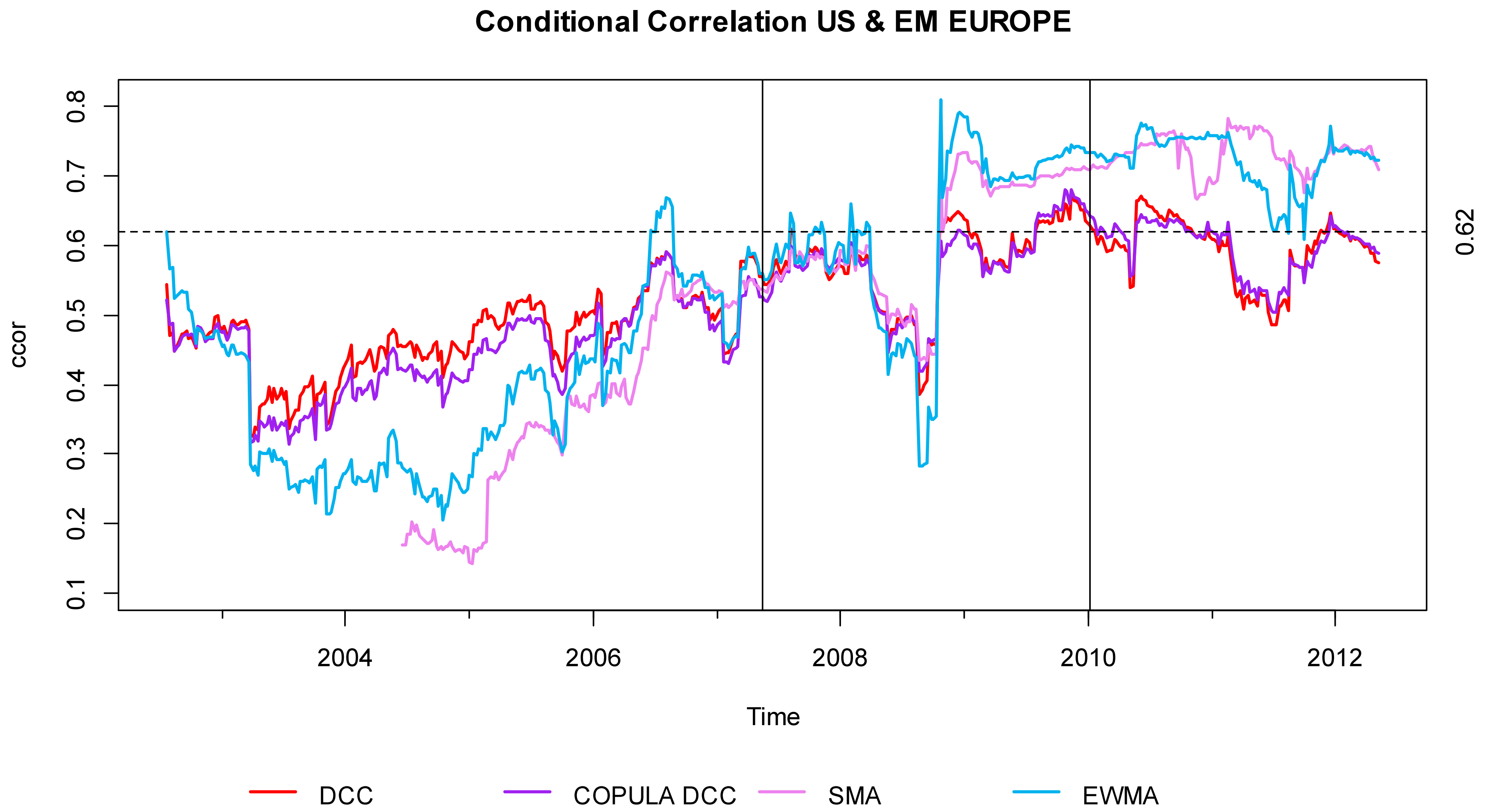
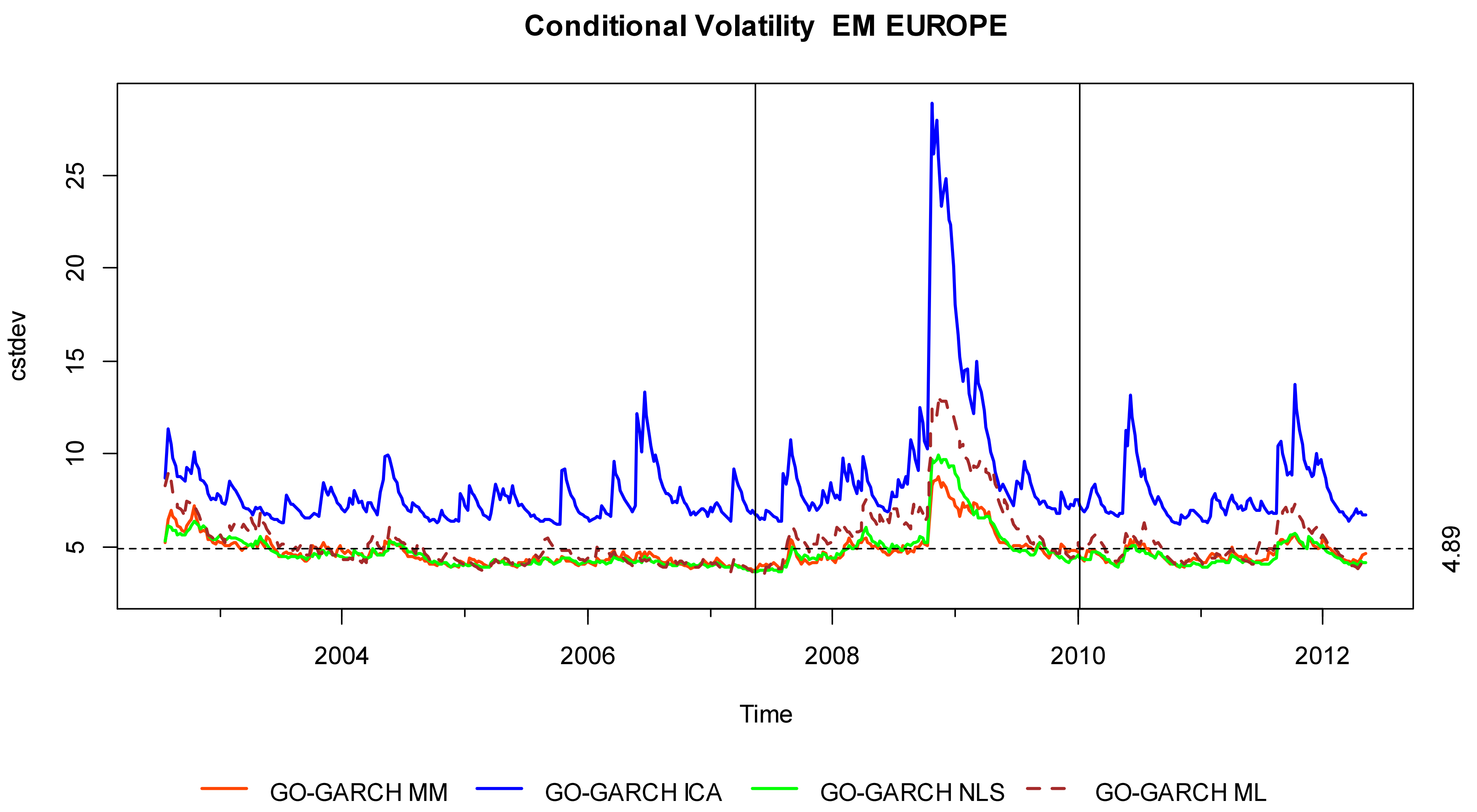

Conditional Correlation US & EM EUROPE
ccor
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.62
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.37 Conditional volatility plots of EM Europe based on nine models



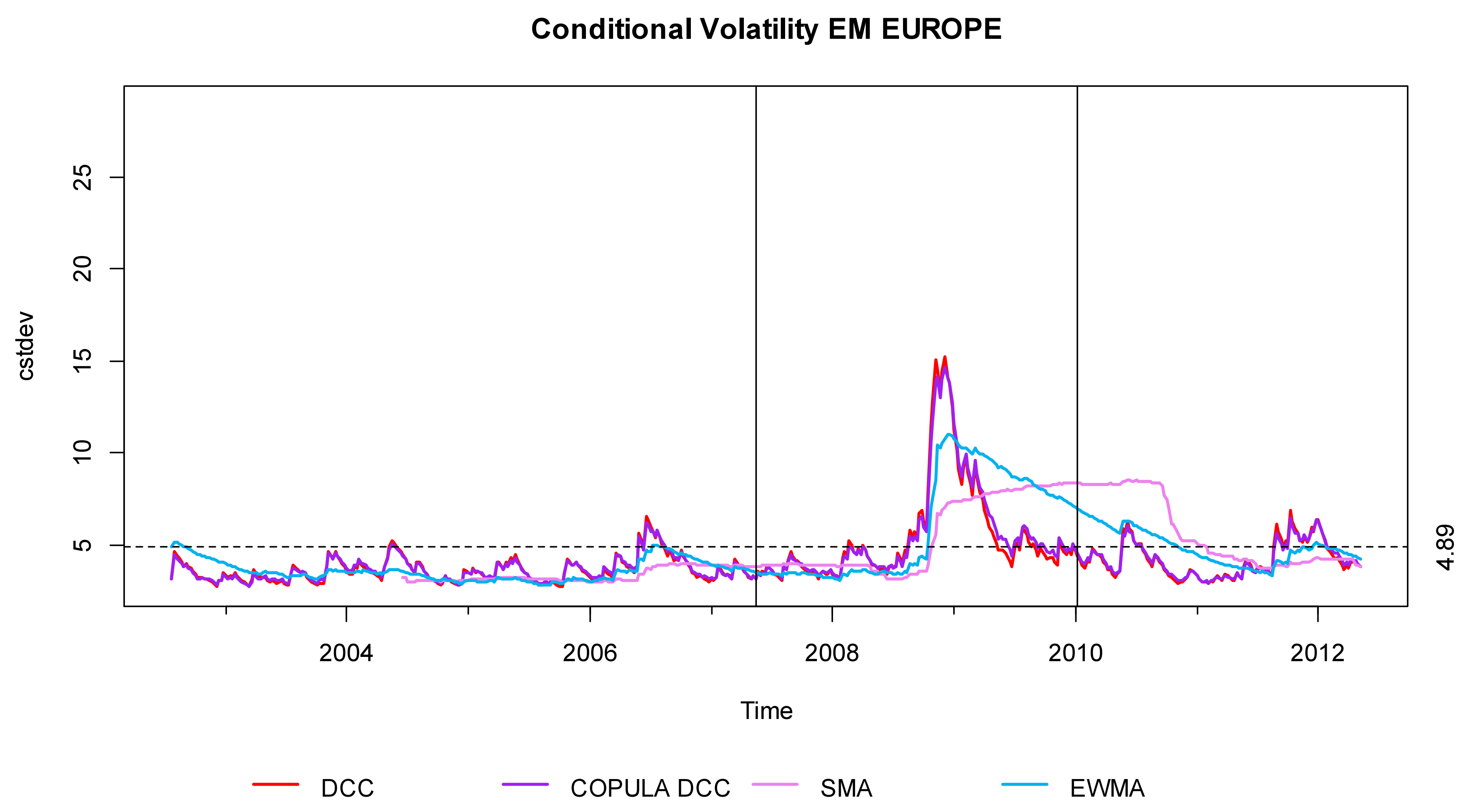
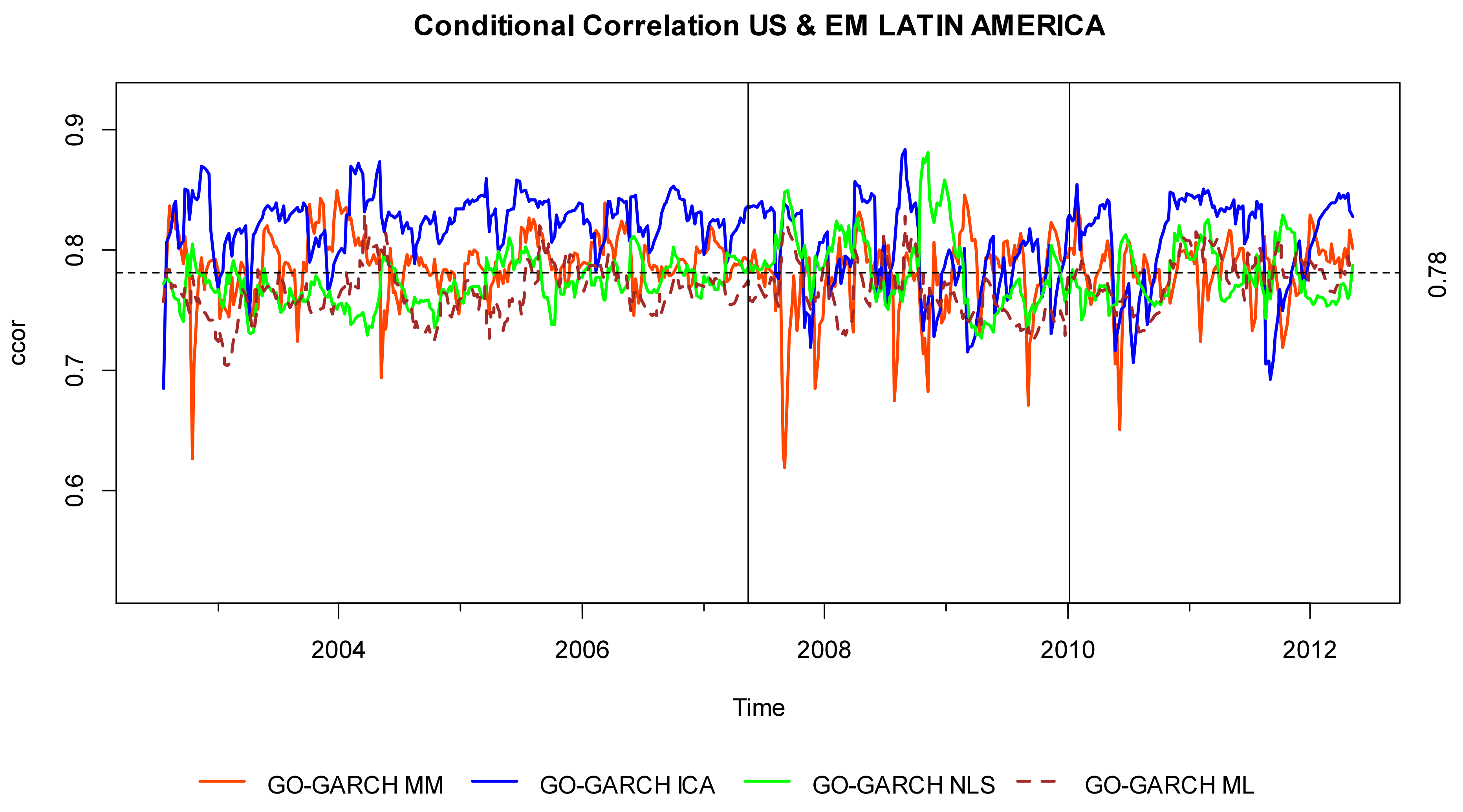

Conditional Volatility EM EUROPE
cstdev
25
20
15
10
5
4.89
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.38 Conditional correlation plots of US & EM Latin America based on nine models



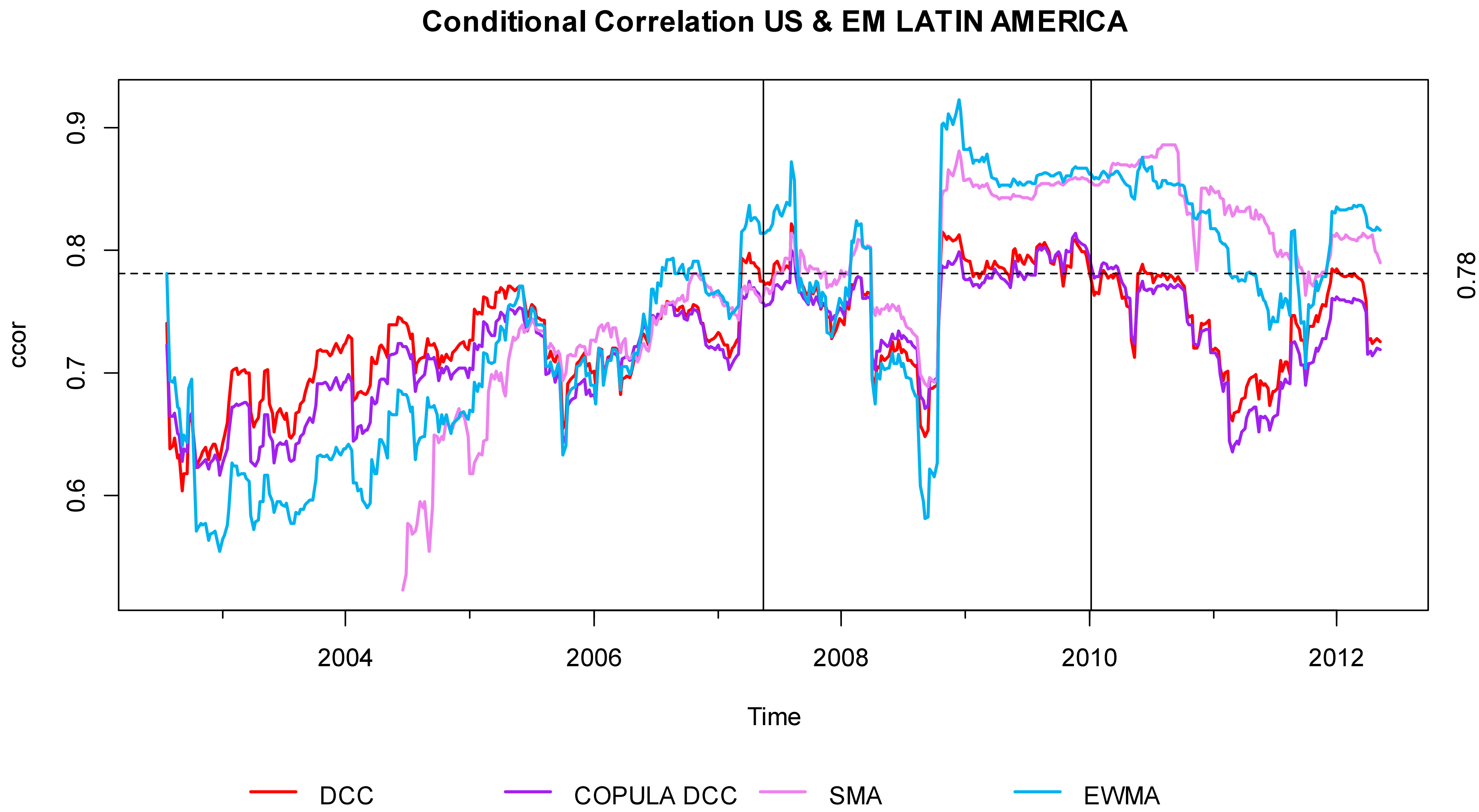
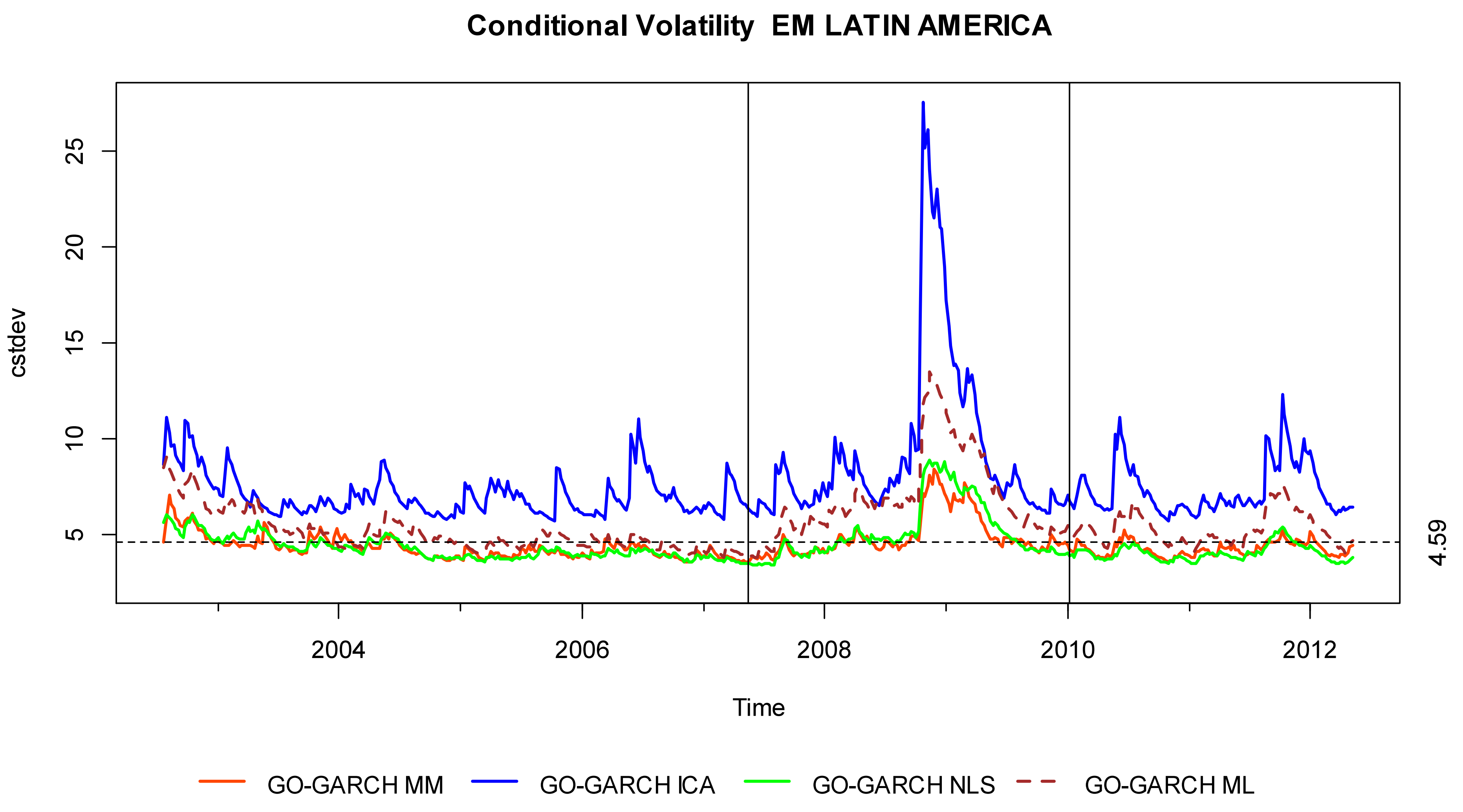
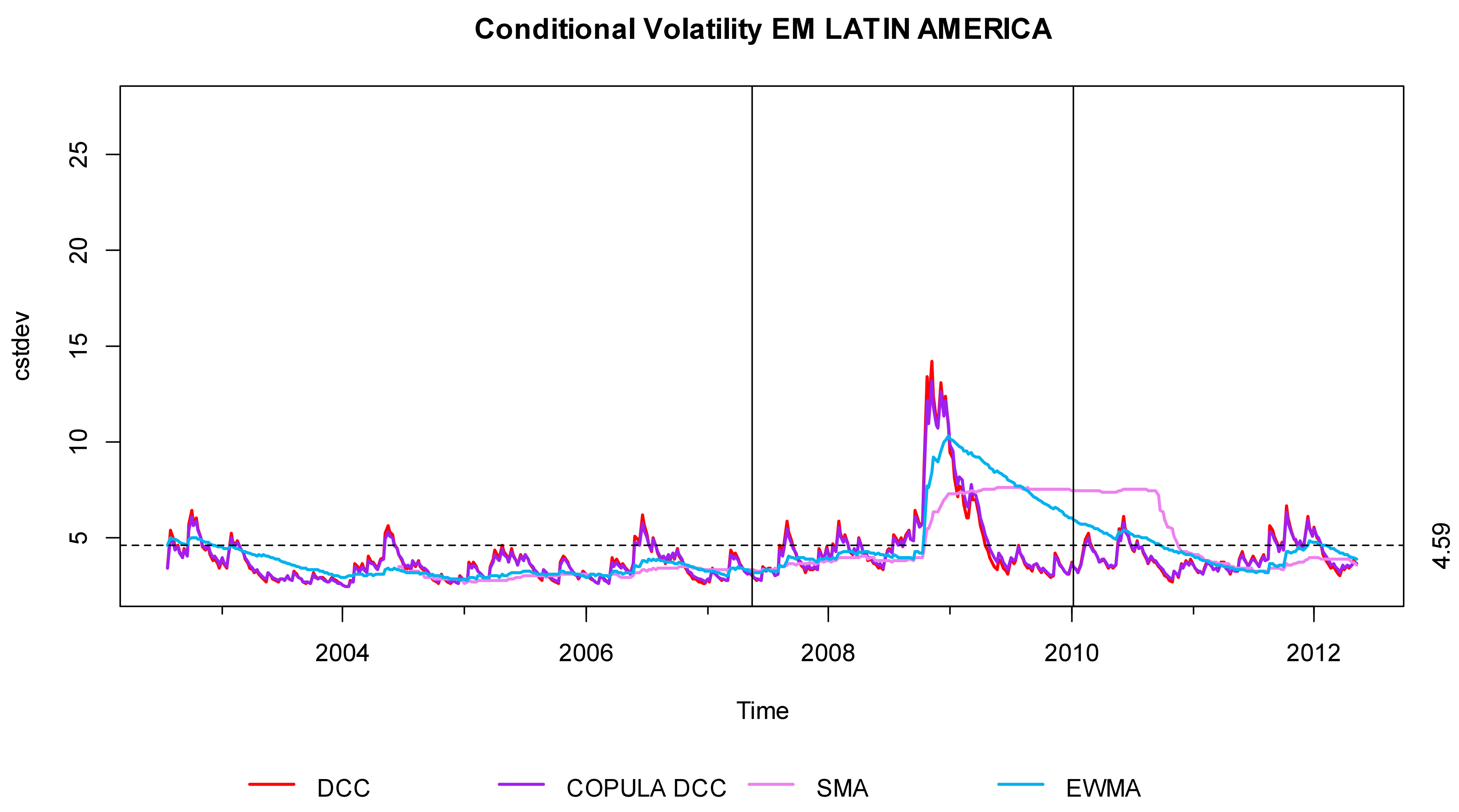

Conditional Correlation US & EM LATIN AMERICA
ccor
0.6
0.7
0.8
0.9
0.78
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

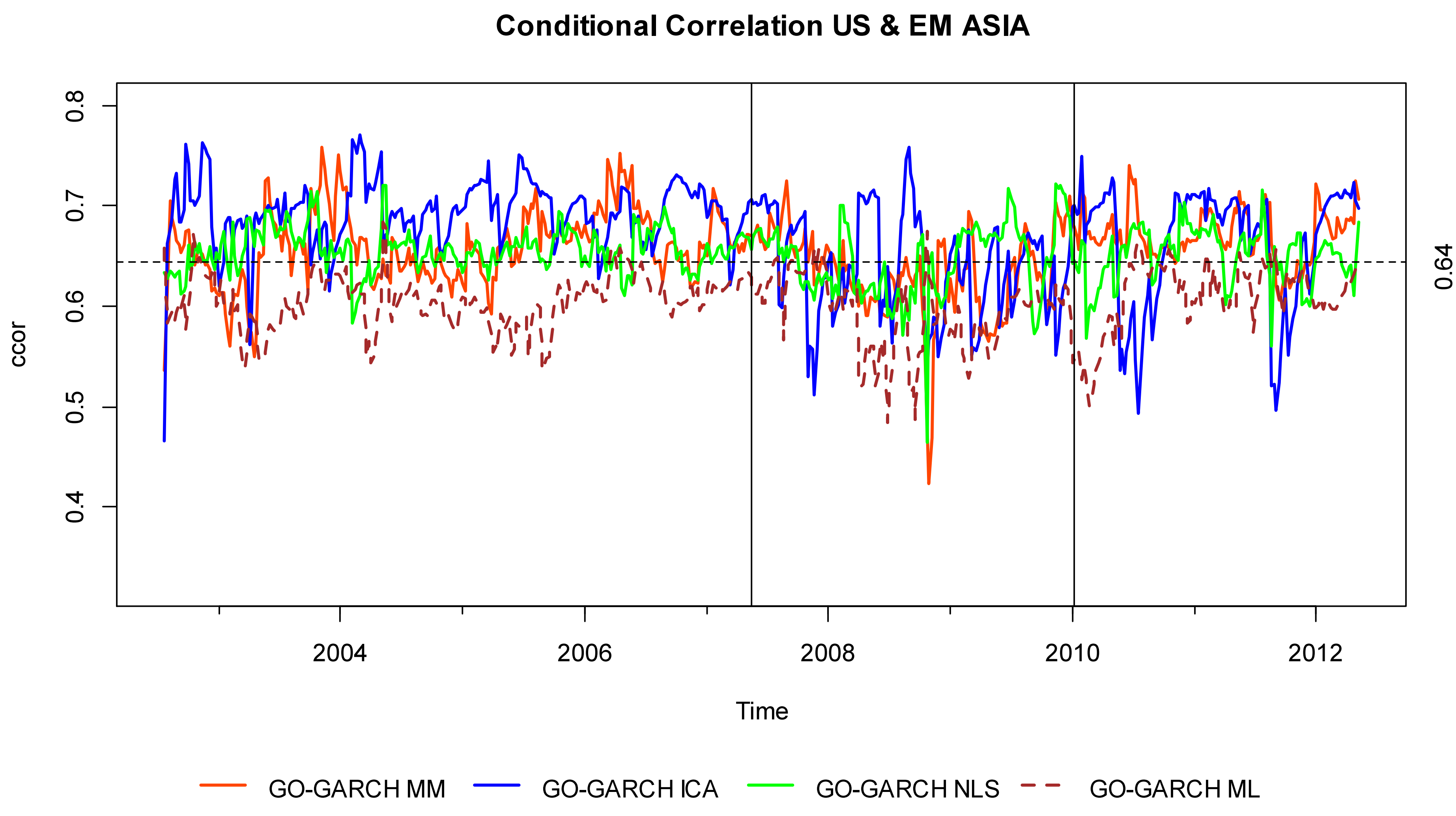
Figure 5.39 Conditional volatility plots of EM Latin America based on nine models





Conditional Volatility EM LATIN AMERICA
cstdev
25
20
15
10
5
4.59
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.40 Conditional correlation plots of US & EM Asia based on nine models



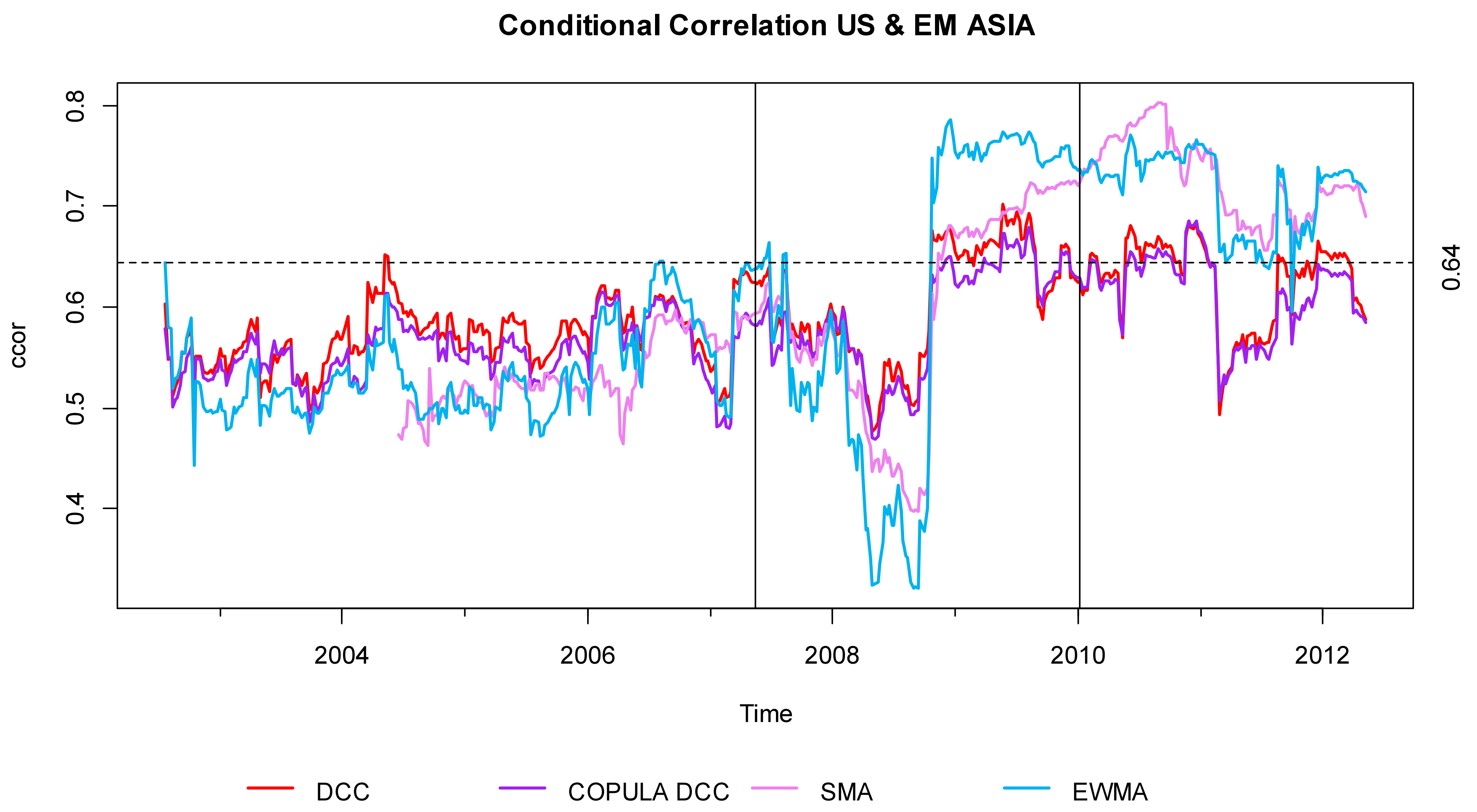
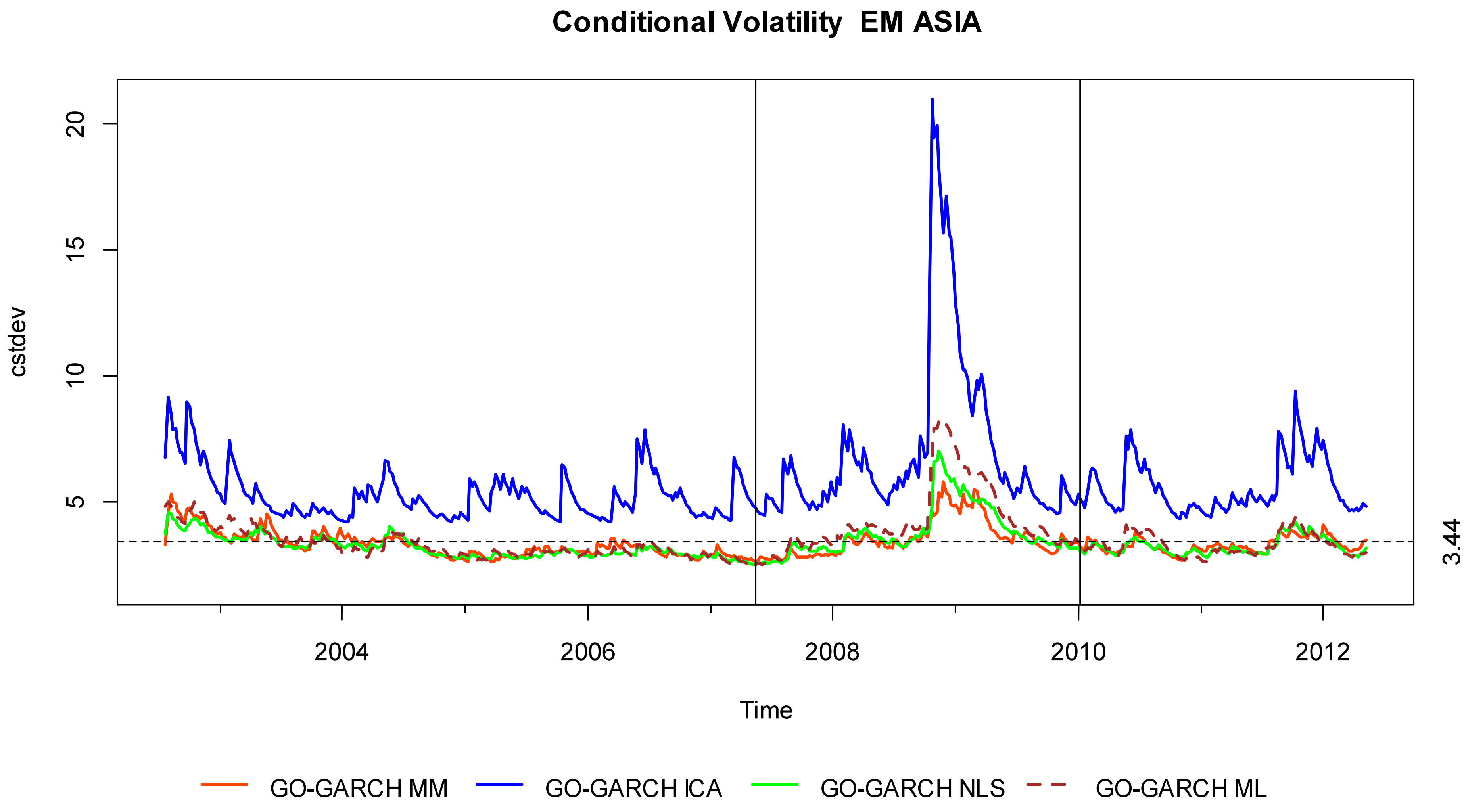
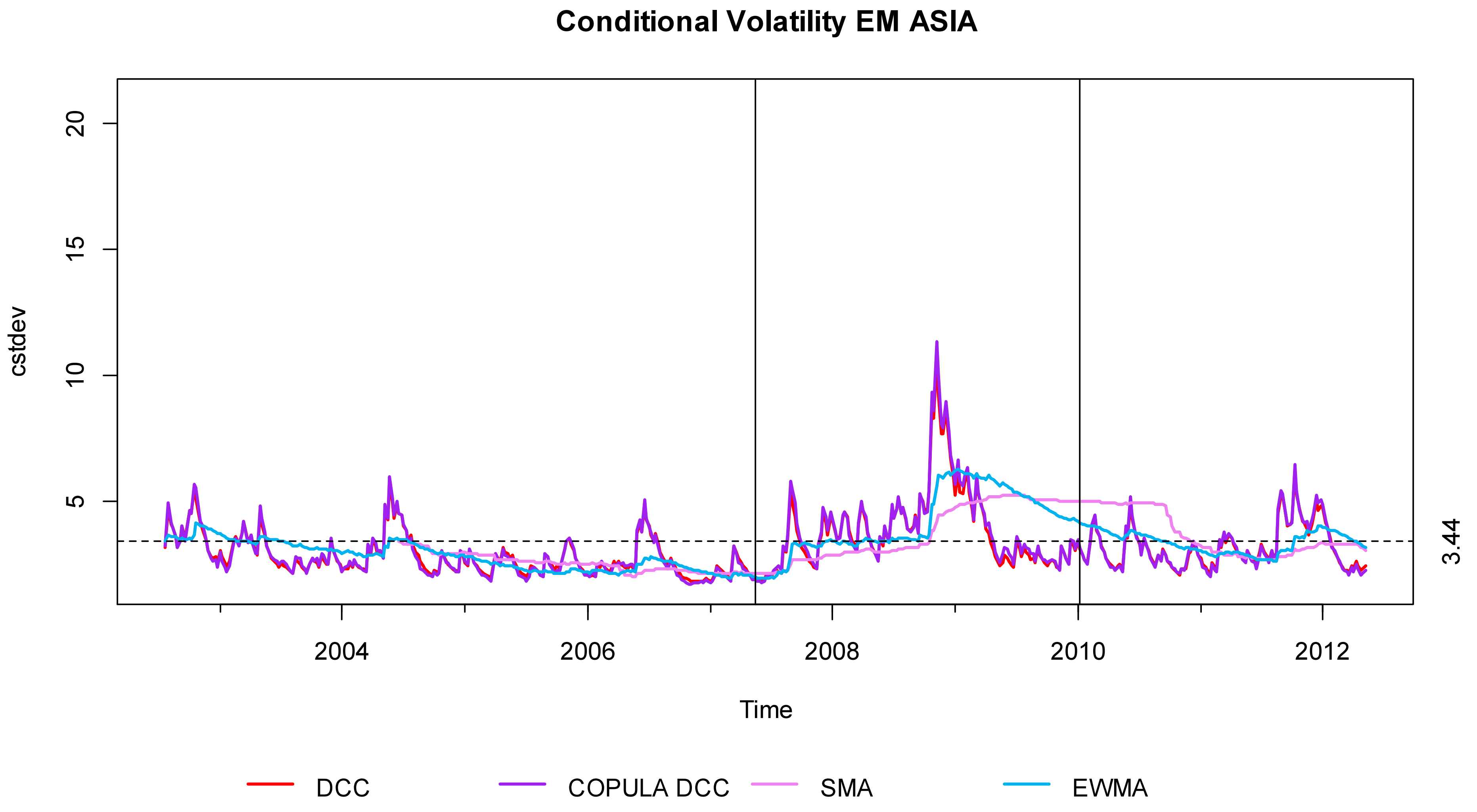

Conditional Correlation US & EM ASIA
ccor
0.4
0.5
0.6
0.7
0.8
0.64
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

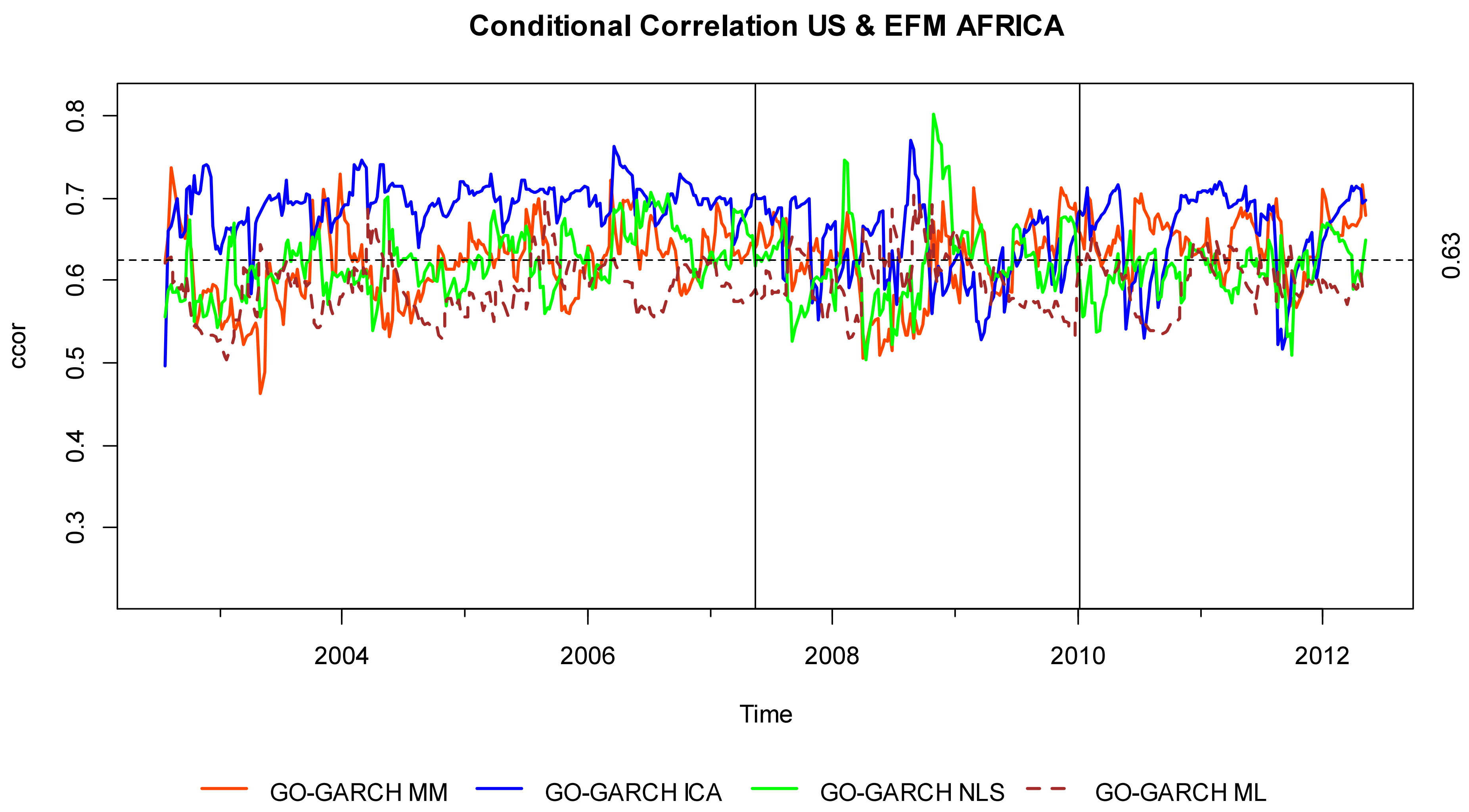
Figure 5.41 Conditional volatility plots of EM Asia based on nine models





Conditional Volatility EM ASIA
cstdev
20
15
10
5
2004
2006
2008
2010
2012
Time
3.44
DCC
COPULA DCC
SMA
EWMA

Figure 5.42 Conditional correlation plots of US & EFM Africa based on nine models



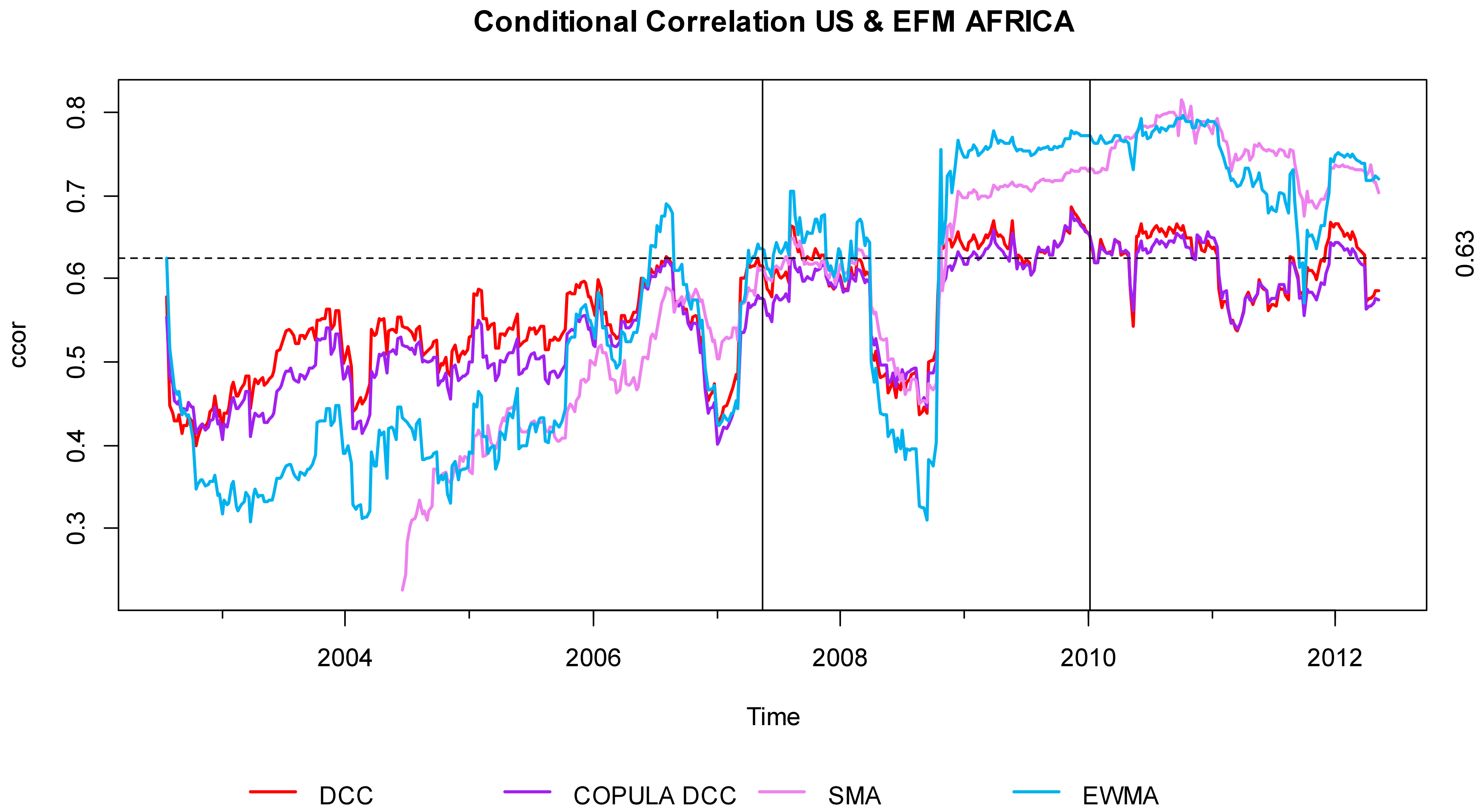
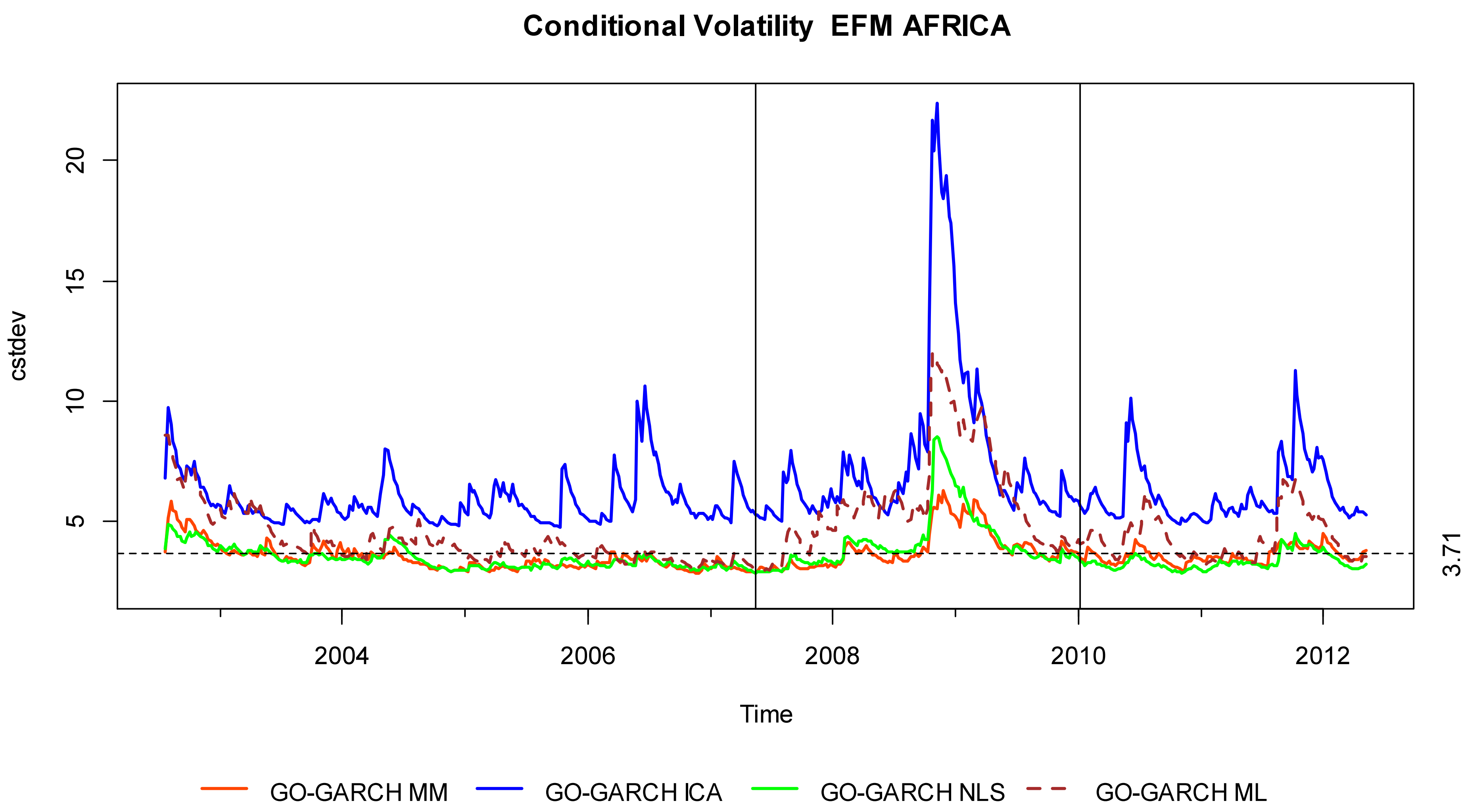

Conditional Correlation US & EFM AFRICA
ccor
0.3
0.4
0.5
0.6
0.7
0.8
0.63
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Figure 5.43 Conditional volatility plots of EFM Africa based on nine models



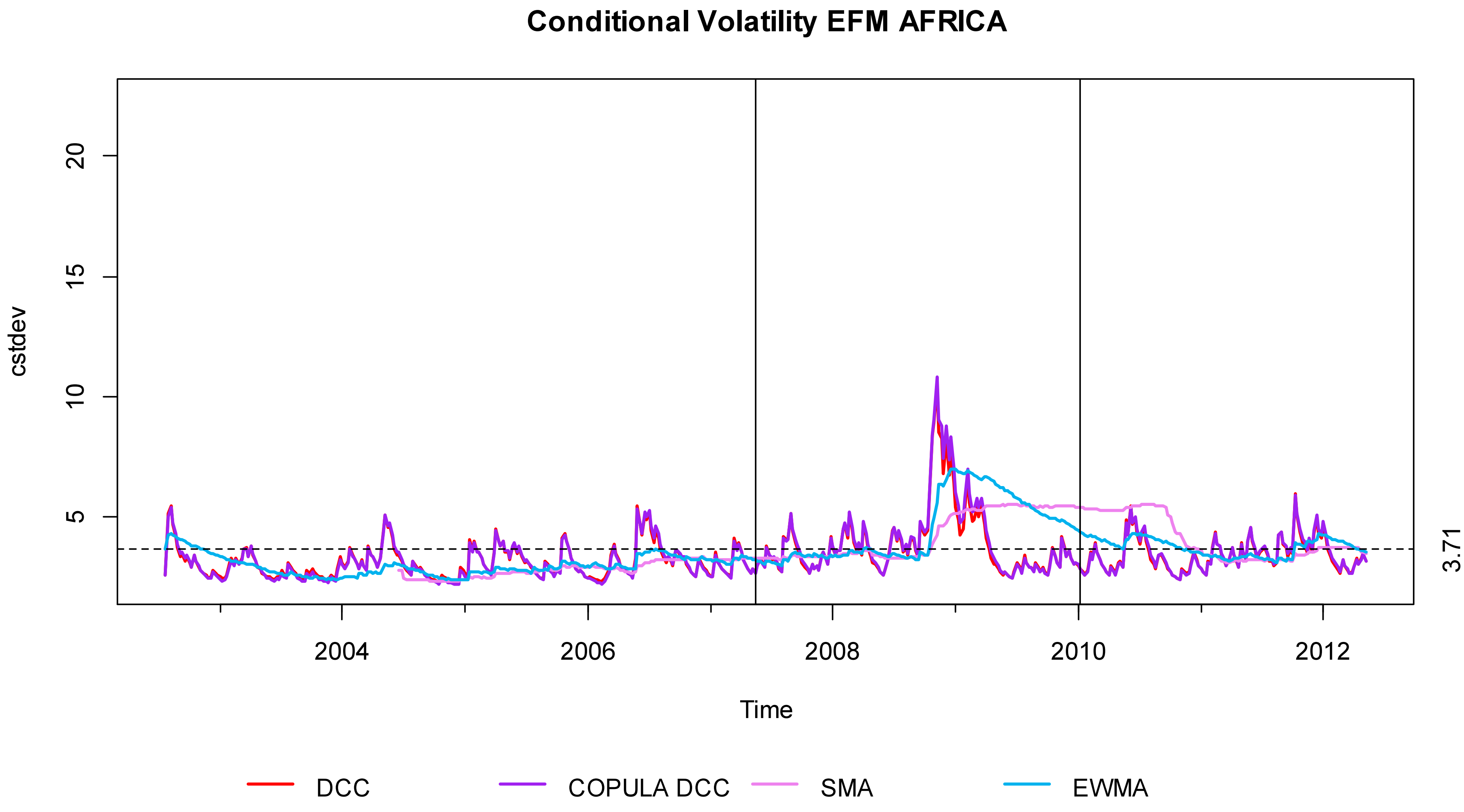

Conditional Volatility EFM AFRICA
cstdev
20
15
10
5
3.71
2004
2006
2008
2010
2012
Time
DCC
COPULA DCC
SMA
EWMA

Table 5.17 Summary statistics of US conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	1.987	4.505	**2.581**	2.404	0.496	**0.192**
GO-GARCH ICA	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	3.458	19.802	**4.886**	4.289	1.984	**0.406**
GO-GARCH NLS	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	1.850	6.072	**2.565**	2.340	0.665	**0.259**
GO-GARCH ML	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	1.985	6.258	**2.731**	2.585	0.587	**0.215**
DCC	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	1.130	9.724	**2.335**	1.954	1.213	**0.519**
COPULA DCC	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	1.063	9.203	**2.379**	1.956	1.278	**0.537**
SMA (100)	512[a]	1.000	1.000	**1.000**	1.000	0.000	**0.000**	1.337	4.361	**2.442**	2.074	1.076	**0.441**
EWMA (0.03, 0.97)	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	1.261	5.344	**2.449**	2.288	1.014	**0.414**
UNCONDITIONAL	512	1.000	1.000	**1.000**	1.000	0.000	**0.000**	2.667	2.667	**2.667**	2.667	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.18 Statistical significance of US conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.000**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	414	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.625**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	414	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**0.001**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	414	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**0.045**	**0.000**	**0.029**	**0.000**	**-**	**0.862**	**0.415**	**0.236**	**0.000**
COPULA DCC	414	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**0.232**	**0.000**	**0.159**	**0.000**	**0.576**	**-**	**0.468**	**0.365**	**0.000**
SMA (100)	414	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**0.200**	**0.000**	**0.130**	**0.000**	**0.451**	**0.901**	**-**	**0.410**	**0.000**
EWMA (0.03, 0.97)	414	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**0.336**	**0.000**	**0.224**	**0.000**	**0.344**	**0.748**	**0.822**	**-**	**0.000**
UNCONDITIONAL	414	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.000**	**0.000**	**0.000**	**0.042**	**0.000**	**0.000**	**0.000**	**0.000**	**-**

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.19 Summary statistics of EMU conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	0.728	0.907	**0.832**	0.833	0.019	**0.023**	2.795	5.673	**3.559**	3.380	0.603	**0.169**
GO-GARCH ICA	512	0.737	0.878	**0.831**	0.839	0.025	**0.030**	5.560	26.853	**7.442**	6.618	2.723	**0.366**
GO-GARCH NLS	512	0.767	0.908	**0.827**	0.827	0.022	**0.026**	2.737	7.406	**3.531**	3.316	0.742	**0.210**
GO-GARCH ML	512	0.867	0.968	**0.932**	0.934	0.019	**0.020**	2.851	9.696	**4.074**	3.791	1.020	**0.250**
DCC	512	0.719	0.852	**0.791**	0.795	0.029	**0.036**	1.602	11.797	**3.285**	2.810	1.593	**0.485**
COPULA DCC	512	0.705	0.845	**0.785**	0.793	0.030	**0.039**	1.689	9.548	**3.225**	2.849	1.413	**0.438**
SMA (100)	512[a]	0.673	0.886	**0.802**	0.822	0.056	**0.070**	1.682	5.884	**3.323**	2.530	1.426	**0.429**
EWMA (0.03, 0.97)	512	0.625	0.925	**0.803**	0.820	0.061	**0.076**	1.671	6.933	**3.343**	2.847	1.367	**0.409**
UNCONDITIONAL	512	0.827	0.827	**0.827**	0.827	0.000	**0.000**	3.651	3.651	**3.651**	3.651	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.20 Statistical significance of EMU conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	-	0.625	0.000	0.000	0.000	0.000	0.000	0.000	0.700	-	0.000	0.054	0.000	0.000	0.000	0.000	0.000	0.000
GO-GARCH ICA	414	0.003	-	0.009	0.000	0.000	0.000	0.000	0.000	0.002	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GO-GARCH NLS	414	0.000	0.720	-	0.000	0.000	0.000	0.000	0.000	0.000	0.609	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000
GO-GARCH ML	414	0.000	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000
DCC	414	0.000	0.000	0.000	0.000	-	0.016	0.000	0.000	0.000	0.101	0.000	0.189	0.000	-	0.856	0.527	0.999	0.000
COPULA DCC	414	0.000	0.000	0.000	0.000	0.009	-	0.000	0.000	0.000	0.011	0.000	0.033	0.000	0.606	-	0.490	0.910	0.000
SMA (100)	414	0.000	0.000	0.000	0.000	0.000	0.000	-	0.718	0.000	0.022	0.000	0.061	0.000	0.795	0.772	-	0.502	0.000
EWMA (0.03, 0.97)	414	0.000	0.000	0.000	0.000	0.017	0.000	0.492	-	0.000	0.145	0.000	0.273	0.000	0.785	0.399	0.562	-	0.000
UNCONDITIONAL	414	0.727	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.21 Summary statistics of Europe ex EMU conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	0.685	0.901	**0.835**	0.837	0.025	**0.030**	2.440	5.381	**3.074**	2.936	0.515	**0.168**
GO-GARCH ICA	512	0.693	0.912	**0.842**	0.854	0.038	**0.045**	4.467	20.510	**5.997**	5.347	2.118	**0.353**
GO-GARCH NLS	512	0.793	0.889	**0.828**	0.826	0.015	**0.018**	2.456	5.595	**3.078**	2.921	0.531	**0.173**
GO-GARCH ML	512	0.807	0.927	**0.879**	0.880	0.019	**0.021**	2.609	9.039	**3.694**	3.425	0.977	**0.264**
DCC	512	0.687	0.848	**0.777**	0.782	0.035	**0.044**	1.413	10.659	**2.754**	2.386	1.360	**0.494**
COPULA DCC	512	0.665	0.834	**0.773**	0.782	0.038	**0.049**	1.463	8.763	**2.709**	2.385	1.226	**0.453**
SMA (100)	512[a]	0.579	0.897	**0.778**	0.812	0.089	**0.115**	1.454	5.467	**2.928**	2.270	1.384	**0.473**
EWMA (0.03, 0.97)	512	0.562	0.938	**0.785**	0.810	0.084	**0.108**	1.434	6.913	**2.867**	2.489	1.308	**0.456**
UNCONDITIONAL	512	0.828	0.828	**0.828**	0.828	0.000	**0.000**	3.144	3.144	**3.144**	3.144	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.22 Statistical significance of Europe ex EMU conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.123**	-	**0.000**	**0.559**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	414	**0.097**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.050**	**0.000**	**0.787**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	414	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.898**
DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.109**	**0.000**	**0.000**	**0.000**	**0.013**	**0.000**	**0.019**	**0.000**	-	**0.996**	**0.642**	**0.813**	**0.000**
COPULA DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.091**	-	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.002**	**0.000**	**0.695**	-	**0.601**	**0.846**	**0.000**
SMA (100)	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.962**	**0.390**	-	**0.368**	**0.000**	**0.199**	**0.000**	**0.253**	**0.000**	**0.322**	**0.148**	-	**0.584**	**0.000**
EWMA (0.03, 0.97)	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.350**	**0.071**	**0.451**	-	**0.001**	**0.317**	**0.000**	**0.387**	**0.000**	**0.248**	**0.107**	**0.851**	-	**0.000**
UNCONDITIONAL	414	**0.013**	**0.634**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.23 Summary statistics of Pacific conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	-0.066	0.773	**0.643**	0.654	0.077	**0.120**	2.075	5.231	**2.653**	2.528	0.487	**0.184**
GO-GARCH ICA	512	0.547	0.752	**0.671**	0.677	0.036	**0.053**	3.446	15.972	**4.629**	4.182	1.503	**0.325**
GO-GARCH NLS	512	0.463	0.701	**0.633**	0.635	0.030	**0.047**	2.046	4.984	**2.677**	2.535	0.510	**0.190**
GO-GARCH ML	512	0.398	0.688	**0.570**	0.575	0.048	**0.084**	2.320	10.345	**3.653**	3.173	1.334	**0.365**
DCC	512	0.378	0.686	**0.563**	0.556	0.059	**0.104**	1.765	7.365	**2.627**	2.469	0.673	**0.256**
COPULA DCC	512	0.380	0.679	**0.547**	0.541	0.058	**0.107**	1.812	6.023	**2.615**	2.508	0.580	**0.222**
SMA (100)	512[a]	0.311	0.789	**0.599**	0.604	0.121	**0.203**	1.946	3.978	**2.702**	2.401	0.662	**0.245**
EWMA (0.03, 0.97)	512	0.272	0.825	**0.573**	0.561	0.142	**0.247**	1.687	4.691	**2.682**	2.532	0.652	**0.243**
UNCONDITIONAL	512	0.623	0.623	**0.623**	0.623	0.000	**0.000**	2.744	2.744	**2.744**	2.744	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.24 Statistical significance of Pacific conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.057**	**0.000**	**-**	**0.000**	**0.877**	**0.000**	**0.041**	**0.269**	**0.023**	**0.720**	**0.000**
GO-GARCH ICA	414	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.797**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**0.055**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.001**	**0.809**	**0.000**	**0.708**	**0.000**	**-**	**0.000**	**0.050**	**0.309**	**0.036**	**0.840**	**0.000**
GO-GARCH ML	414	**0.000**	**0.000**	**0.000**	**-**	**0.436**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	414	**0.000**	**0.000**	**0.000**	**0.067**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.545**	**0.000**	**0.774**	**0.000**	**-**	**0.456**	**0.141**	**0.207**	**0.000**
COPULA DCC	414	**0.000**	**0.000**	**0.000**	**0.005**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.677**	**0.000**	**0.941**	**0.000**	**0.838**	**-**	**0.790**	**0.687**	**0.000**
SMA (100)	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**-**	**0.305**	**0.000**	**0.020**	**0.000**	**0.051**	**0.000**	**0.153**	**0.081**	**-**	**0.381**	**0.000**
EWMA (0.03, 0.97)	414	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.168**	**-**	**0.000**	**0.050**	**0.000**	**0.107**	**0.000**	**0.244**	**0.148**	**0.829**	**-**	**0.000**
UNCONDITIONAL	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.057**	**0.041**	**-**

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.25 Summary statistics of EM BRIC conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	0.539	0.809	**0.724**	0.727	0.037	**0.052**	3.166	6.982	**3.978**	3.838	0.633	**0.159**
GO-GARCH ICA	512	0.633	0.847	**0.765**	0.774	0.036	**0.047**	5.018	23.393	**6.771**	6.041	2.357	**0.348**
GO-GARCH NLS	512	0.642	0.840	**0.713**	0.709	0.025	**0.035**	2.977	8.064	**3.948**	3.727	0.849	**0.215**
GO-GARCH ML	512	0.615	0.754	**0.667**	0.665	0.020	**0.031**	3.293	10.855	**4.746**	4.391	1.297	**0.273**
DCC	512	0.539	0.749	**0.652**	0.644	0.049	**0.076**	2.127	12.682	**3.663**	3.316	1.340	**0.366**
COPULA DCC	512	0.537	0.749	**0.640**	0.637	0.050	**0.078**	2.112	11.727	**3.632**	3.308	1.281	**0.353**
SMA (100)	512[a]	0.464	0.867	**0.691**	0.665	0.102	**0.148**	2.444	6.584	**3.941**	3.405	1.407	**0.357**
EWMA (0.03, 0.97)	512	0.397	0.862	**0.667**	0.646	0.113	**0.170**	2.431	8.375	**3.848**	3.449	1.348	**0.350**
UNCONDITIONAL	512	0.718	0.718	**0.718**	0.718	0.000	**0.000**	4.058	4.058	**4.058**	4.058	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.26 Statistical significance of EM BRIC conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	Conditional volatility MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	414	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.003**	**0.004**	**0.000**	**0.619**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**
GO-GARCH ML	414	**0.000**	**0.000**	**0.000**	**-**	**0.191**	**0.000**	**0.478**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.607**
DCC	414	**0.000**	**0.000**	**0.000**	**0.093**	**-**	**0.001**	**0.000**	**0.000**	**0.000**	**0.060**	**0.000**	**0.158**	**0.000**	**-**	**0.915**	**0.540**	**0.066**	**0.000**
COPULA DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**-**	**0.000**	**0.000**	**0.000**	**0.020**	**0.000**	**0.073**	**0.000**	**0.776**	**-**	**0.575**	**0.059**	**0.000**
SMA (100)	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.353**	**0.000**	**0.575**	**0.000**	**0.401**	**0.000**	**0.059**	**0.027**	**-**	**0.193**	**0.000**
EWMA (0.03, 0.97)	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.801**	**-**	**0.000**	**0.386**	**0.000**	**0.264**	**0.000**	**0.035**	**0.015**	**0.801**	**-**	**0.000**
UNCONDITIONAL	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.27 Summary statistics of EM Europe conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	0.104	0.765	**0.631**	0.640	0.068	**0.108**	3.713	8.780	**4.762**	4.564	0.834	**0.175**
GO-GARCH ICA	512	0.579	0.790	**0.702**	0.705	0.034	**0.048**	6.184	28.877	**8.258**	7.408	2.880	**0.349**
GO-GARCH NLS	512	0.517	0.747	**0.608**	0.606	0.039	**0.064**	3.630	9.898	**4.740**	4.439	1.007	**0.212**
GO-GARCH ML	512	0.291	0.729	**0.498**	0.488	0.080	**0.160**	3.584	13.181	**5.360**	4.884	1.640	**0.306**
DCC	512	0.325	0.673	**0.528**	0.523	0.080	**0.151**	2.730	15.196	**4.274**	3.783	1.792	**0.419**
COPULA DCC	512	0.315	0.679	**0.517**	0.523	0.089	**0.172**	2.716	14.669	**4.312**	3.805	1.751	**0.406**
SMA (100)	512[a]	0.144	0.782	**0.559**	0.581	0.182	**0.326**	2.954	8.499	**4.764**	3.914	1.926	**0.404**
EWMA (0.03, 0.97)	512	0.205	0.809	**0.534**	0.559	0.179	**0.335**	2.801	11.039	**4.557**	3.710	1.898	**0.417**
UNCONDITIONAL	512	0.619	0.619	**0.619**	0.619	0.000	**0.000**	4.895	4.895	**4.895**	4.895	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.28 Statistical significance of EM Europe conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.075**	**0.430**	**0.000**	**-**	**0.000**	**0.023**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	414	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.167**	**0.432**	**0.000**	**0.912**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	414	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.149**	**0.000**	**0.000**	**0.000**	**0.031**	**0.000**	**0.046**	**0.000**	**-**	**0.399**	**0.296**	**0.351**	**0.000**
COPULA DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.065**	**-**	**0.000**	**0.000**	**0.000**	**0.077**	**0.000**	**0.106**	**0.000**	**0.739**	**-**	**0.835**	**0.907**	**0.000**
SMA (100)	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.464**	**0.099**	**-**	**0.115**	**0.000**	**0.390**	**0.000**	**0.373**	**0.000**	**0.020**	**0.043**	**-**	**0.901**	**0.000**
EWMA (0.03, 0.97)	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**	**0.097**	**-**	**0.000**	**0.488**	**0.000**	**0.464**	**0.000**	**0.031**	**0.062**	**0.923**	**-**	**0.000**
UNCONDITIONAL	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.319**	**0.000**	**0.000**	**0.000**	**0.000**	**-**

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.29 Summary statistics of EM Latin America conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	0.619	0.849	**0.784**	0.788	0.030	**0.038**	3.533	8.424	**4.472**	4.284	0.785	**0.176**
GO-GARCH ICA	512	0.685	0.883	**0.812**	0.822	0.034	**0.042**	5.742	27.575	**7.753**	6.933	2.720	**0.351**
GO-GARCH NLS	512	0.727	0.880	**0.777**	0.772	0.025	**0.032**	3.375	8.873	**4.448**	4.169	0.991	**0.223**
GO-GARCH ML	512	0.704	0.829	**0.767**	0.767	0.022	**0.029**	3.786	13.487	**5.621**	5.143	1.619	**0.288**
DCC	512	0.603	0.821	**0.734**	0.732	0.045	**0.061**	2.432	14.229	**4.035**	3.660	1.547	**0.383**
COPULA DCC	512	0.616	0.813	**0.723**	0.723	0.047	**0.065**	2.436	13.166	**4.030**	3.666	1.492	**0.370**
SMA (100)	512[a]	0.523	0.886	**0.777**	0.782	0.072	**0.093**	2.656	7.639	**4.419**	3.656	1.749	**0.396**
EWMA (0.03, 0.97)	512	0.555	0.923	**0.747**	0.758	0.093	**0.124**	2.787	10.343	**4.325**	3.853	1.650	**0.382**
UNCONDITIONAL	512	0.781	0.781	**0.781**	0.781	0.000	**0.000**	4.585	4.585	**4.585**	4.585	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.30 Statistical significance of EM Latin America conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.913**	**0.745**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	414	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.247**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**0.167**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.357**	**0.610**	**0.000**	**0.616**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	414	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.002**	**0.000**	**0.000**	**0.000**	**0.003**	**0.000**	**0.013**	**0.000**	-	**0.751**	**0.704**	**0.044**	**0.000**
COPULA DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	-	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**	**0.011**	**0.000**	**0.993**	-	**0.895**	**0.094**	**0.000**
SMA (100)	414	**0.168**	**0.000**	**0.476**	**0.018**	**0.000**	**0.000**	-	**0.956**	**0.000**	**0.801**	**0.000**	**0.574**	**0.000**	**0.013**	**0.011**	-	**0.084**	**0.000**
EWMA (0.03, 0.97)	414	**0.262**	**0.000**	**0.653**	**0.008**	**0.000**	**0.000**	**0.843**	-	**0.000**	**0.655**	**0.000**	**0.457**	**0.000**	**0.009**	**0.008**	**0.875**	-	**0.000**
UNCONDITIONAL	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.31 Summary statistics of EM Asia conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	0.423	0.757	**0.656**	0.660	0.040	**0.060**	2.616	5.794	**3.364**	3.248	0.552	**0.164**
GO-GARCH ICA	512	0.466	0.770	**0.671**	0.686	0.051	**0.077**	4.196	20.979	**5.819**	5.237	2.086	**0.359**
GO-GARCH NLS	512	0.465	0.721	**0.652**	0.655	0.028	**0.043**	2.492	7.043	**3.358**	3.186	0.672	**0.200**
GO-GARCH ML	512	0.484	0.684	**0.604**	0.607	0.032	**0.054**	2.433	8.201	**3.546**	3.275	0.955	**0.269**
DCC	512	0.476	0.702	**0.593**	0.587	0.048	**0.081**	1.828	10.756	**3.182**	2.821	1.158	**0.364**
COPULA DCC	512	0.469	0.684	**0.579**	0.571	0.047	**0.081**	1.690	11.319	**3.206**	2.864	1.242	**0.388**
SMA (100)	512[a]	0.398	0.802	**0.613**	0.592	0.104	**0.169**	2.011	5.271	**3.300**	2.962	1.012	**0.307**
EWMA (0.03, 0.97)	512	0.321	0.785	**0.599**	0.573	0.115	**0.192**	1.925	6.257	**3.311**	3.243	0.971	**0.293**
UNCONDITIONAL	512	0.644	0.644	**0.644**	0.644	0.000	**0.000**	3.439	3.439	**3.439**	3.439	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.32 Statistical significance of EM Asia conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	-	**0.000**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	-	**0.000**	**0.236**	**0.049**	**0.000**	**0.000**	**0.000**	**0.079**	**0.000**
GO-GARCH ICA	414	**0.001**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.029**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**0.018**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	**0.441**	**0.000**	-	**0.004**	**0.000**	**0.000**	**0.000**	**0.138**	**0.000**
GO-GARCH ML	414	**0.000**	**0.000**	**0.000**	-	**0.341**	**0.000**	**0.882**	**0.023**	**0.000**	**0.000**	**0.000**	**0.001**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	414	**0.000**	**0.000**	**0.000**	**0.538**	-	**0.000**	**0.163**	**0.018**	**0.000**	**0.217**	**0.000**	**0.101**	**0.000**	-	**0.820**	**0.003**	**0.009**	**0.000**
COPULA DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.002**	**0.000**	**0.000**	**0.394**	**0.000**	**0.206**	**0.000**	**0.808**	-	**0.002**	**0.007**	**0.000**
SMA (100)	414	**0.000**	**0.000**	**0.000**	**0.063**	**0.037**	**0.000**	-	**0.266**	**0.000**	**0.586**	**0.000**	**0.959**	**0.005**	**0.154**	**0.270**	-	**0.417**	**0.000**
EWMA (0.03, 0.97)	414	**0.000**	**0.000**	**0.000**	**0.027**	**0.016**	**0.000**	**0.648**	-	**0.000**	**0.570**	**0.000**	**0.995**	**0.007**	**0.153**	**0.266**	**0.970**	-	**0.000**
UNCONDITIONAL	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.302**	**0.000**	**0.000**	**0.003**	**0.006**	-

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.33 Summary statistics of EFM Africa conditional correlations and conditional volatilities based on all models for the whole period

Model	Sample length	Conditional correlation with US						Conditional volatility					
		Min.	Max.	Mean	Median	Std. Dev.	CV	Min.	Max.	Mean	Median	Std. Dev.	CV
GO-GARCH MM	512	0.462	0.737	**0.626**	0.633	0.046	**0.074**	2.856	6.327	**3.617**	3.485	0.612	**0.169**
GO-GARCH ICA	512	0.496	0.771	**0.671**	0.685	0.047	**0.070**	4.788	22.386	**6.442**	5.737	2.277	**0.353**
GO-GARCH NLS	512	0.504	0.802	**0.620**	0.618	0.041	**0.067**	2.876	8.552	**3.605**	3.372	0.792	**0.220**
GO-GARCH ML	512	0.504	0.703	**0.594**	0.593	0.034	**0.058**	2.989	12.038	**4.665**	4.087	1.598	**0.343**
DCC	512	0.399	0.687	**0.567**	0.574	0.069	**0.121**	2.319	10.543	**3.411**	3.157	0.999	**0.293**
COPULA DCC	512	0.402	0.680	**0.550**	0.556	0.071	**0.129**	2.191	10.804	**3.434**	3.185	1.079	**0.314**
SMA (100)	512[a]	0.225	0.815	**0.606**	0.618	0.140	**0.231**	2.344	5.548	**3.686**	3.331	1.013	**0.275**
EWMA (0.03, 0.97)	512	0.308	0.796	**0.569**	0.593	0.161	**0.283**	2.394	7.017	**3.584**	3.355	1.010	**0.282**
UNCONDITIONAL	512	0.625	0.625	**0.625**	0.625	0.000	**0.000**	3.709	3.709	**3.709**	3.709	0.000	**0.000**

Notes: The period runs from 26 July 2002 to 11 May 2012. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. [a] *The first 99 SMA(100) estimates are not available as it is based on 100 observations.*

Table 5.34 Statistical significance of EFM Africa conditional correlations and conditional volatilities between models for the whole period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	414	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.673**	**0.097**	**0.000**	-	**0.000**	**0.042**	**0.000**	**0.000**	**0.000**	**0.276**	**0.682**	**0.000**
GO-GARCH ICA	414	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.050**	**0.520**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	414	**0.005**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.911**	**0.012**	**0.000**	**0.757**	**0.000**	-	**0.000**	**0.000**	**0.001**	**0.474**	**0.055**	**0.000**
GO-GARCH ML	414	**0.000**	**0.000**	**0.000**	-	**0.313**	**0.000**	**0.005**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.015**
DCC	414	**0.000**	**0.000**	**0.000**	**0.001**	-	**0.001**	**0.000**	**0.000**	**0.000**	**0.333**	**0.000**	**0.268**	**0.000**	-	**0.852**	**0.001**	**0.000**	**0.000**
COPULA DCC	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	-	**0.000**	**0.000**	**0.000**	**0.737**	**0.000**	**0.595**	**0.000**	**0.631**	-	**0.003**	**0.000**	**0.000**
SMA (100)	414	**0.000**	**0.000**	**0.013**	**0.180**	**0.005**	**0.000**	-	**0.206**	**0.001**	**0.017**	**0.000**	**0.058**	**0.000**	**0.006**	**0.032**	-	**0.119**	**0.000**
EWMA (0.03, 0.97)	414	**0.020**	**0.000**	**0.221**	**0.011**	**0.000**	**0.000**	**0.364**	-	**0.000**	**0.003**	**0.000**	**0.016**	**0.000**	**0.001**	**0.009**	**0.603**	-	**0.000**
UNCONDITIONAL	414	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	-

Notes: The period runs from 11 June 2004 to 11 May 2012 because the first 99 SMA(100) estimates are not available as it is based on 100 observations. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.35 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on GO-GARCH MM model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	2.244	2.241	0.312%	0.759	0.918
	124/124	-	-	-	-	-	2.270	2.328	2.555%	0.004***	0.125
EMU	62/62	0.840	0.829	-1.310%	0.000***	0.000***	3.104	3.337	7.506%	0.000***	0.000***
	124/124	0.840	0.827	-1.548%	0.000***	0.000***	3.110	3.438	10.547%	0.000***	0.000***
EUROPE ex EMU	62/62	0.846	0.839	-0.827%	0.018**	0.069*	2.743	2.844	3.682%	0.008***	0.012**
	124/124	0.844	0.838	-0.711%	0.013**	0.048**	2.750	2.907	5.709%	0.000***	0.000***
PACIFIC	62/62	0.638	0.669	4.859%	0.001***	0.012**	2.373	2.458	3.582%	0.010***	0.017**
	124/124	0.637	0.657	3.140%	0.003***	0.001***	2.359	2.547	7.969%	0.000***	0.000***
BRIC	62/62	0.742	0.725	-2.291%	0.001***	0.001***	3.590	3.730	3.900%	0.011**	0.011**
	124/124	0.739	0.726	-1.759%	0.000***	0.000***	3.577	3.840	7.353%	0.000***	0.000***
EM EUROPE	62/62	0.625	0.632	1.120%	0.384	0.293	4.199	4.476	6.597%	0.000***	0.000***

	124/124	0.628	0.630	0.318%	0.686	0.372	4.189	4.598	9.764%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.793	0.778	-1.892%	0.001***	0.001***	4.037	4.149	2.774%	0.088*	0.092*
	124/124	0.792	0.782	-1.263%	0.001***	0.008***	4.023	4.249	5.618%	0.000***	0.000***
EM ASIA	62/62	0.676	0.673	-0.444%	0.558	0.982	2.998	3.156	5.270%	0.000***	0.000***
	124/124	0.671	0.672	0.149%	0.805	0.698	2.988	3.279	9.739%	0.000***	0.000***
EMF AFRICA	62/62	0.644	0.649	0.776%	0.318	0.239	3.219	3.475	7.953%	0.000***	0.000***
	124/124	0.635	0.650	2.362%	0.000***	0.000***	3.192	3.595	6.390%	0.000***	0.000***

Notes: [a] *The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007.* [b] *The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are 0.042% and 5.957%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.36 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on GO-GARCH ICA model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	4.442	4.514	1.621%	0.695	0.867
	124/124	-	-	-	-	-	4.274	4.697	9.897%	0.001***	0.003***
EMU	62/62	0.845	0.826	-2.249%	0.000***	0.000***	7.329	6.814	-7.027%	0.071*	0.041**
	124/124	0.844	0.825	-2.251%	0.000***	0.000***	6.933	7.050	1.688%	0.523	0.412
EUROPE ex EMU	62/62	0.866	0.836	-3.464%	0.000***	0.000***	5.846	5.499	-5.936%	0.100	0.028**
	124/124	0.862	0.834	-3.248%	0.000***	0.000***	5.530	5.688	2.857%	0.247	0.197
PACIFIC	62/62	0.696	0.665	-4.454%	0.000***	0.000***	4.260	4.245	-0.352%	0.900	0.974
	124/124	0.691	0.668	-3.329%	0.000***	0.000***	4.168	4.410	5.806%	0.006***	0.013**
BRIC	62/62	0.780	0.760	-2.564%	0.001***	0.069*	6.365	3.172	-3.032%	0.308	0.092
	124/124	0.783	0.762	-2.682%	0.000***	0.000***	6.124	6.406	4.605%	0.037**	0.214
EM EUROPE	62/62	0.726	0.695	-4.270%	0.000***	0.000***	7.968	7.568	-5.020%	0.139	0.027**

	124/124	0.723	0.695	-3.873%	0.000***	0.000***	7.554	7.799	3.243%	0.169	0.343
EM LATIN AMERICA	62/62	0.826	0.807	-2.300%	0.001***	0.195	7.182	7.066	-1.615%	0.581	0.309
	124/124	0.828	0.808	-2.415%	0.000***	0.002***	6.955	7.330	5.392%	0.013**	0.069*
EM ASIA	62/62	0.694	0.661	-4.755%	0.000***	0.023**	5.278	5.319	0.777%	0.800	0.732
	124/124	0.697	0.662	-5.022%	0.000***	0.000***	5.165	5.565	7.744%	0.001***	0.003***
EMF AFRICA	62/62	0.701	0.661	-5.706%	0.000***	0.000***	6.318	5.913	-6.410%	0.074*	0.017**
	124/124	0.701	0.661	-5.706%	0.000***	0.000***	5.961	6.148	3.137%	0.217	0.259

*Notes: [a] The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007. [b] The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are -3.643% and 0.965%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.37 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on GO-GARCH NLS model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	2.136	2.326	8.895%	0.000***	0.000***
	124/124	-	-	-	-	-	2.166	2.396	10.619%	0.000***	0.000***
EMU	62/62	0.844	0.825	-2.251%	0.000***	0.000***	3.085	3.316	7.488%	0.000***	0.000***
	124/124	0.837	0.827	-1.195%	0.000***	0.000***	3.097	3.336	7.717%	0.000***	0.000***
EUROPE ex EMU	62/62	0.823	0.833	1.215%	0.000***	0.000***	2.664	2.880	8.108%	0.000***	0.000***
	124/124	0.822	0.834	1.460%	0.000***	0.000***	2.698	2.914	8.006%	0.000***	0.000***
PACIFIC	62/62	0.643	0.639	-0.622%	0.311	0.736	2.314	2.486	7.433%	0.000***	0.000***
	124/124	0.640	0.639	-0.156%	0.662	0.894	2.334	2.545	9.040%	0.000***	0.000***
BRIC	62/62	0.715	0.706	-1.259%	0.011**	0.038**	3.400	3.530	3.824%	0.004***	0.017**
	124/124	0.716	0.705	-1.536%	0.000***	0.000***	3.413	3.645	6.798%	0.000***	0.000***
EM EUROPE	62/62	0.602	0.603	0.166%	0.909	0.918	4.073	4.340	6.555%	0.000***	0.000***

	124/124	0.609	0.588	-3.448%	0.000***	0.000***	4.107	4.464	8.692%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.781	0.780	-0.128%	0.833	0.434	3.883	3.927	1.133%	0.354	0.605
	124/124	0.779	0.778	-0.128%	0.651	0.086*	3.890	4.034	3.702%	0.001***	0.038**
EM ASIA	62/62	0.656	0.656	0.000%	0.854	0.527	2.898	3.109	7.281%	0.000***	0.000***
	124/124	0.657	0.651	-0.913%	0.042**	0.361	2.892	3.221	11.376%	0.000***	0.000***
EMF AFRICA	62/62	0.657	0.607	-7.610%	0.000***	0.000***	3.216	3.172	-1.368%	0.191	0.186
	124/124	0.641	0.612	-4.524%	0.000***	0.000***	3.200	3.328	4.000%	0.000***	0.027**

Notes: [a] *The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007.* [b] *The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are -1.308% and 6.628%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.38 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on GO-GARCH ML model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	2.328	2.479	6.486%	0.000***	0.000***
	124/124	-	-	-	-	-	2.333	2.625	12.516%	0.000***	0.000***
EMU	62/62	0.932	0.948	1.717%	0.000***	0.000***	3.331	3.729	11.948%	0.000***	0.000***
	124/124	0.933	0.950	1.822%	0.000***	0.000***	3.378	3.926	16.223%	0.000***	0.000***
EUROPE ex EMU	62/62	0.883	0.888	0.566%	0.012**	0.009***	3.015	3.314	9.917%	0.000***	0.000***
	124/124	0.886	0.892	0.677%	0.000***	0.000***	3.047	3.470	13.883%	0.000***	0.000***
PACIFIC	62/62	0.620	0.575	-7.258%	0.000***	0.000***	2.643	3.222	21.907%	0.000***	0.000***
	124/124	0.592	0.577	-2.534%	0.004***	0.003***	2.738	3.377	23.338%	0.000***	0.000***
BRIC	62/62	0.660	0.669	1.364%	0.005***	0.011**	3.751	4.322	15.226%	0.000***	0.000***
	124/124	0.665	0.671	0.902%	0.013**	0.005***	3.847	4.396	14.271%	0.000***	0.000***
EM EUROPE	62/62	0.441	0.493	11.791%	0.000***	0.001***	4.097	4.802	17.208%	0.000***	0.000***

	124/124	0.476	0.478	0.420%	0.798	0.723	4.258	4.971	16.745%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.767	0.773	0.782%	0.098*	0.304	4.338	5.087	17.266%	0.000***	0.000***
	124/124	0.770	0.779	1.169%	0.000***	0.000***	4.463	5.252	17.679%	0.000***	0.000***
EM ASIA	62/62	0.622	0.604	-2.894%	0.003***	0.173	2.919	3.219	10.277%	0.000***	0.000***
	124/124	0.607	0.612	0.824%	0.215	0.019**	2.927	3.274	11.855%	0.000***	0.000***
EMF AFRICA	62/62	0.593	0.595	0.337%	0.763	0.386	3.379	4.153	22.906%	0.000***	0.000***
	124/124	0.598	0.597	-0.167%	0.815	0.685	3.570	4.301	20.476%	0.000***	0.000***

Notes: [a] *The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007.* [b] *The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are 0.595% and 15.563%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.39 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on DCC model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	1.720	2.140	24.42%	0.000***	0.020**
	124/124	-	-	-	-	-	1.734	2.304	32.872%	0.000***	0.000***
EMU	62/62	0.788	0.786	-0.254%	0.790	0.099*	2.367	3.397	43.515%	0.000***	0.000***
	124/124	0.771	0.782	1.427%	0.000***	0.000***	2.318	3.787	63.374%	0.000***	0.000***
EUROPE ex EMU	62/62	0.766	0.797	4.047%	0.000***	0.000***	2.091	2.634	25.968%	0.000***	0.000***
	124/124	0.749	0.796	6.275%	0.000***	0.000***	2.068	2.837	37.186%	0.000***	0.000***
PACIFIC	62/62	0.571	0.574	0.525%	0.593	0.273	2.373	2.416	1.812%	0.548	0.567
	124/124	0.553	0.599	8.318%	0.000***	0.000***	2.303	2.545	10.508%	0.000***	0.000***
BRIC	62/62	0.624	0.683	9.455%	0.000***	0.000***	3.206	3.473	8.328%	0.030**	0.003***
	124/124	0.629	0.668	6.200%	0.000***	0.000***	3.096	3.688	19.121%	0.000***	0.000***
EM EUROPE	62/62	0.514	0.606	17.899%	0.000***	0.000***	4.058	3.931	-3.130%	0.416	0.349

	124/124	0.496	0.582	17.339%	0.000***	0.000***	3.748	4.197	11.980%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.724	0.739	2.072%	0.005***	0.004***	3.664	3.851	5.104%	0.162	0.112
	124/124	0.719	0.729	1.391%	0.014**	0.008***	3.511	4.003	14.013%	0.000***	0.000***
EM ASIA	62/62	0.575	0.634	10.261%	0.000***	0.000***	2.533	2.933	15.792%	0.001***	0.000***
	124/124	0.571	0.618	8.231%	0.000***	0.000***	2.516	3.164	25.755%	0.000***	0.000***
EMF AFRICA	62/62	0.532	0.613	15.226%	0.000***	0.000***	3.326	3.300	-0.782%	0.840	0.962
	124/124	0.530	0.599	13.019%	0.000***	0.000***	3.218	3.440	6.899%	0.010***	0.003***

Notes: [a] *The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007.* [b] *The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are 7.589% and 19.041%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.40 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on Copula DCC model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	1.633	2.158	32.149%	0.000***	0.001***
	124/124	-	-	-	-	-	1.648	2.339	41.930%	0.000***	0.000***
EMU	62/62	0.793	0.791	-0.252%	0.722	0.277	2.316	3.378	45.855%	0.000***	0.000***
	124/124	0.774	0.788	1.809%	0.000***	0.000***	2.260	3.733	65.177%	0.000***	0.000***
EUROPE ex EMU	62/62	0.768	0.800	4.167%	0.000***	0.000***	1.989	2.635	32.479%	0.000***	0.000***
	124/124	0.744	0.801	7.661%	0.000***	0.000***	1.948	2.800	43.737%	0.000***	0.000***
PACIFIC	62/62	0.563	0.562	-0.178%	0.822	0.974	2.358	2.418	2.545%	0.333	0.275
	124/124	0.538	0.594	10.409%	0.000***	0.000***	2.294	2.528	10.201%	0.000***	0.000***
BRIC	62/62	0.625	0.692	10.720%	0.000***	0.000***	3.178	3.418	7.552%	0.053*	0.011**
	124/124	0.628	0.668	6.369%	0.000***	0.000***	3.078	3.633	18.031%	0.000***	0.000***
EM EUROPE	62/62	0.516	0.620	20.155%	0.000***	0.000***	4.092	3.973	-2.908%	0.422	0.383

	124/124	0.488	0.597	22.336%	0.000***	0.000***	3.791	4.207	10.973%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.737	0.748	1.493%	0.041**	0.000***	3.645	3.846	5.514%	0.107	0.069
	124/124	0.726	0.729	0.413%	0.483	0.091*	3.490	4.000	14.613%	0.000***	0.000***
EM ASIA	62/62	0.568	0.635	11.796%	0.000***	0.000***	2.468	2.925	18.517%	0.001***	0.000***
	124/124	0.562	0.613	9.075%	0.000***	0.000***	2.458	3.165	28.763%	0.000***	0.000***
EMF AFRICA	62/62	0.535	0.628	17.383%	0.000***	0.000***	3.332	3.305	-0.810%	0.835	0.970
	124/124	0.525	0.611	16.381%	0.000***	0.000***	3.210	3.469	8.069%	0.004***	0.001***

*Notes: [a] The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007. [b] The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are 8.734% and 21.244%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.41 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on SMA model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	1.399	3.746	167.763%	0.000***	0.000***
	124/124	-	-	-	-	-	1.436	3.116	116.992%	0.000***	0.000***
EMU	62/62	0.764	0.853	11.649%	0.000***	0.000***	1.973	5.118	159.402%	0.000***	0.000***
	124/124	0.742	0.840	13.208%	0.000***	0.000***	1.938	4.500	132.198%	0.000***	0.000***
EUROPE ex EMU	62/62	0.714	0.849	18.908%	0.000***	0.000***	1.746	4.606	163.803%	0.000***	0.000***
	124/124	0.668	0.853	27.695%	0.000***	0.000***	1.677	3.758	124.091%	0.000***	0.000***
PACIFIC	62/62	0.568	0.706	24.296%	0.000***	0.000***	2.134	3.429	60.684%	0.000***	0.000***
	124/124	0.522	0.703	34.674%	0.000***	0.000***	2.206	2.934	33.001%	0.000***	0.000***
BRIC	62/62	0.644	0.828	28.571%	0.000***	0.000***	2.905	5.396	85.749%	0.000***	0.000***
	124/124	0.625	0.796	27.360%	0.000***	0.000***	2.845	4.371	53.638%	0.000***	0.000***
EM EUROPE	62/62	0.507	0.730	43.984%	0.000***	0.000***	3.738	7.097	89.861%	0.000***	0.000***

	124/124	0.414	0.732	76.812%	0.000***	0.000***	3.428	5.582	62.835%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.752	0.856	13.830%	0.000***	0.000***	3.308	6.227	88.241%	0.000***	0.000***
	124/124	0.731	0.830	13.543%	0.000***	0.000***	3.127	4.926	57.531%	0.000***	0.000***
EM ASIA	62/62	0.565	0.760	34.513%	0.000***	0.000***	2.199	4.290	95.089%	0.000***	0.000***
	124/124	0.543	0.728	34.070%	0.000***	0.000***	2.418	3.654	51.117%	0.000***	0.000***
EMF AFRICA	62/62	0.545	0.773	41.835%	0.000***	0.000***	3.153	4.718	49.635%	0.000***	0.000***
	124/124	0.493	0.752	52.535%	0.000***	0.000***	2.950	4.073	38.068%	0.000***	0.000***

Notes: [a] *The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007.* [b] *The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are 31.093% and 90.539%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.42 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on EWMA model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	1.410	2.963	110.142%	0.000***	0.000***
	124/124	-	-	-	-	-	1.445	2.808	94.325%	0.000***	0.000***
EMU	62/62	0.813	0.839	3.198%	0.000***	0.000***	2.177	4.244	94.947%	0.000***	0.000***
	124/124	0.764	0.831	8.770%	0.000***	0.000***	2.008	4.193	108.815%	0.000***	0.000***
EUROPE ex EMU	62/62	0.774	0.853	10.207%	0.000***	0.000***	1.910	3.600	88.482%	0.000***	0.000***
	124/124	0.710	0.855	20.423%	0.000***	0.000***	1.744	3.342	91.628%	0.000***	0.000***
PACIFIC	62/62	0.614	0.682	11.075%	0.000***	0.000***	2.227	2.815	26.403%	0.000***	0.000***
	124/124	0.541	0.711	31.423%	0.000***	0.000***	2.169	2.683	23.698%	0.000***	0.000***
BRIC	62/62	0.646	0.811	25.542%	0.000***	0.000***	3.129	4.176	33.461%	0.000***	0.000***
	124/124	0.637	0.776	21.821%	0.000***	0.000***	2.884	3.912	35.645%	0.000***	0.000***
EM EUROPE	62/62	0.543	0.746	37.385%	0.000***	0.000***	4.087	5.436	33.007%	0.000***	0.000***

	124/124	0.464	0.722	55.603%	0.000***	0.000***	3.572	4.848	35.722%	0.000***	0.000***
EM LATIN AMERICA	62/62	0.769	0.841	9.363%	0.000***	0.000***	3.435	4.756	38.457%	0.000***	0.000***
	124/124	0.742	0.815	9.838%	0.000***	0.000***	3.250	4.332	33.292%	0.000***	0.000***
EM ASIA	62/62	0.588	0.739	25.68%	0.000***	0.000***	2.292	3.453	50.654%	0.000***	0.000***
	124/124	0.555	0.715	28.829%	0.000***	0.000***	2.317	3.364	45.188%	0.000***	0.000***
EMF AFRICA	62/62	0.562	0.770	37.011%	0.259	0.314	3.274	3.861	17.929%	0.000***	0.000***
	124/124	0.512	0.737	43.945%	0.000***	0.000***	3.069	3.741	21.896%	0.000***	0.000***

*Notes: [a] The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007. [b] The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are 23.757% and 54.650%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.*

Table 5.43 Statistical significance of differences between pre-crisis and post-crisis mean: conditional correlations and conditional volatilities (US and developed/emerging/frontier region stock markets) based on unconditional model

Index	Sample length before/after	Mean correlation with US pre-crisis period[a]	Mean correlation with US post-crisis period[b]	Percentage change in mean correlation	Welch two sample t test p-value	Wilcoxon rank sum test p-value	Mean volatility pre-crisis period[a]	Mean volatility post-crisis period[b]	Percentage change in mean volatility	Welch two sample t test p-value	Wilcoxon rank sum test p-value
US	62/62	-	-	-	-	-	1.456	2.278	56.51%	NA	0.000***
	124/124	-	-	-	-	-	1.407	2.550	81.218%	NA	0.000***
EMU	62/62	0.874	0.796	-8.924%	NA	0.000***	2.280	3.575	56.837%	NA	0.000***
	124/124	0.807	0.833	3.222%	NA	0.000***	2.005	4.076	103.306%	NA	0.000***
EUROPE ex EMU	62/62	0.845	0.859	1.657%	NA	0.000***	2.043	2.727	33.504%	NA	0.000***
	124/124	0.766	0.861	12.402%	NA	0.000***	1.789	2.988	67.003%	NA	0.000***
PACIFIC	62/62	0.674	0.692	2.671%	NA	0.000***	2.124	2.218	4.424%	NA	0.000***
	124/124	0.599	0.731	22.037%	NA	0.000***	2.010	2.447	21.729%	NA	0.000***
BRIC	62/62	0.681	0.763	12.041%	NA	0.000***	3.265	2.997	-8.208%	NA	0.000***
	124/124	0.670	0.756	12.836%	NA	0.000***	2.903	3.459	19.144%	NA	0.000***
EM EUROPE	62/62	0.599	0.750	25.209%	NA	0.000***	4.303	3.659	-14.961%	NA	0.000***

	124/124	0.541	0.731	35.120%	NA	0.000***	3.721	4.042	8.630%	NA	0.000***
EM LATIN AMERICA	62/62	0.815	0.792	-2.822%	NA	0.000***	3.592	3.387	-5.724%	NA	0.000***
	124/124	0.784	0.807	2.934%	NA	0.000***	3.345	3.730	11.521%	NA	0.000***
EM ASIA	62/62	0.606	0.687	13.366%	NA	0.000***	2.240	2.792	24.635%	NA	0.000***
	124/124	0.595	0.703	18.151%	NA	0.000***	2.080	3.110	49.496%	NA	0.000***
EMF AFRICA	62/62	0.634	0.740	16.719%	NA	0.000***	3.459	3.246	-6.178%	NA	0.000***
	124/124	0.581	0.721	24.096%	NA	0.000***	3.263	3.507	7.478%	NA	0.000***

Notes: [a] *The 62 observation period runs from 10 March 2006 to 11 May 2007; the 124 observation period runs from 31 December 2004 to 11 May 2007.* [b] *The 62 observation period runs from 1 January 2010 to 4 March 2011; the 124 observation period runs from 1 January 2010 to 11 May 2012. The average percentage changes across all samples for the mean of conditional correlations and conditional volatilities are 11.920% and 28.354%, respectively. Tests results for a 176 observation period pre-crisis running from 2 January 2004 to 11 May 2007 and a 124 observation post-crisis period running from 1 January 2010 to 11 May 2012 are available upon request from author. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. NA Not available as Welch t test cannot be performed.*

Table 5.44 Statistical significance of US conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.000**	**0.000**	**0.149**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.014**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.284**	**0.000**	**0.000**	**0.000**
COPULA DCC	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.351**	**-**	**0.002**	**0.004**	**0.047**
SMA (100)	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.408**	**0.000**
EWMA (0.03, 0.97)	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.311**	**-**	**0.003**
UNCONDITIONAL	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.45 Statistical significance of EMU conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	**0.001**	**0.018**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.567**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.011**	-	**0.774**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.046**	**0.757**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.508**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.007**	**0.000**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.816**	**0.006**	**0.930**	**0.047**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.011**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.545**	-	**0.003**	**0.918**	**0.047**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.034**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.019**	**0.038**	**0.000**	-	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.225**	**0.554**	**0.000**	**0.000**	-

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.46 Statistical significance of Europe ex EMU conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.509**	**-**	**0.000**	**0.049**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.158**	**0.000**	**0.879**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.588**	**0.004**	**0.651**	**0.098**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.156**	**-**	**0.000**	**0.524**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.207**	**-**	**0.005**	**0.691**	**0.047**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.992**	**0.338**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.012**	**0.126**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**0.601**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.466**	**0.243**	**0.000**	**0.000**	**-**

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.47 Statistical significance of Pacific conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.000**	**0.273**	**0.002**	**0.000**	**0.000**	**0.000**	**0.027**	**0.047**	**-**	**0.000**	**0.079**	**0.000**	**0.172**	**0.268**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.565**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.013**	**0.000**	**0.029**	**0.000**	**-**	**0.000**	**0.518**	**0.805**	**0.000**	**0.010**	**0.000**
GO-GARCH ML	62	**0.041**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.990**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.016**	**0.357**	**0.000**	**0.000**	**0.945**	**0.000**	**0.338**	**0.000**	**-**	**0.840**	**0.000**	**0.102**	**0.000**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.017**	**-**	**0.224**	**0.000**	**0.000**	**0.777**	**0.000**	**0.358**	**0.000**	**0.886**	**-**	**0.000**	**0.053**	**0.000**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.148**	**0.472**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.057**	**0.509**
EWMA (0.03, 0.97)	62	**0.034**	**0.000**	**0.001**	**0.471**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.008**	**0.000**	**0.023**	**0.016**	**0.002**	**-**	**0.021**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.293**	**0.000**	**-**

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.48 Statistical significance of EM BRIC conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.001**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.090**	**0.000**	**0.001**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.110**	**0.420**	**0.155**	**0.000**	**0.001**	**0.000**	**0.094**	**0.000**	-	**0.910**	**0.047**	**0.751**	**0.003**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.065**	-	**0.003**	**0.003**	**0.000**	**0.000**	**0.000**	**0.030**	**0.000**	**0.784**	-	**0.073**	**0.584**	**0.003**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.187**	**0.001**	-	**0.411**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	**0.008**	-	**0.012**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.032**	**0.214**	**0.005**	**0.737**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.434**	**0.641**	**0.000**	-	**0.003**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.651**	**0.374**	**0.000**	**0.002**	-

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.49 Statistical significance of EM Europe conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.035**	**0.104**	**0.008**	**0.018**	**0.000**	**0.042**	**0.001**
GO-GARCH ICA	62	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.186**	**0.005**	**0.000**	**-**	**0.544**	**0.067**	**0.121**	**0.000**	**0.403**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.032**	**0.000**	**0.529**	**-**	**0.048**	**0.088**	**0.000**	**0.304**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.224**	**0.467**	**0.117**	**0.000**	**0.241**	**0.000**	**0.902**	**0.746**	**-**	**0.637**	**0.251**	**0.110**	**0.000**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.156**	**-**	**0.695**	**0.005**	**0.000**	**0.349**	**0.000**	**0.863**	**0.966**	**0.831**	**-**	**0.162**	**0.224**	**0.001**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.028**	**0.309**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.009**	**0.003**	**-**	**0.009**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.082**	**0.005**	**0.001**	**-**	**0.000**	**0.117**	**0.000**	**0.837**	**0.880**	**0.829**	**0.964**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.230**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.006**	**0.000**	**0.000**	**0.000**	**0.035**	**0.054**	**0.000**	**0.001**	**-**

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.50 Statistical significance of EM Latin America conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.030**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.030**	**0.000**	**0.005**	**0.000**	**-**	**0.000**	**0.007**	**0.003**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.258**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.380**	**0.004**	**0.000**	**0.000**	**0.001**	**0.000**	**0.050**	**0.000**	**-**	**0.994**	**0.026**	**0.260**	**0.742**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.309**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.016**	**0.000**	**0.846**	**-**	**0.026**	**0.302**	**0.322**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.014**	**0.000**	**-**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.001**	**-**	**0.051**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.017**	**0.661**	**0.000**	**0.000**	**0.001**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.030**	**0.034**	**0.001**	**-**	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.439**	**0.569**	**0.000**	**0.000**	**-**

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.51 Statistical significance of EM Asia conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.061**	**0.190**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.001**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.011**	**0.000**	**-**	**0.691**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.073**	**0.000**	**0.591**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.015**	**0.001**	**0.264**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.370**	**0.038**	**0.452**	**0.047**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.021**	**-**	**0.256**	**0.003**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.665**	**-**	**0.302**	**0.863**	**0.322**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**0.627**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.007**	**-**	**0.489**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.505**	**0.008**	**0.001**	**-**	**0.098**	**0.000**	**0.000**	**0.000**	**0.000**	**0.016**	**0.083**	**0.008**	**-**	**0.098**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	**0.020**	**0.001**	**0.111**	**-**

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.52 Statistical significance of EFM Africa conditional correlations and conditional volatilities between models for the short pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.000**	**0.030**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.047**	**-**	**0.000**	**0.699**	**0.000**	**0.443**	**0.508**	**0.443**	**0.158**	**0.000**
GO-GARCH ICA	62	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.023**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.950**	**0.000**	**-**	**0.000**	**0.449**	**0.544**	**0.782**	**0.057**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.087**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.013**	**0.020**	**0.000**	**0.021**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.046**	**0.152**	**0.334**	**0.000**	**0.276**	**0.000**	**0.255**	**0.581**	**-**	**0.907**	**0.982**	**0.170**	**0.000**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.118**	**-**	**0.699**	**0.021**	**0.000**	**0.266**	**0.000**	**0.246**	**0.636**	**0.964**	**-**	**0.990**	**0.188**	**0.000**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.454**	**0.274**	**-**	**0.066**	**0.000**	**0.096**	**0.000**	**0.060**	**0.000**	**0.074**	**0.074**	**-**	**0.003**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.004**	**0.450**	**0.036**	**0.143**	**-**	**0.000**	**0.197**	**0.000**	**0.122**	**0.006**	**0.590**	**0.562**	**0.001**	**-**	**0.000**
UNCONDITIONAL	62	**0.014**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.003**	**0.155**	**0.190**	**0.000**	**0.000**	**-**

Notes: The period runs from 10 March 2006 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.53 Statistical significance of US conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**0.000**	**0.000**	**0.063**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.002**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.176**	**0.000**	**0.000**	**0.000**
COPULA DCC	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.133**	-	**0.000**	**0.000**	**0.000**
SMA (100)	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.072**	**0.000**
EWMA (0.03, 0.97)	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.370**	-	**0.000**
UNCONDITIONAL	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.54 Statistical significance of EMU conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.002**	**0.187**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.591**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.010**	**-**	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.128**	**0.001**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.467**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.694**	**0.000**	**0.000**	**0.000**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**-**	**0.000**	**0.013**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.223**	**-**	**0.000**	**0.000**	**0.000**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.005**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.104**	**0.005**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.095**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**-**	**0.061**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.857**	**-**

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.55 Statistical significance of Europe ex EMU conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.018**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.017**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.067**	**0.000**	**0.000**	**0.000**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.009**	**-**	**0.000**	**0.000**	**0.000**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.056**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.022**	**-**

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.56 Statistical significance of Pacific conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**0.000**	**0.492**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.266**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.528**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.138**	**0.000**	-	**0.000**	**0.006**	**0.001**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.101**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.009**	**0.000**	**0.094**	**0.000**	**0.328**	**0.000**	-	**0.820**	**0.087**	**0.002**	**0.000**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.006**	**0.298**	**0.000**	**0.025**	**0.000**	**0.152**	**0.000**	**0.858**	-	**0.049**	**0.000**	**0.000**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.012**	-	**0.206**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	**0.002**	-	**0.001**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.028**	**0.798**	**0.056**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.065**	-	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.072**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.57 Statistical significance of EM BRIC conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.002**	**0.000**	**0.163**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.954**	**0.008**	**0.020**	**0.159**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**-**	**0.487**	**0.112**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.736**	**-**	**0.006**	**0.016**	**0.101**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.545**	**-**	**0.037**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.063**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.263**	**0.066**	**0.016**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.002**	**0.243**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.014**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.002**	**0.000**	**0.542**	**-**

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.58 Statistical significance of EM Europe conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.008**	**0.340**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	-	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.118**	**0.000**	**0.138**	**0.000**	**0.079**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.423**	**0.001**	**0.054**	**0.010**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.098**	**0.000**	-	**0.000**	**0.008**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.661**	-	**0.000**	**0.003**	**0.101**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.686**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.244**	**0.000**	**0.014**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.047**	**0.011**	**0.029**	-	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.679**	**0.280**	**0.000**	**0.009**	-

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.59 Statistical significance of EM Latin America conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.006**	**0.763**	**0.449**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.951**	**0.000**	**0.028**	**0.482**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**-**	**0.028**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.750**	**-**	**0.000**	**0.021**	**0.482**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.237**	**0.148**	**-**	**0.226**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.003**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.226**	**0.001**	**0.036**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.007**	**0.011**	**0.000**	**0.000**	**-**

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.60 Statistical significance of EM Asia conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.001**	**0.060**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.059**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.019**	**0.000**	**0.118**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.302**	**0.727**	**0.051**	**0.000**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.097**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.503**	-	**0.119**	**0.495**	**0.000**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.152**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.106**	**0.494**	-	**0.003**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.168**	**0.031**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.016**	**0.001**	-	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.61 Statistical significance of EFM Africa conditional correlations and conditional volatilities between models for the long pre-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.000**	**0.237**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.408**	**0.000**	**0.087**	**0.129**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.190**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.729**	**0.000**	**-**	**0.000**	**0.073**	**0.102**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.673**	**0.000**	**0.766**	**0.000**	**-**	**0.810**	**0.020**	**0.797**	**0.010**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.156**	**0.000**	**0.779**	**0.000**	**0.874**	**0.000**	**0.923**	**-**	**0.036**	**0.835**	**0.005**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.124**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.003**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.152**	**0.046**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.022**	**0.036**	**0.001**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.452**	**0.391**	**0.000**	**0.000**	**-**

Notes: The period runs from 31 December 2004 to 11 May 2007. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.62 Statistical significance of US conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.000**	**0.116**	**0.000**	**0.010**	**0.031**	**0.000**	**0.000**	**0.186**
GO-GARCH ICA	62	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.009**	**0.000**	**0.000**
GO-GARCH NLS	62	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.030**	**0.000**	**-**	**0.000**	**0.004**	**0.014**	**0.000**	**0.000**	**0.322**
GO-GARCH ML	62	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**-**	**0.001**	**0.002**	**0.000**	**0.000**	**0.000**
DCC	62	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**0.257**	**0.000**	**0.078**	**0.002**	**-**	**0.747**	**0.000**	**0.000**	**0.003**
COPULA DCC	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**0.379**	**0.000**	**0.125**	**0.004**	**0.842**	**-**	**0.000**	**0.000**	**0.021**
SMA (100)	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.128**	**0.000**	**0.107**	**0.000**	**0.164**	**0.252**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.63 Statistical significance of EMU conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.113**	**0.186**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.229**	**0.000**	**0.138**	**0.284**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.453**	**-**	**0.089**	**0.000**	**0.000**	**0.000**	**0.000**	**0.019**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.162**	**0.882**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.642**	**0.000**	**-**	**0.000**	**0.239**	**0.449**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.001**	**0.000**	**0.000**	**0.000**	**0.098**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.211**	**0.000**	**0.000**	**0.000**	**0.674**	**0.000**	**0.576**	**0.025**	**-**	**0.630**	**0.000**	**0.000**	**0.003**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.522**	**-**	**0.000**	**0.000**	**0.000**	**0.696**	**0.000**	**0.567**	**0.002**	**0.917**	**-**	**0.000**	**0.000**	**0.003**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.002**	**0.006**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.801**	**0.274**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.001**	**0.198**	**0.058**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.64 Statistical significance of Europe ex EMU conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	**0.149**	**0.017**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**0.000**	-	**0.000**	**0.196**	**0.000**	**0.001**	**0.001**	**0.000**	**0.000**	**0.008**
GO-GARCH ICA	62	**0.600**	-	**0.014**	**0.000**	**0.000**	**0.000**	**0.211**	**0.958**	**0.322**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.015**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.043**	**0.692**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.352**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.072**	**0.000**	**0.000**	**0.000**	**0.054**	**0.000**	**0.024**	**0.000**	-	**0.282**	**0.000**	**0.000**	**0.003**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.277**	-	**0.000**	**0.000**	**0.000**	**0.007**	**0.000**	**0.002**	**0.000**	**0.969**	-	**0.000**	**0.000**	**0.008**
SMA (100)	62	**0.023**	**0.052**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.554**	**0.509**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.005**	**0.000**	**0.000**	**0.000**	**0.000**	**0.333**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.009**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.362**	**0.198**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.65 Statistical significance of Pacific conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.591**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.024**	**0.000**	**-**	**0.000**	**0.329**	**0.000**	**0.025**	**0.142**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.537**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.401**	**0.000**	**-**	**0.000**	**0.008**	**0.044**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.544**	**0.033**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.032**	**0.009**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.532**	**-**	**0.014**	**0.000**	**0.000**	**0.000**	**0.414**	**0.000**	**0.192**	**0.000**	**-**	**0.446**	**0.000**	**0.000**	**0.186**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.086**	**0.018**	**-**	**0.000**	**0.000**	**0.000**	**0.389**	**0.000**	**0.141**	**0.000**	**0.916**	**-**	**0.000**	**0.000**	**0.003**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.001**	**0.098**	**0.000**	**0.000**	**0.000**	**0.081**	**0.000**	**0.000**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.026**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**-**	**0.742**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.023**	**0.016**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.66 Statistical significance of EM BRIC conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.008**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.127**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	-	**0.000**	**0.053**	**0.007**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.033**	**0.005**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.207**	**0.000**
DCC	62	**0.000**	**0.000**	**0.008**	**0.000**	-	**0.270**	**0.000**	**0.000**	**0.000**	**0.007**	**0.000**	**0.555**	**0.000**	-	**0.651**	**0.000**	**0.000**	**0.000**
COPULA DCC	62	**0.000**	**0.000**	**0.002**	**0.000**	**0.723**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.174**	**0.000**	**0.597**	-	**0.000**	**0.000**	**0.000**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.148**	**0.000**	**0.000**	**0.000**	-	**0.000**
UNCONDITIONAL	62	**0.000**	**0.627**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.67 Statistical significance of EM Europe conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.000**	**0.000**	**0.000**	**0.003**	**0.001**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.034**	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.816**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	**-**	**0.000**	**0.010**	**0.000**	**0.000**	**0.000**	**0.000**	**0.031**	**0.000**	**-**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	62	**0.037**	**0.000**	**0.016**	**0.000**	**-**	**0.329**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**-**	**0.571**	**0.000**	**0.000**	**0.509**
COPULA DCC	62	**0.063**	**0.000**	**0.001**	**0.000**	**0.521**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.767**	**-**	**0.000**	**0.000**	**0.322**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.003**	**0.000**	**0.000**	**0.090**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.186**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.046**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.015**	**0.003**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.68 Statistical significance of EM Latin America conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	-	**0.000**	**0.673**	**0.076**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	-	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.270**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.650**	**0.000**	-	**0.114**	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**0.000**	**0.000**	-	**0.000**	**0.019**	**0.026**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.261**	**0.000**	**0.079**	-	**0.006**	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.022**	**0.000**
DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.437**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**0.491**	**0.000**	-	**0.930**	**0.000**	**0.000**	**0.000**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.612**	-	**0.000**	**0.000**	**0.000**	**0.002**	**0.000**	**0.376**	**0.000**	**0.926**	-	**0.000**	**0.000**	**0.000**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.002**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**0.000**	**0.000**	-	**0.000**
UNCONDITIONAL	62	**0.000**	**0.005**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.69 Statistical significance of EM Asia conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.138**	**0.022**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.247**	**0.875**	**0.001**	**0.001**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.192**	**-**	**0.003**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.509**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.517**	**-**	**0.000**	**0.012**	**0.000**	**0.000**	**0.000**	**0.000**	**0.240**	**0.000**	**-**	**0.375**	**0.002**	**0.004**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	62	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.311**	**0.000**	**0.064**	**-**	**0.000**	**0.001**	**0.000**	**0.002**	**0.000**
DCC	62	**0.000**	**0.041**	**0.024**	**0.000**	**-**	**0.038**	**0.000**	**0.000**	**0.000**	**0.011**	**0.000**	**0.039**	**0.003**	**-**	**0.774**	**0.000**	**0.000**	**1.000**
COPULA DCC	62	**0.000**	**0.005**	**0.000**	**0.000**	**0.300**	**-**	**0.000**	**0.000**	**0.000**	**0.013**	**0.000**	**0.043**	**0.004**	**0.941**	**-**	**0.000**	**0.000**	**1.000**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**0.000**	**0.003**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.078**	**0.125**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.70 Statistical significance of EFM Africa conditional correlations and conditional volatilities between models for the short post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	62	**-**	**0.006**	**0.000**	**0.000**	**0.023**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.001**	**0.001**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	62	**0.129**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	62	**0.000**	**0.000**	**-**	**0.191**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.521**	**0.511**	**0.000**	**0.000**	**0.001**
GO-GARCH ML	62	**0.000**	**0.000**	**0.050**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.117**	**0.000**
DCC	62	**0.002**	**0.000**	**0.000**	**0.000**	**-**	**0.082**	**0.000**	**0.000**	**0.000**	**0.065**	**0.000**	**0.159**	**0.000**	**-**	**0.879**	**0.000**	**0.000**	**0.047**
COPULA DCC	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.522**	**-**	**0.000**	**0.000**	**0.000**	**0.081**	**0.000**	**0.160**	**0.000**	**0.974**	**-**	**0.000**	**0.000**	**0.021**
SMA (100)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.380**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.472**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	62	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.004**	**0.000**	**0.531**	**0.516**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 4 March 2011. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.71 Statistical significance of US conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**0.000**	**0.891**	**0.000**	**0.003**	**0.009**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.078**	**0.000**	-	**0.000**	**0.001**	**0.003**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.159**
DCC	124	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**1.000**	**0.712**	**0.000**	**0.271**	**0.000**	-	**0.656**	**0.000**	**0.000**	**0.000**
COPULA DCC	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**1.000**	**0.901**	**0.000**	**0.524**	**0.002**	**0.721**	-	**0.000**	**0.000**	**0.000**
SMA (100)	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.232**	**0.000**
EWMA (0.03, 0.97)	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**1.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**
UNCONDITIONAL	124	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	-	**0.000**	**0.000**	**0.000**	**0.033**	**0.003**	**0.013**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.72 Statistical significance of EMU conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.013**	**0.970**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**-**	**0.000**	**0.006**	**0.000**	**0.871**	**0.905**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.539**	**-**	**0.224**	**0.000**	**0.000**	**0.000**	**0.081**	**0.084**	**0.035**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.929**	**0.611**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**0.012**	**0.000**	**-**	**0.000**	**0.518**	**0.205**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.003**	**0.001**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.530**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**0.000**	**0.327**	**-**	**0.764**	**0.000**	**0.000**	**0.000**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.477**	**-**	**0.000**	**0.000**	**0.000**	**0.005**	**0.000**	**0.000**	**0.094**	**0.706**	**-**	**0.000**	**0.000**	**0.000**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.456**	**0.241**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.138**	**0.035**
EWMA (0.03, 0.97)	124	**0.118**	**0.098**	**0.139**	**0.000**	**0.000**	**0.000**	**0.013**	**-**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**0.000**	**0.001**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.008**	**0.001**	**0.000**	**0.000**	**0.000**	**0.001**	**0.630**	**-**	**0.000**	**0.000**	**0.000**	**0.007**	**0.024**	**0.001**	**0.000**	**0.014**	**-**

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.73 Statistical significance of Europe ex EMU conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**0.061**	**0.019**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.916**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	124	**0.335**	-	**0.004**	**0.000**	**0.000**	**0.000**	**0.022**	**0.050**	**0.005**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.061**	**0.909**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.836**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.514**	**0.338**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.474**	**0.000**	**0.000**	**0.000**	**0.373**	**0.000**	**0.334**	**0.000**	-	**0.520**	**0.000**	**0.000**	**0.000**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.606**	-	**0.000**	**0.000**	**0.000**	**0.096**	**0.000**	**0.079**	**0.000**	**0.751**	-	**0.000**	**0.000**	**0.000**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.646**	**0.482**	**0.000**	**0.000**	**0.000**	**0.010**	**0.000**	**0.000**	-	**0.432**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.500**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.048**	**0.000**	**0.000**	**0.000**	-	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.001**	**0.000**	**0.058**	**0.002**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.74 Statistical significance of Pacific conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**0.224**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.817**	**0.000**	**0.040**	**0.084**	**0.000**	**0.000**	**0.002**
GO-GARCH ICA	124	**0.062**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.001**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.962**	**0.000**	-	**0.000**	**0.044**	**0.091**	**0.000**	**0.000**	**0.019**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.085**	**0.000**	**0.000**	**0.000**	**0.931**	**0.000**	**0.954**	**0.000**	-	**0.596**	**0.000**	**0.000**	**0.348**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.002**	**0.054**	-	**0.000**	**0.000**	**0.000**	**0.635**	**0.000**	**0.663**	**0.000**	**0.794**	-	**0.000**	**0.000**	**0.482**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.499**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.252**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.246**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.008**	**0.001**	**0.000**	-	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.033**	**0.021**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.75 Statistical significance of EM BRIC conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.424**	**0.232**	**0.000**
GO-GARCH ICA	124	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.061**	**0.005**	**0.013**	**0.001**	**0.010**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.001**	**0.281**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.070**	**-**	**0.025**	**0.000**	**0.000**	**0.000**	**0.071**	**0.000**	**0.522**	**0.000**	**-**	**0.474**	**0.000**	**0.001**	**0.639**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.481**	**0.053**	**-**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	**0.882**	**0.000**	**0.526**	**-**	**0.000**	**0.000**	**0.019**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.003**	**0.000**	**0.000**	**0.000**	**0.000**	**0.851**	**0.000**	**0.000**	**-**	**0.575**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.006**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.253**	**0.000**	**0.000**	**0.000**	**0.021**	**0.002**	**0.001**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.109**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	**0.012**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.76 Statistical significance of EM Europe conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.001**	**0.002**	**0.000**	**0.000**	**0.610**	**0.124**	**0.000**
GO-GARCH ICA	124	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	-	**0.000**	**0.114**	**0.016**	**0.000**	**0.000**	**0.000**	**0.017**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.018**	**0.002**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.626**	**0.224**	**0.000**
DCC	124	**0.000**	**0.000**	**0.325**	**0.000**	-	**0.348**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**	-	**0.745**	**0.000**	**0.000**	**0.482**
COPULA DCC	124	**0.000**	**0.000**	**0.070**	**0.000**	**0.496**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	**0.000**	**0.937**	-	**0.000**	**0.000**	**0.815**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.222**	**0.159**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	-	**0.224**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.022**	-	**0.482**	**0.006**	**0.000**	**0.000**	**0.266**	**0.000**	**0.000**	**0.000**	-	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.773**	**0.011**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.078**	**0.045**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.77 Statistical significance of EM Latin America conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	-	**0.000**	**0.005**	**0.030**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.084**	**0.533**	**0.000**
GO-GARCH ICA	124	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.109**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.145**	**0.000**	-	**0.245**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.016**	**0.017**	**0.393**	**0.002**	**0.000**
GO-GARCH ML	124	**0.204**	**0.000**	**0.786**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.013**	**0.000**	**0.000**	**0.000**	**0.003**	**0.000**	**0.770**	**0.000**	-	**0.909**	**0.000**	**0.000**	**0.815**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.017**	-	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.649**	**0.000**	**0.913**	-	**0.000**	**0.000**	**0.348**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.016**	**0.000**	**0.000**	**0.000**	**0.000**	**0.059**	**0.000**	**0.000**	-	**0.723**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.139**	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	-	**0.000**	**0.265**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.001**	-	**0.000**
UNCONDITIONAL	124	**0.000**	**0.969**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.034**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.78 Statistical significance of EM Asia conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	Conditional volatility MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.106**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.017**	**0.196**	**0.000**	**0.000**	**0.240**	**0.131**	**0.000**
GO-GARCH ICA	124	**0.116**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.057**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.153**	**0.000**	**-**	**0.670**	**0.003**	**0.003**	**0.011**	**0.007**	**0.639**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.555**	**0.000**	**0.000**	**0.000**	**0.919**	**0.000**	**0.285**	**-**	**0.001**	**0.002**	**0.016**	**0.088**	**0.159**
DCC	124	**0.000**	**0.000**	**0.000**	**0.007**	**-**	**0.001**	**0.000**	**0.000**	**0.000**	**0.161**	**0.000**	**0.498**	**0.206**	**-**	**0.685**	**0.000**	**0.000**	**0.001**
COPULA DCC	124	**0.000**	**0.000**	**0.000**	**0.823**	**0.020**	**-**	**0.000**	**0.000**	**0.000**	**0.192**	**0.000**	**0.525**	**0.235**	**0.995**	**-**	**0.000**	**0.000**	**0.010**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.062**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.440**	**0.000**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.011**	**-**	**0.000**	**0.066**	**0.000**	**0.003**	**0.099**	**0.021**	**0.030**	**0.001**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.469**	**0.512**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 5.79 Statistical significance of EFM Africa conditional correlations and conditional volatilities between models for the long post-crisis period

Model	Sample length	Conditional correlation with US									Conditional volatility								
		MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC	MM	ICA	NLS	ML	DCC	COP	SMA	EWMA	UNC
GO-GARCH MM	124	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.023**	**0.002**	**0.482**
GO-GARCH ICA	124	**0.064**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH NLS	124	**0.000**	**0.000**	**-**	**0.000**	**0.067**	**0.755**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.873**	**0.592**	**0.000**	**0.000**	**0.000**
GO-GARCH ML	124	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.006**	**0.000**	**0.000**
DCC	124	**0.000**	**0.000**	**0.161**	**0.000**	**-**	**0.053**	**0.000**	**0.000**	**0.000**	**0.023**	**0.000**	**0.106**	**0.000**	**-**	**0.798**	**0.000**	**0.000**	**0.002**
COPULA DCC	124	**0.000**	**0.000**	**0.856**	**0.001**	**0.126**	**-**	**0.000**	**0.000**	**0.000**	**0.073**	**0.000**	**0.048**	**0.000**	**0.737**	**-**	**0.000**	**0.000**	**0.001**
SMA (100)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.044**	**0.000**	**0.000**	**0.000**	**0.000**	**0.054**	**0.000**	**0.000**	**-**	**0.772**	**0.001**
EWMA (0.03, 0.97)	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	**-**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**
UNCONDITIONAL	124	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.003**	**0.000**	**0.000**	**0.000**	**0.272**	**0.554**	**0.000**	**0.000**	**-**

Notes: The period runs from 1 January 2010 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

6 COMPARISON OF THE IMPACT OF DIFFERENT METHODOLOGIES ON PORTFOLIO PERFORMANCE

6.1 INTRODUCTION, AIMS, OBJECTIVES AND CONTRIBUTION

As I have identified in the conclusion of Chapter 5, I am going to compare different covariance estimation models, namely COPULA DCC, DCC, GO-GARCH ICA, GO-GARCH MM, EWMA and sample covariance methodology, in terms of out-of-sample comparison in the investment portfolio context. Different testing approaches have been identified in Section 2.5.

In this chapter I apply the same approach estimating efficient portfolios as can be found elsewhere in the literature (for example, Giamouridis and Vrontos 2007, Harris and Mazibas 2010, Syriopoulos and Roumpis 2009). The novel contribution made in this chapter is that whilst other studies that have examined the relative performance of optimal portfolios estimated using different conditional covariance models (for example, Caporin and McAleer (2014), Engle (2002), Giamouridis and Vrontos 2007, Harris and Mazibas 2010), they do not consider the specific group of models that I have chosen in this thesis. I believe my dataset is also unique. This enables me to undertake portfolio optimisation using conditional covariance models that are both centred on a major financial crisis such as occurred in 2007 and also take account of regional developed and emerging/frontier market perspectives. My work makes a further contribution given there is little in the literature in respect to the treatment of transaction costs.

The remainder of this chapter is structured as follows. First, the data and methodology are described in Section 6.2. Further on the hypotheses of the chapter are presented in Section 6.3. Next, the results in terms of temporal descriptive analysis, testing hypotheses, portfolio rebalancing and approximated transaction costs are reported in Section 6.4. The discussion of results is presented in Section 6.5. Finally, the conclusions are drawn in Section 6.6.

6.2 DATA AND METHODOLOGY

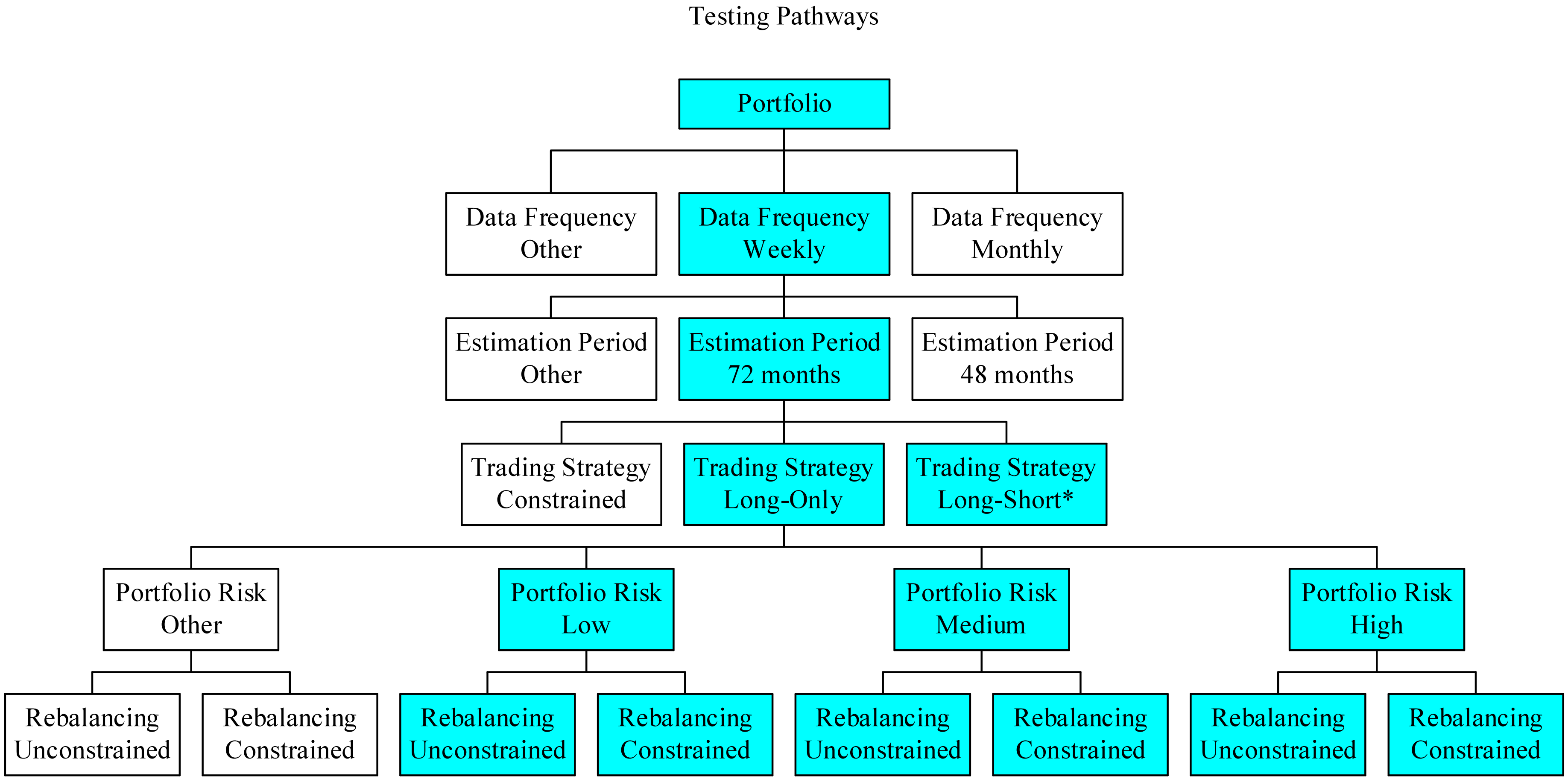
The comparison of different covariance models can be based on in-sample and out-of-sample comparison. The out-of-sample comparison consists of direct and indirect methods. For more details please look at Section 2.5.

In my PhD thesis I will focus only on out-of-sample indirect comparison of different covariance models in the context of investment portfolio performance. This is because the optimal in-sample model does not guarantee the optimal out-of-sample performance, which is the key aspect for the financial industry (Bauwens *et al*. 2012).

This comparison based on portfolio performance can be quite a complicated issue as there are many different methods used in the literature (for example Bauwens *et al*. 2012, Engle and Colacito 2006, Engle and Sheppard 2001, Giamouridis and Vrontos 2007, Jithendranathan 2007, Patton and Sheppard 2009, Syriopoulos and Roumpis 2009, identified in Section 2.5).

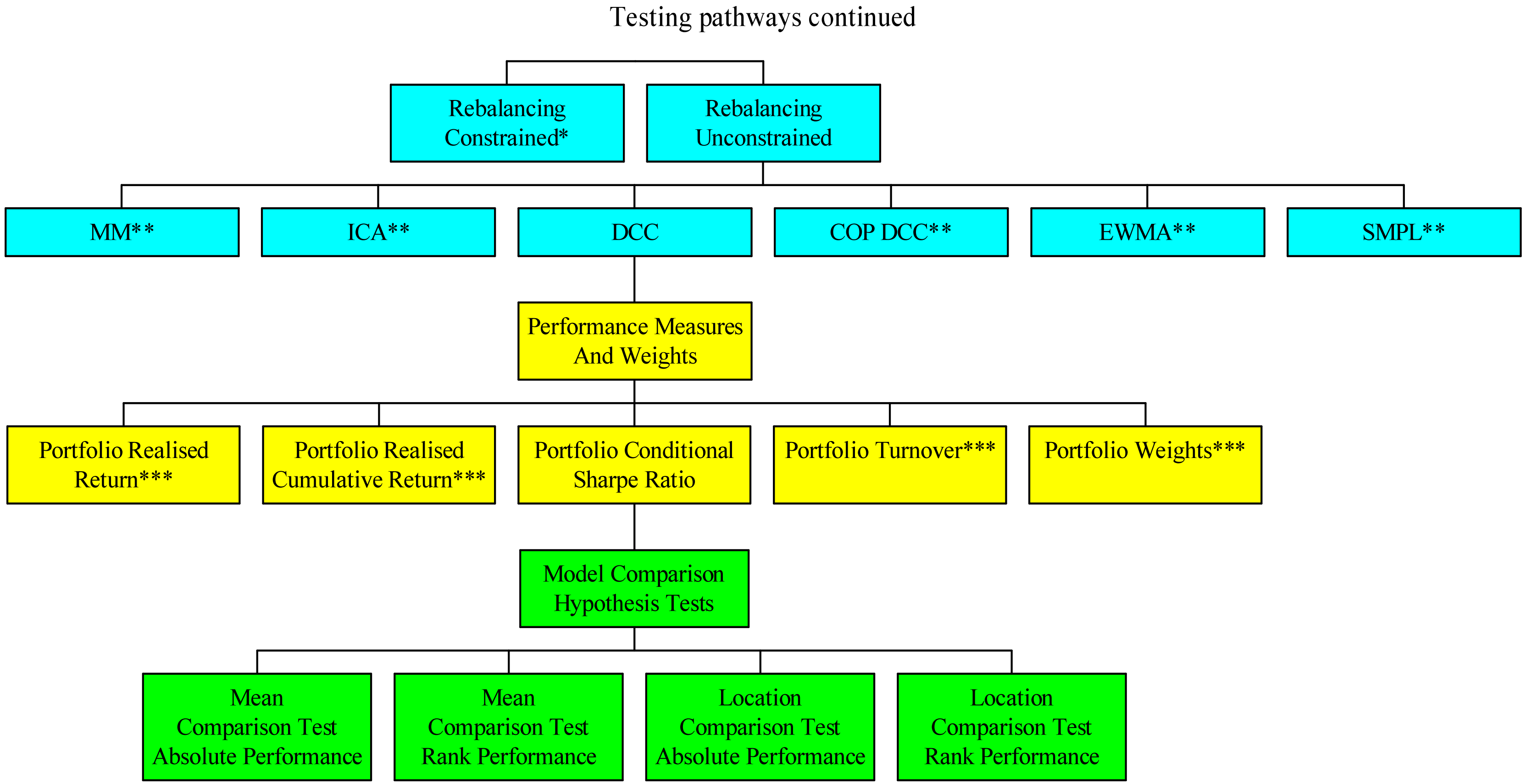
The main issue I face in this chapter is how to deal with the complexity of the task. Below I present the diagram (Figure 6.1 and Figure 6.2) that identifies the issues and the different approaches available to me and the actual approaches I take. The diagram identifies the main potential testing pathways. The actual pathways examined are shown using blue (Figure 6.1). In Figure 6.2, the portfolio performance measures are shown in yellow and the model comparison hypothesis tests are coloured green.

Figure 6.1 Portfolio testing pathways



* The Long-Short trading strategy pathway follows the same pathway as the Long-Only trading strategy. The additional detail has been omitted due to size constraints.

Figure 6.2 Portfolio testing pathways continued



* The constrained rebalancing doesn't follow the same pathway as the unconstrained rebalancing. The analysis limits only to the mean comparison of performance measures without statistical testing. The additional detail has been omitted due to the size constraints.

** The MM, ICA, COP DCC, EWMA and SPML follows the same pathway as the DCC. The additional detail has been omitted due to the size constraints.

*** The hypothesis testing of the other performance measures follow the same structure as the Portfolio Conditional Sharpe Ratio. The additional detail has been omitted due to the size constraints.

6.2.1 DATA FREQUENCY

The first aspect that needs to be considered is the frequency of the data used. For example, Giamouridis and Vrontos (2007) use monthly returns, Jithendranathan (2007) and Syriopoulos and Roumpis (2009) use weekly data and Engle and Sheppard (2001) make use of daily data.

I have decided to work with the weekly returns because of the data constraints; weekly data allows me to obtain a sample large enough to perform the estimation of the dynamic models and the out-of-sample comparison. This provides me with 513 weekly observations. The use of weekly data also ensures direct comparability with the data and models used in the previous chapters of my thesis.

6.2.2 ESTIMATION PERIOD

The estimation periods used also vary in different studies. Some of them use a fixed-length estimation window whereas other use a growing window. For instance, Cha and Jithendranathan (2009) follow the industry practice of using five-year rolling windows. However, their sensitivity analysis shows that using three-, four- and five-year windows does not have an impact on their results.

For my study I considered using 48-month (four-year) and 72-month (six-year) estimation rolling windows covering the period from 19 July 2002 to 11 May 2012. However, the conclusions drawn from my results were quite similar for both cases and hence, in order to conserve space, only results based on the 72-month estimation period are reported in this thesis. The lack of variation in the results using different windows is consistent, for example, with Cha and Jithendranathan (2009) and DeMiguel *et al*. (2009a).

6.2.3 TRADING STRATEGY

The literature mainly focuses on the two main trading strategies, namely, long-only (short selling is not allowed) and long-short (short selling is not constrained). In addition, some studies use other restrictions on the portfolio weights. For example, Cha and Jithendranathan (2009) restrict combined investment in emerging markets to 20% or that the individual emerging market investment cannot exceed 3%.

Trading strategies chosen for the purpose of this thesis are long-only and long-short as they are the most popular in the literature. Using two trading strategies provides robustness checks for my analysis. The main focus in this thesis is the long-short strategy as it is not a constrained strategy and therefore can fully respond to the market conditions, e.g. it allows the short position in a falling market.

6.2.4 OPTIMISATION PROCEDURES AND PORTFOLIO RISK

The Markowitz (1952) mean-variance analysis is employed. For details please refer back to Section 2.2.2. According to Giamouridis and Vrontos (2007) and Syriopoulos and Roumpis (2009), the mean-variance is very common approach in practice.

The expected return of a portfolio (i.e. $E(R_p)$) of n assets can be calculated as a weighted averages of expected returns of assets (Markowitz 1952):

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) \tag{6.1}$$

Whereas the variance of portfolio returns (i.e. σ_p^2):

$$\sigma_P^2 = \sum_{i=1}^{n} w_i^2\sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j>i}^{n} w_i w_j \sigma_{ij} = \sum_{i=1}^{n} w_i^2\sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j>i}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij} \quad (6.2)$$

or the standard deviation of portfolio returns (i.e. σ_p):

$$\sigma_P = \sqrt{\sum_{i=1}^{n} w_i^2\sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j>i}^{n} w_i w_j \sigma_{ij} = \sum_{i=1}^{n} w_i^2\sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j>i}^{n} w_i w_j \sigma_i \sigma_j \rho_{ij}} \quad (6.3)$$

Where w_i is weight of asset (relative amount invested in security) *i* in the portfolio, $E(R_i)$ is expected return of asset *i*, σ_i^2 is variance of asset *i* returns, σ_{ij} is covariance between asset *i* and *j* returns, σ_i is standard deviation of asset *i* returns, ρ_{ij} is correlation between asset *i* and *j* returns;

6.2.4.1 PORTFOLIO OPTIMISATION INPUTS

I use 72-month rolling windows for the estimation of the inputs of the mean-variance analysis. Following industry practice as suggested by Cha and Jithendranathan (2009), I use a sample average as a proxy for expected asset return. Covariances, variances and correlations are estimated based on the six models that have been chosen at the end of the previous chapter (see Section 5.6), namely GO-GARCH MM, GO-GARCH ICA, DCC, copula DCC, EWMA and sample covariance model, which are called in short MM, ICA, DCC, COP, EWMA and SMPL, respectively. In order to capture the time-varying nature of covariances, variances and correlations I follow the approach of Cha and Jithendranathan (2009). Given the rolling window for the estimation, the ends of the period values (i.e. the last, most recent covariances, variances and correlations) are used as the inputs for portfolio optimisation.

6.2.4.2 Risk minimisation formulation

Following Markowitz, the mean-variance analysis can be represented as the risk minimisation formulation (Fabozzi *et al*. 2007) (see Section 2.2.2.2):

$$\min_{w} w'\Sigma w \tag{6.4}$$

subject to constraints

$$w'\mu = \mu_0 \tag{6.5}$$

$$w'\iota = 1 \tag{6.6}$$

where symbol $'$ means transposition, $w' = (w_1, w_2, \dots, w_N)'$ is the vector of assets' weights, Σ is the $N \times N$covariance matrix, $\mu = (\mu_1, \mu_2, \dots, \mu_N)'$ is the vector of assets' expected returns, μ_0 is the target return and $\iota = (1,1,\dots,1)'$.

One of the common additional constraints added to the optimisation is the long-only constraint ($w \geq 0$) which means that none of the assets' weights can be negative. This could be for legal or practical reasons (Fabozzi *et al*. 2007).

6.2.4.3 Different risk portfolios

For the robustness of our analysis I use three different risk portfolios: global minimum variance (low), medium and high-risk portfolio.

In order to find the global MVP we need to solve the following problem (Fabozzi *et al*. 2007):

$$\min_{w} w'\Sigma w \tag{6.7}$$

subject to constraints

$$w'\iota = 1 \tag{6.8}$$

with the solution given as:

$$w = \frac{1}{\iota'\Sigma^{-1}\iota}\Sigma^{-1}\iota \tag{6.9}$$

The main reason to use global MVP is that it has been argued in the literature that the global minimum portfolio does not suffer from the estimation errors because of the estimation of the expected returns (Chan *et al*. 1999, Syriopoulos and Roumpis 2009).

In addition, for the robustness of the analysis I also use medium and high-risk portfolio. This is similar to Cha and Jithendranathan (2009) and Jithendranathan (2007). Given the expected MVP portfolio return and the expected assets' returns, I choose the maximum return out of assets' returns. Two equidistant returns between global MVP return and maximum asset return are chosen as target portfolio returns for the portfolio optimisations. The first equidistant return closer to MVP return denotes medium-risk portfolio return, whereas the second one (closer to the maximum asset return) stands for high-risk portfolio.

The 72-month rolling period is moved by 1 month. This gives us 48 rolling windows.

6.2.5 REBALANCING

The academic and practitioner literature suggests a number of approaches to rebalancing a portfolio. The most popular is the periodic rebalancing where the portfolio is adjusted to the target weights on some sort of time interval e.g. monthly, quarterly or yearly (Sun *et al*. 2006). The main disadvantage of this approach is that it is not related to market conditions.

The other approach is based on idea that the portfolio is rebalanced only when portfolio weights move beyond a certain tolerance level e.g. ±5% (Sun *et al*. 2006). The main disadvantage of this method is that the portfolio needs to be monitored on a very frequent basis, e.g. daily.

The hybrid approach is the combination of periodic and tolerance methods. This means that the portfolio manager monitors their portfolio on a set time interval, but it is rebalanced only when the weights deviate from the target weight by more than the thresholds set (Jaconetti *et al*. 2010).

The cost of rebalancing refers not only to the transaction costs, e.g. bid-ask spread, brokerage commissions, purchasing or redemption fees, but also to taxes, e.g. tax on capital gain, and time and labour costs related to the monitoring/rebalancing process (Jaconetti *et al*. 2010, Sun *et al*. 2006, Tokat and Wicas 2007).

The main focus of my thesis is the comparison of different covariance models and not finding the optimal rebalancing method, because there is no universally optimal rebalancing method (Jaconetti *et al*. 2010, Tokat and Wicas 2007). The general consensus among academics and practitioners is that the frequent portfolio rebalancing will offset the benefits associated with their use (Ferri 2013, Jaconetti *et al*. 2010, Kaegi 2012, Lim 2013, Morningstar 2013, Sun *et al*. 2006, Tokat and Wicas 2007).

In my thesis I follow the approach of Cha and Jithendranathan (2009), Giamouridis and Vrontos (2007) and Jithendranathan (2007) and use monthly rebalancing. This is unconstrained rebalancing, as the weights are dictated by the optimisation procedure. To more fully reflect the practices of professional portfolio managers I also apply the constraints to the portfolio rebalancing process. Although practitioners tend to use threshold or hybrid methods I use smoothing of weights for ease of application. This effectively results in lower portfolio turnover levels and as such can be seen to be equivalent to the hybrid and threshold methods used by professional portfolio managers.

The smoothing of portfolio weights is based on the EWMA with 4-, 8- and 12-month smoothing periods. These periods are chosen so that a comparative analysis can be made.

6.2.6 Performance measures and weights

Following Giamouridis and Vrontos (2007) and Syriopoulos and Roumpis (2009), I will look at the main four portfolio performance measures and changes of portfolio weights.

6.2.6.1 Realised portfolio returns

First, the realised portfolio returns over 1 month. Given the optimal weights I calculate buy-and-hold portfolio returns over a 1-month holding period, which can be expressed as:

$$R_{p,t+1} = w_t' R_{t+1} \tag{6.10}$$

where symbol $'$ means transposition, $w_t = (w_1, w_2, \dots, w_N)_t'$ is the vector of assets' weights at time t, $R_{t+1} = (R_1, R_2, \dots, R_N)_{t+1}'$ is the vector of assets' realised returns at time $t+1$.

6.2.6.2 Realised cumulative portfolio returns

The second measure is the cumulative realised monthly portfolio returns. This gives us a clearer indication of cumulative performance over time.

6.2.6.3 Conditional Sharpe ratio

Third, I look at the conditional version of the Sharpe ratio (CSR) (Sharpe 1998). This allows us to compare the realised portfolio returns on a risk-adjusted basis. The conditional Sharpe ratio is calculated as follows:

$$CSR_{p,t+1} = \frac{R_{p,t+1}}{\sqrt{Var(R_p)_t}} \tag{6.11}$$

where $R_{p,t+1}$ is the realised portfolio return at time $t+1$, $\sqrt{Var(R_p)_t}$ is the standard deviation of portfolio at time t based on Equation 6.3.

Please note that portfolio standard deviation is converted from a weekly to monthly basis by multiplying the weekly standard deviation by $\sqrt{(365/12)/7} \cong \sqrt{4.345} \cong 2.085$. The conditional Sharpe ratio is given on a monthly basis.

6.2.6.4 Portfolio turnover

The last measure is monthly portfolio turnover (PT), which is defined as the sum of absolute changes in the portfolio weights from previous month to the next month (Giamouridis and Vrontos 2007). This can be represented by the formula:

$$PT_{t+1} = \sum_{i=1}^{n} \left| w_{i,t+1} - w_{i,t} \right| \tag{6.12}$$

where PT_{t+1} is the PT at time $t+1$, $w_{i,t}$ weight of asset i in the portfolio at time t.

PT represents the percentage of a portfolio that needs to be reallocated/liquidated at particular point in time. This could be used as a proxy for transaction costs.

6.2.6.5 Portfolio weights

This allows us to compare composition and changes in portfolio weights of different covariance models on a monthly basis.

6.2.6.6 Model comparison hypothesis tests

In order to test the differences between different performance measures based on the different covariance models, the Welch (1938) t and Wilcoxon (1945) rank sum tests are used. This is consistent with the other chapter of this thesis. The differences in the mean and location values are compared by the Welch t and Wilcoxon rank sum tests, respectively.

The financial crisis resulted in excessive volatility levels in the returns. The consequence of this was very high standard errors, which led to low levels of power in hypothesis tests. I also undertake a series of rank-based hypothesis tests. This controls for excessive volatility as the standard errors are based on relative rather than absolute values.

6.3 Hypotheses

In this chapter I undertake tests for statistical significance on the relative performance of different covariance models in a portfolio context.

My expectations of different covariance models in terms of their performance are based on Sections 5.5 and 5.6. I have discussed a number of factors: practical estimation issues, dealing with structural breaks and non-normality in the data. In addition I have considered the results obtained in Chapter 5 in terms of the level and variability of the correlations and volatilities. I have identified DCC and copula DCC as the most potential promising methodologies in terms of the portfolio performance. Copula DCC is expected to perform better than DCC as it fits non-normal data better.

My hypotheses can be seen as an extension of the work of Giamouridis and Vrontos (2007), Harris and Mazibas (2010) and Vrontos *et al.* (2013) that is applied in different contexts. The first paper, for example, relates to hedge funds and compares static and dynamic covariance models using portfolio outputs identified in my hypotheses below. Where my work differs from this paper in that it: (i) uses a different dataset, (ii) uses a dataset that incorporates a period of financial crisis, (iii) uses different covariance models and (iv) focuses on the extension of DCC by using copula approach.

On this basis, I develop the following hypotheses:

H1. DCC and copula DCC differ from the other covariance models:

H1a. In terms of the mean realised returns;

H1b. In terms of the mean cumulative realised returns;

H1c. In terms of the mean conditional Sharpe ratio;

H1d. In terms of the mean portfolio turnover.

H2. Copula DCC differs from DCC:

H2a. In terms of the mean realised returns;

H2b. In terms of the mean cumulative realised returns;

H2c. In terms of the mean conditional Sharpe ratio;

H2d. In terms of the mean portfolio turnover.

H3. Sample covariance model differs from time-varying covariance models in terms of mean weightings within the portfolio.

The expectation with regards to Hypothesis 3 is that they will differ because time-varying techniques will result in greater rebalancing within the portfolio.

6.4 RESULTS

In this section I examine the temporal analysis of the portfolio performance measures and weights of different covariance models. Secondly, I perform the analysis in order to test the hypotheses of this chapter by comparing the mean and location values of covariance models with respect to the portfolio performance measures and weightings, and testing significance of the differences by means of the Welch t and Wilcoxon rank sum tests. Thirdly, the impact of the constrained and unconstrained rebalancing is analysed with respect to the portfolio performance measures. Finally, I approximate the impact of transaction costs on the profitability of rebalancing.

All the results are obtained using R (2013) and its packages, mainly rmgarch (Ghalanos 2012), gogarch (Pfaff 2009), fPortfolio (Wuertz *et al*. 2011) and fPortfolioBacktest (Wuertz *et al*. 2009).

6.4.1 Temporal descriptive analysis

This section presents the temporal descriptive analysis of long-short portfolio performance measures: realised monthly portfolio returns (Figure 6.3), realised cumulative monthly portfolio returns (Figure 6.4), monthly portfolio standard deviation (Figure 6.5), monthly portfolio conditional Sharpe ratio (Figure 6.6), and monthly PT (Figure 6.7). Equivalent results for long-only portfolios are presented in the appendix (Figure 6.17–Figure 6.21). All those aforementioned figures are based on the 72-month estimation window and represent 47 observations (31 July 2008–11 May 2012) apart from portfolio standard deviation, which presents 48 observations (30 June 2008–11 May 2012). The crisis period has been identified in Section 3.1, i.e. it began on 11 May 2007 and ended on 1 January 2010. The vertical line represents the end (1 January 2010) of the financial crisis.

The second part of the temporal analysis focuses on the portfolio weights: US (Figure 6.8), EMU (Figure 6.9), Europe ex EMU (Figure 6.10), Pacific (Figure 6.11), EM BRIC (Figure 6.12), EM Europe (Figure 6.13), EM Latin America (Figure 6.14), EM Asia (Figure 6.15), and EMF Africa (Figure 6.16). Equivalent results for long-only portfolios are presented in the appendix (Figure 6.22–Figure 6.30). All those aforementioned figures are based on the 72-month estimation window and represent 48 observations (30 June 2008–11 May 2012). The vertical line represents the end (1 January 2010) of the financial crisis.

In addition, the descriptive statistics (i.e. minimum, maximum, mean, median, standard deviation and coefficient of variation) that correspond to the aforementioned figures can be found in the appendix. Table 6.30–Table 6.43 refer to the long-only portfolio performance measures and weights, whereas Table 6.44–Table 6.57 apply to long-short portfolio performance measures and weights.

In the previous chapters (4 and 5) I have undertaken the testing of correlations and volatilities before and after the crisis. Because of the methodology applied in this chapter, I am not able to perform this type of testing as before-crisis estimates are not obtainable. This limits our analysis of the impact of the crisis to a tentative descriptive temporal analysis. The main focus of this chapter is the comparison of the different covariance time-varying models in a portfolio context. The statistical analysis undertaken is therefore limited to the relative performance of the different covariance models.

Figure 6.3 Realised monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

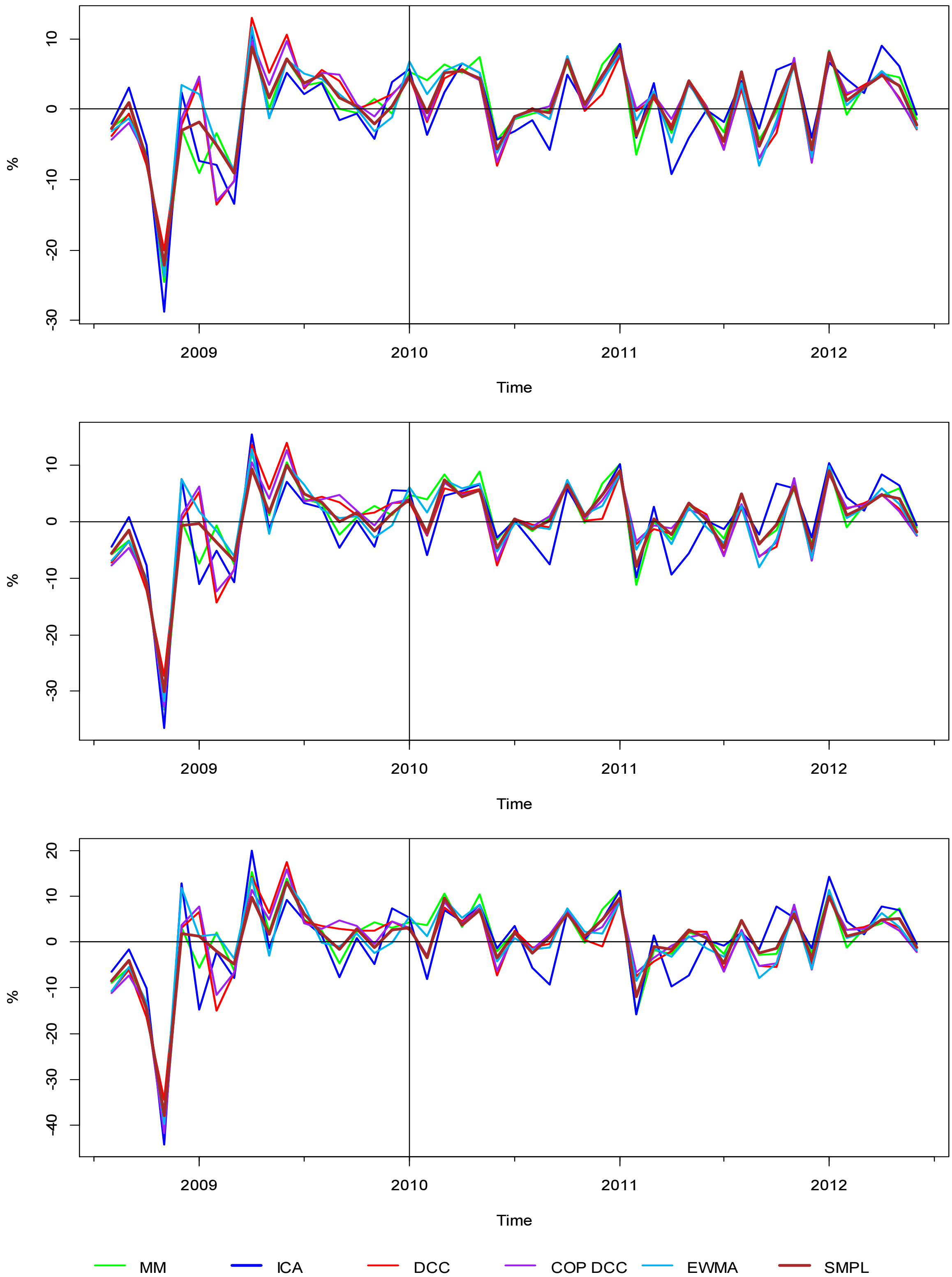


Figure 6.4 Realised cumulative monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

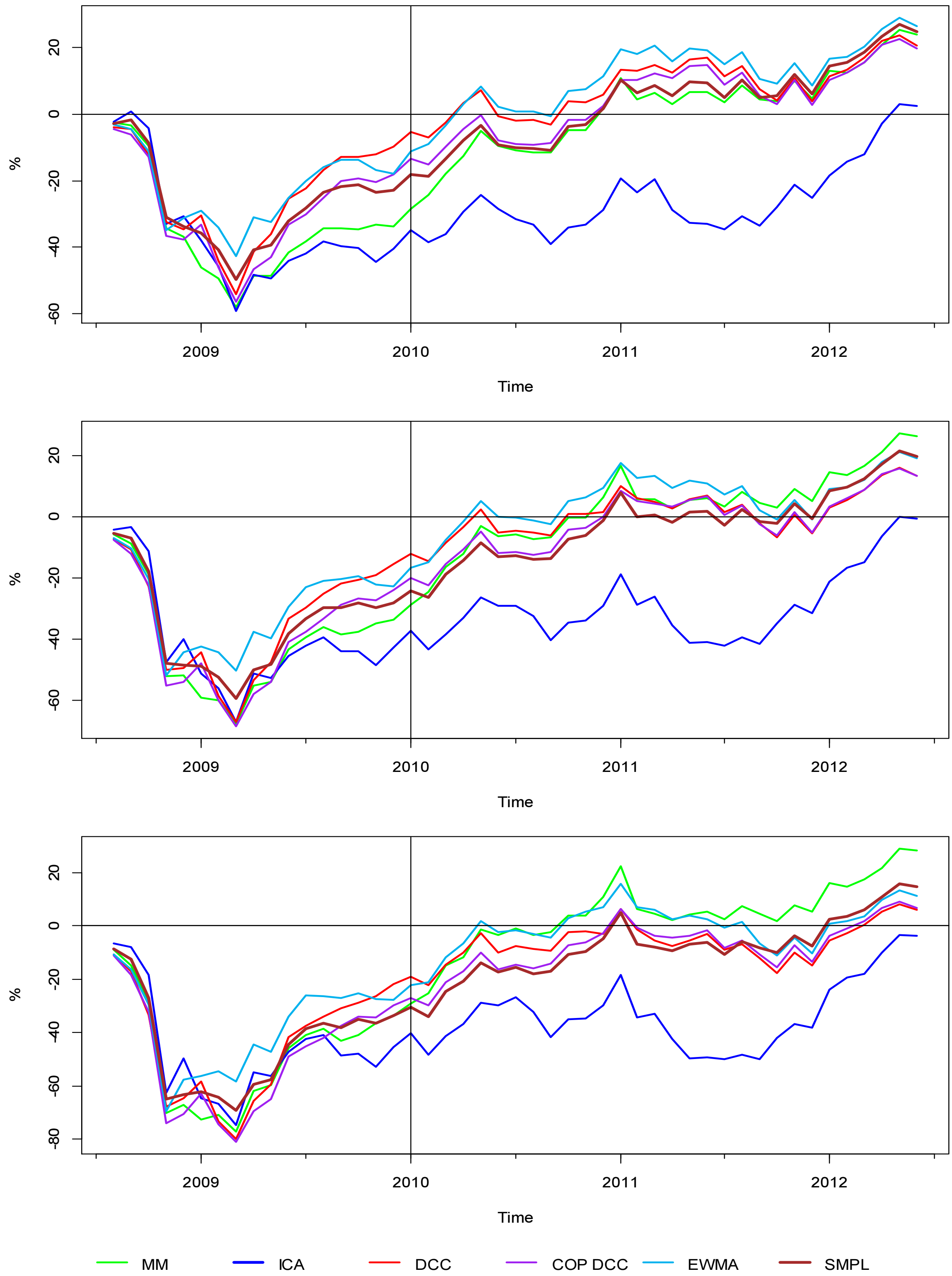


Figure 6.5 Monthly percentage standard deviation of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

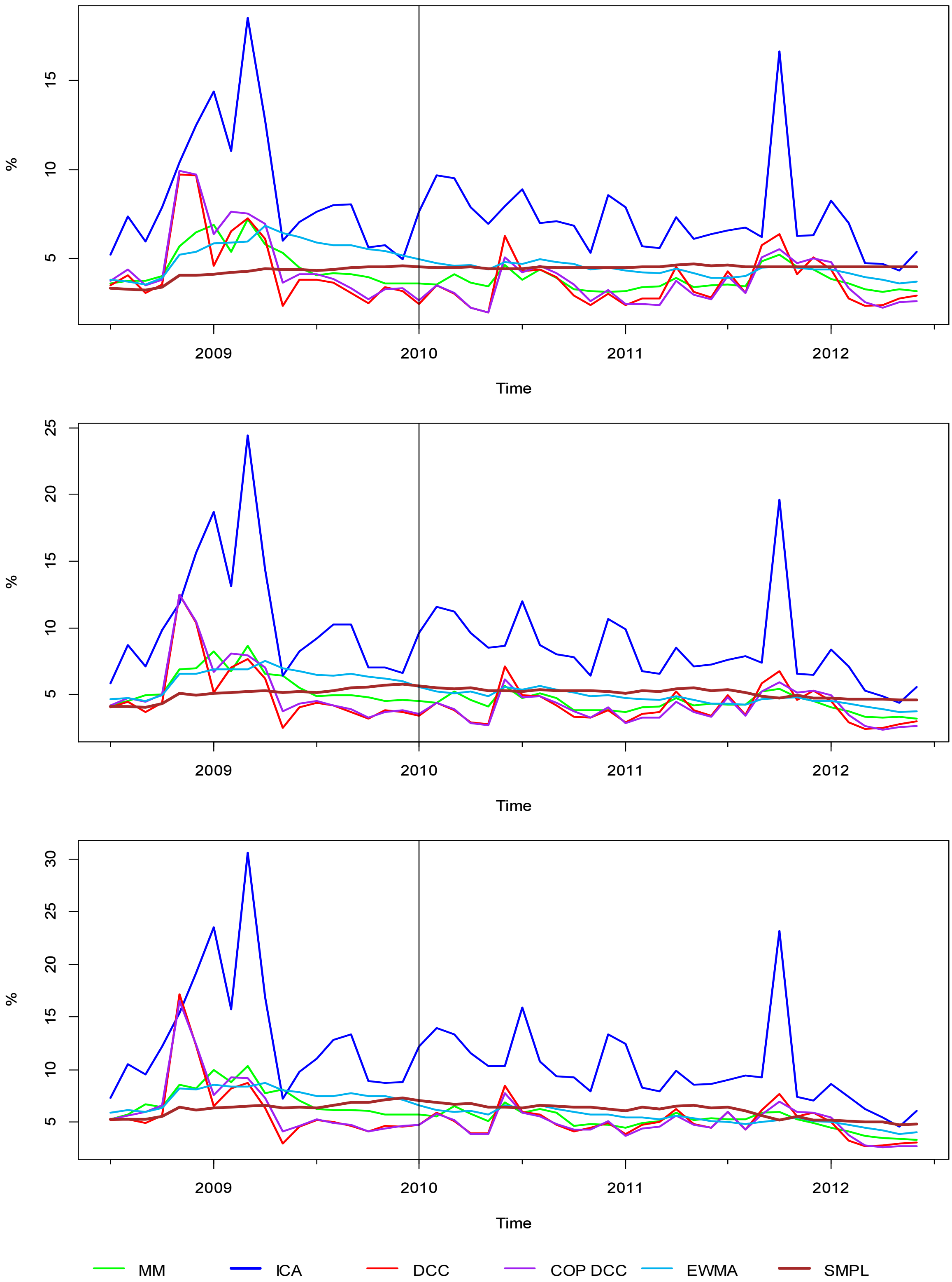


Figure 6.6 Monthly conditional Sharpe ratio of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

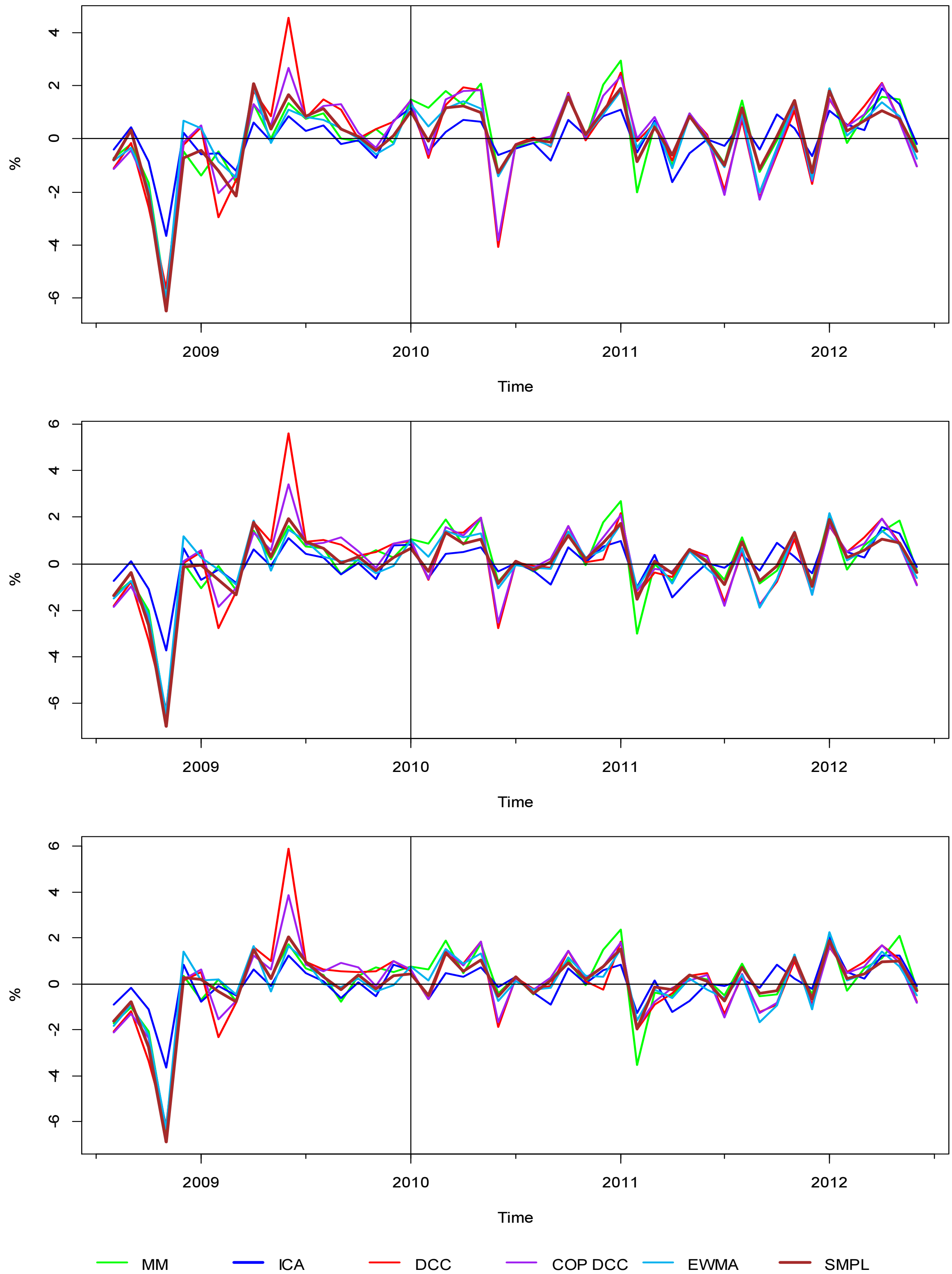


Figure 6.7 Monthly percentage turnover of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

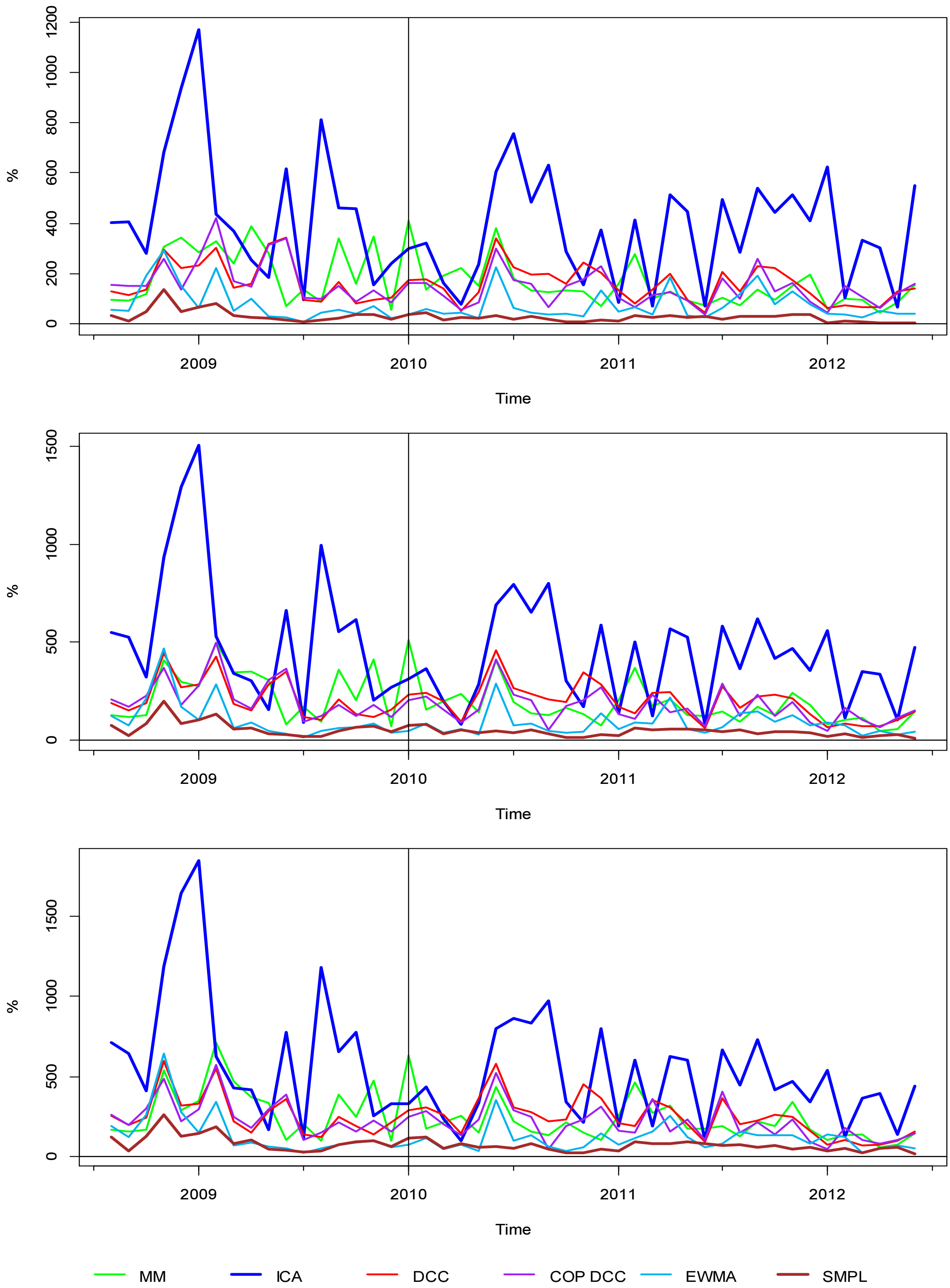


Figure 6.8 Monthly percentage US weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

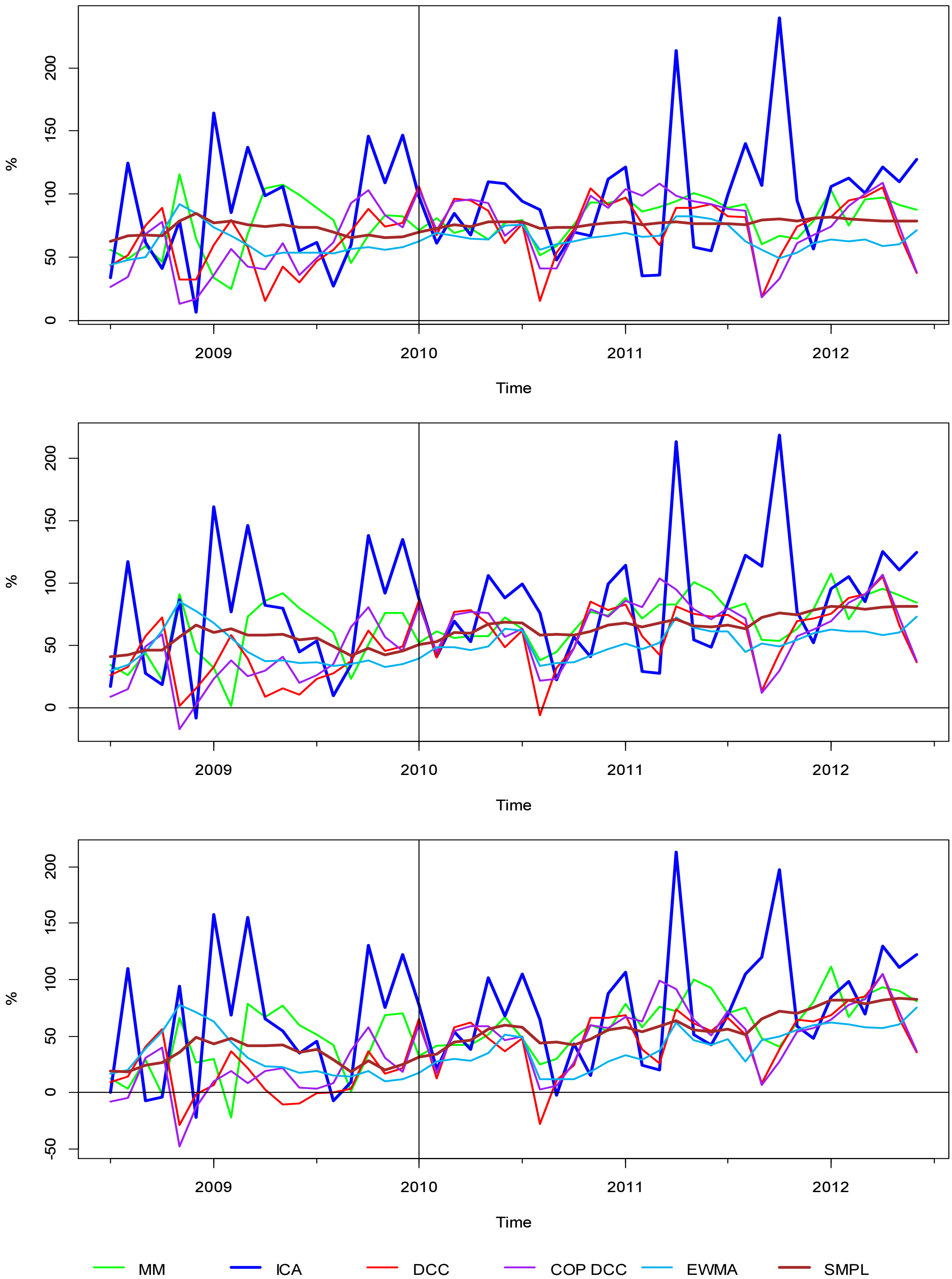


Figure 6.9 Monthly percentage EMU weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

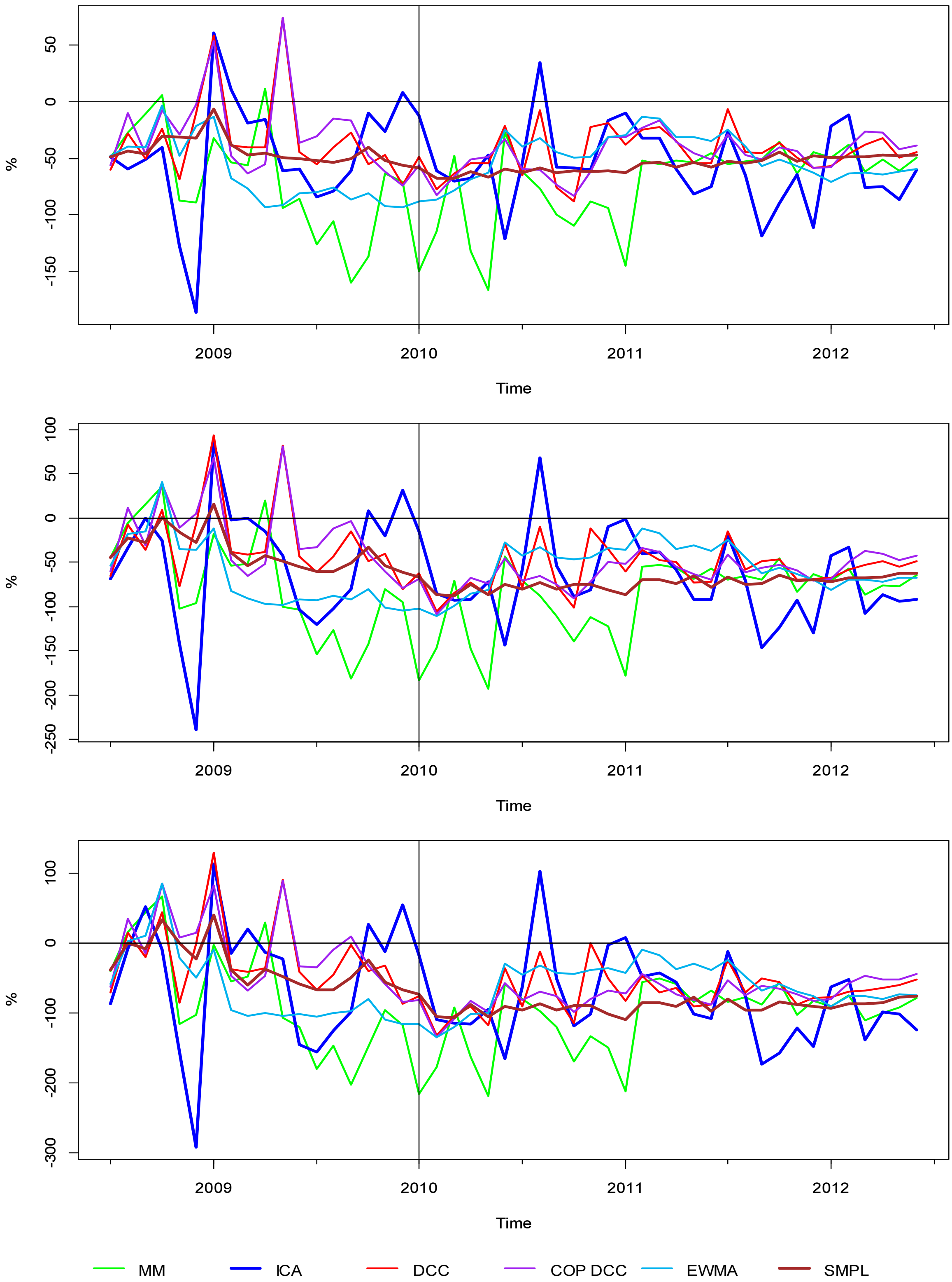


Figure 6.10 Monthly percentage Europe ex EMU weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

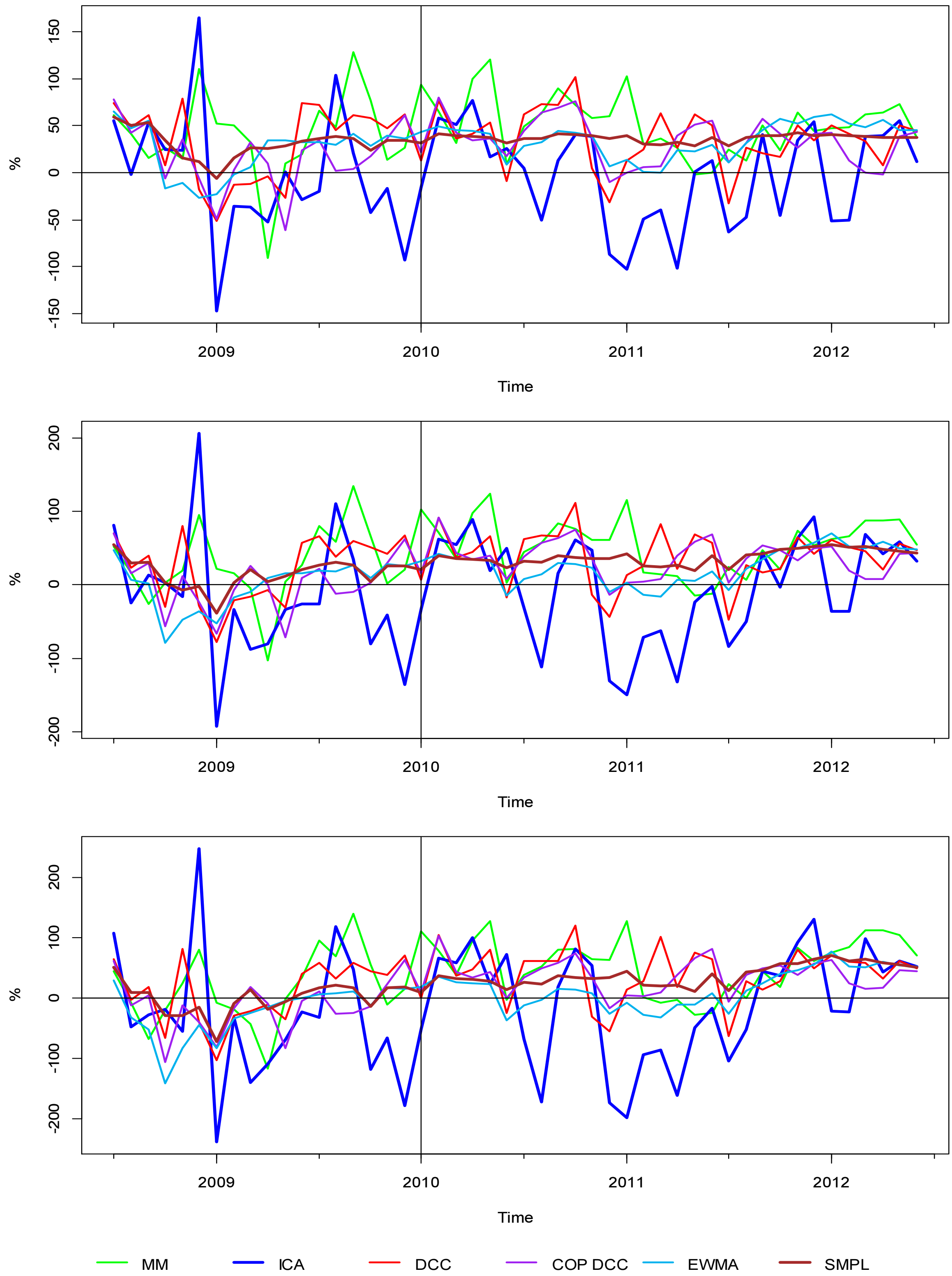


Figure 6.11 Monthly percentage Pacific weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

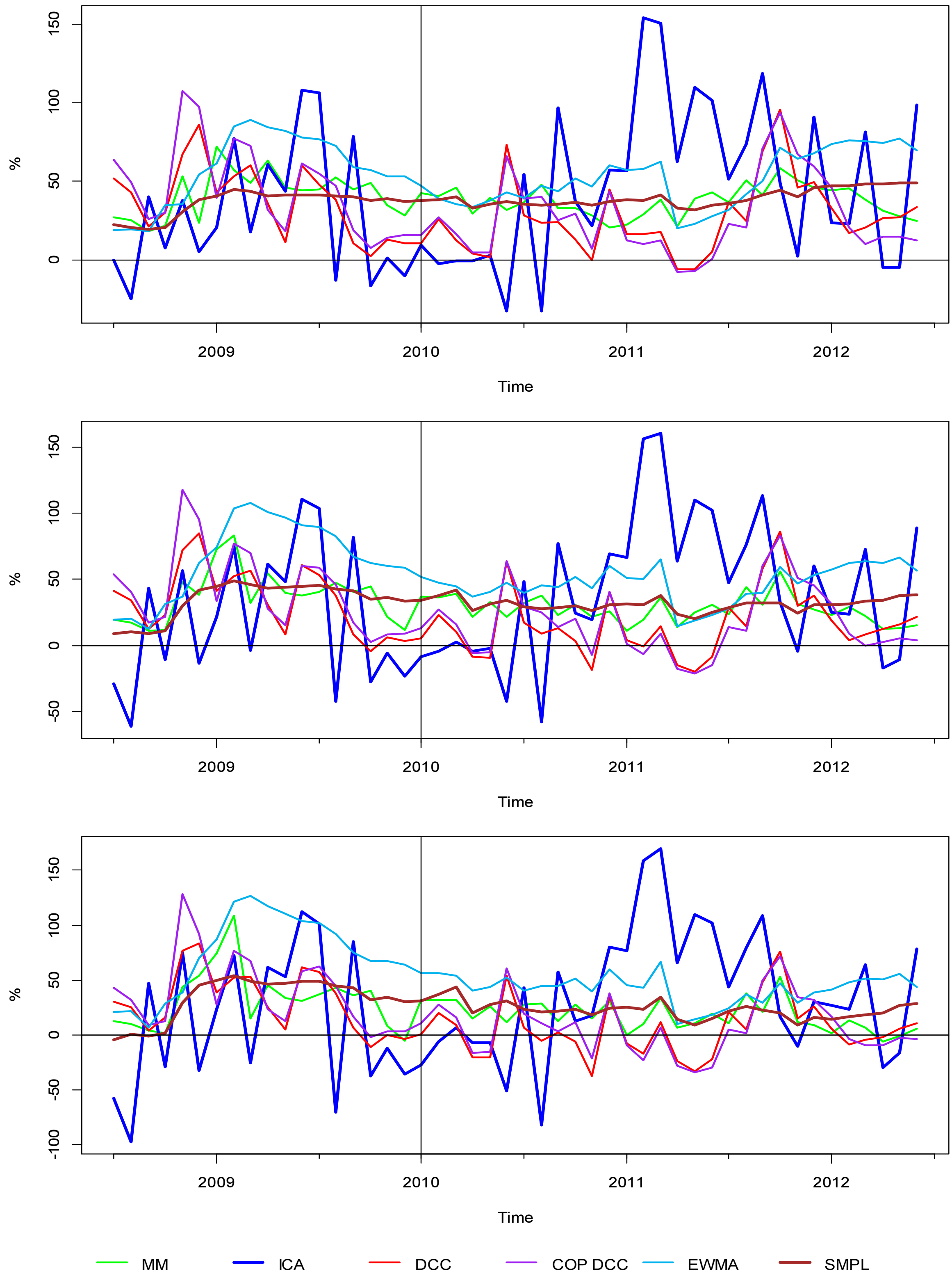


Figure 6.12 Monthly percentage EM BRIC weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

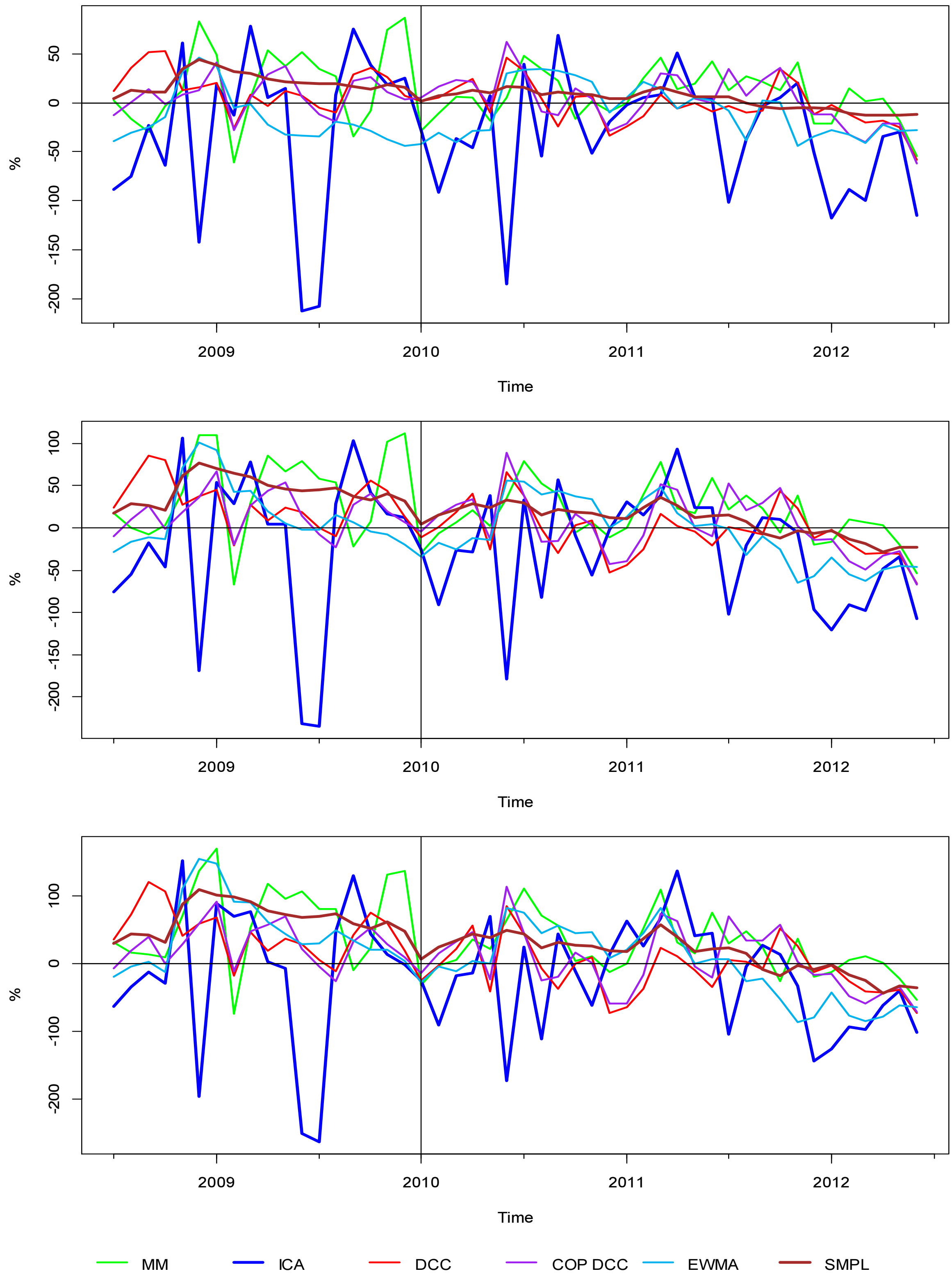


Figure 6.13 Monthly percentage EM Europe weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

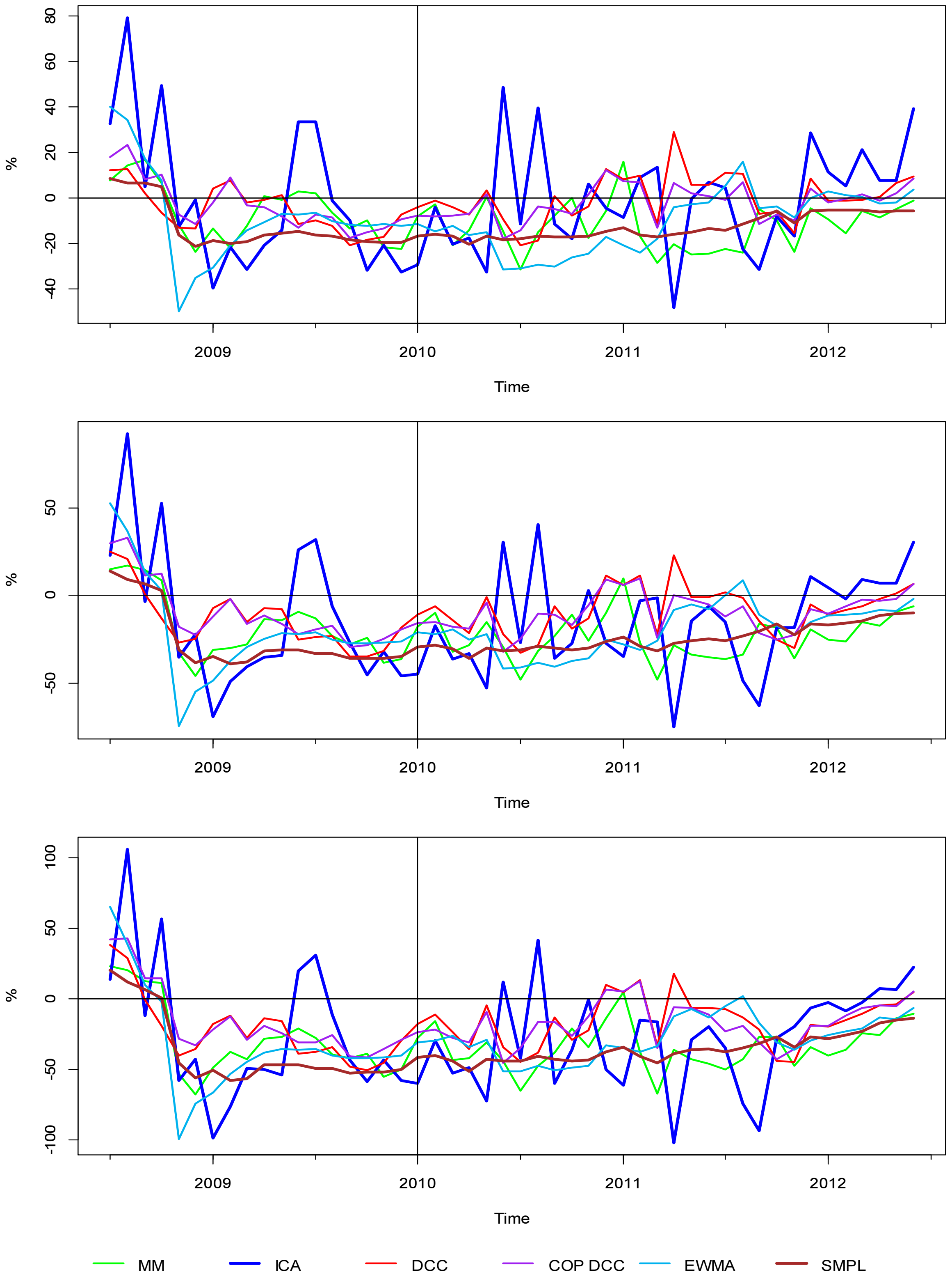


Figure 6.14 Monthly percentage EM Latin America weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

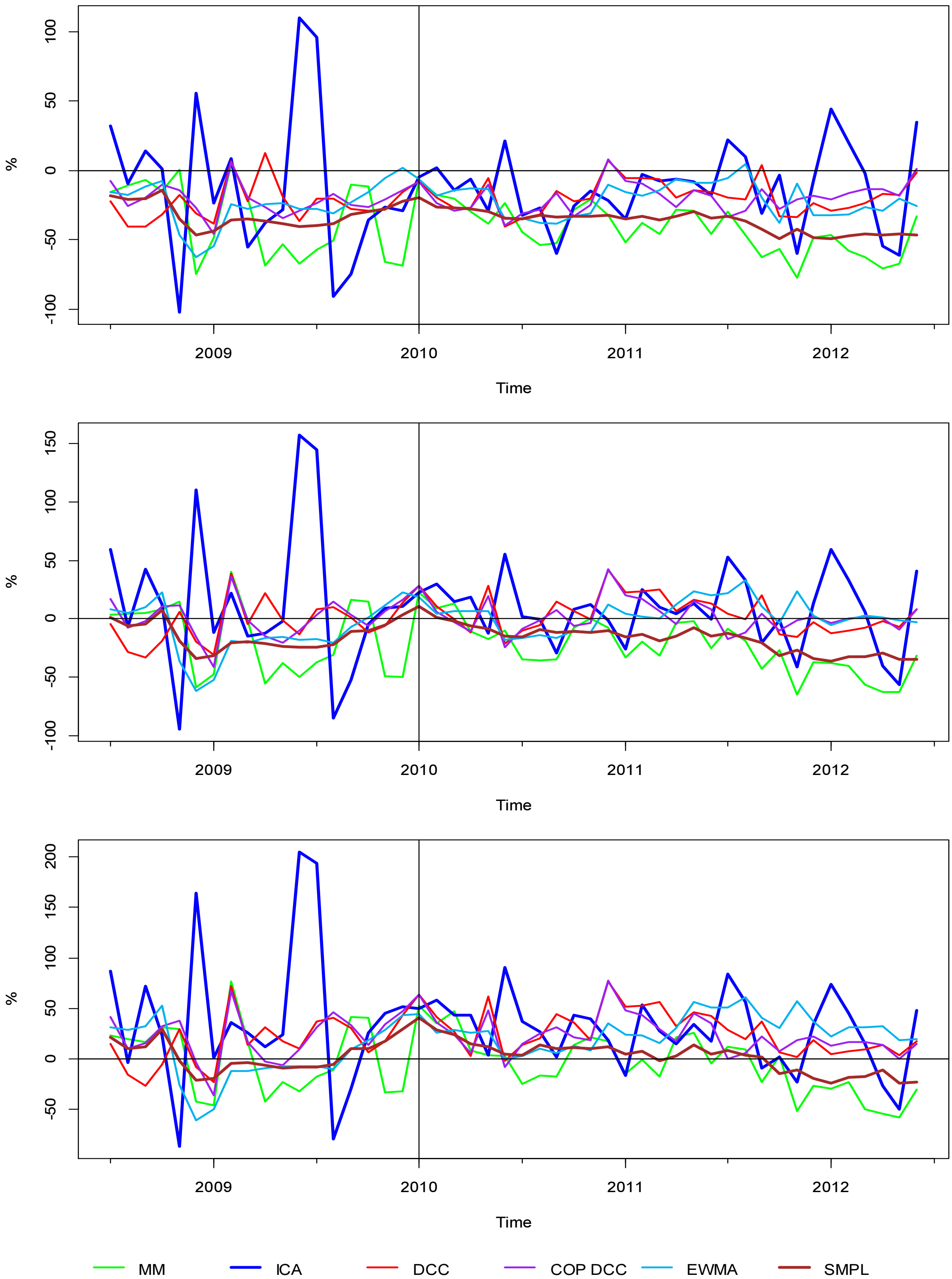


Figure 6.15 Monthly percentage EM Asia weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

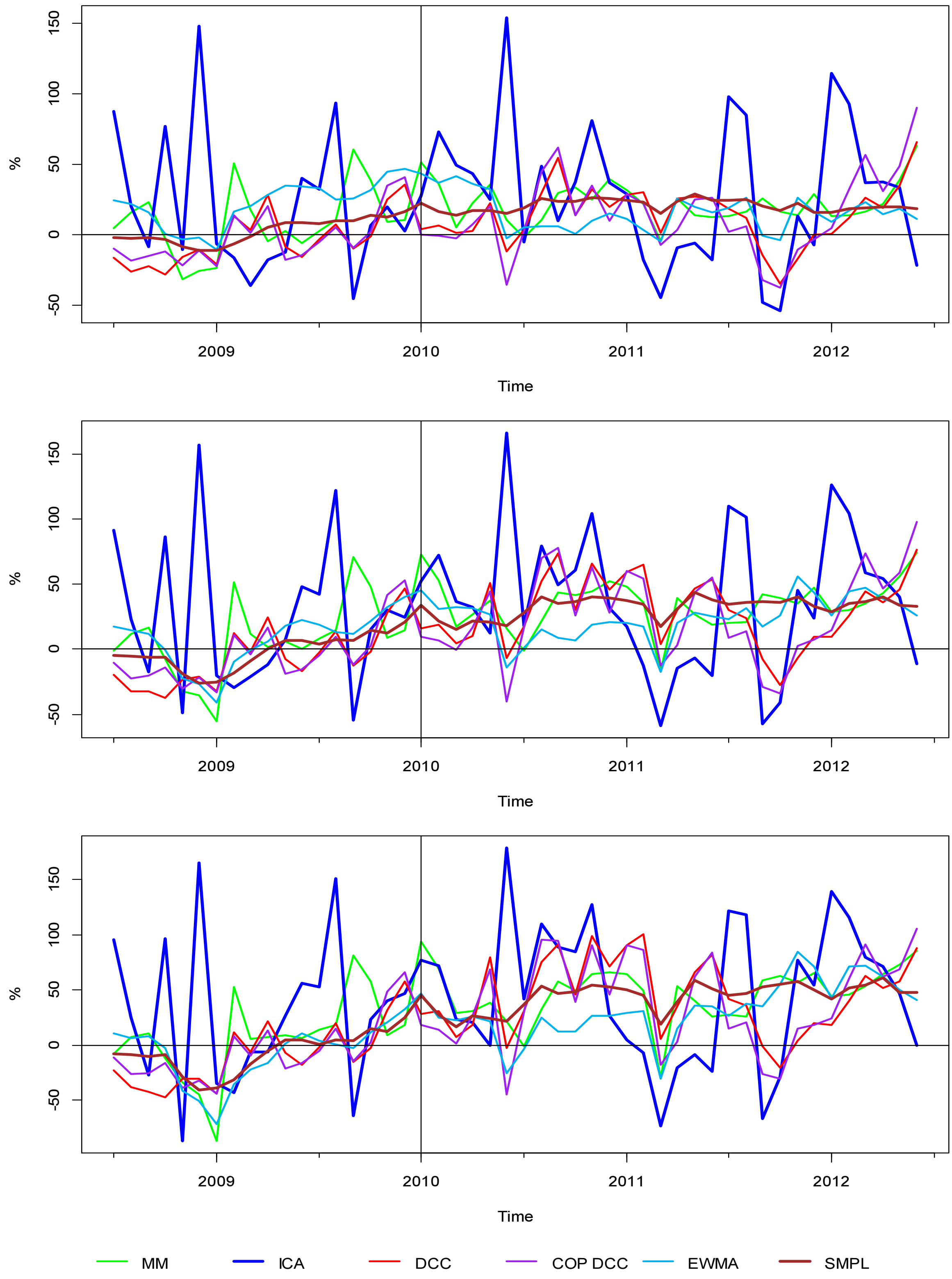
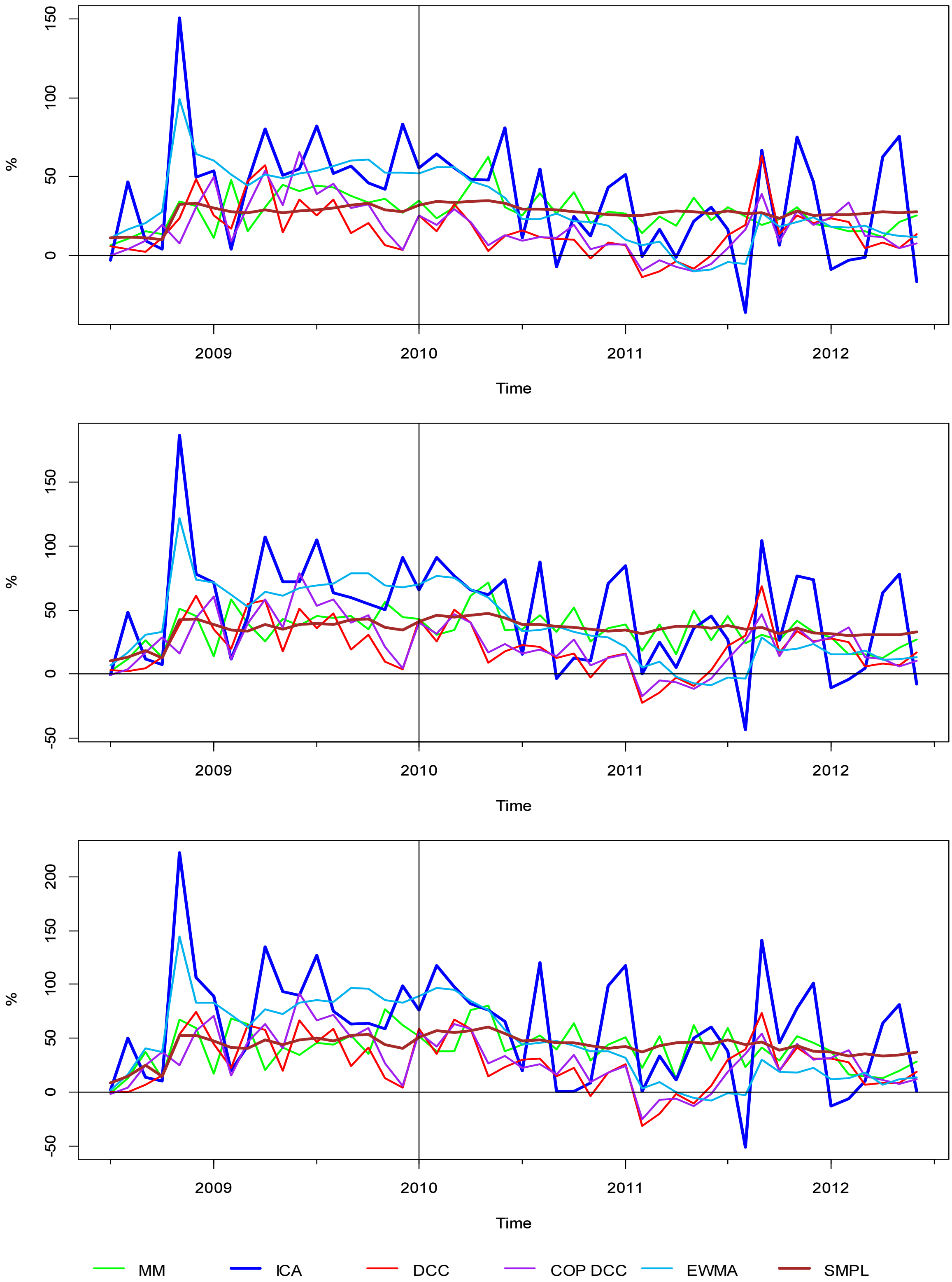


Figure 6.16 Monthly percentage EMF Africa weight of mean-variance long-short portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.



6.4.1.1 Realised returns

The realised monthly long-short portfolio returns seem to be quite similar across different models (Figure 6.3). The range of the returns becomes wider with higher risk but the maximum return is also positively related to risk (Table 6.44). This is in line with the literature (Markowitz 1952, Sharpe 1964) as the higher the risk the higher the expected returns. The financial crisis resulted in a substantial dip in the returns, i.e. the period on the left-hand side of the vertical line. For example, the dip ranges from -20.061% to -44.347% per month across models across different risk levels (Table 6.44). These results obtained for long-short portfolios are consistent with those based on long-only portfolios (Figure 6.17 and Table 6.30).

6.4.1.2 Realised cumulative returns

When it comes to the realised cumulative monthly long-short portfolio returns, the results show that at the beginning portfolio performance is rather similar across models up to around 2009 (Figure 6.4). Beyond 2009, there seem to be much bigger differences in cumulative returns between models. This is consistent with Syriopoulos and Roumpis (2009). ICA produces the worse results, which could be because of the constant mixing matrix (van der Weide 2002).

The crisis resulted in big dip in the cumulative returns. For instance, the dip ranges from -81.091% to -42.607% across models across different risk levels (Table 6.45). Another important observation to notice is that the cumulative returns at the end of the crisis are all negative across models across different risk levels. The final cumulative returns vary from -3.750% to 28.352% across models across different risk levels.

Quite similar behaviour can be seen in Figure 6.18 and Table 6.31, which relate to long-only portfolios. However, the ICA model does not stand out from other models as much as it is for the long-short case. In addition, the cumulative returns across models are quite similar a little beyond 2009. The final cumulative returns are generally lower across models across risk levels as they range from -16.320% to 10.804%. In addition, those final cumulative returns are more spread for long-short than for long-only portfolios.

6.4.1.3 STANDARD DEVIATION

Figure 6.5 and Figure 6.19 present the monthly standard deviation of long-short and long-only portfolios, respectively. The SMPL model produces quite stable estimates whereas ICA estimates are the highest with the highest variation. For example, ICA standard deviation mean value ranges from 7.809% to 11.232% with a standard deviation between 2.955% and 4.965% for long-short portfolios (Table 6.46). DCC and COP exhibit some variation in portfolio standard deviation.

This is consistent with the findings in Chapter 5.

6.4.1.4 CONDITIONAL SHARPE RATIO

Because portfolio risk (standard deviation) is different for different models, the portfolio realised returns should be compared on a risk-adjusted basis. For that reason I examine the conditional Sharpe ratio in Figure 6.6 and Figure 6.20. The patterns are to some extent similar between models. The crisis resulted in the dip in the conditional Sharpe ratio for both long-short and long-only portfolios. For instance, the dip in the conditional Sharpe ratio varies from -7.009% to -3.364% across models across risk levels (Table 6.47).

6.4.1.5 TURNOVER

In terms of long-short portfolio turnover, the SMPL model provides relatively low and stable values (Figure 6.7), which can be confirmed by low mean and standard deviation values in Table 6.48. Other models produce much higher turnover with higher variability. The ICA model seems to be the poorest in that respect. The higher the portfolio risk, the higher the portfolio turnover. This can be confirmed by higher mean values in Table 6.48. This is consistent with findings of Giamouridis and Vrontos (2007). Similar results can be drawn from Figure 6.21 and Table 6.34 for the long-only portfolios.

Preliminary analysis of Figure 6.7 suggests that the crisis resulted generally in slightly higher turnover. However, this does not seem to be the case for long-only instance (Figure 6.21).

6.4.1.6 WEIGHTS

In terms of long-short portfolio weights, SMPL presents generally the lowest variation in comparison to the time-varying covariance models (Figure 6.8–Figure 6.16). This can be confirmed by the CV of the portfolio weights that can be found in the appendix (Table 6.49–Table 6.57). For example, the CV of the US weights for the low-risk portfolio is 0.066, based on the SMPL model, whereas the CV for time-varying models ranges from 0.162 to 0.482 (Table 6.49). The ICA model seems to have the most variation in the weights in general. For example, the range of US weight is between -21.776% and 239.582% across different risk levels for ICA (Table 6.49). In terms of the impact of the crisis there are no discernible patterns across models.

However, for the long-only portfolios weights, the SMPL (ICA) does not consistently provide the lowest (highest) variation among covariance models (Figure 6.22–Figure 6.30). This can be confirmed by the standard deviation and the CV of the portfolio weights, which can be found in the appendix (Table 6.35–Table 6.43). Similarly to the long-short case, the impact of the financial crisis is not so discernible.

6.4.1.7 Regional differences in portfolio weights: developed and emerging/frontier market perspectives

6.4.1.7.1 Weight-risk portfolio relationship

For long-only portfolios as the risk of portfolio increases the mean weights of developed markets fall whereas the weights of emerging/frontier markets rise. This can be seen in Table 6.35–Table 6.43. These results are generally different to those presented by Cha and Jithendranathan (2009). They found that the mean weights of developed market rise and that the mean weights of emerging markets can rise or fall.

In general the same is true with respect to the long-short case (Table 6.49–Table 6.57). However, it is more complicated as for some regions the mean weight is moving from negative to positive, for example, EM Latin America.

The reason for this can possibly be seen as being a consequence of the returns and volatility of returns of emerging/frontier market regions are generally higher than those found in developed regions (see Table 3.1, Table 5.19, Table 5.21, Table 5.23, Table 5.25, Table 5.27, Table 5.29, Table 5.31 and Table 5.33). The result of this is that as portfolio risk increases the weightings of emerging/frontier increases.

6.4.1.7.2 Volatility of weights in the weight-risk portfolio relationship

The volatility of weights for the long-only portfolios, as measure by the standard deviation, are shown in Table 6.35–Table 6.43. From this can be identified that in developed markets, in general, as the portfolio risk increases the volatility falls. This possibly reflects the fact that for higher risk portfolios developed markets have relatively lower weightings.

In terms of emerging/frontier markets the opposite relationship appears to exist; specifically the higher the risk of portfolio the higher volatility of their weights. This also possibly reflects the relative increase in the weightings of assets from these regions. These results are to some extent in line with those presented by Cha and Jithendranathan (2009), who found that for some emerging markets (around half in their sample) the higher the risk of portfolio the higher volatility of weights.

For long-short case (Table 6.49–Table 6.57), the standard deviation of weights is rising as the portfolio risk is increasing irrespective of whether the mean weighting is going up or down. This is the same for both developed and emerging/frontier markets. This may reflect lack of constraints on the optimisation process as the optimisation procedure exploits the smallest differences by taking extreme positions (DeMiguel *et al.* 2009a, Michaud 1989). This finding can be also attributed to the estimation error in sample means (Merton 1980, Michaud 1989). As consequence, elements of the literature focus on the global minimum variance portfolio given that the means are not involved in the portfolio optimisation (noted by DeMiguel *et al.* 2009b). Another approach to reduce estimation error would be to constrain portfolio weights (Frost and Savarino 1988).

6.4.1.7.3 SHOULD PORTFOLIO MANAGERS USE THE DEVELOPED-EMERGING/FRONTIER MARKET CATEGORISATIONS WHEN DETERMINING PORTFOLIO WEIGHTS?

The results from my thesis would suggest that to categorise markets as developed and emerging/frontier is not useful from portfolio optimisation perspective.

If we examine the mean weights of emerging/frontier markets in the long-only portfolios it can be identified that they are not a homogenous group. For example, in EM Europe the mean weights are in the main lower (ranging from 0% to 2.955%) (see Table 6.40). In other areas, however, they are in the main much higher. For example, EM Asia (ranging from 0% to 45.489%) and EFM Africa (ranging from 0% to 24.955%) (see Table 6.42 and Table 6.43).

The developed markets also cannot be considered as homogenous group. For example, in the long-only portfolios the mean weights are in the main lower in EMU (ranging from 0% to 0.879%) but are in the main higher in Pacific region (ranging from 3.101% to 59.839%) (see Table 6.36 and Table 6.38).

We can also see some emerging markets have in the main higher mean weighting than developed, for example, EM Asia (ranging from 0% to 45.489%) versus EMU (ranging from 0% to 0.879%) for long-only portfolios (see Table 6.36 and Table 6.42).

The conclusion is that from portfolio manager perspective they should be cautious about using the developed versus emerging/frontier distinction to determine portfolio weights. This is due to the lack of homogeneity within these two groups.

6.4.2 Hypothesis tests of mean and location comparison of different covariance models

This section focuses on testing the hypotheses of this chapter with respect to the portfolio performance measures and weights.

6.4.2.1 Hypothesis tests with respect to portfolio performance measures

In this section, I test Hypotheses 1 and 2:

H1. DCC and copula DCC differ from the other covariance models:

- H1a. In terms of the mean realised returns;
- H1b. In terms of the mean cumulative realised returns;
- H1c. In terms of the mean conditional Sharpe ratio;

H1d. In terms of the mean portfolio turnover.

H2. Copula DCC differs from DCC:

H2a. In terms of the mean realised returns;

H2b. In terms of the mean cumulative realised returns;

H2c. In terms of the mean conditional Sharpe ratio;

H2d. In terms of the mean portfolio turnover.

The mean values of long-short portfolio performance measures are presented in Table 6.1. As mentioned in Section 6.2, the financial crisis resulted in excessive volatility levels in the returns. The consequence of this was very high standard errors, which led to low levels of power in hypothesis tests. For that reason I also undertake a series of rank-based hypothesis tests. This controls for the excessive volatility as the standard errors are based on relative rather than absolute values. The mean values of long-short portfolio performance measures based on ranks are presented in Table 6.2.

In order to be consistent with the rest of the thesis, the differences in means are tested by Welch t and Wilcoxon rank sum tests. The test results are presented for both absolute and rank-based performance for long-short portfolios for realised monthly portfolio returns (Table 6.3), realised cumulative monthly portfolio returns (Table 6.4), monthly portfolio standard deviation (Table 6.5), monthly conditional Sharpe ratio (Table 6.6) and monthly PT (Table 6.7).

The equivalent tables for long-only portfolios can be found in the appendix. Table 6.26 and Table 6.27 show the mean values of the performance measure based on absolute and rank-based measures, respectively. The Welch t and Wilcoxon rank sum tests results can be found in the appendix in Table 6.58–Table 6.62.

All those aforementioned tables are based on the 72-month estimation window and represent 47 observations (31 July 2008–11 May 2012) apart from portfolio standard deviation, which presents 48 observations (30 June 2008–11 May 2012).

Table 6.1 Performance metrics of mean-variance long-short portfolios between models for the 72-month estimation period

Portfolio statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Realised Return	47	0.510	0.051	0.442	0.422	0.561	0.526
Realised Cumulative Return	47	-11.485	-28.923	-3.298	-7.416	-0.688	-7.325
Standard Deviation	48	4.119	7.809	3.937	4.066	4.736	4.382
Conditional Sharpe Ratio	47	0.159	0.036	0.104	0.101	0.065	0.063
Turnover	47	171.443	396.268	161.238	151.257	75.633	27.777
Realised Return	47	0.557	-0.014	0.284	0.284	0.401	0.418
Realised Cumulative Return	47	-13.009	-33.440	-11.611	-15.009	-7.249	-14.234
Standard Deviation	48	4.833	9.252	4.488	4.588	5.292	5.091
Conditional Sharpe Ratio	47	0.128	0.032	0.072	0.075	0.032	0.036
Turnover	47	201.928	463.817	203.973	186.061	95.559	50.869
Realised Return	47	0.603	-0.080	0.127	0.146	0.242	0.309
Realised Cumulative Return	47	-14.532	-37.956	-19.923	-22.602	-13.810	-21.142
Standard Deviation	48	5.895	11.232	5.468	5.536	6.214	6.139
Conditional Sharpe Ratio	47	0.110	0.032	0.059	0.065	0.009	0.022
Turnover	47	247.141	551.018	251.361	224.047	125.700	76.023

Notes: Sample runs from 31 July 2008 (30 June 2008 for standard deviation) to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages apart from conditional Sharpe ratio.

Table 6.2 Performance metrics of mean-variance long-short portfolios between models for the 72-month estimation period based on ranks

Portfolio statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Realised Return	47	3.617	3.426	3.234	3.447	3.532	3.745
Realised Cumulative Return	47	2.340	1.574	4.596	3.170	5.532	3.787
Standard Deviation	48	2.792	5.938	2.229	2.688	3.854	3.500
Conditional Sharpe Ratio	47	3.830	3.064	3.660	3.809	3.234	3.404
Turnover	47	4.064	5.489	4.298	3.872	2.191	1.085
Realised Return	47	3.681	3.447	3.383	3.383	3.447	3.660
Realised Cumulative Return	47	3.766	1.787	3.957	2.851	5.319	3.319
Standard Deviation	48	2.958	5.896	2.229	2.500	3.771	3.646
Conditional Sharpe Ratio	47	3.723	3.106	3.617	3.681	3.404	3.468
Turnover	47	3.979	5.468	4.298	3.979	2.106	1.170
Realised Return	47	3.809	3.511	3.362	3.340	3.404	3.574
Realised Cumulative Return	47	4.468	1.915	3.383	2.809	5.043	3.383
Standard Deviation	48	3.125	5.896	2.229	2.354	3.625	3.771
Conditional Sharpe Ratio	47	3.830	3.170	3.574	3.681	3.362	3.383
Turnover	47	4.085	5.489	4.298	3.787	2.064	1.277

Notes: Sample runs from 31 July 2008 (30 June 2008 for standard deviation) to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages apart from conditional Sharpe ratio.

Table 6.3 Statistical significance of realised monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	**-**	**0.673**	**0.988**	**0.892**	**1.000**	**0.970**	**-**	**0.746**	**0.886**	**0.982**	**0.821**	**0.904**	**-**	**0.775**	**0.786**	**0.804**	**0.522**	**0.712**
GO-GARCH ICA	47	**0.730**	**-**	**0.827**	**0.775**	**0.752**	**0.833**	**0.723**	**-**	**0.970**	**0.851**	**0.845**	**0.904**	**0.728**	**-**	**0.910**	**0.821**	**0.940**	**0.910**
DCC	47	**0.957**	**0.771**	**-**	**0.868**	**0.922**	**0.994**	**0.856**	**0.851**	**-**	**0.928**	**1.000**	**1.000**	**0.791**	**0.914**	**-**	**0.863**	**0.718**	**0.976**
COPULA DCC	47	**0.945**	**0.784**	**0.988**	**-**	**0.940**	**0.886**	**0.858**	**0.854**	**1.000**	**-**	**0.821**	**0.904**	**0.804**	**0.908**	**0.992**	**-**	**0.729**	**0.892**
EWMA (0.03, 0.97)	47	**0.968**	**0.701**	**0.924**	**0.913**	**-**	**0.964**	**0.917**	**0.793**	**0.937**	**0.938**	**-**	**1.000**	**0.841**	**0.867**	**0.948**	**0.957**	**-**	**0.810**
SAMPLE	47	**0.990**	**0.712**	**0.945**	**0.933**	**0.977**	**-**	**0.923**	**0.779**	**0.925**	**0.926**	**0.991**	**-**	**0.866**	**0.835**	**0.914**	**0.925**	**0.968**	**-**
GO-GARCH MM	47	**-**	**0.624**	**0.288**	**0.667**	**0.832**	**0.829**	**-**	**0.686**	**0.436**	**0.361**	**0.511**	**0.766**	**-**	**0.608**	**0.221**	**0.156**	**0.215**	**0.406**
GO-GARCH ICA	47	**0.643**	**-**	**0.803**	**0.787**	**0.746**	**0.674**	**0.563**	**-**	**0.907**	**0.914**	**0.975**	**0.642**	**0.450**	**-**	**0.760**	**0.862**	**0.859**	**0.979**
DCC	47	**0.308**	**0.658**	**-**	**0.438**	**0.331**	**0.149**	**0.401**	**0.881**	**-**	**0.945**	**0.860**	**0.408**	**0.189**	**0.722**	**-**	**0.997**	**0.890**	**0.510**
COPULA DCC	47	**0.617**	**0.958**	**0.559**	**-**	**0.767**	**0.220**	**0.373**	**0.876**	**1.000**	**-**	**0.863**	**0.281**	**0.158**	**0.679**	**0.953**	**-**	**0.824**	**0.373**
EWMA (0.03, 0.97)	47	**0.798**	**0.788**	**0.403**	**0.790**	**-**	**0.396**	**0.489**	**1.000**	**0.860**	**0.852**	**-**	**0.527**	**0.211**	**0.793**	**0.904**	**0.853**	**-**	**0.569**
SAMPLE	47	**0.671**	**0.390**	**0.121**	**0.300**	**0.443**	**-**	**0.941**	**0.567**	**0.382**	**0.345**	**0.475**	**-**	**0.425**	**0.868**	**0.514**	**0.461**	**0.582**	**-**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.4 Statistical significance of realised cumulative monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.000**	**0.069**	**0.374**	**0.017**	**0.382**	-	**0.000**	**0.904**	**0.488**	**0.320**	**0.527**	-	**0.000**	**0.072**	**0.032**	**0.593**	**0.067**
GO-GARCH ICA	47	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.060**	**0.000**	-	**0.252**	**0.460**	**0.261**	**0.774**	**0.000**	-	**0.447**	**0.225**	**0.370**	**0.331**	**0.000**	-	**0.609**	**0.092**	**0.542**
COPULA DCC	47	**0.359**	**0.000**	**0.314**	-	**0.113**	**0.804**	**0.690**	**0.000**	**0.449**	-	**0.057**	**0.874**	**0.158**	**0.001**	**0.590**	-	**0.037**	**0.970**
EWMA (0.03, 0.97)	47	**0.014**	**0.000**	**0.513**	**0.104**	-	**0.093**	**0.234**	**0.000**	**0.309**	**0.082**	-	**0.066**	**0.894**	**0.000**	**0.191**	**0.072**	-	**0.053**
SAMPLE	47	**0.340**	**0.000**	**0.315**	**0.982**	**0.102**	-	**0.802**	**0.000**	**0.545**	**0.863**	**0.105**	-	**0.231**	**0.000**	**0.797**	**0.767**	**0.114**	-
GO-GARCH MM	47	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.511**	**0.006**	**0.000**	**0.180**	-	**0.000**	**0.001**	**0.000**	**0.139**	**0.000**
GO-GARCH ICA	47	**0.003**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.535**	**0.000**	-	**0.000**	**0.000**	**0.017**	**0.001**	**0.000**	-	**0.111**	**0.000**	**0.953**
COPULA DCC	47	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.048**	**0.001**	**0.000**	**0.000**	-	**0.000**	**0.143**	**0.000**	**0.004**	**0.027**	-	**0.000**	**0.063**
EWMA (0.03, 0.97)	47	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.040**	**0.000**	**0.000**	**0.000**	-	**0.000**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.004**	**0.000**	-	**0.134**	**0.000**	**0.021**	**0.048**	**0.000**	-	**0.000**	**0.000**	**1.000**	**0.026**	**0.000**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.5 Statistical significance of monthly percentage standard deviation of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.000**	**0.024**	**0.155**	**0.000**	**0.000**	-	**0.000**	**0.012**	**0.040**	**0.010**	**0.001**	-	**0.000**	**0.011**	**0.026**	**0.194**	**0.017**
GO-GARCH ICA	48	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	48	**0.533**	**0.000**	-	**0.607**	**0.000**	**0.000**	**0.294**	**0.000**	-	**0.713**	**0.000**	**0.000**	**0.307**	**0.000**	-	**0.962**	**0.000**	**0.000**
COPULA DCC	48	**0.859**	**0.000**	**0.723**	-	**0.000**	**0.001**	**0.461**	**0.000**	**0.802**	-	**0.000**	**0.000**	**0.387**	**0.000**	**0.892**	-	**0.001**	**0.000**
EWMA (0.03, 0.97)	48	**0.001**	**0.000**	**0.006**	**0.022**	-	**0.166**	**0.042**	**0.000**	**0.012**	**0.030**	-	**0.910**	**0.275**	**0.000**	**0.065**	**0.091**	-	**0.622**
SAMPLE	48	**0.087**	**0.000**	**0.091**	**0.240**	**0.007**	-	**0.159**	**0.000**	**0.039**	**0.088**	**0.198**	-	**0.315**	**0.000**	**0.071**	**0.101**	**0.724**	-
GO-GARCH MM	48	-	**0.000**	**0.003**	**0.362**	**0.000**	**0.002**	-	**0.000**	**0.000**	**0.037**	**0.000**	**0.003**	-	**0.000**	**0.000**	**0.001**	**0.007**	**0.003**
GO-GARCH ICA	48	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	48	**0.018**	**0.000**	-	**0.096**	**0.000**	**0.000**	**0.004**	**0.000**	-	**0.371**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.690**	**0.000**	**0.000**
COPULA DCC	48	**0.673**	**0.000**	**0.107**	-	**0.000**	**0.015**	**0.073**	**0.000**	**0.338**	-	**0.000**	**0.001**	**0.002**	**0.000**	**0.647**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	48	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.367**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.726**	**0.035**	**0.000**	**0.000**	**0.000**	-	**0.215**
SAMPLE	48	**0.009**	**0.000**	**0.000**	**0.010**	**0.230**	-	**0.015**	**0.000**	**0.000**	**0.000**	**0.662**	-	**0.019**	**0.000**	**0.000**	**0.000**	**0.613**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.6 Statistical significance of monthly conditional Sharpe ratio of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	**-**	**0.370**	**0.988**	**0.880**	**0.668**	**0.810**	**-**	**0.438**	**0.892**	**0.994**	**0.724**	**0.735**	**-**	**0.335**	**0.763**	**0.886**	**0.547**	**0.718**
GO-GARCH ICA	47	**0.630**	**-**	**0.302**	**0.261**	**0.456**	**0.542**	**0.709**	**-**	**0.420**	**0.362**	**0.712**	**0.588**	**0.758**	**-**	**0.512**	**0.412**	**0.833**	**0.598**
DCC	47	**0.871**	**0.815**	**-**	**0.928**	**0.684**	**0.718**	**0.869**	**0.892**	**-**	**0.982**	**0.833**	**0.804**	**0.878**	**0.925**	**-**	**0.916**	**0.746**	**0.816**
COPULA DCC	47	**0.858**	**0.814**	**0.993**	**-**	**0.662**	**0.652**	**0.869**	**0.874**	**0.993**	**-**	**0.763**	**0.758**	**0.885**	**0.900**	**0.986**	**-**	**0.625**	**0.758**
EWMA (0.03, 0.97)	47	**0.751**	**0.904**	**0.905**	**0.909**	**-**	**0.952**	**0.750**	**0.999**	**0.905**	**0.892**	**-**	**0.988**	**0.731**	**0.922**	**0.876**	**0.853**	**-**	**0.798**
SAMPLE	47	**0.750**	**0.912**	**0.902**	**0.906**	**0.995**	**-**	**0.762**	**0.985**	**0.916**	**0.903**	**0.988**	**-**	**0.765**	**0.965**	**0.908**	**0.887**	**0.964**	**-**
GO-GARCH MM	47	**-**	**0.039**	**0.615**	**0.869**	**0.091**	**0.241**	**-**	**0.103**	**0.762**	**0.890**	**0.347**	**0.443**	**-**	**0.107**	**0.519**	**0.664**	**0.183**	**0.118**
GO-GARCH ICA	47	**0.064**	**-**	**0.119**	**0.096**	**0.303**	**0.266**	**0.125**	**-**	**0.167**	**0.151**	**0.261**	**0.268**	**0.094**	**-**	**0.285**	**0.160**	**0.499**	**0.406**
DCC	47	**0.639**	**0.153**	**-**	**0.729**	**0.219**	**0.436**	**0.768**	**0.213**	**-**	**0.902**	**0.559**	**0.653**	**0.475**	**0.325**	**-**	**0.815**	**0.591**	**0.590**
COPULA DCC	47	**0.952**	**0.068**	**0.677**	**-**	**0.048**	**0.156**	**0.903**	**0.149**	**0.858**	**-**	**0.387**	**0.436**	**0.659**	**0.195**	**0.767**	**-**	**0.365**	**0.341**
EWMA (0.03, 0.97)	47	**0.056**	**0.644**	**0.181**	**0.060**	**-**	**0.518**	**0.347**	**0.444**	**0.541**	**0.408**	**-**	**0.729**	**0.182**	**0.634**	**0.566**	**0.364**	**-**	**0.817**
SAMPLE	47	**0.199**	**0.379**	**0.449**	**0.213**	**0.540**	**-**	**0.418**	**0.327**	**0.647**	**0.492**	**0.831**	**-**	**0.129**	**0.549**	**0.547**	**0.314**	**0.945**	**-**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.7 Statistical significance of monthly percentage turnover of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.000**	**0.916**	**0.695**	**0.000**	**0.000**	-	**0.000**	**0.451**	**0.874**	**0.000**	**0.000**	-	**0.000**	**0.456**	**0.816**	**0.000**	**0.000**
GO-GARCH ICA	47	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.585**	**0.000**	-	**0.456**	**0.000**	**0.000**	**0.927**	**0.000**	-	**0.281**	**0.000**	**0.000**	**0.882**	**0.000**	-	**0.245**	**0.000**	**0.000**
COPULA DCC	47	**0.290**	**0.000**	**0.539**	-	**0.000**	**0.000**	**0.474**	**0.000**	**0.363**	-	**0.000**	**0.000**	**0.403**	**0.000**	**0.272**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	47	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.003**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.005**	-
GO-GARCH MM	47	-	**0.000**	**0.327**	**0.515**	**0.000**	**0.000**	-	**0.000**	**0.107**	**0.707**	**0.000**	**0.000**	-	**0.000**	**0.338**	**0.322**	**0.000**	**0.000**
GO-GARCH ICA	47	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.308**	**0.000**	-	**0.054**	**0.000**	**0.000**	**0.162**	**0.000**	-	**0.128**	**0.000**	**0.000**	**0.360**	**0.000**	-	**0.014**	**0.000**	**0.000**
COPULA DCC	47	**0.419**	**0.000**	**0.033**	-	**0.000**	**0.000**	**1.000**	**0.000**	**0.102**	-	**0.000**	**0.000**	**0.223**	**0.000**	**0.013**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	47	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

6.4.2.1.1 HYPOTHESES 1A AND 2A

The mean realised monthly returns for long-short portfolios are not statistically different from each other for different models for both absolute and rank-based case (Table 6.1, Table 6.2 and Table 6.3). While the results for long-only portfolios show a lack of statistical differences for absolute case, some significant differences are found for low and high-risk portfolios based on ranks (Table 6.26, Table 6.27 and Table 6.58). For the low-risk portfolio, DCC and COP outperform MM, EWMA and SMPL. However, for the high-risk portfolio SMPL outperforms DCC and COP. This is to some extent consistent with findings presented by Vrontos *et al.* (2013). They show that the DCC model is superior to the sample covariance model with respect to the realised returns of low-risk portfolios. Syriopoulos and Roumpis (2009) showed that generally EWMA performs worse than DCC model in the same context.

These results give limited support for Hypothesis 1a. There is also no support for Hypothesis 2a as all the differences between COP and DCC are statistically insignificant.

6.4.2.1.2 HYPOTHESES 1B AND 2B

In terms of the realised cumulative monthly returns for long-short portfolios, some of the mean differences are statistically significant (Table 6.1, Table 6.2 and Table 6.4). DCC and COP outperform ICA in different risk portfolios. DCC outperforms MM in low-risk portfolios, whereas COP underperforms the EWMA in medium and high-risk cases. DCC does not differ significantly from COP performance. The results for the rank-based comparison do not prove consistent outperformance of the DCC and COP models. However, the COP model seems to outperform the DCC model.

For the long-only portfolios, just a few differences are statistically significant on a non-rank basis (Table 6.26, Table 6.27 and Table 6.59). Both COP and DCC outperform MM only in a low-risk scenario. For a medium-risk portfolio, ICA underperforms DCC, but in a high-risk case DCC underperforms EWMA and SMPL. Vrontos *et al.* (2013) found that the DCC model consistently outperforms the sample covariance model with respect to the cumulative realised portfolio returns. COP does not differ significantly from DCC performance. When it comes to the rank-based results, they are similar to the non-rank-based results, so that COP and DCC do not consistently outperform other models. However, DCC does not consistently underperform COP.

There is limited support for Hypotheses 1b and 2b.

6.4.2.1.3 Hypotheses 1c and 2c

The conditional Sharpe ratio for the long-short scenario does not seem to be statistically different across different methodologies (Table 6.1, Table 6.2 and Table 6.6). Some signs of differentials can be found in rank-based testing. COP outperforms ICA and EWMA for a low-risk case (Table 6.2 and Table 6.6). However, in any case COP outperforms DCC.

A similar situation can be found for the long-only case (Table 6.26, Table 6.27 and Table 6.61). There are no statistically significance differences for non-rank-based testing. Some evidence can be found in rank-based performance in low-risk portfolios. Both COP and DCC outperform ICA, EWMA, and SMPL, and only COP is better than MM. Superiority of DCC over SMPL was identified by Vrontos *et al.* (2013) and its superiority with respect to EWMA was noted by Syriopoulos and Roumpis (2009). In no case does COP perform significantly better than DCC.

This means that there is very limited support for Hypothesis 1c and no support for Hypothesis 2c.

6.4.2.1.4 Hypotheses 1d and 2d

When it comes to portfolio turnover, the majority of the differences are statistically significant for long-short portfolios based on non-rank-based and rank-based comparison (Table 6.1, Table 6.2 and Table 6.7). The turnover of COP and DCC portfolios is statistically different from ICA, EWMA and SMPL but not from MM across all risk levels in both cases. This suggests that the COP and DCC portfolio turnover is lower than ICA, but higher than EWMA and SMPL and similar to MM. In addition, the COP and DCC models do not statistically differ from each other in that respect in non-rank-based comparison, but they seem to differ in a rank-based case. This suggests that in a non-rank case DCC turnover is higher.

In terms of long-only comparison, the results are to some extent similar but with some differences (Table 6.26, Table 6.27 and Table 6.62). DCC and COP turnover is statistically different from MM (for low and medium risk only), EWMA and SMPL but not from ICA across different risk levels for both non-rank-based and rank-based comparison. This indicates that DCC and COP have a higher turnover than MM (for low and medium risk only), EWMA and SMPL, and similar to ICA and MM (for a high-risk portfolio). Additionally, COP does not differ from DCC turnover. Harris and Mazibas (2010) found that turnover of long-only portfolio based on EWMA is much lower than DCC irrespective of market condition.

These results generally support Hypothesis 1d but not Hypothesis 2d.

6.4.2.2 Hypothesis tests with respect to portfolio weights

In this section I test Hypothesis 3:

H3. Sample covariance model differs from time-varying covariance models in terms of mean weightings within the portfolio.

The mean values of the long-short portfolio weights are presented in Table 6.8. Similarly to Section 6.4.2.1, I also perform the rank-based comparison (Table 6.9). In order to be consistent with the rest of the thesis, the mean differences are statistically tested by means of Welch t and Wilcoxon rank sum tests (Table 6.10–Table 6.18).

Analogical results are obtained for a long-only portfolio. The mean values based on the absolute and rank-based comparison are presented in the appendix in Table 6.28 and Table 6.29 respectively. The corresponding Welch t and Wilcoxon rank sum tests can be found in the appendix in Table 6.63–Table 6.71.

All the aforementioned tables are based on the 72-month estimation window and represent 48 observations (30 June 2008–11 May 2012).

Table 6.8 Composition of mean-variance long-short portfolios between models for the 72-month estimation period

Portfolio constituents	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
US	48	77.831	93.524	69.426	69.971	63.885	75.235
EMU	48	-71.187	-52.998	-39.767	-39.276	-54.521	-51.229
EUROPE ex EMU	48	47.227	-2.402	34.258	27.748	31.036	34.644
PACIFIC	48	38.873	41.245	30.474	33.768	53.507	37.888
EM BRIC	48	11.923	-30.502	4.188	4.434	-11.044	9.964
EM EUROPE	48	-10.093	-0.944	-2.005	-2.506	-9.764	-12.911
EM LATIN AMERICA	48	-39.644	-11.994	-20.262	-20.026	-22.195	-34.816
EM ASIA	48	17.473	26.583	7.934	8.551	18.216	14.062
EMF AFRICA	48	27.598	37.487	15.753	17.336	30.880	27.162
US	48	66.242	82.474	52.882	54.653	50.726	62.357
EMU	48	-83.348	-61.460	-45.394	-44.436	-58.445	-59.971
EUROPE ex EMU	48	44.141	-10.124	32.311	23.047	16.349	29.212
PACIFIC	48	31.251	34.966	22.609	26.539	53.910	32.399
EM BRIC	48	25.305	-25.068	8.259	8.551	1.971	22.012
EM EUROPE	48	-21.156	-14.108	-10.165	-9.666	-19.701	-24.559
EM LATIN AMERICA	48	-21.483	10.657	1.651	1.558	-1.764	-16.232
EM ASIA	48	24.684	33.718	16.343	15.770	17.903	19.562
EMF AFRICA	48	34.364	48.945	21.503	23.985	39.051	35.219
US	48	54.653	71.425	36.338	39.334	37.567	49.479
EMU	48	-95.510	-69.922	-51.021	-49.597	-62.368	-68.713
EUROPE ex EMU	48	41.055	-17.846	30.365	18.346	1.661	23.781
PACIFIC	48	23.630	28.686	14.744	19.310	54.312	26.911
EM BRIC	48	38.688	-19.635	12.331	12.668	14.985	34.060
EM EUROPE	48	-32.218	-27.272	-18.325	-16.827	-29.637	-36.207
EM LATIN AMERICA	48	-3.323	33.308	23.564	23.142	18.668	2.351
EM ASIA	48	31.895	40.852	24.752	22.989	17.589	25.062
EMF AFRICA	48	41.131	60.404	27.252	30.634	47.222	43.275

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly weights. Values are expressed in percentages.

Table 6.9 Composition of mean-variance long-short portfolios between models for the 72-month estimation period based on ranks

Portfolio constituents	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
US	48	4.063	4.292	3.354	3.396	2.188	3.708
EMU	48	2.688	3.292	4.125	4.229	3.292	3.375
EUROPE ex EMU	48	4.208	2.208	3.792	3.417	3.750	3.625
PACIFIC	48	3.708	3.375	2.708	3.083	4.813	3.313
EM BRIC	48	4.229	2.708	3.438	3.625	2.708	4.292
EM EUROPE	48	2.938	3.854	4.313	4.271	3.354	2.271
EM LATIN AMERICA	48	2.313	4.500	4.063	4.042	3.917	2.167
EM ASIA	48	3.729	3.708	2.917	2.896	4.083	3.667
EMF AFRICA	48	3.875	4.250	2.250	2.438	4.146	4.042
US	48	4.208	4.208	3.188	3.313	2.333	3.750
EMU	48	2.542	3.313	4.188	4.313	3.542	3.104
EUROPE ex EMU	48	4.479	2.479	3.938	3.313	2.979	3.813
PACIFIC	48	3.354	3.521	2.625	3.000	5.042	3.458
EM BRIC	48	4.333	2.625	3.333	3.458	2.875	4.375
EM EUROPE	48	2.979	3.563	4.500	4.500	3.188	2.271
EM LATIN AMERICA	48	2.417	4.417	3.979	4.042	3.896	2.250
EM ASIA	48	3.708	3.896	3.250	3.188	3.479	3.479
EMF AFRICA	48	3.875	4.208	2.313	2.604	4.063	3.938
US	48	4.188	4.229	3.021	3.125	2.542	3.896
EMU	48	2.479	3.354	4.125	4.167	3.813	3.063
EUROPE ex EMU	48	4.333	2.729	4.042	3.542	2.458	3.896
PACIFIC	48	3.125	3.542	2.667	3.042	5.188	3.438
EM BRIC	48	4.375	2.438	3.146	3.354	3.188	4.500
EM EUROPE	48	3.000	3.396	4.417	4.771	3.188	2.229
EM LATIN AMERICA	48	2.458	4.229	4.000	4.104	3.792	2.417
EM ASIA	48	4.021	3.938	3.396	3.188	2.917	3.542
EMF AFRICA	48	3.750	4.292	2.417	2.667	3.979	3.896

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly weights. Values are expressed in percentages.

Table 6.10 Statistical significance of monthly percentage US weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.047**	**0.133**	**0.301**	**0.000**	**0.170**	-	**0.082**	**0.013**	**0.047**	**0.000**	**0.120**	-	**0.140**	**0.003**	**0.014**	**0.000**	**0.168**
GO-GARCH ICA	48	**0.031**	-	**0.002**	**0.005**	**0.000**	**0.028**	**0.039**	-	**0.001**	**0.002**	**0.000**	**0.019**	**0.057**	-	**0.000**	**0.002**	**0.000**	**0.022**
DCC	48	**0.069**	**0.002**	-	**0.762**	**0.042**	**0.779**	**0.010**	**0.000**	-	**0.724**	**0.403**	**0.155**	**0.003**	**0.000**	-	**0.734**	**0.985**	**0.044**
COPULA DCC	48	**0.112**	**0.003**	**0.919**	-	**0.057**	**0.751**	**0.032**	**0.001**	**0.755**	-	**0.256**	**0.359**	**0.015**	**0.001**	**0.643**	-	**0.713**	**0.155**
EWMA (0.03, 0.97)	48	**0.000**	**0.000**	**0.155**	**0.156**	-	**0.000**	**0.000**	**0.000**	**0.619**	**0.394**	-	**0.000**	**0.001**	**0.000**	**0.817**	**0.744**	-	**0.005**
SAMPLE	48	**0.384**	**0.007**	**0.115**	**0.197**	**0.000**	-	**0.301**	**0.007**	**0.028**	**0.090**	**0.000**	-	**0.294**	**0.009**	**0.014**	**0.062**	**0.003**	-
GO-GARCH MM	48	-	**0.199**	**0.023**	**0.053**	**0.000**	**0.197**	-	**0.456**	**0.002**	**0.007**	**0.000**	**0.083**	-	**0.466**	**0.001**	**0.001**	**0.000**	**0.209**
GO-GARCH ICA	48	**0.536**	-	**0.008**	**0.007**	**0.000**	**0.027**	**1.000**	-	**0.007**	**0.011**	**0.000**	**0.041**	**0.910**	-	**0.003**	**0.004**	**0.000**	**0.076**
DCC	48	**0.024**	**0.013**	-	**0.873**	**0.000**	**0.230**	**0.002**	**0.009**	-	**0.696**	**0.007**	**0.055**	**0.000**	**0.002**	-	**0.726**	**0.138**	**0.003**
COPULA DCC	48	**0.043**	**0.021**	**0.898**	-	**0.000**	**0.356**	**0.006**	**0.022**	**0.700**	-	**0.002**	**0.159**	**0.001**	**0.004**	**0.749**	-	**0.057**	**0.009**
EWMA (0.03, 0.97)	48	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.005**	**0.001**	-	**0.000**	**0.000**	**0.000**	**0.141**	**0.069**	-	**0.000**
SAMPLE	48	**0.229**	**0.103**	**0.226**	**0.312**	**0.000**	-	**0.115**	**0.206**	**0.057**	**0.143**	**0.000**	-	**0.296**	**0.332**	**0.003**	**0.008**	**0.000**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.11 Statistical significance of monthly percentage EMU weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.097**	**0.000**	**0.000**	**0.058**	**0.011**	-	**0.086**	**0.000**	**0.000**	**0.008**	**0.012**	-	**0.144**	**0.000**	**0.000**	**0.002**	**0.012**
GO-GARCH ICA	48	**0.035**	-	**0.044**	**0.045**	**0.680**	**0.319**	**0.054**	-	**0.110**	**0.079**	**0.713**	**0.504**	**0.080**	-	**0.108**	**0.084**	**0.379**	**0.450**
DCC	48	**0.000**	**0.079**	-	**0.997**	**0.016**	**0.009**	**0.000**	**0.113**	-	**0.945**	**0.138**	**0.013**	**0.000**	**0.156**	-	**0.951**	**0.308**	**0.017**
COPULA DCC	48	**0.000**	**0.069**	**0.934**	-	**0.011**	**0.010**	**0.000**	**0.092**	**0.900**	-	**0.110**	**0.006**	**0.000**	**0.125**	**0.885**	-	**0.312**	**0.005**
EWMA (0.03, 0.97)	48	**0.017**	**0.831**	**0.008**	**0.006**	-	**0.387**	**0.006**	**0.756**	**0.071**	**0.051**	-	**0.985**	**0.003**	**0.554**	**0.225**	**0.167**	-	**0.472**
SAMPLE	48	**0.002**	**0.782**	**0.012**	**0.009**	**0.396**	-	**0.005**	**0.870**	**0.024**	**0.015**	**0.790**	-	**0.013**	**0.922**	**0.045**	**0.029**	**0.428**	-
GO-GARCH MM	48	-	**0.215**	**0.000**	**0.000**	**0.081**	**0.010**	-	**0.126**	**0.000**	**0.000**	**0.005**	**0.020**	-	**0.071**	**0.000**	**0.000**	**0.000**	**0.029**
GO-GARCH ICA	48	**0.136**	-	**0.094**	**0.021**	**0.744**	**0.632**	**0.053**	-	**0.074**	**0.019**	**0.455**	**0.882**	**0.027**	-	**0.149**	**0.044**	**0.237**	**0.729**
DCC	48	**0.000**	**0.023**	-	**0.790**	**0.024**	**0.002**	**0.000**	**0.017**	-	**0.738**	**0.074**	**0.000**	**0.000**	**0.036**	-	**0.964**	**0.414**	**0.000**
COPULA DCC	48	**0.000**	**0.013**	**0.707**	-	**0.006**	**0.004**	**0.000**	**0.007**	**0.637**	-	**0.026**	**0.000**	**0.000**	**0.031**	**0.876**	-	**0.372**	**0.000**
EWMA (0.03, 0.97)	48	**0.105**	**1.000**	**0.012**	**0.006**	-	**0.522**	**0.006**	**0.569**	**0.044**	**0.017**	-	**0.256**	**0.000**	**0.254**	**0.312**	**0.266**	-	**0.028**
SAMPLE	48	**0.027**	**0.813**	**0.003**	**0.002**	**0.792**	-	**0.070**	**0.565**	**0.000**	**0.000**	**0.171**	-	**0.062**	**0.438**	**0.000**	**0.000**	**0.022**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.12 Statistical significance of monthly percentage Europe ex EMU weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.000**	**0.146**	**0.004**	**0.011**	**0.030**	-	**0.000**	**0.259**	**0.012**	**0.001**	**0.064**	-	**0.001**	**0.265**	**0.027**	**0.000**	**0.052**
GO-GARCH ICA	48	**0.000**	-	**0.000**	**0.003**	**0.001**	**0.000**	**0.000**	-	**0.001**	**0.014**	**0.057**	**0.007**	**0.001**	-	**0.009**	**0.044**	**0.291**	**0.035**
DCC	48	**0.082**	**0.000**	-	**0.192**	**0.253**	**0.268**	**0.180**	**0.001**	-	**0.122**	**0.010**	**0.129**	**0.320**	**0.004**	-	**0.122**	**0.001**	**0.105**
COPULA DCC	48	**0.006**	**0.002**	**0.327**	-	**0.477**	**0.437**	**0.011**	**0.009**	**0.235**	-	**0.298**	**0.428**	**0.027**	**0.025**	**0.204**	-	**0.044**	**0.659**
EWMA (0.03, 0.97)	48	**0.012**	**0.000**	**0.594**	**0.542**	-	**0.718**	**0.001**	**0.032**	**0.034**	**0.319**	-	**0.024**	**0.000**	**0.218**	**0.003**	**0.055**	-	**0.003**
SAMPLE	48	**0.028**	**0.000**	**0.942**	**0.132**	**0.320**	-	**0.036**	**0.001**	**0.635**	**0.281**	**0.015**	-	**0.059**	**0.008**	**0.425**	**0.465**	**0.003**	-
GO-GARCH MM	48	-	**0.000**	**0.248**	**0.017**	**0.103**	**0.050**	-	**0.000**	**0.075**	**0.001**	**0.000**	**0.006**	-	**0.000**	**0.316**	**0.010**	**0.000**	**0.059**
GO-GARCH ICA	48	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.008**	**0.015**	**0.000**	**0.000**	-	**0.001**	**0.023**	**0.736**	**0.001**
DCC	48	**0.243**	**0.000**	-	**0.298**	**0.846**	**0.641**	**0.120**	**0.000**	-	**0.058**	**0.005**	**0.510**	**0.397**	**0.001**	-	**0.112**	**0.000**	**0.473**
COPULA DCC	48	**0.022**	**0.000**	**0.272**	-	**0.288**	**0.526**	**0.001**	**0.022**	**0.061**	-	**0.247**	**0.100**	**0.020**	**0.029**	**0.129**	-	**0.000**	**0.378**
EWMA (0.03, 0.97)	48	**0.168**	**0.000**	**0.900**	**0.289**	-	**0.641**	**0.000**	**0.151**	**0.003**	**0.281**	-	**0.001**	**0.000**	**0.429**	**0.000**	**0.000**	-	**0.000**
SAMPLE	48	**0.077**	**0.000**	**0.610**	**0.501**	**0.676**	-	**0.028**	**0.000**	**0.668**	**0.078**	**0.002**	-	**0.149**	**0.001**	**0.617**	**0.211**	**0.000**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.13 Statistical significance of monthly percentage Pacific weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	0.648	0.006	0.030	0.000	0.680	-	0.881	0.010	0.055	0.000	0.244	-	0.707	0.024	0.157	0.000	0.120
GO-GARCH ICA	48	0.742	-	0.612	0.864	0.062	0.858	0.648	-	0.371	0.592	0.061	0.991	0.592	-	0.253	0.433	0.028	0.951
DCC	48	0.032	0.170	-	0.779	0.000	0.007	0.051	0.158	-	0.622	0.000	0.002	0.092	0.160	-	0.567	0.000	0.003
COPULA DCC	48	0.252	0.356	0.536	-	0.000	0.036	0.342	0.349	0.499	-	0.000	0.017	0.455	0.357	0.480	-	0.000	0.018
EWMA (0.03, 0.97)	48	0.000	0.108	0.000	0.000	-	0.000	0.000	0.029	0.000	0.000	-	0.000	0.000	0.011	0.000	0.000	-	0.000
SAMPLE	48	0.627	0.635	0.043	0.329	0.000	-	0.660	0.747	0.017	0.209	0.000	-	0.379	0.846	0.012	0.156	0.000	-
GO-GARCH MM	48	-	0.487	0.000	0.046	0.000	0.204	-	0.662	0.006	0.162	0.000	0.662	-	0.335	0.046	0.499	0.000	0.182
GO-GARCH ICA	48	0.387	-	0.446	0.682	0.005	0.878	0.658	-	0.116	0.364	0.004	0.806	0.261	-	0.119	0.379	0.001	0.636
DCC	48	0.001	0.088	-	0.304	0.000	0.017	0.009	0.022	-	0.357	0.000	0.003	0.087	0.025	-	0.374	0.000	0.004
COPULA DCC	48	0.047	0.475	0.235	-	0.000	0.366	0.252	0.205	0.238	-	0.000	0.094	0.784	0.225	0.244	-	0.000	0.141
EWMA (0.03, 0.97)	48	0.000	0.000	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000	0.000	0.000	0.000	-	0.000
SAMPLE	48	0.148	0.869	0.030	0.452	0.000	-	0.690	0.868	0.003	0.138	0.000	-	0.208	0.779	0.005	0.198	0.000	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.14 Statistical significance of monthly percentage EM BRIC weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.001**	**0.218**	**0.271**	**0.000**	**0.922**	-	**0.001**	**0.054**	**0.061**	**0.005**	**0.962**	-	**0.001**	**0.020**	**0.023**	**0.058**	**0.927**
GO-GARCH ICA	48	**0.000**	-	**0.012**	**0.010**	**0.428**	**0.001**	**0.000**	-	**0.060**	**0.045**	**0.182**	**0.001**	**0.000**	-	**0.125**	**0.093**	**0.065**	**0.001**
DCC	48	**0.179**	**0.002**	-	**0.910**	**0.001**	**0.106**	**0.030**	**0.009**	-	**0.893**	**0.294**	**0.025**	**0.011**	**0.034**	-	**0.956**	**0.796**	**0.012**
COPULA DCC	48	**0.200**	**0.002**	**0.959**	-	**0.001**	**0.187**	**0.032**	**0.008**	**0.966**	-	**0.278**	**0.040**	**0.010**	**0.031**	**0.970**	-	**0.870**	**0.017**
EWMA (0.03, 0.97)	48	**0.000**	**0.074**	**0.003**	**0.003**	-	**0.000**	**0.006**	**0.037**	**0.401**	**0.376**	-	**0.002**	**0.040**	**0.030**	**0.803**	**0.824**	-	**0.053**
SAMPLE	48	**0.699**	**0.000**	**0.134**	**0.165**	**0.000**	-	**0.641**	**0.000**	**0.025**	**0.026**	**0.004**	-	**0.624**	**0.000**	**0.011**	**0.010**	**0.057**	-
GO-GARCH MM	48	-	**0.000**	**0.022**	**0.059**	**0.000**	**0.776**	-	**0.000**	**0.007**	**0.006**	**0.000**	**0.875**	-	**0.000**	**0.001**	**0.001**	**0.000**	**0.934**
GO-GARCH ICA	48	**0.000**	-	**0.028**	**0.005**	**0.643**	**0.000**	**0.000**	-	**0.033**	**0.005**	**0.201**	**0.000**	**0.000**	-	**0.022**	**0.001**	**0.008**	**0.000**
DCC	48	**0.022**	**0.041**	-	**0.642**	**0.021**	**0.005**	**0.004**	**0.058**	-	**0.715**	**0.194**	**0.001**	**0.001**	**0.053**	-	**0.447**	**0.852**	**0.000**
COPULA DCC	48	**0.076**	**0.010**	**0.563**	-	**0.003**	**0.029**	**0.006**	**0.019**	**0.699**	-	**0.043**	**0.001**	**0.001**	**0.007**	**0.511**	-	**0.532**	**0.000**
EWMA (0.03, 0.97)	48	**0.000**	**1.000**	**0.028**	**0.006**	-	**0.000**	**0.000**	**0.491**	**0.177**	**0.066**	-	**0.000**	**0.000**	**0.034**	**0.901**	**0.581**	-	**0.000**
SAMPLE	48	**0.838**	**0.000**	**0.004**	**0.022**	**0.000**	-	**0.884**	**0.000**	**0.001**	**0.001**	**0.000**	-	**0.667**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.15 Statistical significance of monthly percentage EM Europe weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	0.127	0.001	0.001	0.962	0.205	-	0.518	0.000	0.000	0.587	0.170	-	0.922	0.000	0.000	0.441	0.177
GO-GARCH ICA	48	0.033	-	0.518	0.612	0.161	0.033	0.190	-	0.153	0.125	0.607	0.229	0.459	-	0.077	0.046	0.887	0.504
DCC	48	0.001	0.799	-	0.707	0.002	0.000	0.001	0.458	-	0.997	0.003	0.000	0.001	0.180	-	0.801	0.006	0.000
COPULA DCC	48	0.001	0.703	0.806	-	0.003	0.000	0.000	0.399	0.867	-	0.001	0.000	0.000	0.116	0.713	-	0.001	0.000
EWMA (0.03, 0.97)	48	0.911	0.055	0.008	0.010	-	0.123	0.703	0.329	0.013	0.008	-	0.056	0.594	0.738	0.020	0.008	-	0.039
SAMPLE	48	0.164	0.004	0.000	0.000	0.237	-	0.244	0.046	0.000	0.000	0.175	-	0.312	0.171	0.000	0.000	0.154	-
GO-GARCH MM	48	-	0.014	0.000	0.000	0.253	0.175	-	0.236	0.000	0.000	0.507	0.042	-	0.407	0.000	0.000	0.640	0.013
GO-GARCH ICA	48	0.023	-	0.462	0.774	0.192	0.001	0.144	-	0.066	0.183	0.427	0.024	0.310	-	0.031	0.013	0.934	0.054
DCC	48	0.000	0.226	-	0.439	0.006	0.000	0.000	0.016	-	0.584	0.000	0.000	0.000	0.009	-	0.406	0.000	0.000
COPULA DCC	48	0.000	0.213	0.875	-	0.004	0.000	0.000	0.010	1.000	-	0.000	0.000	0.000	0.000	0.168	-	0.000	0.000
EWMA (0.03, 0.97)	48	0.241	0.199	0.005	0.002	-	0.001	0.510	0.331	0.000	0.000	-	0.001	0.534	0.579	0.000	0.000	-	0.000
SAMPLE	48	0.025	0.000	0.000	0.000	0.000	-	0.012	0.000	0.000	0.000	0.001	-	0.006	0.001	0.000	0.000	0.000	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.16 Statistical significance of monthly percentage EM Latin America weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.202**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.229**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.305**
GO-GARCH ICA	48	**0.000**	-	**0.175**	**0.194**	**0.091**	**0.000**	**0.000**	-	**0.205**	**0.180**	**0.090**	**0.000**	**0.000**	-	**0.305**	**0.213**	**0.138**	**0.000**
DCC	48	**0.000**	**0.183**	-	**0.597**	**0.847**	**0.000**	**0.000**	**0.217**	-	**0.945**	**0.622**	**0.000**	**0.000**	**0.266**	-	**0.997**	**0.617**	**0.000**
COPULA DCC	48	**0.000**	**0.190**	**0.922**	-	**0.648**	**0.000**	**0.000**	**0.206**	**0.978**	-	**0.654**	**0.000**	**0.000**	**0.239**	**0.926**	-	**0.675**	**0.000**
EWMA (0.03, 0.97)	48	**0.000**	**0.104**	**0.479**	**0.391**	-	**0.000**	**0.000**	**0.094**	**0.358**	**0.344**	-	**0.000**	**0.000**	**0.101**	**0.335**	**0.355**	-	**0.000**
SAMPLE	48	**0.159**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.210**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.271**	**0.000**	**0.000**	**0.000**	**0.000**	-
GO-GARCH MM	48	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.247**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.365**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.407**
GO-GARCH ICA	48	**0.000**	-	**0.048**	**0.017**	**0.015**	**0.000**	**0.000**	-	**0.082**	**0.066**	**0.082**	**0.000**	**0.000**	-	**0.185**	**0.225**	**0.192**	**0.000**
DCC	48	**0.000**	**0.213**	-	**0.937**	**0.415**	**0.000**	**0.000**	**0.201**	-	**0.967**	**0.748**	**0.000**	**0.000**	**0.517**	-	**0.897**	**0.609**	**0.000**
COPULA DCC	48	**0.000**	**0.177**	**0.942**	-	**0.504**	**0.000**	**0.000**	**0.237**	**0.826**	-	**0.675**	**0.000**	**0.000**	**0.709**	**0.712**	-	**0.450**	**0.000**
EWMA (0.03, 0.97)	48	**0.000**	**0.082**	**0.601**	**0.635**	-	**0.000**	**0.000**	**0.134**	**0.793**	**0.615**	-	**0.000**	**0.000**	**0.249**	**0.531**	**0.318**	-	**0.000**
SAMPLE	48	**0.598**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.564**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.881**	**0.000**	**0.000**	**0.000**	**0.000**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.17 Statistical significance of monthly percentage EM Asia weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.751**	**0.033**	**0.018**	**0.762**	**0.500**	-	**0.557**	**0.140**	**0.091**	**0.133**	**0.182**	-	**0.587**	**0.268**	**0.192**	**0.029**	**0.138**
GO-GARCH ICA	48	**0.244**	-	**0.079**	**0.106**	**0.807**	**0.344**	**0.318**	-	**0.151**	**0.113**	**0.157**	**0.250**	**0.409**	-	**0.210**	**0.136**	**0.071**	**0.221**
DCC	48	**0.028**	**0.021**	-	**0.916**	**0.013**	**0.151**	**0.164**	**0.064**	-	**0.768**	**0.628**	**0.450**	**0.370**	**0.154**	-	**0.740**	**0.547**	**0.801**
COPULA DCC	48	**0.064**	**0.030**	**0.901**	-	**0.008**	**0.057**	**0.161**	**0.062**	**0.932**	-	**0.275**	**0.352**	**0.279**	**0.119**	**0.840**	-	**0.910**	**0.562**
EWMA (0.03, 0.97)	48	**0.835**	**0.269**	**0.008**	**0.029**	-	**0.187**	**0.166**	**0.070**	**0.770**	**0.710**	-	**0.433**	**0.044**	**0.031**	**0.350**	**0.494**	-	**0.182**
SAMPLE	48	**0.300**	**0.095**	**0.086**	**0.185**	**0.118**	-	**0.293**	**0.104**	**0.545**	**0.509**	**0.683**	-	**0.310**	**0.131**	**0.966**	**0.785**	**0.240**	-
GO-GARCH MM	48	-	**0.961**	**0.015**	**0.016**	**0.245**	**0.759**	-	**0.530**	**0.206**	**0.129**	**0.515**	**0.453**	-	**0.836**	**0.082**	**0.018**	**0.001**	**0.078**
GO-GARCH ICA	48	**0.958**	-	**0.060**	**0.094**	**0.704**	**0.723**	**0.639**	-	**0.071**	**0.127**	**0.141**	**0.169**	**0.832**	-	**0.102**	**0.067**	**0.014**	**0.169**
DCC	48	**0.011**	**0.036**	-	**0.703**	**0.000**	**0.011**	**0.186**	**0.108**	-	**0.893**	**0.476**	**0.521**	**0.075**	**0.185**	-	**0.579**	**0.179**	**0.748**
COPULA DCC	48	**0.016**	**0.043**	**0.948**	-	**0.002**	**0.005**	**0.148**	**0.087**	**0.861**	-	**0.351**	**0.211**	**0.016**	**0.064**	**0.559**	-	**0.486**	**0.195**
EWMA (0.03, 0.97)	48	**0.306**	**0.350**	**0.000**	**0.001**	-	**0.071**	**0.480**	**0.277**	**0.479**	**0.388**	-	**0.905**	**0.001**	**0.009**	**0.154**	**0.409**	-	**0.025**
SAMPLE	48	**0.833**	**0.908**	**0.006**	**0.012**	**0.176**	-	**0.454**	**0.257**	**0.453**	**0.363**	**1.000**	-	**0.098**	**0.267**	**0.632**	**0.234**	**0.023**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.18 Statistical significance of monthly percentage EMF Africa weight of mean-variance long-short portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.065**	**0.000**	**0.000**	**0.740**	**0.680**	-	**0.041**	**0.000**	**0.006**	**0.768**	**0.702**	-	**0.042**	**0.004**	**0.025**	**0.638**	**0.411**
GO-GARCH ICA	48	**0.065**	-	**0.001**	**0.002**	**0.420**	**0.063**	**0.026**	-	**0.001**	**0.002**	**0.232**	**0.042**	**0.017**	-	**0.000**	**0.002**	**0.205**	**0.035**
DCC	48	**0.000**	**0.000**	-	**0.702**	**0.001**	**0.000**	**0.001**	**0.000**	-	**0.597**	**0.004**	**0.000**	**0.003**	**0.000**	-	**0.523**	**0.014**	**0.000**
COPULA DCC	48	**0.001**	**0.001**	**0.638**	-	**0.003**	**0.000**	**0.005**	**0.000**	**0.550**	-	**0.016**	**0.001**	**0.024**	**0.001**	**0.506**	-	**0.043**	**0.002**
EWMA (0.03, 0.97)	48	**0.390**	**0.276**	**0.000**	**0.002**	-	**0.638**	**0.334**	**0.187**	**0.001**	**0.005**	-	**0.675**	**0.315**	**0.151**	**0.003**	**0.012**	-	**0.904**
SAMPLE	48	**0.817**	**0.046**	**0.000**	**0.000**	**0.292**	-	**0.723**	**0.030**	**0.000**	**0.001**	**0.396**	-	**0.505**	**0.027**	**0.000**	**0.002**	**0.479**	-
GO-GARCH MM	48	-	**0.053**	**0.000**	**0.000**	**0.340**	**0.570**	-	**0.082**	**0.000**	**0.000**	**0.395**	**0.861**	-	**0.050**	**0.000**	**0.001**	**0.432**	**0.751**
GO-GARCH ICA	48	**0.282**	-	**0.000**	**0.000**	**0.350**	**0.270**	**0.349**	-	**0.000**	**0.000**	**0.353**	**0.254**	**0.145**	-	**0.000**	**0.000**	**0.163**	**0.095**
DCC	48	**0.000**	**0.000**	-	**0.420**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.230**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.401**	**0.000**	**0.000**
COPULA DCC	48	**0.000**	**0.000**	**0.482**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.267**	-	**0.000**	**0.000**	**0.001**	**0.000**	**0.335**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	48	**0.355**	**0.771**	**0.000**	**0.000**	-	**0.745**	**0.550**	**0.696**	**0.000**	**0.000**	-	**0.662**	**0.503**	**0.405**	**0.000**	**0.000**	-	**0.627**
SAMPLE	48	**0.574**	**0.565**	**0.000**	**0.000**	**0.736**	-	**0.839**	**0.463**	**0.000**	**0.000**	**0.703**	-	**0.651**	**0.270**	**0.000**	**0.000**	**0.800**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

In general, the mean values of the long-short portfolio weights based on the SMPL model differ from the time-varying models (Table 6.8–Table 6.18). There are 12, 34, 38, 34 and 30 (out of 54) statistically significant p-values in Table 6.10–Table 6.18 (absolute comparison) with respect to SMPL against MM, ICA, DCC, COP and EWMA. These constitute 22%, 63%, 70%, 63% and 56%, respectively. For the rank-based, the percentage figures are 37%, 52%, 78%, 67% and 72%, respectively. Similar findings with respect to the average weights of optimal portfolios were presented by Vrontos *et al.* (2013). They showed that there are some differences between DCC and SMPL based portfolios.

For the long-only portfolios the differences are less pronounced (Table 6.28–Table 6.29 and Table 6.63–Table 6.71). In terms of absolute comparison there are 11, 14, 22, 18 and 21 (out of 54) statistically significant p-values in Table 6.63–Table 6.71 with regards to SMPL against MM, ICA, DCC, COP and EWMA. These account for 20%, 26%, 41%, 33% and 39%, respectively. The rank-based comparison provides quite similar results: 15%, 28%, 50%, 48% and 50%, respectively.

I prefer the long-short portfolios as the long-only portfolios restrict the short position, which cannot fully respond to the bear phases. This suggests that there is evidence for Hypothesis 3.

The main reasons for the difference in the mean portfolio composition could be due to the rebalancing effect (Hypothesis 1d) or the different estimates of correlations and volatilities (Section 5.4.2).

6.4.3 Unconstrained versus constrained rebalancing

In order to reduce the high portfolio turnover found in the previous sections, I investigate the impact of constrained rebalancing on the mean values of realised monthly portfolio returns (Table 6.19), realised cumulative monthly portfolio returns (Table 6.20), monthly portfolio standard deviation (Table 6.21), monthly conditional Sharpe ratio (Table 6.22) and monthly PT (Table 6.23) for long-short portfolios.

As in the previous sections, the results for long-only portfolios can be found in the Appendix in Table 6.72–Table 6.76, namely realised monthly portfolio returns (Table 6.72), realised cumulative monthly portfolio returns (Table 6.73), monthly portfolio standard deviation (Table 6.74), monthly conditional Sharpe ratio (Table 6.75) and monthly PT (Table 6.76).

Table 6.19–Table 6.23 and Table 6.72–Table 6.76 correspond to unconstrained (no smoothing of portfolio weights) and constrained (smoothing of portfolio weights) rebalancing based on the exponential weighted moving average (EWMA(4), EWMA(8) and EWMA(12)).

All the aforementioned tables are based on the 72-month estimation window and represent 47 observations (31 July 2008–11 May 2012) apart from portfolio standard deviation, which presents 48 observations (30 June 2008–11 May 2012).

In order to conserve space and maintain the focus of this thesis I do not perform any statistical testing of the differences in the means of the aforementioned portfolio performance measures.

Table 6.19 Mean realised monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	0.510	0.051	0.442	0.422	0.561	0.526
EWMA (4) smoothing	47	0.545	0.375	0.448	0.379	0.377	0.507
EWMA (8) smoothing	47	0.608	0.420	0.397	0.328	0.316	0.504
EWMA (12) smoothing	47	0.640	0.458	0.376	0.311	0.311	0.509
No smoothing	47	0.557	-0.014	0.284	0.284	0.401	0.418
EWMA (4) smoothing	47	0.541	0.349	0.319	0.253	0.209	0.402
EWMA (8) smoothing	47	0.561	0.414	0.251	0.185	0.108	0.385
EWMA (12) smoothing	47	0.568	0.467	0.218	0.159	0.084	0.381
No smoothing	47	0.603	-0.080	0.127	0.146	0.242	0.309
EWMA (4) smoothing	47	0.538	0.324	0.189	0.127	0.040	0.297
EWMA (8) smoothing	47	0.515	0.409	0.104	0.041	-0.099	0.266
EWMA (12) smoothing	47	0.496	0.476	0.059	0.006	-0.142	0.253

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

Table 6.20 Mean realised cumulative monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	-11.485	-28.923	-3.298	-7.416	-0.688	-7.325
EWMA (4) smoothing	47	-9.602	-18.435	-5.287	-9.021	-8.892	-8.090
EWMA (8) smoothing	47	-7.501	-16.420	-7.650	-11.211	-12.608	-8.312
EWMA (12) smoothing	47	-6.429	-14.510	-8.726	-12.096	-13.623	-8.130
No smoothing	47	-13.009	-33.440	-11.611	-15.009	-7.249	-14.234
EWMA (4) smoothing	47	-12.996	-21.398	-13.075	-16.484	-15.956	-15.094
EWMA (8) smoothing	47	-12.434	-18.695	-15.911	-19.228	-20.974	-15.737
EWMA (12) smoothing	47	-12.103	-16.082	-17.194	-20.236	-22.489	-15.629
No smoothing	47	-14.532	-37.956	-19.923	-22.602	-13.810	-21.142
EWMA (4) smoothing	47	-16.389	-24.361	-20.863	-23.948	-23.020	-22.097
EWMA (8) smoothing	47	-17.367	-20.969	-24.172	-27.244	-29.339	-23.163
EWMA (12) smoothing	47	-17.777	-17.654	-25.662	-28.375	-31.355	-23.128

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

Table 6.21 Mean monthly percentage standard deviation of mean-variance long-short portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	48	4.119	7.809	3.937	4.066	4.736	4.382
EWMA (4) smoothing	48	4.119	7.809	3.937	4.066	4.736	4.382
EWMA (8) smoothing	48	4.119	7.809	3.937	4.066	4.736	4.382
EWMA (12) smoothing	48	4.119	7.809	3.937	4.066	4.736	4.382
No smoothing	48	4.833	9.252	4.488	4.588	5.292	5.091
EWMA (4) smoothing	48	4.833	9.252	4.488	4.588	5.292	5.091
EWMA (8) smoothing	48	4.833	9.252	4.488	4.588	5.292	5.091
EWMA (12) smoothing	48	4.833	9.252	4.488	4.588	5.292	5.091
No smoothing	48	5.895	11.232	5.468	5.536	6.214	6.139
EWMA (4) smoothing	48	5.895	11.232	5.468	5.536	6.214	6.139
EWMA (8) smoothing	48	5.895	11.232	5.468	5.536	6.214	6.139
EWMA (12) smoothing	48	5.895	11.232	5.468	5.536	6.214	6.139

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

Table 6.22 Mean monthly conditional Sharpe ratio of mean-variance long-short portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	0.159	0.036	0.104	0.101	0.065	0.063
EWMA (4) smoothing	47	0.161	0.065	0.134	0.101	0.030	0.060
EWMA (8) smoothing	47	0.174	0.065	0.122	0.088	0.018	0.059
EWMA (12) smoothing	47	0.179	0.066	0.116	0.083	0.017	0.060
No smoothing	47	0.128	0.032	0.072	0.075	0.032	0.036
EWMA (4) smoothing	47	0.125	0.057	0.103	0.079	0.003	0.034
EWMA (8) smoothing	47	0.129	0.057	0.089	0.065	-0.012	0.031
EWMA (12) smoothing	47	0.129	0.059	0.082	0.058	-0.017	0.030
No smoothing	47	0.110	0.032	0.059	0.065	0.009	0.022
EWMA (4) smoothing	47	0.102	0.057	0.086	0.071	-0.015	0.021
EWMA (8) smoothing	47	0.099	0.058	0.072	0.056	-0.033	0.016
EWMA (12) smoothing	47	0.095	0.059	0.065	0.050	-0.040	0.013

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics.

Table 6.23 Mean monthly percentage turnover of mean-variance long-short portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	171.443	396.268	161.238	151.257	75.633	27.777
EWMA (4) smoothing	47	61.791	134.292	58.438	58.558	38.059	13.512
EWMA (8) smoothing	47	34.961	73.971	32.867	33.634	25.186	9.318
EWMA (12) smoothing	47	24.695	51.721	23.118	23.986	19.351	7.469
No smoothing	47	201.928	463.817	203.973	186.061	95.559	50.869
EWMA (4) smoothing	47	75.203	160.545	71.952	70.386	47.166	23.407
EWMA (8) smoothing	47	42.810	88.601	40.662	40.478	31.682	16.051
EWMA (12) smoothing	47	30.352	62.283	28.966	29.138	24.704	12.814
No smoothing	47	247.141	551.018	251.361	224.047	125.700	76.023
EWMA (4) smoothing	47	93.789	193.736	87.844	84.423	60.606	34.386
EWMA (8) smoothing	47	53.270	107.951	50.037	48.711	40.844	23.454
EWMA (12) smoothing	47	37.948	75.561	35.783	35.241	31.941	18.708

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

6.4.3.1 Realised returns

In terms of mean realised monthly returns for long-short portfolios, the impact of smoothing is mixed (Table 6.19). However, in general smoothing has negative impact on realised returns. The ICA model consistently produces better realised returns with smoothing. The size of the impact varies across different models. This could be because of the different correlation and volatility estimates across different models.

For the long-only portfolios, the results are in line with those for the long-short portfolios (Table 6.72). The main difference is that the majority of mean realised returns are negative. This could be because the short selling restriction does not allow a full response to market conditions.

6.4.3.2 Realised cumulative returns

The results for the long-short portfolios provide, in general, the evidence that portfolio smoothing has a negative impact with the exception of ICA, which confirms smoothing has a positive impact across different risk profiles (Table 6.20). This could be because of the different correlation and volatility estimates across different models.

A similar situation can be found for the long-only case (Table 6.73), apart from the fact that ICA no longer provides consistent evidence of a positive impact.

Giamouridis and Vrontos (2007) provided evidence that less frequent rebalancing has a negative impact on cumulative portfolio returns.

6.4.3.3 Standard deviation

The portfolio standard deviation is not affected by portfolio weight smoothing (Table 6.21 and Table 6.74). This is because the smoothing of portfolio weights is done after the optimal portfolio has been found.

6.4.3.4 Conditional Sharpe ratio

In order to compare the returns between models the returns are adjusted for the risk.

In terms of the long-short portfolios, smoothing has a negative impact on EWMA and SMPL, a positive impact on ICA and DCC and a mixed impact on MM and COP (Table 6.22). However, the size of the impact varies across different models.

The situation for long-only portfolios looks a bit different (Table 6.75). The positive impact of smoothing can still be observed on EWMA and SMPL and the mixed impact on MM and COP. However, the impact of smoothing on ICA and DCC is mixed and not positive as it is in the long-short case.

6.4.3.5 Turnover

As expected, the PT results for both long-short and long-only portfolios show a negative impact of weight smoothing across all models across different risk profiles (Table 6.23 and Table 6.76). The main reason for applying weight smoothing was to reduce PT.

6.4.4 The impact of approximated transaction costs on rebalancing benefits

Table 6.24 takes into consideration the impact of approximated transaction costs. This table identifies that after adjusting for transaction costs the returns from using all methodologies are negative. It is interesting to note, however, that the losses using the SMPL method are the lowest and statistically different (Table 6.77–Table 6.80).[9] This can be put down to the much lower transaction costs.

[9] Similar results can be found with respect to the long-only portfolios (Table 6.81–Table 6.85); however, not all the SMPL returns adjusted for approximated transaction costs are statistically different from the other models.

Table 6.24 Mean realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-short portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	-64.981	-151.323	-61.151	-57.358	-28.331	-10.085
EWMA (4) smoothing	47	-23.060	-50.925	-21.875	-21.990	-14.161	-4.654
EWMA (8) smoothing	47	-12.747	-27.837	-12.158	-12.520	-9.305	-3.056
EWMA (12) smoothing	47	-8.794	-19.299	-8.455	-8.851	-7.081	-2.345
No smoothing	47	-76.580	-177.193	-77.633	-70.791	-36.102	-19.014
EWMA (4) smoothing	47	-28.186	-60.979	-27.167	-26.634	-17.808	-8.539
EWMA (8) smoothing	47	-15.792	-33.431	-15.282	-15.278	-11.994	-5.747
EWMA (12) smoothing	47	-11.027	-23.325	-10.847	-10.972	-9.352	-4.514
No smoothing	47	-93.805	-210.569	-95.893	-85.440	-47.776	-28.732
EWMA (4) smoothing	47	-35.289	-73.683	-33.367	-32.122	-23.111	-12.838
EWMA (8) smoothing	47	-19.834	-40.829	-19.010	-18.566	-15.702	-8.693
EWMA (12) smoothing	47	-14.000	-28.388	-13.610	-13.456	-12.344	-6.893

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean realised monthly portfolio returns adjusted for the approximated mean monthly portfolio transaction costs i.e. $Mean\ realised\ return - Mean\ transaction\ costs$*. The approximated mean monthly portfolio transaction costs are calculated as the mean monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points.*[10,11] *Values are expressed in percentages*

[10] The approximated mean monthly portfolio transaction costs can be found in the appendix in Table 6.86.

[11] There are a number of different estimates of transaction costs. For example, Sun *et al.* (2006) find that the transaction costs are 60 basis points for emerging markets, 40 basis points for developed markets and 30 basis points for US equity. French (2008) estimates the trading costs on US market to be 11 basis points. DeMiguel *et al.* (2009a) use 50 basis points as transaction costs. The estimated 38.2 basis points is the average of these values.

These findings clearly support the comments on rebalancing made by professional practitioners. For example, Morningstar (2013) says:

‘Do not rebalance too often: You needn’t worry about rebalancing every quarter, or even every year. Morningstar has found that investors who rebalance their investments at 18-month intervals reaped many of the same benefits as those who rebalanced more often. Moreover, investors who rebalance less frequently save themselves unnecessary labour and, in the case of taxable investments, a good bit of money.’

Even though the time-varying methods indicate optimal rebalancing of between 75.633% and 551.018% per month for unconstrained rebalancing (Table 6.1), perhaps we should consider rebalancing only on annual basis. For instance, Kaegi (2012) states:

‘…too frequent rebalancing results in high transaction costs… In our view, yearly rebalancing is an appropriate frequency for most private investors with a meaningfully long investment horizon.’

As a caveat, if we refer back to Table 6.24 it can be noted that smoothing has a positive impact on reducing the losses for all models. This can possibly be put down to the reduced PT (Table 6.23). Examining this issue in more detail is, however, beyond the scope of this thesis.

6.5 Discussion

Discussing the results in terms of in attempting to distinguish between ‘good’ and ‘bad’ models is problematical. Engle and Sheppard (2008), using different performance criteria to test covariance models, failed to *consistently* identify that one model is superior to the others.

For example, they found that the comparisons made in terms of simple specification tests were disappointing. Engle and Sheppard (2008) suggested:

'Some flaws in the models, specifically the failure of many of the specifications to adequately capture variation in the conditional *variances*, can be easily addressed in some of the models examined. The correlation models can be trivially enhanced by choosing series specific univariate specifications to better describe the dynamics of the data. Alternatively, additional lags of innovations or conditional variances may be adequate to improve the properties of the forecast standardised residuals.'

In this thesis I have followed the methodology suggested by Engle and Sheppard (2008) and have tested different GARCH specifications in terms of modelling volatility in order to address this issue. An interesting feature I found was the differences in correlations at different points of the market cycle (Chapters 4 and 5). These results confirm what other people in literature have found (Bekaert and Wu 2000, Longin and Solnik 2001, You and Daigler 2010). Those differences in correlation, as well as the volatilities, have an impact on PT rates but, as found in this thesis, have no impact on portfolio returns.

The main findings of this chapter are that there is not much difference in terms of portfolio performance between different covariance models with respect to the mean realised returns and mean risk-adjusted returns (Table 6.1–Table 6.3 and Table 6.6). This is surprising as we had expected COP to outperform DCC and the two would outperform GO-GARCH MM and ICA, and the two benchmarks we use, namely EWMA and SMPL.

The advantage of using the DCC and COP models over the standard SMPL approach in the portfolio performance context was found by Righi and Ceretta (2012). In addition, they show the superiority of COP over standard DCC. This is in contrast to my findings and could be because of the use of difference performance criteria. They examine variance difference and relative reduction rather than returns as I do.

The *ex post* returns of high-risk DCC-based portfolios are significantly higher than high-risk SMPL-based portfolios (Jithendranathan 2007). However, for low risk the *ex post* returns are not significantly different from each other. My results do not prove the superiority of DCC returns over SMPL in terms of portfolio returns for all three risk profiles.

Mean realised portfolio returns based on time-varying models are generally statistically higher than from those based on the SPML model but only for low-risk portfolios. They are not different from each other in high-risk portfolios. This was found by Giamouridis and Vrontos (2007) in their study. These results to some extent correspond to my results. However, when they consider the risk-adjusted returns they find that all models produce statistically different results. This is not in line with my findings. As far as the portfolio turnover is concerned, they admit that the SPML model achieves a substantially lower turnover irrespective of the risk level. This is exactly what my findings suggest. In terms of portfolio weights, they find that there is more variability in portfolio composition for high-risk portfolios than for low-risk portfolios. This is line with my results.

DCC, EWMA and two other time-varying models do not provide empirically different results in terms of portfolio performance, i.e. return, risk and risk-adjusted returns (Syriopoulos and Roumpis 2009). Apart from portfolio risk, these empirical conclusions are in line with my analysis.

What is clear from this evidence is that using different performance criteria can result in very different conclusions. The fact that there are no clear rules for choosing the performance criteria means that it is very hard to make direct comparisons between many of the studies found in the literature. It really depends on the objective of the researcher or practitioner.

One of the reasons I do not find outperformance in terms of returns may be that DCC assumes that the conditional correlation dynamic (ARMA-type) structure is the same for all the assets. In other words, the degree of sensitivity of correlation to news is the same for all the assets (Hafner and Franses 2009). Using data from my study, I have estimated four DCC models based on nine assets, US & EMU, US & EM BRIC and US & EFM Africa. The estimates of DCC equations are presented in Table 6.25.

Table 6.25 Conditional correlation equation parameter estimates for four DCC models

DCC	NINE ASSETS	TWO ASSETS: US & EMU	TWO ASSETS: US & EM BRIC	TWO ASSETS: US & EFM AFRICA
α	0.023365	0.053713	0.028835	0.054911
β	0.937110	0.720979	0.916123	0.873650

Notes: Estimation based on 513 observations (from 19 July 2002 to 11 May 2012) using R (2013) and RM-GARCH package (Ghalanos, 2012). DCC equation: $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha v_{t-1} v'_{t-1} + \beta Q_{t-1}$, *where* v_t *represents standardised residuals by their conditional standard deviation.*

The results in Table 6.25 suggest in the context of my data set that using one structure for all correlations may be too restrictive. To overcome that simplification would be to allow different dynamics for each correlation. For example, the asymmetric generalised DCC model can address this issue (Cappiello *et al.* 2006). However, the generalisation comes at cost of additional parameters and complexity. Interestingly, for small size portfolios DCC performs well in a non-return context (Engle and Sheppard 2001) even in comparison with generalised DCC (Hafner and Franses 2009). In my thesis I have a small size portfolio that consists of nine assets.

Another possible reason for the poor performance of the multivariate GARCH models could be because of the difficulty of obtaining reliable estimates of model parameters. Finding estimates in local optima rather than in global optima biases the results (Engle and Sheppard 2008). In order to avoid problems associated with estimating conditional means, comparison of the different covariance models should be performed in terms of global MVP (Engle and Sheppard 2008).

One of the possible limitations of the GO-GARCH models used in my thesis is that they are based on the constant mixing matrix. This could mean that they may not be the most efficient models (van der Weide 2002).

I have identified the non-normality in the data (Table 3.1 and Table 3.2 in Chapter 3). According to the literature, fat tails as well as asymmetry in the data can be modelled to some extend by the GARCH models (Bolerslev 1986, He and Teräsvirta 1999a, He and Teräsvirta 1999b, Zivot 2013, Zivot and Wang 2006). Our expectations were that COP would outperform DCC as the skew Student t distribution for margins with Student copula, which is used in our COP model, is designed to capture the asymmetry and fat tails of empirical distribution. COP did not, however, outperform DCC in my thesis. This suggests that distribution-based differences were not substantial enough to have a discernible impact on portfolio performance. We can speculate this may potentially have been because of the impact of the financial crisis on the distribution.

As indicated by several papers in the literature comparing relative performances of time-varying methodologies is difficult (Engle and Sheppard 2008). Using different performance criteria can result in very different conclusions. The fact that there are no clear rules for choosing the performance criteria means that it is very hard to make direct comparisons between many of the studies found in the literature. It really depends on the objective of the researcher or practitioner.

6.6 CONCLUSIONS

The main finding of this chapter is that market conditions have a big impact on changes on correlations, which in turn have a significant impact on portfolio weights and therefore levels of turnover/transactions. Rather surprisingly, however, there is no corresponding increase in portfolio performance in terms of returns. If transaction costs are also taken into account the cost of rebalancing more than outweigh any benefits associated with it. I also find that the developed and emerging/frontier markets categorisations are of limited use when it comes to determining portfolio weightings.

6.7 APPENDICES

Figure 6.17 Realised monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

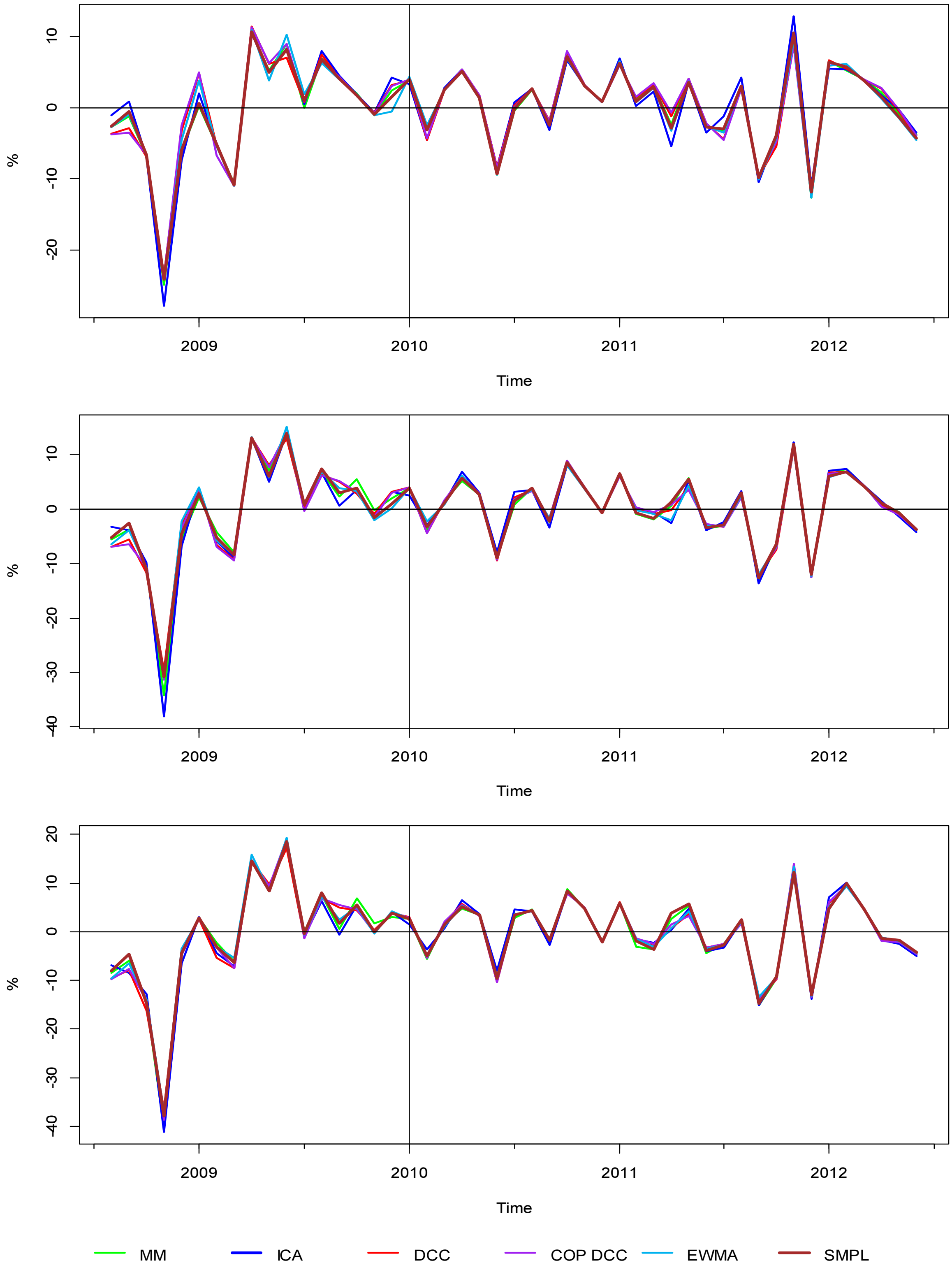


Figure 6.18 Realised cumulative monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

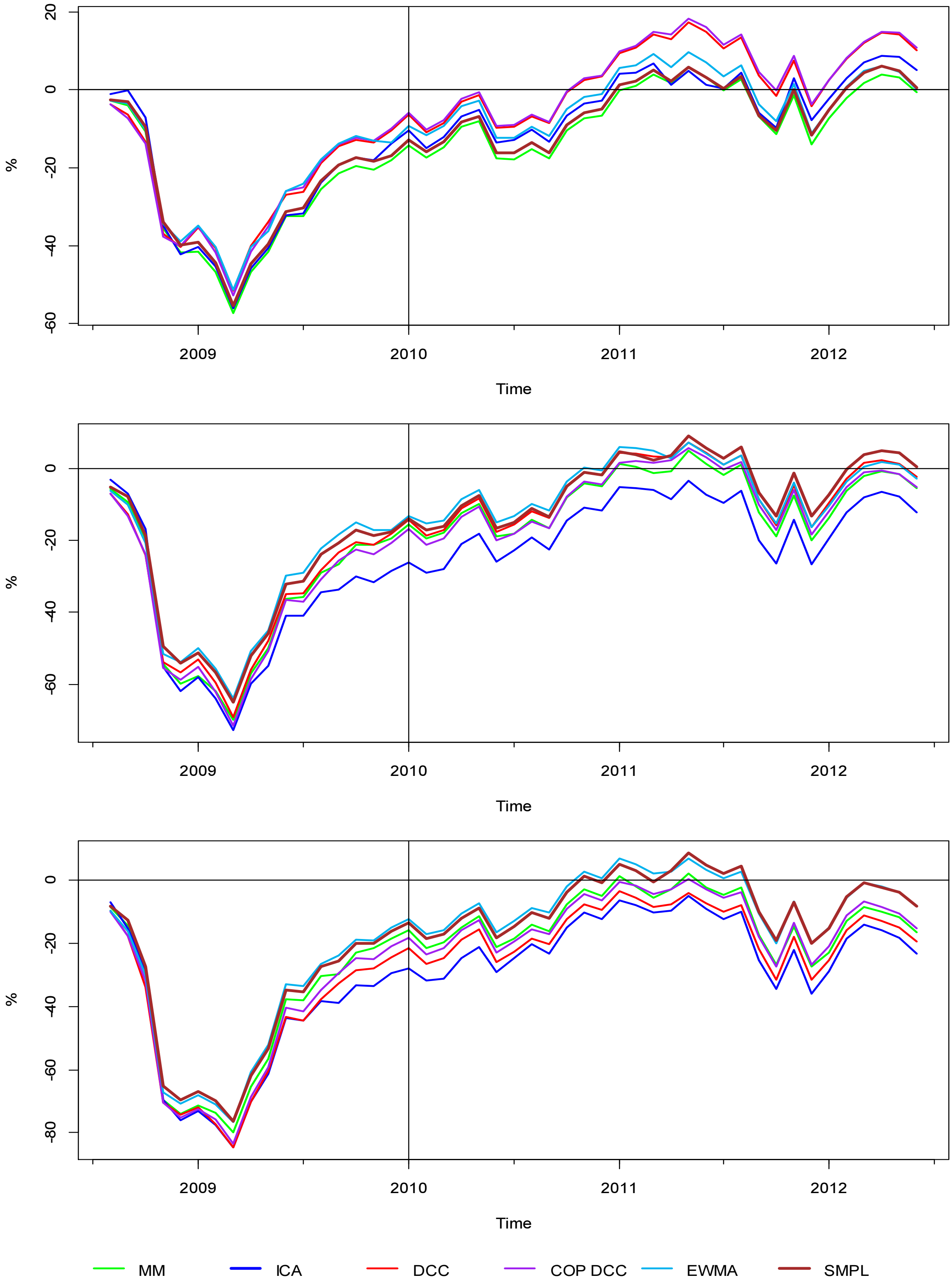


Figure 6.19 Monthly percentage standard deviation of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

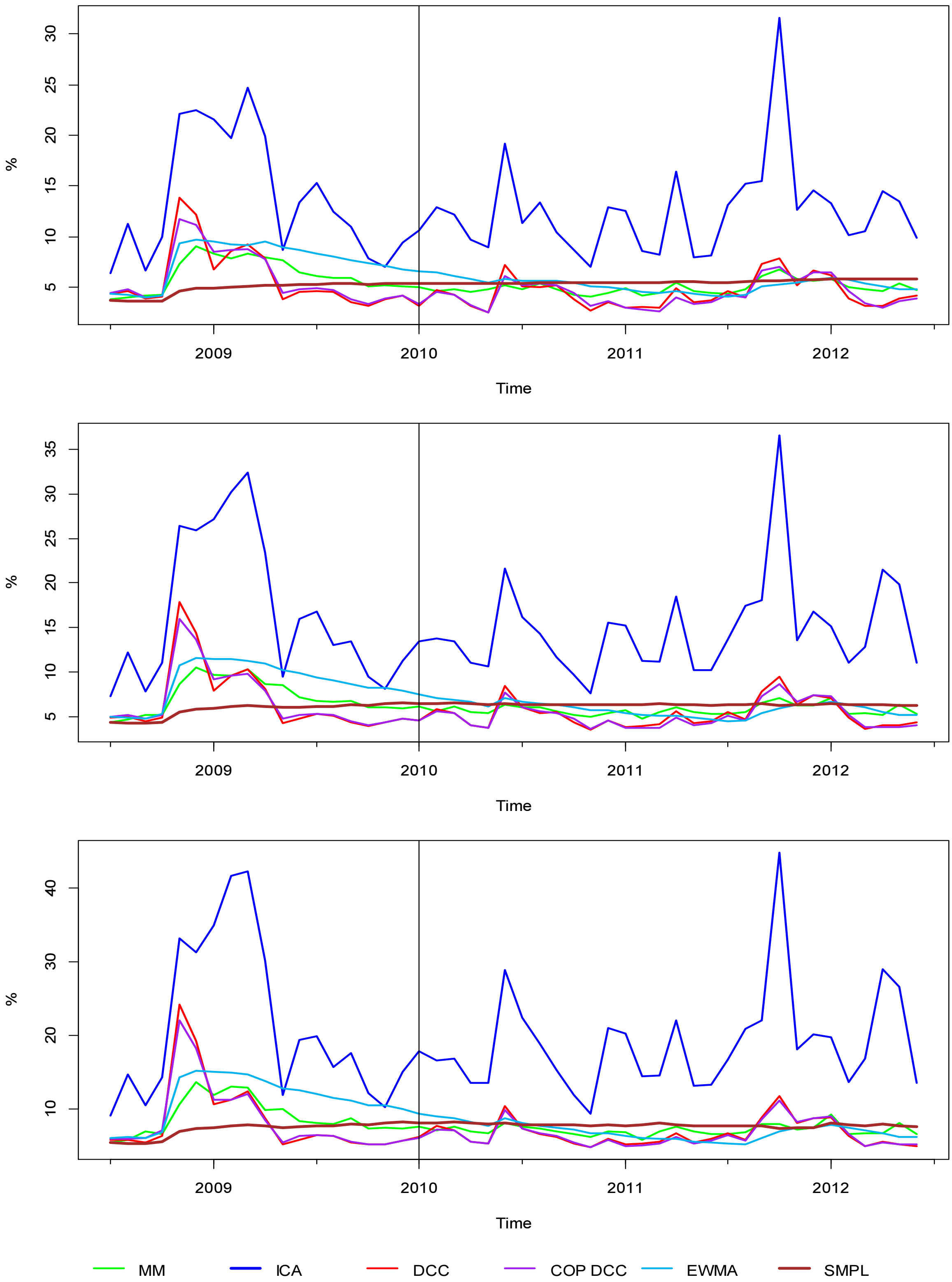


Figure 6.20 Monthly conditional Sharpe ratio of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

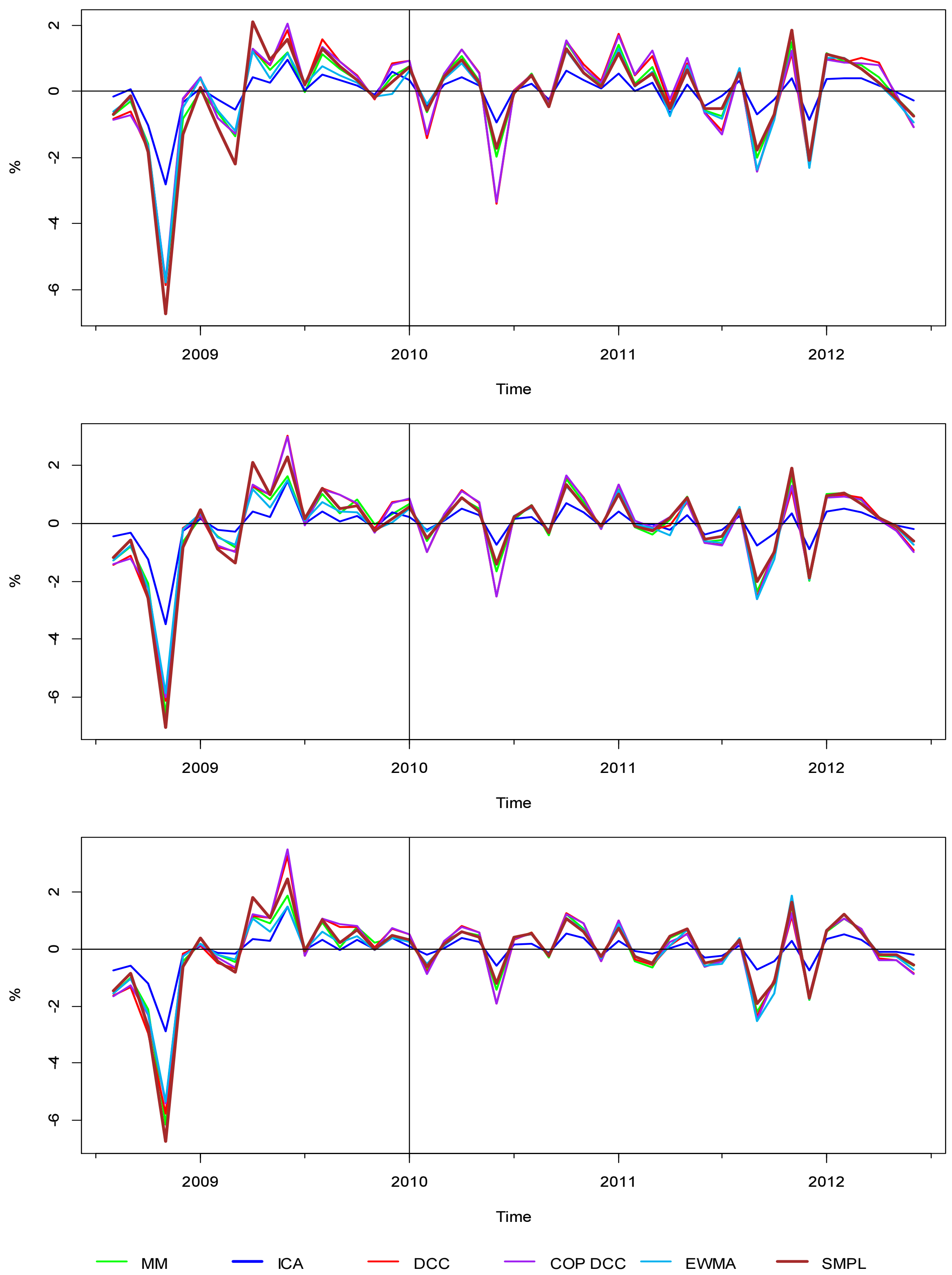


Figure 6.21 Monthly percentage turnover of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

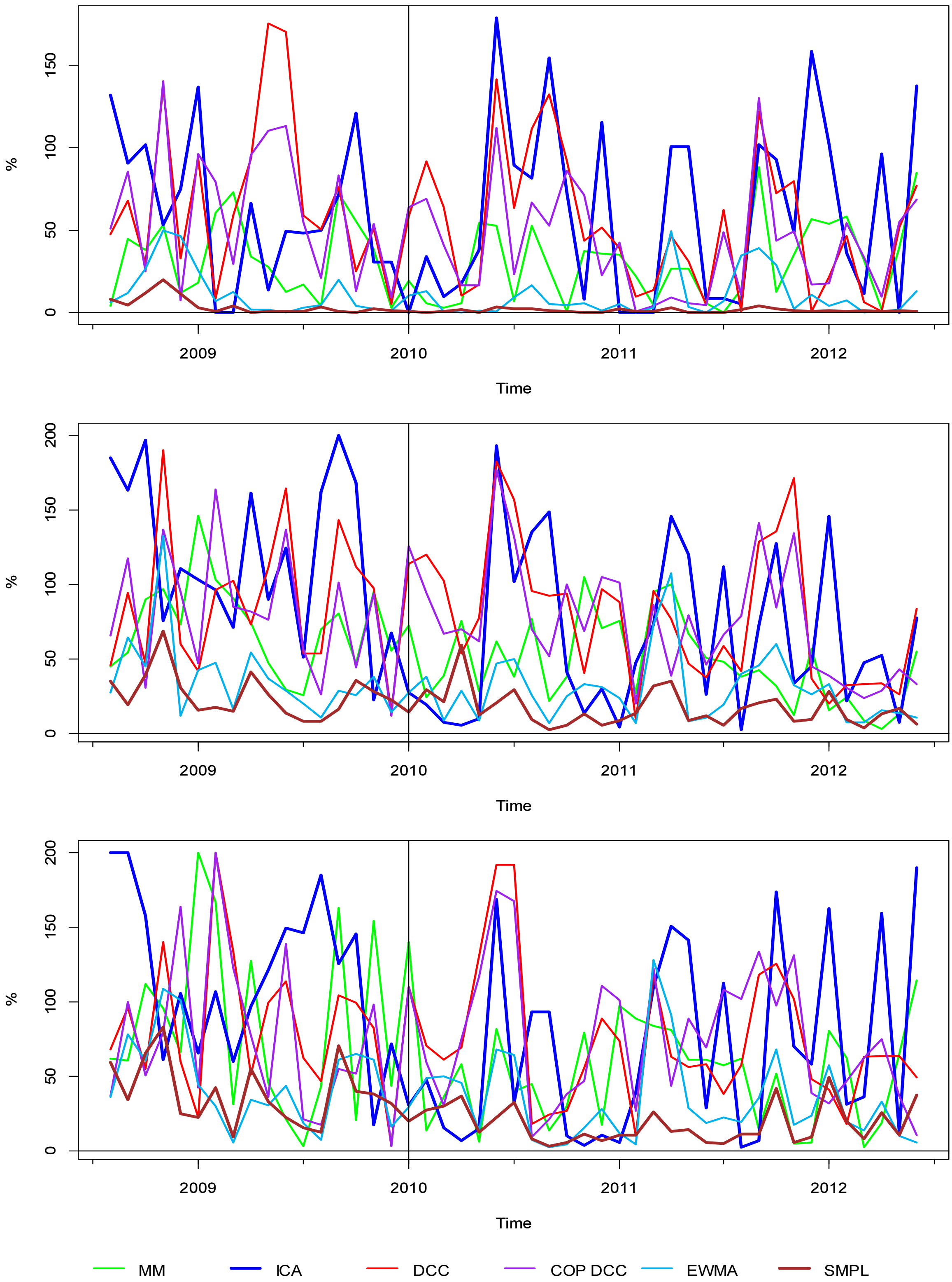


Figure 6.22 Monthly percentage US weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

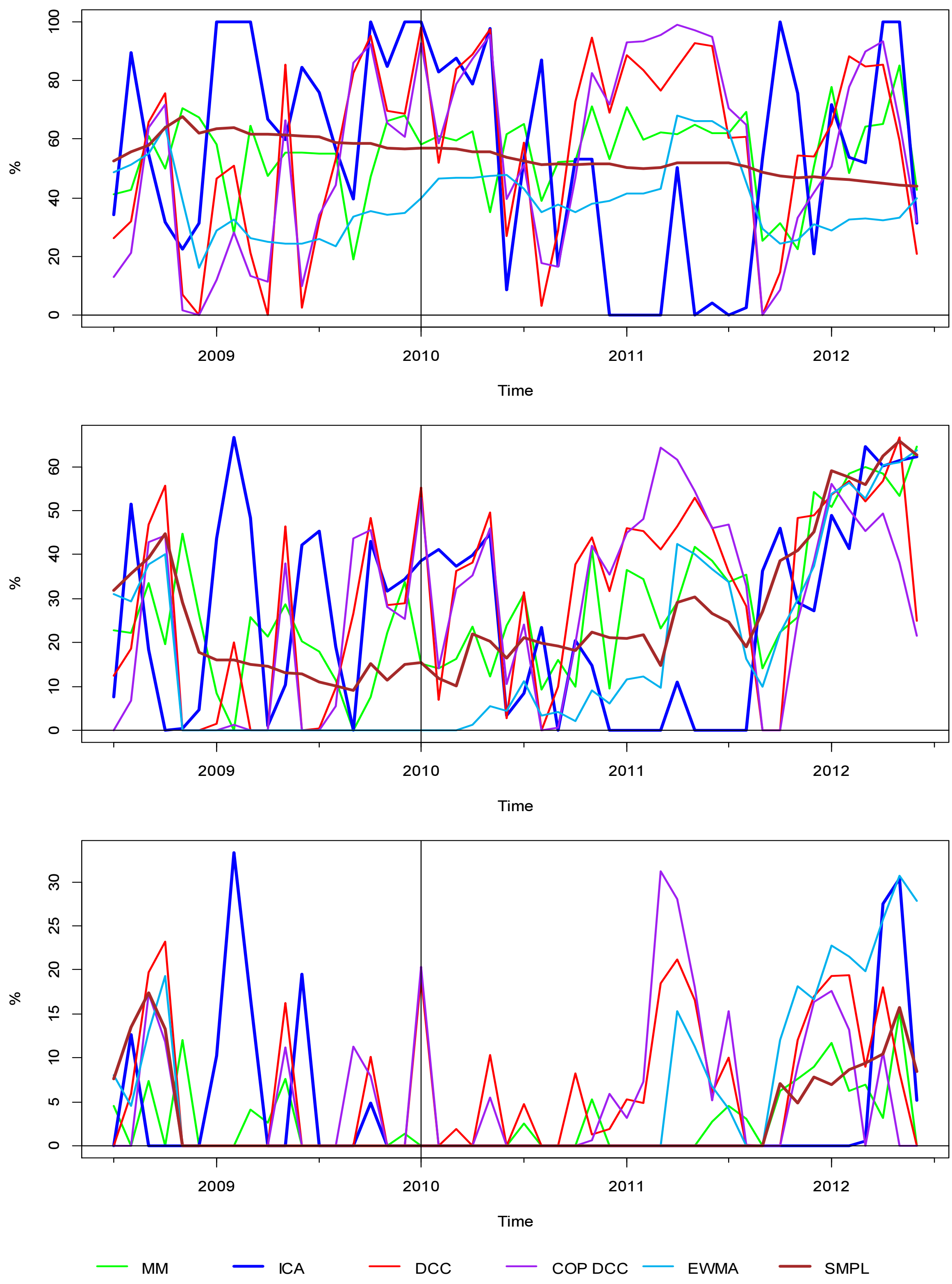


Figure 6.23 Monthly percentage EMU weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

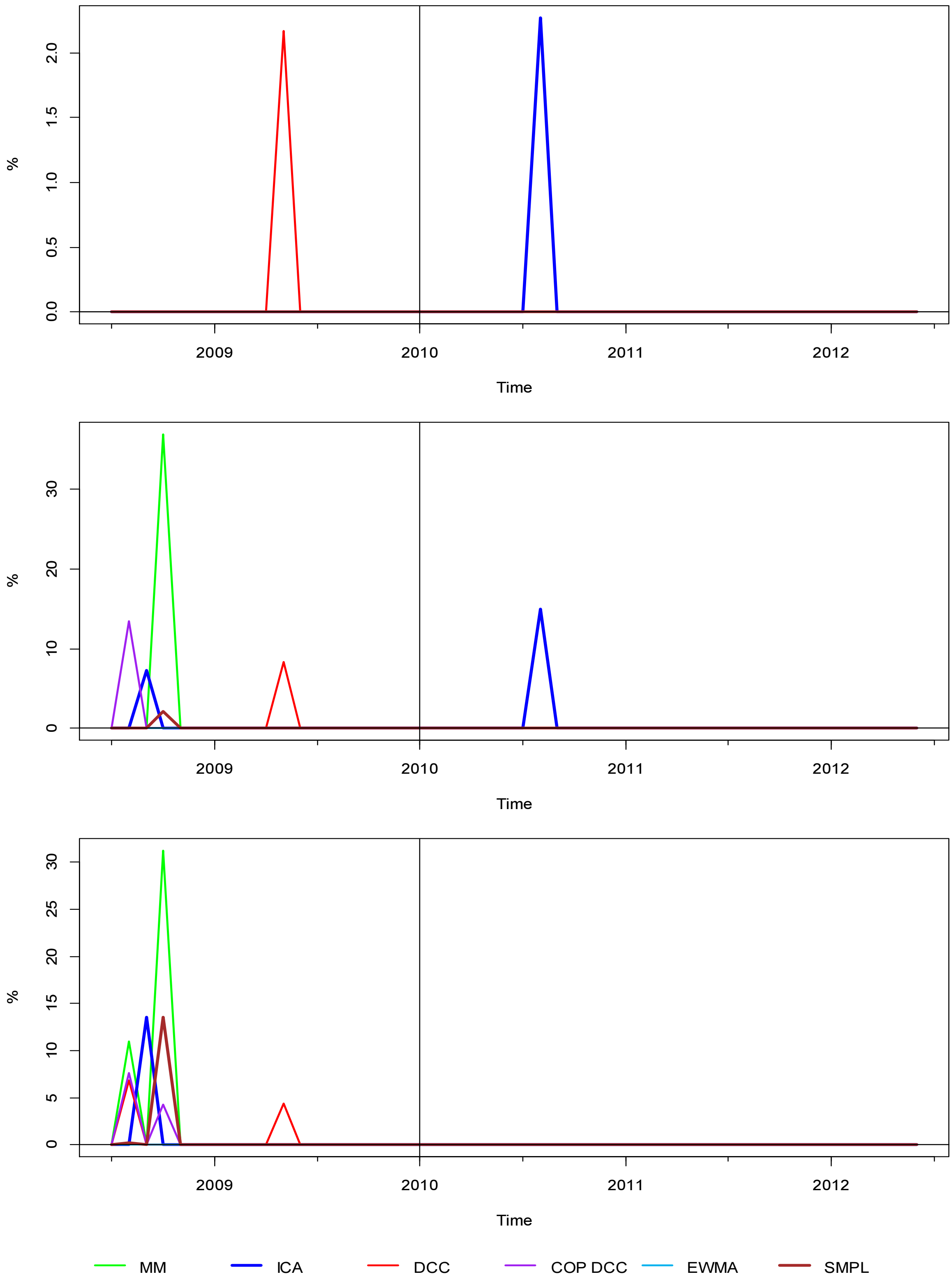


Figure 6.24 Monthly percentage Europe ex EMU weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

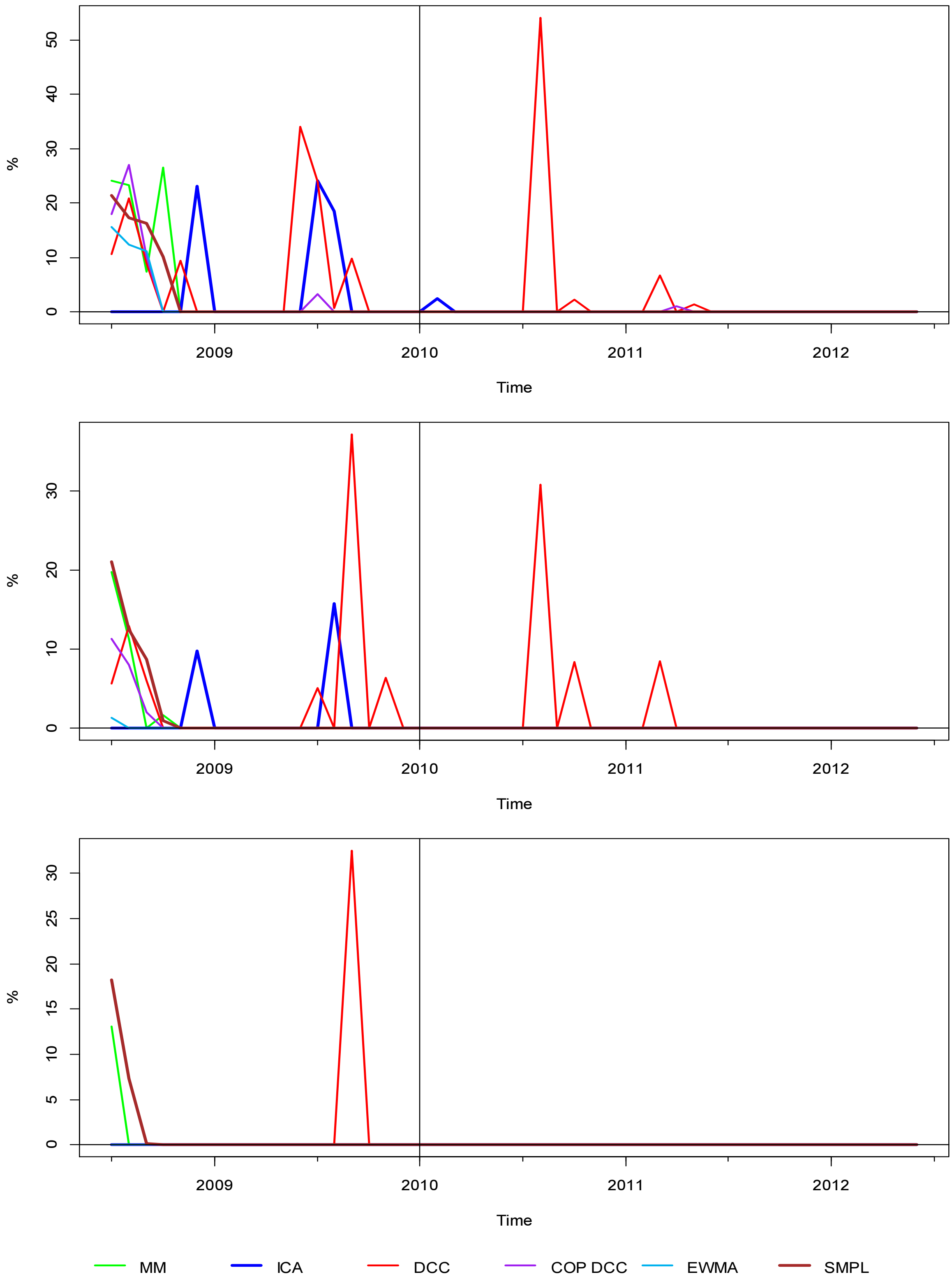


Figure 6.25 Monthly percentage Pacific weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

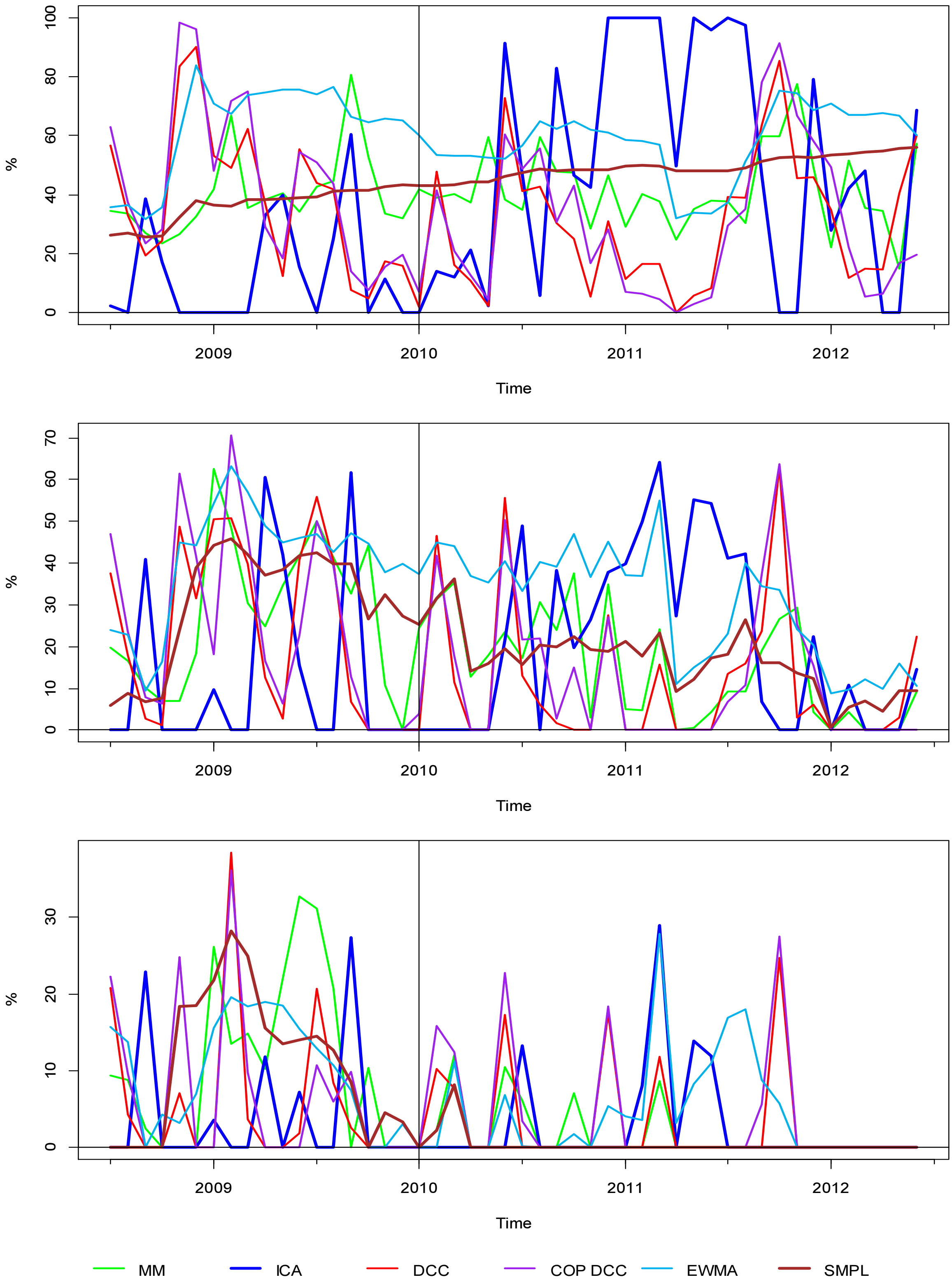


Figure 6.26 Monthly percentage EM BRIC weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

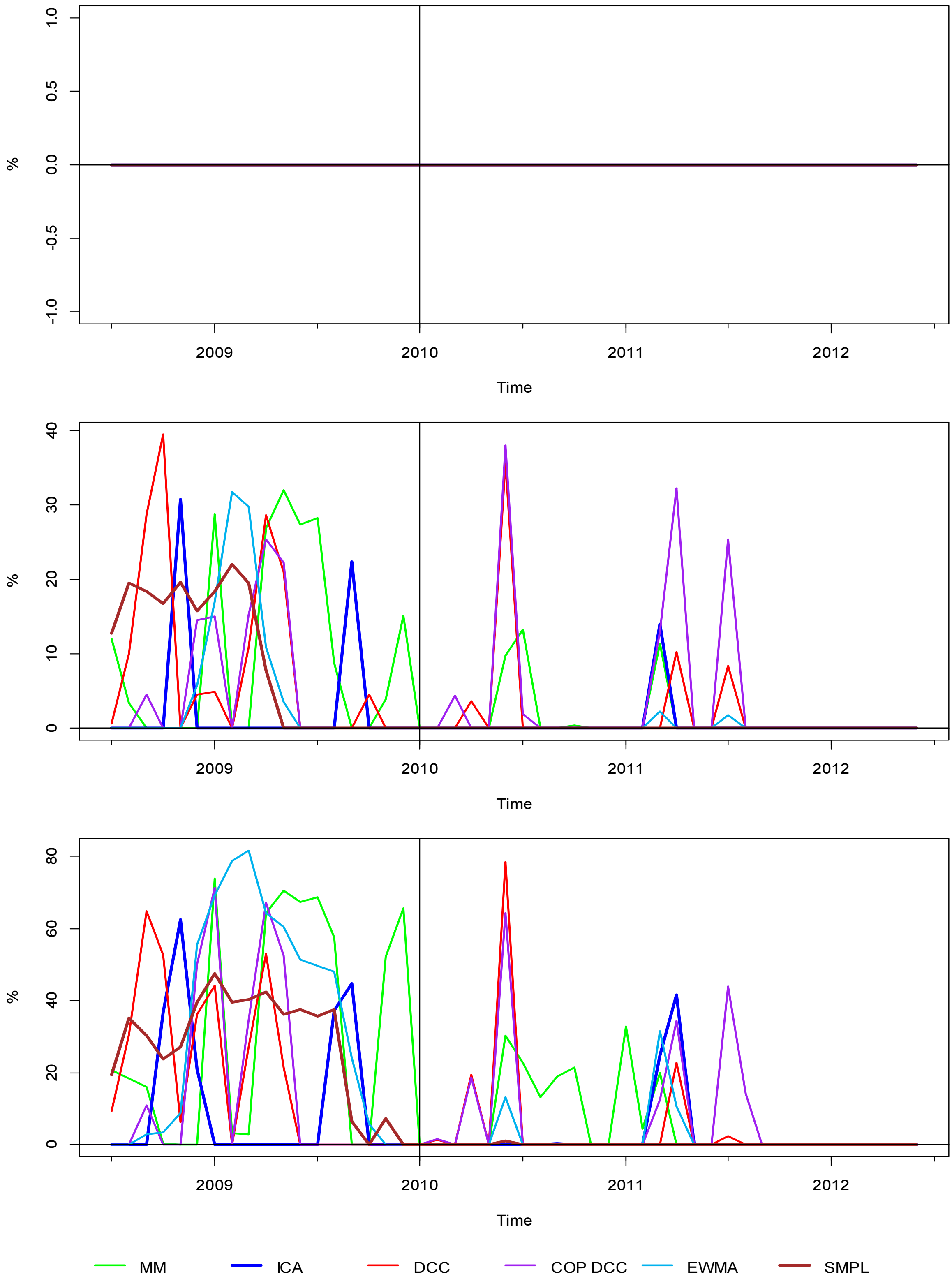


Figure 6.27 Monthly percentage EM Europe weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

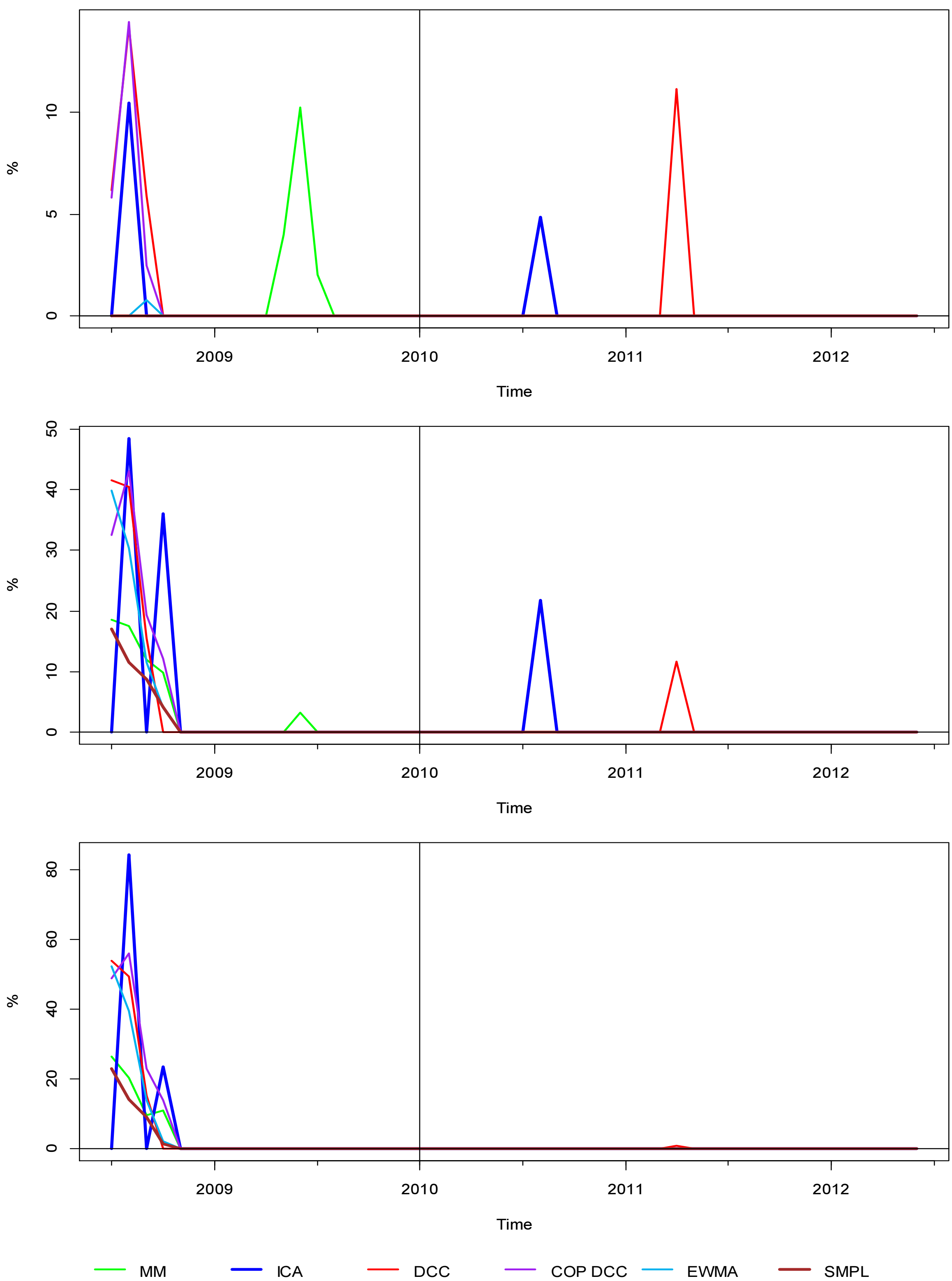


Figure 6.28 Monthly percentage EM Latin America weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

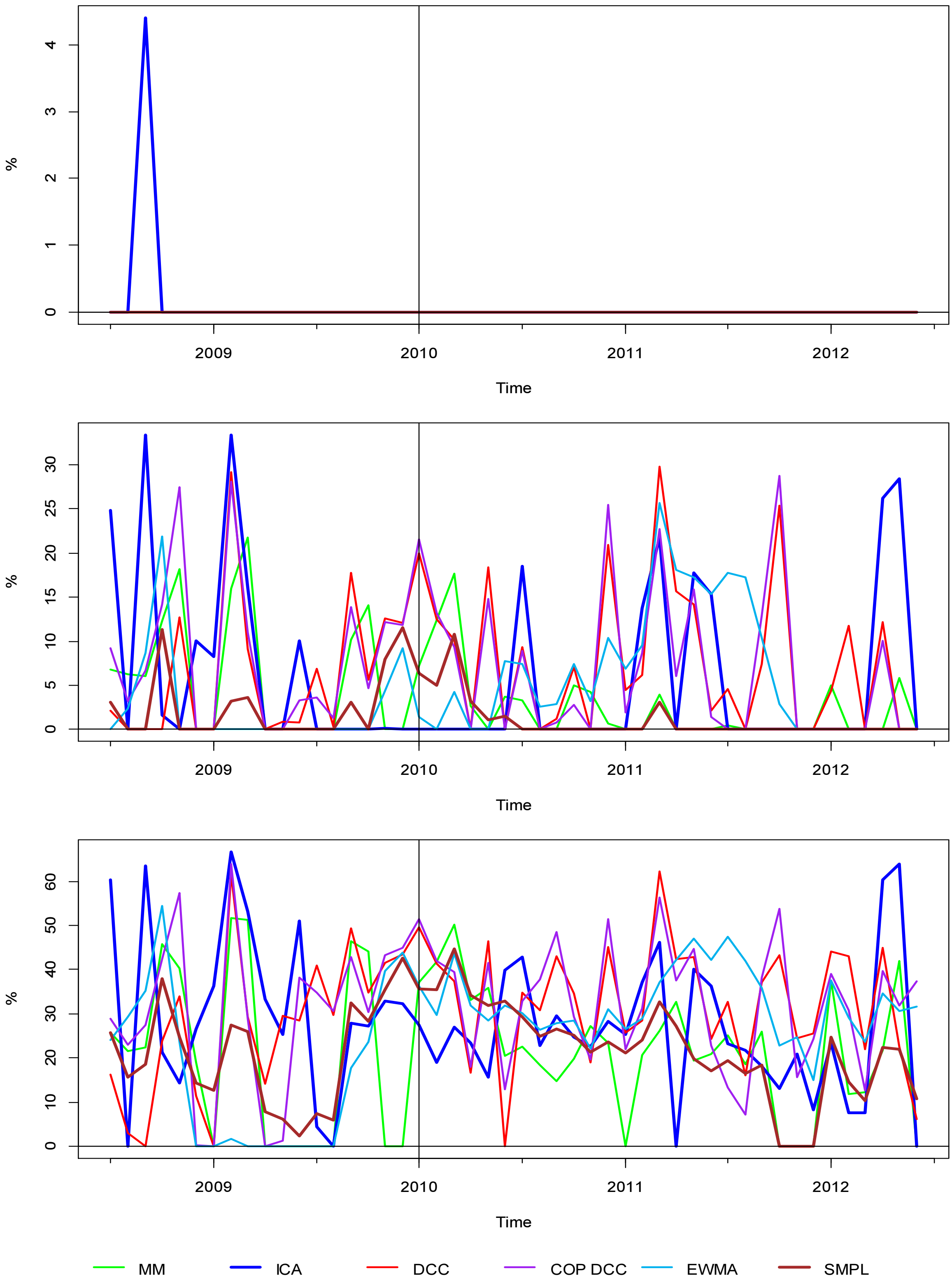


Figure 6.29 Monthly percentage EM Asia weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

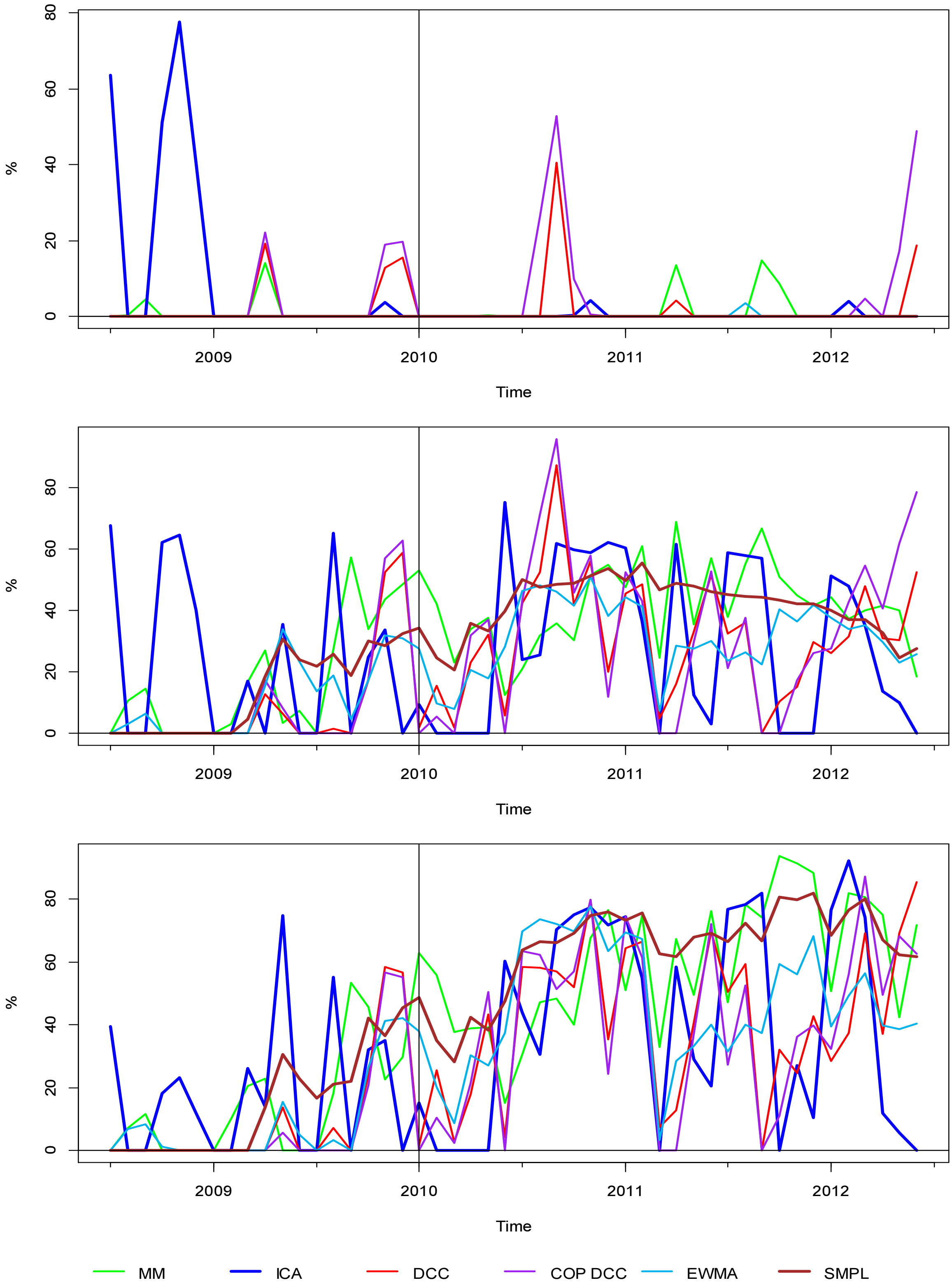


Figure 6.30 Monthly percentage EMF Africa weight of mean-variance long-only portfolios between models for the 72-month estimation period

Note: Top, middle and bottom graphs represent low, medium and high risk respectively.

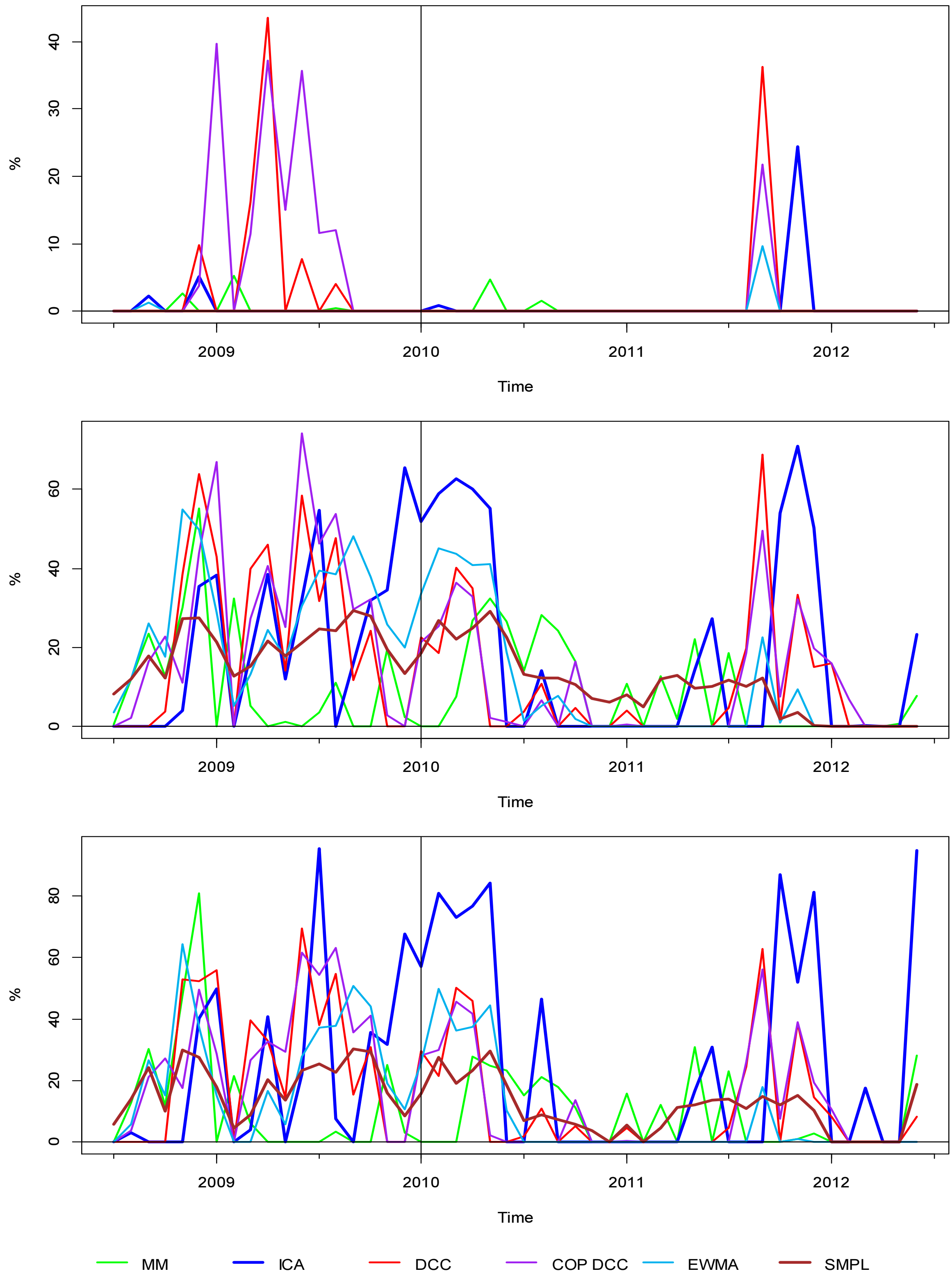


Table 6.26 Performance metrics of mean-variance long-only portfolios between models for the 72-month estimation period

Portfolio statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Realised Return	47	-0.014	0.107	0.215	0.230	0.001	0.010
Realised Cumulative Return	47	-14.283	-11.594	-6.690	-6.343	-9.814	-12.797
Standard Deviation	48	5.437	12.980	4.971	4.939	6.116	5.270
Conditional Sharpe Ratio	47	-0.046	-0.020	-0.022	-0.012	-0.093	-0.072
Turnover	47	31.275	61.233	58.427	49.288	10.816	2.417
Realised Return	47	-0.115	-0.257	-0.051	-0.113	-0.062	0.011
Realised Cumulative Return	47	-18.722	-24.454	-16.657	-18.739	-14.699	-14.639
Standard Deviation	48	6.327	15.508	5.854	5.782	6.985	6.118
Conditional Sharpe Ratio	47	-0.092	-0.052	-0.078	-0.071	-0.121	-0.076
Turnover	47	55.974	83.758	82.459	76.715	32.026	19.663
Realised Return	47	-0.347	-0.496	-0.412	-0.324	-0.175	-0.174
Realised Cumulative Return	47	-23.231	-29.823	-27.401	-24.376	-18.360	-18.723
Standard Deviation	48	7.896	19.827	7.422	7.340	8.707	7.642
Conditional Sharpe Ratio	47	-0.123	-0.060	-0.114	-0.082	-0.141	-0.099
Turnover	47	63.800	85.925	77.669	76.327	38.304	25.603

Notes: The sample runs from 31 July 2008 (30 June 2008 for standard deviation) to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages apart from conditional Sharpe ratio.

Table 6.27 Performance metrics of mean-variance long-only portfolios between models for the 72-month estimation period based on ranks

Portfolio statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Realised Return	47	3.234	3.638	3.979	3.936	2.872	3.340
Realised Cumulative Return	47	1.277	3.043	4.596	5.255	4.213	2.617
Standard Deviation	48	3.000	5.958	2.292	2.438	3.896	3.417
Conditional Sharpe Ratio	47	3.511	3.064	3.915	4.085	3.106	3.319
Turnover	47	3.702	4.340	4.617	4.511	2.468	1.362
Realised Return	47	3.404	3.574	3.532	3.340	3.383	3.766
Realised Cumulative Return	47	2.553	1.340	4.043	2.489	5.277	5.298
Standard Deviation	48	3.188	5.958	2.396	2.229	3.854	3.375
Conditional Sharpe Ratio	47	3.532	3.255	3.745	3.447	3.298	3.723
Turnover	47	3.702	4.191	4.596	4.511	2.362	1.638
Realised Return	47	3.511	3.149	3.277	3.319	3.830	3.915
Realised Cumulative Return	47	3.745	1.383	1.915	3.106	5.468	5.383
Standard Deviation	48	3.271	5.958	2.375	2.292	3.708	3.396
Conditional Sharpe Ratio	47	3.489	3.340	3.532	3.511	3.319	3.809
Turnover	47	3.723	4.149	4.255	4.170	2.702	2.000

Notes: The sample runs from 31 July 2008 (30 June 2008 for standard deviation) to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages apart from conditional Sharpe ratio.

Table 6.28 Composition of mean-variance long-only portfolios between models for the 72-month estimation period

Portfolio constituents	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
US	48	55.253	55.586	57.427	54.917	39.029	54.188
EMU	48	0.000	0.047	0.045	0.000	0.000	0.000
EUROPE ex EMU	48	1.699	1.419	3.814	1.237	0.815	1.352
PACIFIC	48	41.239	36.763	33.168	34.834	59.839	44.460
EM BRIC	48	0.000	0.000	0.000	0.000	0.000	0.000
EM EUROPE	48	0.338	0.319	0.779	0.473	0.016	0.000
EM LATIN AMERICA	48	0.000	0.092	0.000	0.000	0.000	0.000
EM ASIA	48	1.166	5.096	2.320	4.610	0.072	0.000
EMF AFRICA	48	0.306	0.677	2.448	3.929	0.229	0.000
US	48	27.589	25.604	29.961	27.477	17.424	26.637
EMU	48	0.769	0.463	0.173	0.281	0.000	0.043
EUROPE ex EMU	48	0.682	0.532	2.521	0.444	0.028	0.902
PACIFIC	48	19.652	17.734	16.002	17.336	33.997	21.873
EM BRIC	48	4.605	1.401	4.408	4.410	2.142	3.553
EM EUROPE	48	1.277	2.216	2.275	2.230	1.786	0.867
EM LATIN AMERICA	48	3.826	5.821	7.240	7.410	4.893	1.557
EM ASIA	48	31.979	26.946	22.369	23.957	23.750	30.839
EMF AFRICA	48	9.622	19.283	15.050	16.454	15.980	13.728
US	48	2.592	3.356	6.436	5.575	5.789	2.737
EMU	48	0.879	0.282	0.233	0.249	0.000	0.287
EUROPE ex EMU	48	0.272	0.000	0.678	0.000	0.000	0.534
PACIFIC	48	5.189	3.101	4.103	4.898	6.599	4.351
EM BRIC	48	15.545	5.612	9.799	9.934	13.750	10.569
EM EUROPE	48	1.404	2.244	2.482	2.955	2.241	0.998
EM LATIN AMERICA	48	21.428	28.198	30.811	31.726	26.279	21.640
EM ASIA	48	42.320	32.253	29.013	27.700	32.045	45.489
EMF AFRICA	48	10.371	24.955	16.447	16.962	13.297	13.396

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly weights. Values are expressed in percentages.

Table 6.29 Composition of mean-variance long-only portfolios between models for the 72-month estimation period based on ranks

Portfolio constituents	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
US	48	3.813	3.875	3.896	3.583	2.313	3.521
EMU	48	3.479	3.542	3.542	3.479	3.479	3.479
EUROPE ex EMU	48	3.448	3.448	3.844	3.500	3.313	3.448
PACIFIC	48	3.333	2.917	2.781	3.115	5.146	3.708
EM BRIC	48	3.500	3.500	3.500	3.500	3.500	3.500
EM EUROPE	48	3.552	3.469	3.646	3.563	3.406	3.365
EM LATIN AMERICA	48	3.490	3.552	3.490	3.490	3.490	3.490
EM ASIA	48	3.583	3.698	3.490	3.854	3.219	3.156
EMF AFRICA	48	3.479	3.573	3.615	3.802	3.344	3.188
US	48	3.885	3.438	4.052	3.438	2.333	3.854
EMU	48	3.510	3.563	3.500	3.500	3.438	3.490
EUROPE ex EMU	48	3.479	3.396	3.844	3.406	3.292	3.583
PACIFIC	48	3.333	3.177	2.719	2.958	5.271	3.542
EM BRIC	48	3.781	3.146	3.656	3.625	3.281	3.510
EM EUROPE	48	3.510	3.531	3.573	3.594	3.448	3.344
EM LATIN AMERICA	48	3.344	3.250	4.146	4.021	3.604	2.635
EM ASIA	48	4.375	3.344	2.948	3.250	2.969	4.115
EMF AFRICA	48	3.292	3.542	3.292	3.604	3.542	3.729
US	48	3.292	3.010	4.188	3.760	3.677	3.073
EMU	48	3.583	3.469	3.521	3.521	3.406	3.500
EUROPE ex EMU	48	3.500	3.448	3.510	3.448	3.448	3.646
PACIFIC	48	3.594	3.135	3.219	3.500	4.146	3.406
EM BRIC	48	3.969	3.125	3.375	3.417	3.656	3.458
EM EUROPE	48	3.448	3.490	3.594	3.615	3.510	3.344
EM LATIN AMERICA	48	2.823	3.375	4.135	4.281	3.583	2.802
EM ASIA	48	4.135	3.375	3.021	2.844	3.344	4.281
EMF AFRICA	48	3.323	3.677	3.521	3.625	3.094	3.760

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly weights. Values are expressed in percentages.

Table 6.30 Descriptive statistics of realised monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	-24.903	-27.923	-23.643	-23.791	-24.081	-24.199
Maximum	47	10.700	12.905	11.451	11.396	10.999	10.721
Mean	47	**-0.014**	**0.107**	**0.215**	**0.230**	**0.001**	**0.010**
Median	47	1.206	1.664	1.722	1.744	1.226	1.054
Standard Deviation	47	6.526	6.893	6.427	6.508	6.470	6.417
Coefficient of Variation	47	**-467.230**	**64.605**	**29.943**	**28.310**	**4864.304**	**640.831**
Minimum	47	-34.206	-38.124	-29.718	-31.409	-30.771	-30.823
Maximum	47	13.756	13.885	13.104	14.156	15.133	13.879
Mean	47	**-0.115**	**-0.257**	**-0.051**	**-0.113**	**-0.062**	**0.011**
Median	47	0.776	0.684	0.824	0.753	0.753	1.113
Standard Deviation	47	7.996	8.393	7.647	7.833	7.617	7.627
Coefficient of Variation	47	**-69.669**	**-32.620**	**-150.987**	**-69.242**	**-122.624**	**681.746**
Minimum	47	-40.499	-41.237	-36.629	-38.641	-37.187	-37.827
Maximum	47	18.696	17.733	17.163	19.064	19.308	18.595
Mean	47	**-0.347**	**-0.496**	**-0.412**	**-0.324**	**-0.175**	**-0.174**
Median	47	1.651	-0.202	0.772	1.462	0.726	1.477
Standard Deviation	47	9.338	9.361	9.082	9.265	8.995	9.033
Coefficient of Variation	47	**-26.892**	**-18.879**	**-22.042**	**-28.554**	**-51.373**	**-51.807**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.31 Descriptive statistics of realised cumulative monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	-57.375	-56.158	-51.594	-52.810	-51.263	-55.292
Maximum	47	5.821	8.774	17.190	18.283	9.562	6.041
Mean	47	**-14.283**	**-11.594**	**-6.690**	**-6.343**	**-9.814**	**-12.797**
Median	47	-10.669	-6.985	-4.233	-3.802	-8.007	-9.597
Standard Deviation	47	15.992	16.766	17.852	18.268	15.143	15.679
Coefficient of Variation	47	**-1.120**	**-1.446**	**-2.669**	**-2.880**	**-1.543**	**-1.225**
Minimum	47	-70.016	-72.884	-69.048	-71.501	-64.078	-65.121
Maximum	47	4.861	-3.243	7.103	5.774	7.151	9.061
Mean	47	**-18.722**	**-24.454**	**-16.657**	**-18.739**	**-14.699**	**-14.639**
Median	47	-14.247	-20.006	-12.623	-14.919	-10.471	-11.253
Standard Deviation	47	19.559	18.473	19.937	20.008	18.610	19.269
Coefficient of Variation	47	**-1.045**	**-0.755**	**-1.197**	**-1.068**	**-1.266**	**-1.316**
Minimum	47	-79.805	-84.683	-84.697	-83.281	-76.535	-76.346
Maximum	47	2.329	-5.040	-3.471	0.360	6.925	8.716
Mean	47	**-23.231**	**-29.823**	**-27.401**	**-24.376**	**-18.360**	**-18.723**
Median	47	-16.320	-24.557	-21.294	-17.882	-12.285	-12.692
Standard Deviation	47	22.117	21.076	21.691	22.699	22.967	22.696
Coefficient of Variation	47	**-0.952**	**-0.707**	**-0.792**	**-0.931**	**-1.251**	**-1.212**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.32 Descriptive statistics of monthly percentage standard deviation of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	3.814	6.401	2.482	2.541	3.975	3.578
Maximum	48	9.044	31.591	13.842	11.734	9.703	5.825
Mean	48	**5.437**	**12.980**	**4.971**	**4.939**	**6.116**	**5.270**
Median	48	5.015	12.296	4.215	4.360	5.649	5.401
Standard Deviation	48	1.282	5.262	2.334	2.072	1.746	0.564
Coefficient of Variation	48	**0.236**	**0.405**	**0.469**	**0.419**	**0.285**	**0.107**
Minimum	48	4.394	7.261	3.489	3.674	4.494	4.229
Maximum	48	10.543	36.585	17.821	15.988	11.568	6.529
Mean	48	**6.327**	**15.508**	**5.854**	**5.782**	**6.985**	**6.118**
Median	48	6.006	13.551	4.852	5.031	6.315	6.312
Standard Deviation	48	1.463	6.707	2.754	2.509	2.147	0.584
Coefficient of Variation	48	**0.231**	**0.432**	**0.470**	**0.434**	**0.307**	**0.095**
Minimum	48	5.463	9.177	4.927	4.827	5.261	5.356
Maximum	48	13.766	44.811	24.232	22.085	15.283	8.302
Mean	48	**7.896**	**19.827**	**7.422**	**7.340**	**8.707**	**7.642**
Median	48	7.396	17.267	6.146	6.237	7.551	7.807
Standard Deviation	48	1.857	8.651	3.598	3.299	3.001	0.708
Coefficient of Variation	48	**0.235**	**0.436**	**0.485**	**0.449**	**0.345**	**0.093**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.33 Descriptive statistics of monthly conditional Sharpe ratio of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	-5.834	-2.809	-5.864	-5.764	-5.788	-6.748
Maximum	47	1.510	0.970	1.874	2.055	1.798	2.118
Mean	47	**-0.046**	**-0.020**	**-0.022**	**-0.012**	**-0.093**	**-0.072**
Median	47	0.245	0.101	0.487	0.464	0.218	0.200
Standard Deviation	47	1.280	0.603	1.448	1.434	1.254	1.422
Coefficient of Variation	47	**-27.691**	**-30.339**	**-64.673**	**-122.074**	**-13.524**	**-19.872**
Minimum	47	-6.605	-3.464	-6.124	-5.992	-5.860	-7.055
Maximum	47	1.620	1.471	3.021	2.988	1.887	2.297
Mean	47	**-0.092**	**-0.052**	**-0.078**	**-0.071**	**-0.121**	**-0.076**
Median	47	0.122	0.052	0.224	0.199	0.083	0.173
Standard Deviation	47	1.367	0.682	1.456	1.434	1.273	1.462
Coefficient of Variation	47	**-14.904**	**-13.095**	**-18.612**	**-20.110**	**-10.479**	**-19.210**
Minimum	47	-6.155	-2.881	-5.760	-5.423	-5.369	-6.757
Maximum	47	1.872	1.489	3.283	3.501	1.892	2.459
Mean	47	**-0.123**	**-0.060**	**-0.114**	**-0.082**	**-0.141**	**-0.099**
Median	47	0.201	-0.016	0.133	0.144	0.121	0.181
Standard Deviation	47	1.282	0.605	1.382	1.342	1.203	1.392
Coefficient of Variation	47	**-10.380**	**-10.014**	**-12.121**	**-16.416**	**-8.547**	**-13.995**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.34 Descriptive statistics of monthly percentage turnover of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	0.306	0.000	0.582	0.749	0.004	0.025
Maximum	47	87.996	178.612	175.421	140.212	49.753	20.113
Mean	47	**31.275**	**61.233**	**58.427**	**49.288**	**10.816**	**2.417**
Median	47	28.080	49.874	51.388	48.847	5.051	1.081
Standard Deviation	47	23.905	50.897	44.914	36.920	13.674	3.721
Coefficient of Variation	47	**0.764**	**0.831**	**0.769**	**0.749**	**1.264**	**1.539**
Minimum	47	2.746	2.244	9.304	11.782	6.584	2.039
Maximum	47	146.003	200.000	190.125	176.509	132.081	68.380
Mean	47	**55.974**	**83.758**	**82.459**	**76.715**	**32.026**	**19.663**
Median	47	53.871	72.904	83.552	69.969	27.528	16.275
Standard Deviation	47	31.051	60.727	46.158	40.162	25.035	13.899
Coefficient of Variation	47	**0.555**	**0.725**	**0.560**	**0.524**	**0.782**	**0.707**
Minimum	47	2.531	2.865	3.775	3.424	2.790	3.275
Maximum	47	200.000	200.000	200.000	200.000	128.205	82.937
Mean	47	**63.800**	**85.925**	**77.669**	**76.327**	**38.304**	**25.603**
Median	47	60.561	71.898	63.917	69.715	30.110	22.454
Standard Deviation	47	47.650	63.560	45.942	48.197	29.799	18.963
Coefficient of Variation	47	**0.747**	**0.740**	**0.592**	**0.631**	**0.778**	**0.741**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.35 Descriptive statistics of monthly percentage US weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	19.180	0.000	0.000	0.000	16.072	44.032
Maximum	48	85.100	100.000	97.932	98.956	67.897	67.697
Mean	48	**55.253**	**55.586**	**57.427**	**54.917**	**39.029**	**54.188**
Median	48	58.957	54.262	62.976	62.319	36.598	52.436
Standard Deviation	48	14.302	35.561	30.947	32.409	12.380	5.948
Coefficient of Variation	48	**0.259**	**0.640**	**0.539**	**0.590**	**0.317**	**0.110**
Minimum	48	0.000	0.000	0.000	0.000	0.000	9.041
Maximum	48	64.522	66.667	66.661	64.303	63.595	65.796
Mean	48	**27.589**	**25.604**	**29.961**	**27.477**	**17.424**	**26.637**
Median	48	23.796	25.353	33.887	32.591	7.604	20.991
Standard Deviation	48	16.159	21.986	20.978	21.076	20.780	15.886
Coefficient of Variation	48	**0.586**	**0.859**	**0.700**	**0.767**	**1.193**	**0.596**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	15.360	33.333	23.228	31.207	30.717	17.403
Mean	48	**2.592**	**3.356**	**6.436**	**5.575**	**5.789**	**2.737**
Median	48	0.000	0.000	1.968	0.000	0.000	0.000
Standard Deviation	48	3.869	8.290	7.768	8.130	9.175	4.920
Coefficient of Variation	48	**1.493**	**2.470**	**1.207**	**1.458**	**1.585**	**1.798**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.36 Descriptive statistics of monthly percentage EMU weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	0.000	2.270	2.171	0.000	0.000	0.000
Mean	48	**0.000**	**0.047**	**0.045**	**0.000**	**0.000**	**0.000**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	0.000	0.328	0.313	0.000	0.000	0.000
Coefficient of Variation	48	**#DIV/0!**	**6.928**	**6.928**	**#DIV/0!**	**#DIV/0!**	**#DIV/0!**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	36.915	15.016	8.315	13.478	0.000	2.082
Mean	48	**0.769**	**0.463**	**0.173**	**0.281**	**0.000**	**0.043**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	5.328	2.385	1.200	1.945	0.000	0.301
Coefficient of Variation	48	**6.928**	**5.148**	**6.928**	**6.928**	**#DIV/0!**	**6.928**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	31.229	13.525	6.794	7.626	0.000	13.532
Mean	48	**0.879**	**0.282**	**0.233**	**0.249**	**0.000**	**0.287**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	4.746	1.952	1.154	1.253	0.000	1.953
Coefficient of Variation	48	**5.397**	**6.928**	**4.965**	**5.038**	**#DIV/0!**	**6.800**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. #DIV/0! represents the error of division by zero.

Table 6.37 Descriptive statistics of monthly percentage Europe ex EMU weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	26.521	24.177	54.054	26.960	15.528	21.351
Mean	48	**1.699**	**1.419**	**3.814**	**1.237**	**0.815**	**1.352**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	6.104	5.398	10.140	4.818	3.222	4.684
Coefficient of Variation	48	**3.593**	**3.803**	**2.659**	**3.894**	**3.955**	**3.463**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	19.706	15.808	37.134	11.339	1.355	21.079
Mean	48	**0.682**	**0.532**	**2.521**	**0.444**	**0.028**	**0.902**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	3.251	2.654	7.247	1.992	0.196	3.684
Coefficient of Variation	48	**4.770**	**4.987**	**2.875**	**4.489**	**6.928**	**4.083**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	13.037	0.000	32.527	0.000	0.000	18.209
Mean	48	**0.272**	**0.000**	**0.678**	**0.000**	**0.000**	**0.534**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	1.882	0.000	4.695	0.000	0.000	2.812
Coefficient of Variation	48	**6.928**	**#DIV/0!**	**6.928**	**#DIV/0!**	**#DIV/0!**	**5.263**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. #DIV/0! represents the error of division by zero.

Table 6.38 Descriptive statistics of monthly percentage Pacific weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	14.900	0.000	0.000	0.000	31.731	25.762
Maximum	48	80.820	100.000	90.161	98.410	83.928	55.968
Mean	48	**41.239**	**36.763**	**33.168**	**34.834**	**59.839**	**44.460**
Median	48	38.123	26.496	32.039	28.739	62.175	46.910
Standard Deviation	48	13.581	37.374	23.627	26.802	13.603	7.976
Coefficient of Variation	48	**0.329**	**1.017**	**0.712**	**0.769**	**0.227**	**0.179**
Minimum	48	0.000	0.000	0.000	0.000	8.672	0.749
Maximum	48	62.650	64.216	63.163	70.621	63.137	45.894
Mean	48	**19.652**	**17.734**	**16.002**	**17.336**	**33.997**	**21.873**
Median	48	18.148	3.386	6.100	9.349	37.256	19.366
Standard Deviation	48	15.971	21.753	19.734	20.347	14.625	12.501
Coefficient of Variation	48	**0.813**	**1.227**	**1.233**	**1.174**	**0.430**	**0.572**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	32.684	28.988	38.426	36.151	27.819	28.264
Mean	48	**5.189**	**3.101**	**4.103**	**4.898**	**6.599**	**4.351**
Median	48	0.000	0.000	0.000	0.000	3.783	0.000
Standard Deviation	48	8.696	7.190	8.264	8.947	7.425	7.761
Coefficient of Variation	48	**1.676**	**2.319**	**2.014**	**1.827**	**1.125**	**1.784**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.39 Descriptive statistics of monthly percentage EM BRIC weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	0.000	0.000	0.000	0.000	0.000	0.000
Mean	48	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	0.000	0.000	0.000	0.000	0.000	0.000
Coefficient of Variation	48	**#DIV/0!**	**#DIV/0!**	**#DIV/0!**	**#DIV/0!**	**#DIV/0!**	**#DIV/0!**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	31.997	30.739	39.476	38.025	31.710	22.045
Mean	48	**4.605**	**1.401**	**4.408**	**4.410**	**2.142**	**3.553**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	9.193	5.741	9.750	9.468	6.734	7.230
Coefficient of Variation	48	**1.996**	**4.099**	**2.212**	**2.147**	**3.144**	**2.035**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	73.878	62.604	78.493	71.387	81.666	47.554
Mean	48	**15.545**	**5.612**	**9.799**	**9.934**	**13.750**	**10.569**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	24.219	14.545	19.458	20.339	24.813	16.506
Coefficient of Variation	48	**1.558**	**2.592**	**1.986**	**2.047**	**1.805**	**1.562**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. #DIV/0! represents the error of division by zero.

Table 6.40 Descriptive statistics of monthly percentage EM Europe weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	10.225	10.446	14.179	14.420	0.779	0.000
Mean	48	**0.338**	**0.319**	**0.779**	**0.473**	**0.016**	**0.000**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	1.590	1.649	2.800	2.246	0.112	0.000
Coefficient of Variation	48	**4.712**	**5.174**	**3.597**	**4.747**	**6.928**	**#DIV/0!**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	18.529	48.478	41.495	43.033	39.838	17.104
Mean	48	**1.277**	**2.216**	**2.275**	**2.230**	**1.786**	**0.867**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	4.194	9.100	8.619	8.240	7.298	3.210
Coefficient of Variation	48	**3.286**	**4.107**	**3.788**	**3.695**	**4.086**	**3.702**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	26.544	84.191	53.708	55.967	52.223	23.077
Mean	48	**1.404**	**2.244**	**2.482**	**2.955**	**2.241**	**0.998**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	5.120	12.547	10.567	11.137	9.488	4.062
Coefficient of Variation	48	**3.647**	**5.592**	**4.258**	**3.768**	**4.233**	**4.070**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. #DIV/0! represents the error of division by zero.

Table 6.41 Descriptive statistics of monthly percentage EM Latin America weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	0.000	4.399	0.000	0.000	0.000	0.000
Mean	48	**0.000**	**0.092**	**0.000**	**0.000**	**0.000**	**0.000**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	0.000	0.635	0.000	0.000	0.000	0.000
Coefficient of Variation	48	**#DIV/0!**	**6.928**	**#DIV/0!**	**#DIV/0!**	**#DIV/0!**	**#DIV/0!**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	21.757	33.391	29.780	28.760	25.625	11.534
Mean	48	**3.826**	**5.821**	**7.240**	**7.410**	**4.893**	**1.557**
Median	48	0.000	0.000	4.537	3.450	0.733	0.000
Standard Deviation	48	5.832	10.099	8.342	8.700	6.874	3.110
Coefficient of Variation	48	**1.524**	**1.735**	**1.152**	**1.174**	**1.405**	**1.997**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	51.668	66.667	62.228	63.849	54.506	44.658
Mean	48	**21.428**	**28.198**	**30.811**	**31.726**	**26.279**	**21.640**
Median	48	21.319	26.029	31.770	32.441	29.003	23.072
Standard Deviation	48	16.546	17.485	15.166	15.750	14.869	11.228
Coefficient of Variation	48	**0.772**	**0.620**	**0.492**	**0.496**	**0.566**	**0.519**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. #DIV/0! represents the error of division by zero.

Table 6.42 Descriptive statistics of monthly percentage EM Asia weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	14.740	77.564	40.635	52.869	3.469	0.000
Mean	48	**1.166**	**5.096**	**2.320**	**4.610**	**0.072**	**0.000**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	3.643	16.680	7.349	11.759	0.501	0.000
Coefficient of Variation	48	**3.124**	**3.273**	**3.168**	**2.551**	**6.928**	**#DIV/0!**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	68.802	75.026	87.159	95.788	51.029	55.492
Mean	48	**31.979**	**26.946**	**22.369**	**23.957**	**23.750**	**30.839**
Median	48	35.629	20.602	16.748	17.263	26.144	33.876
Standard Deviation	48	19.940	26.899	21.981	26.423	15.460	17.570
Coefficient of Variation	48	**0.624**	**0.998**	**0.983**	**1.103**	**0.651**	**0.570**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	93.783	92.411	85.503	87.254	77.749	81.803
Mean	48	**42.320**	**32.253**	**29.013**	**27.700**	**32.045**	**45.489**
Median	48	44.074	24.574	25.081	21.051	35.401	55.121
Standard Deviation	48	29.393	31.211	27.473	28.806	25.621	28.757
Coefficient of Variation	48	**0.695**	**0.968**	**0.947**	**1.040**	**0.800**	**0.632**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. #DIV/0! represents the error of division by zero.

Table 6.43 Descriptive statistics of monthly percentage EMF Africa weight of mean-variance long-only portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	5.258	24.334	43.529	39.725	9.690	0.000
Mean	48	**0.306**	**0.677**	**2.448**	**3.929**	**0.229**	**0.000**
Median	48	0.000	0.000	0.000	0.000	0.000	0.000
Standard Deviation	48	1.086	3.578	8.446	9.919	1.406	0.000
Coefficient of Variation	48	**3.552**	**5.283**	**3.450**	**2.525**	**6.154**	**#DIV/0!**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	55.247	70.860	68.754	74.216	54.977	29.337
Mean	48	**9.622**	**19.283**	**15.050**	**16.454**	**15.980**	**13.728**
Median	48	2.284	2.259	3.921	7.256	8.609	12.289
Standard Deviation	48	12.690	23.785	19.868	19.721	17.649	9.078
Coefficient of Variation	48	**1.319**	**1.233**	**1.320**	**1.199**	**1.104**	**0.661**
Minimum	48	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	48	80.934	95.487	69.633	63.284	64.333	30.325
Mean	48	**10.371**	**24.955**	**16.447**	**16.962**	**13.297**	**13.396**
Median	48	0.513	1.548	4.609	5.646	0.000	12.949
Standard Deviation	48	15.830	32.679	21.454	20.104	18.152	9.302
Coefficient of Variation	48	**1.526**	**1.310**	**1.304**	**1.185**	**1.365**	**0.694**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean. #DIV/0! represents the error of division by zero.

Table 6.44 Descriptive statistics of realised monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	-24.588	-28.797	-20.061	-23.600	-23.692	-22.152
Maximum	47	9.463	11.092	13.018	9.743	11.632	8.882
Mean	47	**0.510**	**0.051**	**0.442**	**0.422**	**0.561**	**0.526**
Median	47	-0.002	0.725	1.533	1.427	0.529	0.651
Standard Deviation	47	6.030	6.807	6.162	6.269	5.992	5.571
Coefficient of Variation	47	**11.814**	**133.471**	**13.947**	**14.846**	**10.680**	**10.593**
Minimum	47	-33.153	-36.572	-27.327	-32.702	-31.768	-30.074
Maximum	47	12.365	15.526	14.058	12.764	12.801	10.129
Mean	47	**0.557**	**-0.014**	**0.284**	**0.284**	**0.401**	**0.418**
Median	47	0.618	0.631	1.368	1.917	0.650	0.565
Standard Deviation	47	7.319	8.203	7.174	7.422	7.086	6.564
Coefficient of Variation	47	**13.145**	**-570.114**	**25.242**	**26.140**	**17.657**	**15.718**
Minimum	47	-41.717	-44.347	-34.592	-41.805	-39.844	-37.996
Maximum	47	15.268	19.959	17.496	15.785	13.971	13.039
Mean	47	**0.603**	**-0.080**	**0.127**	**0.146**	**0.242**	**0.309**
Median	47	2.183	0.895	2.364	2.406	0.852	1.291
Standard Deviation	47	8.933	9.991	8.484	8.867	8.524	7.895
Coefficient of Variation	47	**14.809**	**-125.225**	**67.008**	**60.919**	**35.280**	**25.518**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.45 Descriptive statistics of realised cumulative monthly percentage returns of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	-58.086	-59.199	-54.216	-56.341	-42.607	-49.713
Maximum	47	25.400	3.204	23.584	22.480	29.048	26.926
Mean	47	**-11.485**	**-28.923**	**-3.298**	**-7.416**	**-0.688**	**-7.325**
Median	47	-5.048	-32.709	-0.634	-4.395	2.178	-3.703
Standard Deviation	47	22.445	14.330	19.145	20.310	19.420	19.500
Coefficient of Variation	47	**-1.954**	**-0.495**	**-5.804**	**-2.738**	**-28.239**	**-2.662**
Minimum	47	-67.588	-66.988	-67.067	-68.716	-52.075	-59.403
Maximum	47	27.208	-0.046	15.871	15.738	21.111	21.378
Mean	47	**-13.009**	**-33.440**	**-11.611**	**-15.009**	**-7.249**	**-14.234**
Median	47	-5.845	-35.588	-5.340	-10.738	-1.054	-8.699
Standard Deviation	47	25.915	15.146	20.946	22.402	20.392	20.964
Coefficient of Variation	47	**-1.992**	**-0.453**	**-1.804**	**-1.493**	**-2.813**	**-1.473**
Minimum	47	-77.089	-74.778	-79.918	-81.091	-69.382	-69.094
Maximum	47	29.016	-3.295	8.158	8.997	15.649	15.831
Mean	47	**-14.532**	**-37.956**	**-19.923**	**-22.602**	**-13.810**	**-21.142**
Median	47	-2.306	-41.121	-10.046	-14.369	-6.453	-13.945
Standard Deviation	47	29.905	16.735	23.123	24.839	21.848	22.725
Coefficient of Variation	47	**-2.058**	**-0.441**	**-1.161**	**-1.099**	**-1.582**	**-1.075**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.46 Descriptive statistics of monthly percentage standard deviation of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	3.130	4.318	1.958	1.968	3.567	3.257
Maximum	48	7.196	18.543	9.722	9.961	6.849	4.685
Mean	48	**4.119**	**7.809**	**3.937**	**4.066**	**4.736**	**4.382**
Median	48	3.799	7.047	3.424	3.586	4.532	4.512
Standard Deviation	48	0.990	2.955	1.757	1.807	0.810	0.346
Coefficient of Variation	48	**0.240**	**0.378**	**0.446**	**0.444**	**0.171**	**0.079**
Minimum	48	3.198	4.374	2.457	2.335	3.672	4.060
Maximum	48	8.641	24.421	12.470	12.464	7.553	5.771
Mean	48	**4.833**	**9.252**	**4.488**	**4.588**	**5.292**	**5.091**
Median	48	4.587	8.310	3.930	4.196	4.921	5.215
Standard Deviation	48	1.183	3.901	1.931	1.961	0.989	0.412
Coefficient of Variation	48	**0.245**	**0.422**	**0.430**	**0.427**	**0.187**	**0.081**
Minimum	48	3.281	4.535	2.716	2.585	3.850	4.781
Maximum	48	10.348	30.635	17.111	16.565	8.748	7.268
Mean	48	**5.895**	**11.232**	**5.468**	**5.536**	**6.214**	**6.139**
Median	48	5.737	9.684	4.972	5.012	5.970	6.373
Standard Deviation	48	1.532	4.965	2.430	2.414	1.303	0.662
Coefficient of Variation	48	**0.260**	**0.442**	**0.444**	**0.436**	**0.210**	**0.108**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.47 Descriptive statistics of monthly conditional Sharpe ratio of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	-6.081	-3.643	-5.641	-6.179	-6.054	-6.499
Maximum	47	2.960	1.896	4.557	2.681	1.956	2.062
Mean	47	**0.159**	**0.036**	**0.104**	**0.101**	**0.065**	**0.063**
Median	47	0.000	0.106	0.419	0.468	0.118	0.144
Standard Deviation	47	1.492	0.905	1.765	1.652	1.370	1.419
Coefficient of Variation	47	**9.369**	**25.121**	**16.952**	**16.384**	**21.050**	**22.416**
Minimum	47	-6.593	-3.735	-6.264	-6.573	-6.456	-7.009
Maximum	47	2.709	1.602	5.615	3.401	2.168	1.959
Mean	47	**0.128**	**0.032**	**0.072**	**0.075**	**0.032**	**0.036**
Median	47	0.133	0.081	0.359	0.501	0.143	0.106
Standard Deviation	47	1.519	0.904	1.797	1.623	1.401	1.427
Coefficient of Variation	47	**11.843**	**28.675**	**25.087**	**21.762**	**43.924**	**39.517**
Minimum	47	-6.480	-3.652	-6.131	-6.302	-6.314	-6.882
Maximum	47	2.370	2.018	5.903	3.862	2.257	2.059
Mean	47	**0.110**	**0.032**	**0.059**	**0.065**	**0.009**	**0.022**
Median	47	0.339	0.067	0.351	0.409	0.156	0.226
Standard Deviation	47	1.490	0.894	1.731	1.547	1.370	1.384
Coefficient of Variation	47	**13.496**	**27.865**	**29.334**	**23.869**	**158.782**	**64.072**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.48 Descriptive statistics of monthly percentage turnover of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	47	44.670	66.719	44.639	35.325	7.724	2.769
Maximum	47	409.866	1170.325	342.638	421.621	290.079	136.493
Mean	47	**171.443**	**396.268**	**161.238**	**151.257**	**75.633**	**27.777**
Median	47	135.780	402.015	141.199	146.040	50.718	25.083
Standard Deviation	47	102.100	239.030	76.703	80.257	63.380	22.578
Coefficient of Variation	47	**0.596**	**0.603**	**0.476**	**0.531**	**0.838**	**0.813**
Minimum	47	48.179	81.077	64.380	46.615	14.159	9.042
Maximum	47	512.588	1505.036	460.282	499.198	467.539	199.100
Mean	47	**201.928**	**463.817**	**203.973**	**186.061**	**95.559**	**50.869**
Median	47	168.675	416.553	195.321	173.604	77.498	45.503
Standard Deviation	47	118.842	302.555	95.917	93.840	83.181	33.698
Coefficient of Variation	47	**0.589**	**0.652**	**0.470**	**0.504**	**0.870**	**0.662**
Minimum	47	58.509	99.431	72.588	49.757	23.694	16.972
Maximum	47	715.836	1848.051	597.964	576.775	644.999	261.707
Mean	47	**247.141**	**551.018**	**251.361**	**224.047**	**125.700**	**76.023**
Median	47	192.899	440.061	231.289	213.773	90.109	66.392
Standard Deviation	47	148.711	373.089	123.938	115.552	108.822	45.419
Coefficient of Variation	47	**0.602**	**0.677**	**0.493**	**0.516**	**0.866**	**0.597**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.49 Descriptive statistics of monthly percentage US weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	25.247	6.421	15.349	13.650	44.020	62.761
Maximum	48	115.762	239.582	106.374	108.745	92.249	84.395
Mean	48	**77.831**	**93.524**	**69.426**	**69.971**	**63.885**	**75.235**
Median	48	79.426	96.461	74.658	73.868	62.913	76.218
Standard Deviation	48	19.886	45.101	24.580	27.451	10.367	4.961
Coefficient of Variation	48	**0.256**	**0.482**	**0.354**	**0.392**	**0.162**	**0.066**
Minimum	48	1.776	-7.678	-5.901	-16.997	30.423	40.931
Maximum	48	107.348	218.544	105.232	106.983	85.020	81.650
Mean	48	**66.242**	**82.474**	**52.882**	**54.653**	**50.726**	**62.357**
Median	48	71.299	82.971	57.536	58.307	49.115	62.499
Standard Deviation	48	23.058	48.256	26.719	28.734	13.344	11.588
Coefficient of Variation	48	**0.348**	**0.585**	**0.505**	**0.526**	**0.263**	**0.186**
Minimum	48	-21.696	-21.776	-28.673	-47.644	10.504	18.604
Maximum	48	111.416	212.909	105.147	105.221	77.790	83.556
Mean	48	**54.653**	**71.425**	**36.338**	**39.334**	**37.567**	**49.479**
Median	48	58.749	67.938	37.334	43.242	34.321	47.757
Standard Deviation	48	28.242	52.970	31.074	32.013	19.366	18.801
Coefficient of Variation	48	**0.517**	**0.742**	**0.855**	**0.814**	**0.515**	**0.380**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.50 Descriptive statistics of monthly percentage EMU weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	-165.941	-186.174	-88.037	-83.123	-92.876	-67.597
Maximum	48	10.987	60.346	73.326	73.800	-3.783	-7.058
Mean	48	**-71.187**	**-52.998**	**-39.767**	**-39.276**	**-54.521**	**-51.229**
Median	48	-58.709	-59.567	-44.463	-44.743	-56.546	-52.215
Standard Deviation	48	40.615	42.720	28.768	28.777	24.373	10.904
Coefficient of Variation	48	**-0.571**	**-0.806**	**-0.723**	**-0.733**	**-0.447**	**-0.213**
Minimum	48	-192.295	-239.412	-105.298	-108.801	-110.792	-87.360
Maximum	48	35.582	86.428	93.730	81.061	40.842	15.978
Mean	48	**-83.348**	**-61.460**	**-45.394**	**-44.436**	**-58.445**	**-59.971**
Median	48	-73.588	-69.477	-48.445	-51.498	-62.593	-66.323
Standard Deviation	48	51.284	58.553	37.474	36.860	32.402	22.611
Coefficient of Variation	48	**-0.615**	**-0.953**	**-0.826**	**-0.829**	**-0.554**	**-0.377**
Minimum	48	-218.650	-292.649	-132.921	-135.526	-134.762	-110.214
Maximum	48	65.634	112.510	129.056	88.322	85.467	39.014
Mean	48	**-95.510**	**-69.922**	**-51.021**	**-49.597**	**-62.368**	**-68.713**
Median	48	-92.723	-82.040	-62.580	-60.316	-68.640	-84.758
Standard Deviation	48	63.641	77.302	48.738	47.653	42.113	35.616
Coefficient of Variation	48	**-0.666**	**-1.106**	**-0.955**	**-0.961**	**-0.675**	**-0.518**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.51 Descriptive statistics of monthly percentage Europe ex EMU weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	-90.843	-147.627	-51.581	-61.788	-26.724	-6.279
Maximum	48	128.722	165.186	102.123	79.609	65.111	59.466
Mean	48	**47.227**	**-2.402**	**34.258**	**27.748**	**31.036**	**34.644**
Median	48	48.532	3.213	43.317	34.782	35.730	37.064
Standard Deviation	48	37.232	58.676	35.007	29.524	22.682	10.376
Coefficient of Variation	48	**0.788**	**-24.426**	**1.022**	**1.064**	**0.731**	**0.300**
Minimum	48	-103.419	-193.302	-77.599	-71.978	-78.803	-38.843
Maximum	48	134.360	206.913	111.674	91.787	69.989	55.512
Mean	48	**44.141**	**-10.124**	**32.311**	**23.047**	**16.349**	**29.212**
Median	48	50.447	-19.555	42.809	27.768	18.918	30.810
Standard Deviation	48	44.625	77.736	41.038	34.700	30.698	18.410
Coefficient of Variation	48	**1.011**	**-7.678**	**1.270**	**1.506**	**1.878**	**0.630**
Minimum	48	-115.995	-238.977	-103.617	-106.374	-141.145	-71.407
Maximum	48	139.998	248.640	121.225	103.965	77.609	71.003
Mean	48	**41.055**	**-17.846**	**30.365**	**18.346**	**1.661**	**23.781**
Median	48	44.980	-22.609	39.600	20.869	7.393	23.333
Standard Deviation	48	55.476	100.535	49.134	42.583	41.369	28.588
Coefficient of Variation	48	**1.351**	**-5.633**	**1.618**	**2.321**	**24.901**	**1.202**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.52 Descriptive statistics of monthly percentage Pacific weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	17.912	-32.951	-6.162	-7.686	18.068	19.397
Maximum	48	71.783	154.076	95.772	107.413	89.117	48.868
Mean	48	**38.873**	**41.245**	**30.474**	**33.768**	**53.507**	**37.888**
Median	48	39.068	37.151	26.099	25.407	53.582	38.265
Standard Deviation	48	12.092	48.231	23.727	28.090	19.848	7.020
Coefficient of Variation	48	**0.311**	**1.169**	**0.779**	**0.832**	**0.371**	**0.185**
Minimum	48	10.930	-61.117	-19.436	-20.892	12.503	8.989
Maximum	48	83.124	160.271	85.748	117.750	107.861	49.229
Mean	48	**31.251**	**34.966**	**22.609**	**26.539**	**53.910**	**32.399**
Median	48	30.837	29.085	15.544	17.643	51.768	32.000
Standard Deviation	48	15.300	53.957	26.023	30.528	23.019	9.524
Coefficient of Variation	48	**0.490**	**1.543**	**1.151**	**1.150**	**0.427**	**0.294**
Minimum	48	-5.775	-97.451	-36.873	-34.218	6.937	-4.002
Maximum	48	108.907	169.904	83.310	128.086	126.605	53.906
Mean	48	**23.630**	**28.686**	**14.744**	**19.310**	**54.312**	**26.911**
Median	48	17.421	25.508	6.420	11.978	47.892	24.930
Standard Deviation	48	21.320	61.406	29.161	33.730	29.103	14.399
Coefficient of Variation	48	**0.902**	**2.141**	**1.978**	**1.747**	**0.536**	**0.535**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.53 Descriptive statistics of monthly percentage EM BRIC weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	-61.007	-212.746	-57.890	-61.847	-43.805	-12.776
Maximum	48	86.887	78.048	52.946	62.622	45.666	43.803
Mean	48	**11.923**	**-30.502**	**4.188**	**4.434**	**-11.044**	**9.964**
Median	48	9.384	-15.858	4.781	4.717	-21.735	10.483
Standard Deviation	48	32.335	69.099	22.813	23.867	26.610	13.306
Coefficient of Variation	48	**2.712**	**-2.265**	**5.447**	**5.383**	**-2.410**	**1.335**
Minimum	48	-67.153	-235.391	-65.354	-66.621	-64.607	-28.046
Maximum	48	112.176	106.853	85.971	88.475	100.575	76.917
Mean	48	**25.305**	**-25.068**	**8.259**	**8.551**	**1.971**	**22.012**
Median	48	18.986	-7.320	2.899	8.449	-2.273	21.608
Standard Deviation	48	41.946	78.835	33.479	32.851	39.305	24.925
Coefficient of Variation	48	**1.658**	**-3.145**	**4.053**	**3.842**	**19.946**	**1.132**
Minimum	48	-73.298	-262.822	-72.819	-71.394	-85.562	-43.316
Maximum	48	170.181	152.034	120.199	114.328	155.484	110.031
Mean	48	**38.688**	**-19.635**	**12.331**	**12.668**	**14.985**	**34.060**
Median	48	27.288	-8.344	8.027	12.204	8.137	33.069
Standard Deviation	48	53.738	91.953	45.146	42.837	57.748	36.722
Coefficient of Variation	48	**1.389**	**-4.683**	**3.661**	**3.382**	**3.854**	**1.078**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.54 Descriptive statistics of monthly percentage EM Europe weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	-31.393	-48.180	-20.862	-18.124	-50.117	-21.295
Maximum	48	16.756	79.299	28.948	23.252	39.798	8.348
Mean	48	**-10.093**	**-0.944**	**-2.005**	**-2.506**	**-9.764**	**-12.911**
Median	48	-9.975	-4.267	-1.324	-3.677	-11.176	-16.220
Standard Deviation	48	11.680	26.677	10.607	9.238	16.613	7.557
Coefficient of Variation	48	**-1.157**	**-28.263**	**-5.290**	**-3.687**	**-1.701**	**-0.585**
Minimum	48	-48.198	-75.273	-34.629	-31.883	-74.825	-38.991
Maximum	48	17.132	92.650	25.221	32.887	52.552	14.192
Mean	48	**-21.156**	**-14.108**	**-10.165**	**-9.666**	**-19.701**	**-24.559**
Median	48	-24.664	-18.316	-9.453	-11.735	-22.151	-29.074
Standard Deviation	48	15.704	33.342	15.015	14.191	21.151	12.525
Coefficient of Variation	48	**-0.742**	**-2.363**	**-1.477**	**-1.468**	**-1.074**	**-0.510**
Minimum	48	-67.608	-102.367	-50.776	-45.642	-99.533	-57.792
Maximum	48	22.634	106.002	38.123	42.523	65.307	20.035
Mean	48	**-32.218**	**-27.272**	**-18.325**	**-16.827**	**-29.637**	**-36.207**
Median	48	-36.933	-32.417	-18.368	-20.630	-33.979	-41.447
Standard Deviation	48	20.680	41.053	20.216	19.637	26.302	17.641
Coefficient of Variation	48	**-0.642**	**-1.505**	**-1.103**	**-1.167**	**-0.887**	**-0.487**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.55 Descriptive statistics of monthly percentage EM Latin America weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	-77.226	-102.252	-40.190	-45.893	-62.797	-49.094
Maximum	48	4.299	109.901	12.826	7.681	4.815	-13.983
Mean	48	**-39.644**	**-11.994**	**-20.262**	**-20.026**	**-22.195**	**-34.816**
Median	48	-45.120	-11.791	-20.488	-20.091	-21.638	-34.855
Standard Deviation	48	21.836	40.502	12.835	10.704	13.776	8.658
Coefficient of Variation	48	**-0.551**	**-3.377**	**-0.633**	**-0.535**	**-0.621**	**-0.249**
Minimum	48	-64.684	-94.761	-33.417	-40.847	-61.916	-36.308
Maximum	48	40.525	157.486	41.666	42.480	32.805	10.409
Mean	48	**-21.483**	**10.657**	**1.651**	**1.558**	**-1.764**	**-16.232**
Median	48	-26.147	8.991	-0.700	0.234	1.366	-15.293
Standard Deviation	48	26.164	46.862	17.312	15.088	18.908	11.932
Coefficient of Variation	48	**-1.218**	**4.397**	**10.484**	**9.683**	**-10.721**	**-0.735**
Minimum	48	-58.168	-87.270	-26.644	-35.801	-61.034	-23.863
Maximum	48	76.752	205.071	76.345	77.279	60.795	40.686
Mean	48	**-3.323**	**33.308**	**23.564**	**23.142**	**18.668**	**2.351**
Median	48	-3.176	30.632	19.036	19.698	24.919	4.044
Standard Deviation	48	31.796	55.304	23.594	21.045	25.899	15.678
Coefficient of Variation	48	**-9.569**	**1.660**	**1.001**	**0.909**	**1.387**	**6.668**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.56 Descriptive statistics of monthly percentage EM Asia weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	-31.566	-53.899	-34.497	-37.430	-10.503	-10.999
Maximum	48	63.169	154.052	65.622	89.939	46.949	28.787
Mean	48	**17.473**	**26.583**	**7.934**	**8.551**	**18.216**	**14.062**
Median	48	16.255	22.758	5.452	3.320	18.163	16.859
Standard Deviation	48	19.895	49.835	21.819	26.337	14.623	10.845
Coefficient of Variation	48	**1.139**	**1.875**	**2.750**	**3.080**	**0.803**	**0.771**
Minimum	48	-54.918	-59.014	-37.717	-39.933	-41.119	-25.916
Maximum	48	74.361	166.356	76.839	97.819	55.604	43.483
Mean	48	**24.684**	**33.718**	**16.343**	**15.770**	**17.903**	**19.562**
Median	48	26.915	30.958	14.939	9.681	20.393	25.015
Standard Deviation	48	27.123	55.954	30.942	34.255	19.864	19.777
Coefficient of Variation	48	**1.099**	**1.659**	**1.893**	**2.172**	**1.110**	**1.011**
Minimum	48	-86.371	-86.929	-47.589	-44.576	-71.736	-40.833
Maximum	48	93.970	178.661	100.199	105.700	84.398	61.081
Mean	48	**31.895**	**40.852**	**24.752**	**22.989**	**17.589**	**25.062**
Median	48	35.359	40.911	20.613	15.154	22.279	31.923
Standard Deviation	48	36.079	65.381	41.492	43.605	32.638	29.116
Coefficient of Variation	48	**1.131**	**1.600**	**1.676**	**1.897**	**1.856**	**1.162**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.57 Descriptive statistics of monthly percentage EMF Africa weight of mean-variance long-short portfolios between models for the 72-month estimation period

Descriptive statistics	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
Minimum	48	6.192	-36.544	-13.609	-10.296	-10.033	9.919
Maximum	48	62.770	150.887	63.319	65.277	99.289	34.710
Mean	48	**27.598**	**37.487**	**15.753**	**17.336**	**30.880**	**27.162**
Median	48	26.444	46.430	13.453	12.538	23.508	27.778
Standard Deviation	48	11.716	34.517	16.123	16.749	23.549	5.646
Coefficient of Variation	48	**0.425**	**0.921**	**1.024**	**0.966**	**0.763**	**0.208**
Minimum	48	2.720	-43.675	-22.184	-17.319	-8.498	10.074
Maximum	48	71.761	186.524	68.558	78.592	121.846	47.643
Mean	48	**34.364**	**48.945**	**21.503**	**23.985**	**39.051**	**35.219**
Median	48	34.640	57.415	18.532	20.218	32.717	36.241
Standard Deviation	48	14.563	41.854	19.944	20.576	30.003	8.001
Coefficient of Variation	48	**0.424**	**0.855**	**0.928**	**0.858**	**0.768**	**0.227**
Minimum	48	-0.752	-50.806	-30.758	-25.033	-7.799	9.142
Maximum	48	80.752	222.161	74.336	91.908	144.403	60.576
Mean	48	**41.131**	**60.404**	**27.252**	**30.634**	**47.222**	**43.275**
Median	48	40.686	63.633	23.900	27.179	42.301	44.905
Standard Deviation	48	19.479	51.046	24.590	25.018	36.917	10.580
Coefficient of Variation	48	**0.474**	**0.845**	**0.902**	**0.817**	**0.782**	**0.244**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. The coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.

Table 6.58 Statistical significance of realised monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.874**	**0.781**	**0.781**	**0.964**	**0.976**	-	**0.964**	**0.964**	**0.994**	**0.970**	**0.958**	-	**0.976**	**0.958**	**0.928**	**0.934**	**0.874**
GO-GARCH ICA	47	**0.931**	-	**0.946**	**0.898**	**0.892**	**0.892**	**0.933**	-	**0.952**	**0.976**	**0.958**	**0.964**	**0.939**	-	**0.988**	**0.964**	**0.916**	**0.880**
DCC	47	**0.865**	**0.938**	-	**0.994**	**0.792**	**0.804**	**0.968**	**0.901**	-	**0.970**	**0.946**	**0.982**	**0.973**	**0.965**	-	**0.994**	**0.934**	**0.904**
COPULA DCC	47	**0.856**	**0.929**	**0.991**	-	**0.769**	**0.775**	**0.999**	**0.932**	**0.969**	-	**0.988**	**0.994**	**0.991**	**0.929**	**0.963**	-	**0.982**	**0.940**
EWMA (0.03, 0.97)	47	**0.991**	**0.939**	**0.873**	**0.865**	-	**0.988**	**0.974**	**0.906**	**0.994**	**0.975**	-	**0.922**	**0.928**	**0.866**	**0.899**	**0.937**	-	**0.952**
SAMPLE	47	**0.986**	**0.944**	**0.878**	**0.869**	**0.995**	-	**0.938**	**0.871**	**0.969**	**0.938**	**0.963**	-	**0.928**	**0.866**	**0.899**	**0.937**	**1.000**	-
GO-GARCH MM	47	-	**0.373**	**0.017**	**0.018**	**0.184**	**0.846**	-	**0.631**	**0.733**	**0.821**	**0.935**	**0.347**	-	**0.333**	**0.544**	**0.629**	**0.416**	**0.288**
GO-GARCH ICA	47	**0.292**	-	**0.714**	**0.762**	**0.127**	**0.541**	**0.639**	-	**0.902**	**0.587**	**0.556**	**0.631**	**0.363**	-	**0.614**	**0.516**	**0.077**	**0.040**
DCC	47	**0.020**	**0.397**	-	**0.886**	**0.002**	**0.032**	**0.715**	**0.912**	-	**0.598**	**0.602**	**0.463**	**0.519**	**0.740**	-	**0.902**	**0.104**	**0.054**
COPULA DCC	47	**0.034**	**0.468**	**0.903**	-	**0.005**	**0.039**	**0.859**	**0.553**	**0.617**	-	**0.936**	**0.188**	**0.597**	**0.657**	**0.903**	-	**0.127**	**0.068**
EWMA (0.03, 0.97)	47	**0.266**	**0.063**	**0.002**	**0.004**	-	**0.057**	**0.947**	**0.595**	**0.668**	**0.905**	-	**0.301**	**0.360**	**0.069**	**0.100**	**0.128**	-	**0.880**
SAMPLE	47	**0.696**	**0.420**	**0.035**	**0.058**	**0.131**	-	**0.264**	**0.596**	**0.502**	**0.236**	**0.233**	-	**0.232**	**0.036**	**0.050**	**0.066**	**0.780**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.59 Statistical significance of realised cumulative monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.210**	**0.015**	**0.012**	**0.109**	**0.508**	-	**0.039**	**0.390**	**0.916**	**0.167**	**0.135**	-	**0.026**	**0.160**	**0.752**	**0.087**	**0.123**
GO-GARCH ICA	47	**0.428**	-	**0.114**	**0.107**	**0.625**	**0.583**	**0.148**	-	**0.011**	**0.043**	**0.002**	**0.002**	**0.143**	-	**0.354**	**0.050**	**0.001**	**0.001**
DCC	47	**0.032**	**0.173**	-	**0.804**	**0.222**	**0.042**	**0.613**	**0.052**	-	**0.451**	**0.598**	**0.488**	**0.358**	**0.584**	-	**0.261**	**0.004**	**0.006**
COPULA DCC	47	**0.027**	**0.150**	**0.926**	-	**0.189**	**0.038**	**0.997**	**0.154**	**0.614**	-	**0.194**	**0.165**	**0.805**	**0.231**	**0.511**	-	**0.052**	**0.077**
EWMA (0.03, 0.97)	47	**0.168**	**0.590**	**0.363**	**0.319**	-	**0.245**	**0.310**	**0.012**	**0.624**	**0.313**	-	**0.976**	**0.298**	**0.013**	**0.053**	**0.205**	-	**0.910**
SAMPLE	47	**0.650**	**0.720**	**0.081**	**0.069**	**0.351**	-	**0.311**	**0.013**	**0.619**	**0.314**	**0.988**	-	**0.332**	**0.016**	**0.061**	**0.230**	**0.939**	-
GO-GARCH MM	47	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.973**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
GO-GARCH ICA	47	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.005**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.000**	**0.000**	-	**0.000**	**0.006**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	-	**0.000**	**0.000**	**0.000**
COPULA DCC	47	**0.000**	**0.000**	**0.011**	-	**0.000**	**0.000**	**0.619**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	47	**0.000**	**0.000**	**0.071**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.358**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.100**
SAMPLE	47	**0.000**	**0.059**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.898**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.537**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.60 Statistical significance of monthly percentage standard deviation of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.000**	**0.001**	**0.003**	**0.049**	**0.177**	-	**0.000**	**0.000**	**0.000**	**0.281**	**0.091**	-	**0.000**	**0.000**	**0.000**	**0.597**	**0.065**
GO-GARCH ICA	48	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	48	**0.229**	**0.000**	-	**0.807**	**0.000**	**0.000**	**0.296**	**0.000**	-	**0.962**	**0.000**	**0.000**	**0.420**	**0.000**	-	**0.991**	**0.001**	**0.001**
COPULA DCC	48	**0.161**	**0.000**	**0.945**	-	**0.000**	**0.000**	**0.197**	**0.000**	**0.894**	-	**0.000**	**0.000**	**0.313**	**0.000**	**0.908**	-	**0.001**	**0.000**
EWMA (0.03, 0.97)	48	**0.033**	**0.000**	**0.008**	**0.003**	-	**0.113**	**0.083**	**0.000**	**0.027**	**0.013**	-	**0.399**	**0.115**	**0.000**	**0.061**	**0.036**	-	**0.939**
SAMPLE	48	**0.410**	**0.000**	**0.392**	**0.291**	**0.002**	-	**0.360**	**0.000**	**0.519**	**0.371**	**0.009**	-	**0.380**	**0.000**	**0.680**	**0.539**	**0.020**	-
GO-GARCH MM	48	-	**0.000**	**0.002**	**0.011**	**0.000**	**0.052**	-	**0.000**	**0.000**	**0.000**	**0.003**	**0.177**	-	**0.000**	**0.000**	**0.000**	**0.026**	**0.244**
GO-GARCH ICA	48	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	48	**0.007**	**0.000**	-	**0.337**	**0.000**	**0.001**	**0.001**	**0.000**	-	**0.453**	**0.000**	**0.004**	**0.000**	**0.000**	-	**0.659**	**0.000**	**0.003**
COPULA DCC	48	**0.017**	**0.000**	**0.592**	-	**0.000**	**0.002**	**0.000**	**0.000**	**0.535**	-	**0.000**	**0.001**	**0.000**	**0.000**	**0.745**	-	**0.000**	**0.001**
EWMA (0.03, 0.97)	48	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.189**	**0.005**	**0.000**	**0.000**	**0.000**	-	**0.190**	**0.087**	**0.000**	**0.000**	**0.000**	-	**0.421**
SAMPLE	48	**0.126**	**0.000**	**0.000**	**0.001**	**0.099**	-	**0.482**	**0.000**	**0.002**	**0.000**	**0.110**	-	**0.643**	**0.000**	**0.001**	**0.000**	**0.323**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.61 Statistical significance of monthly conditional Sharpe ratio of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	**-**	**0.335**	**0.646**	**0.641**	**0.735**	**0.940**	**-**	**0.488**	**0.982**	**0.928**	**0.775**	**0.988**	**-**	**0.493**	**0.940**	**0.886**	**0.892**	**0.952**
GO-GARCH ICA	47	**0.899**	**-**	**0.135**	**0.121**	**0.512**	**0.438**	**0.859**	**-**	**0.382**	**0.382**	**0.609**	**0.484**	**0.761**	**-**	**0.630**	**0.630**	**0.567**	**0.451**
DCC	47	**0.933**	**0.991**	**-**	**0.994**	**0.447**	**0.635**	**0.963**	**0.912**	**-**	**0.958**	**0.684**	**0.845**	**0.973**	**0.808**	**-**	**0.946**	**0.833**	**0.982**
COPULA DCC	47	**0.902**	**0.971**	**0.972**	**-**	**0.407**	**0.641**	**0.944**	**0.934**	**0.982**	**-**	**0.712**	**0.880**	**0.878**	**0.921**	**0.909**	**-**	**0.752**	**0.946**
EWMA (0.03, 0.97)	47	**0.859**	**0.721**	**0.802**	**0.771**	**-**	**0.845**	**0.913**	**0.743**	**0.879**	**0.858**	**-**	**0.775**	**0.947**	**0.684**	**0.921**	**0.823**	**-**	**0.816**
SAMPLE	47	**0.928**	**0.819**	**0.868**	**0.840**	**0.939**	**-**	**0.957**	**0.919**	**0.994**	**0.987**	**0.873**	**-**	**0.931**	**0.860**	**0.960**	**0.950**	**0.878**	**-**
GO-GARCH MM	47	**-**	**0.188**	**0.212**	**0.014**	**0.061**	**0.480**	**-**	**0.437**	**0.582**	**0.878**	**0.419**	**0.521**	**-**	**0.771**	**0.988**	**0.936**	**0.504**	**0.281**
GO-GARCH ICA	47	**0.244**	**-**	**0.030**	**0.062**	**0.279**	**0.305**	**0.497**	**-**	**0.189**	**0.618**	**0.579**	**0.305**	**0.718**	**-**	**0.411**	**0.647**	**0.719**	**0.429**
DCC	47	**0.180**	**0.047**	**-**	**0.705**	**0.023**	**0.081**	**0.505**	**0.248**	**-**	**0.399**	**0.179**	**0.920**	**0.893**	**0.661**	**-**	**0.942**	**0.578**	**0.376**
COPULA DCC	47	**0.057**	**0.018**	**0.628**	**-**	**0.005**	**0.014**	**0.799**	**0.658**	**0.398**	**-**	**0.678**	**0.419**	**0.948**	**0.700**	**0.952**	**-**	**0.593**	**0.416**
EWMA (0.03, 0.97)	47	**0.144**	**0.917**	**0.016**	**0.004**	**-**	**0.418**	**0.408**	**0.914**	**0.144**	**0.641**	**-**	**0.155**	**0.550**	**0.959**	**0.504**	**0.557**	**-**	**0.095**
SAMPLE	47	**0.483**	**0.529**	**0.073**	**0.022**	**0.489**	**-**	**0.542**	**0.264**	**0.949**	**0.426**	**0.156**	**-**	**0.270**	**0.263**	**0.391**	**0.367**	**0.095**	**-**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.62 Statistical significance of monthly percentage turnover of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.015**	**0.002**	**0.022**	**0.000**	**0.000**	-	**0.064**	**0.005**	**0.016**	**0.000**	**0.000**	-	**0.151**	**0.095**	**0.189**	**0.006**	**0.000**
GO-GARCH ICA	47	**0.001**	-	**0.994**	**0.498**	**0.000**	**0.000**	**0.007**	-	**0.798**	**0.845**	**0.000**	**0.000**	**0.060**	-	**0.758**	**0.707**	**0.001**	**0.000**
DCC	47	**0.000**	**0.777**	-	**0.465**	**0.000**	**0.000**	**0.002**	**0.907**	-	**0.572**	**0.000**	**0.000**	**0.154**	**0.473**	-	**0.718**	**0.000**	**0.000**
COPULA DCC	47	**0.006**	**0.196**	**0.284**	-	**0.000**	**0.000**	**0.006**	**0.509**	**0.521**	-	**0.000**	**0.000**	**0.208**	**0.412**	**0.890**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	47	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.005**	**0.003**	**0.000**	**0.000**	**0.000**	-	**0.051**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.016**	-
GO-GARCH MM	47	-	**0.015**	**0.000**	**0.002**	**0.000**	**0.000**	-	**0.080**	**0.002**	**0.002**	**0.000**	**0.000**	-	**0.179**	**0.158**	**0.222**	**0.002**	**0.000**
GO-GARCH ICA	47	**0.049**	-	**0.824**	**0.907**	**0.000**	**0.000**	**0.150**	-	**0.588**	**0.907**	**0.000**	**0.000**	**0.267**	-	**0.769**	**0.634**	**0.000**	**0.000**
DCC	47	**0.001**	**0.382**	-	**0.632**	**0.000**	**0.000**	**0.001**	**0.229**	-	**0.613**	**0.000**	**0.000**	**0.105**	**0.759**	-	**0.947**	**0.000**	**0.000**
COPULA DCC	47	**0.002**	**0.592**	**0.673**	-	**0.000**	**0.000**	**0.003**	**0.332**	**0.743**	-	**0.000**	**0.000**	**0.192**	**0.953**	**0.778**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	47	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**	-	**0.006**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.63 Statistical significance of monthly percentage US weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	**-**	**0.728**	**0.222**	**0.605**	**0.000**	**0.105**	**-**	**0.545**	**0.457**	**0.892**	**0.002**	**0.545**	**-**	**0.098**	**0.031**	**0.176**	**0.643**	**0.444**
GO-GARCH ICA	48	**0.952**	**-**	**0.968**	**0.772**	**0.008**	**0.427**	**0.616**	**-**	**0.265**	**0.609**	**0.060**	**0.585**	**0.565**	**-**	**0.003**	**0.012**	**0.115**	**0.600**
DCC	48	**0.660**	**0.787**	**-**	**0.835**	**0.001**	**0.048**	**0.536**	**0.323**	**-**	**0.438**	**0.006**	**0.397**	**0.003**	**0.064**	**-**	**0.480**	**0.239**	**0.006**
COPULA DCC	48	**0.948**	**0.923**	**0.699**	**-**	**0.011**	**0.453**	**0.977**	**0.671**	**0.564**	**-**	**0.023**	**0.783**	**0.025**	**0.189**	**0.597**	**-**	**0.529**	**0.033**
EWMA (0.03, 0.97)	48	**0.000**	**0.003**	**0.000**	**0.002**	**-**	**0.000**	**0.009**	**0.064**	**0.004**	**0.021**	**-**	**0.001**	**0.030**	**0.176**	**0.710**	**0.904**	**-**	**0.196**
SAMPLE	48	**0.636**	**0.789**	**0.480**	**0.879**	**0.000**	**-**	**0.772**	**0.793**	**0.384**	**0.826**	**0.017**	**-**	**0.873**	**0.657**	**0.007**	**0.042**	**0.046**	**-**
GO-GARCH MM	48	**-**	**0.610**	**0.531**	**0.536**	**0.000**	**0.235**	**-**	**0.255**	**0.523**	**0.198**	**0.000**	**0.937**	**-**	**0.209**	**0.001**	**0.045**	**0.236**	**0.364**
GO-GARCH ICA	48	**0.865**	**-**	**0.703**	**0.418**	**0.000**	**0.257**	**0.229**	**-**	**0.126**	**0.908**	**0.032**	**0.349**	**0.301**	**-**	**0.000**	**0.004**	**0.017**	**0.601**
DCC	48	**0.792**	**0.958**	**-**	**0.423**	**0.000**	**0.237**	**0.602**	**0.123**	**-**	**0.061**	**0.000**	**0.422**	**0.001**	**0.000**	**-**	**0.169**	**0.041**	**0.000**
COPULA DCC	48	**0.485**	**0.470**	**0.382**	**-**	**0.000**	**0.893**	**0.176**	**1.000**	**0.088**	**-**	**0.003**	**0.232**	**0.081**	**0.009**	**0.121**	**-**	**0.382**	**0.004**
EWMA (0.03, 0.97)	48	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.002**	**0.000**	**0.001**	**-**	**0.000**	**0.141**	**0.018**	**0.059**	**0.761**	**-**	**0.026**
SAMPLE	48	**0.298**	**0.334**	**0.233**	**0.848**	**0.000**	**-**	**0.908**	**0.247**	**0.517**	**0.188**	**0.000**	**-**	**0.346**	**0.804**	**0.000**	**0.006**	**0.014**	**-**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.64 Statistical significance of monthly percentage EMU weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	**-**	**0.327**	**0.327**	**1.000**	**1.000**	**1.000**	**-**	**0.584**	**1.000**	**1.000**	**0.327**	**1.000**	**-**	**0.568**	**0.975**	**0.975**	**0.159**	**0.992**
GO-GARCH ICA	48	**0.322**	**-**	**1.000**	**0.327**	**0.327**	**0.327**	**0.718**	**-**	**0.568**	**0.568**	**0.159**	**0.551**	**0.423**	**-**	**0.584**	**0.584**	**0.327**	**0.568**
DCC	48	**0.322**	**0.975**	**-**	**0.327**	**0.327**	**0.327**	**0.453**	**0.454**	**-**	**1.000**	**0.327**	**1.000**	**0.363**	**0.881**	**-**	**1.000**	**0.159**	**1.000**
COPULA DCC	48	**1.000**	**0.322**	**0.322**	**-**	**1.000**	**1.000**	**0.553**	**0.682**	**0.745**	**-**	**0.327**	**1.000**	**0.377**	**0.921**	**0.948**	**-**	**0.159**	**1.000**
EWMA (0.03, 0.97)	48	**1.000**	**0.322**	**0.322**	**1.000**	**-**	**1.000**	**0.322**	**0.185**	**0.322**	**0.322**	**-**	**0.327**	**0.206**	**0.322**	**0.169**	**0.176**	**-**	**0.159**
SAMPLE	48	**1.000**	**0.322**	**0.322**	**1.000**	**1.000**	**-**	**0.351**	**0.232**	**0.470**	**0.407**	**0.322**	**-**	**0.427**	**0.989**	**0.868**	**0.909**	**0.313**	**-**
GO-GARCH MM	48	**-**	**0.325**	**0.325**	**1.000**	**1.000**	**1.000**	**-**	**0.552**	**0.983**	**0.983**	**0.516**	**1.000**	**-**	**0.468**	**0.982**	**0.982**	**0.153**	**0.477**
GO-GARCH ICA	48	**0.263**	**-**	**1.000**	**0.325**	**0.325**	**0.325**	**0.591**	**-**	**0.538**	**0.538**	**0.216**	**0.543**	**0.283**	**-**	**0.482**	**0.477**	**0.496**	**0.976**
DCC	48	**0.263**	**1.000**	**-**	**0.325**	**0.325**	**0.325**	**0.899**	**0.527**	**-**	**1.000**	**0.538**	**0.989**	**0.525**	**0.597**	**-**	**1.000**	**0.160**	**0.501**
COPULA DCC	48	**1.000**	**0.263**	**0.263**	**-**	**1.000**	**1.000**	**0.899**	**0.527**	**1.000**	**-**	**0.538**	**0.989**	**0.456**	**0.534**	**1.000**	**-**	**0.153**	**0.491**
EWMA (0.03, 0.97)	48	**1.000**	**0.263**	**0.263**	**1.000**	**-**	**1.000**	**0.254**	**0.138**	**0.347**	**0.347**	**-**	**0.516**	**0.057**	**0.498**	**0.168**	**0.078**	**-**	**0.458**
SAMPLE	48	**1.000**	**0.263**	**0.263**	**1.000**	**1.000**	**-**	**0.761**	**0.405**	**0.883**	**0.883**	**0.274**	**-**	**0.321**	**0.709**	**0.776**	**0.687**	**0.149**	**-**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.65 Statistical significance of monthly percentage Europe ex EMU weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.957**	**0.039**	**0.778**	**0.667**	**0.957**	-	**0.655**	**0.066**	**1.000**	**0.300**	**0.702**	-	**0.327**	**1.000**	**0.327**	**0.327**	**0.320**
GO-GARCH ICA	48	**0.813**	-	**0.036**	**0.766**	**0.667**	**0.970**	**0.806**	-	**0.030**	**0.682**	**0.551**	**0.417**	**0.322**	-	**0.327**	**1.000**	**1.000**	**0.082**
DCC	48	**0.219**	**0.153**	-	**0.064**	**0.015**	**0.038**	**0.113**	**0.079**	-	**0.061**	**0.007**	**0.144**	**0.580**	**0.322**	-	**0.327**	**0.327**	**0.330**
COPULA DCC	48	**0.682**	**0.862**	**0.117**	-	**0.482**	**0.755**	**0.667**	**0.854**	**0.061**	-	**0.300**	**0.678**	**0.322**	**1.000**	**0.322**	-	**1.000**	**0.082**
EWMA (0.03, 0.97)	48	**0.378**	**0.507**	**0.056**	**0.615**	-	**0.667**	**0.171**	**0.196**	**0.021**	**0.157**	-	**0.168**	**0.322**	**1.000**	**0.322**	**1.000**	-	**0.082**
SAMPLE	48	**0.756**	**0.948**	**0.132**	**0.906**	**0.514**	-	**0.756**	**0.574**	**0.172**	**0.451**	**0.107**	-	**0.592**	**0.194**	**0.856**	**0.194**	**0.194**	-
GO-GARCH MM	48	-	**0.792**	**0.016**	**0.474**	**0.465**	**0.965**	-	**0.609**	**0.038**	**0.681**	**0.183**	**0.646**	-	**0.472**	**0.994**	**0.472**	**0.472**	**0.155**
GO-GARCH ICA	48	**1.000**	-	**0.039**	**0.683**	**0.332**	**0.813**	**0.533**	-	**0.014**	**0.892**	**0.454**	**0.346**	**0.253**	-	**0.491**	**1.000**	**1.000**	**0.035**
DCC	48	**0.027**	**0.055**	-	**0.074**	**0.002**	**0.015**	**0.022**	**0.012**	-	**0.013**	**0.001**	**0.102**	**0.880**	**0.336**	-	**0.491**	**0.491**	**0.160**
COPULA DCC	48	**0.697**	**0.758**	**0.046**	-	**0.140**	**0.504**	**0.394**	**0.929**	**0.003**	-	**0.338**	**0.376**	**0.253**	**1.000**	**0.336**	-	**1.000**	**0.035**
EWMA (0.03, 0.97)	48	**0.262**	**0.395**	**0.001**	**0.092**	-	**0.423**	**0.063**	**0.415**	**0.001**	**0.132**	-	**0.076**	**0.253**	**1.000**	**0.336**	**1.000**	-	**0.035**
SAMPLE	48	**1.000**	**1.000**	**0.021**	**0.673**	**0.214**	-	**0.381**	**0.191**	**0.116**	**0.078**	**0.011**	-	**0.136**	**0.038**	**0.208**	**0.038**	**0.038**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.66 Statistical significance of monthly percentage Pacific weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	**-**	**0.116**	**0.045**	**0.039**	**0.000**	**0.013**	**-**	**0.114**	**0.063**	**0.124**	**0.000**	**0.273**	**-**	**0.098**	**0.449**	**0.643**	**0.061**	**0.583**
GO-GARCH ICA	48	**0.439**	**-**	**0.610**	**0.461**	**0.000**	**0.016**	**0.624**	**-**	**0.778**	**0.734**	**0.000**	**0.020**	**0.203**	**-**	**0.316**	**0.260**	**0.000**	**0.249**
DCC	48	**0.044**	**0.575**	**-**	**0.843**	**0.000**	**0.001**	**0.322**	**0.684**	**-**	**0.836**	**0.000**	**0.003**	**0.532**	**0.528**	**-**	**0.837**	**0.009**	**0.894**
COPULA DCC	48	**0.144**	**0.772**	**0.747**	**-**	**0.000**	**0.008**	**0.537**	**0.926**	**0.745**	**-**	**0.000**	**0.014**	**0.872**	**0.281**	**0.652**	**-**	**0.023**	**0.943**
EWMA (0.03, 0.97)	48	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.395**	**0.021**	**0.123**	**0.313**	**-**	**0.016**
SAMPLE	48	**0.161**	**0.169**	**0.003**	**0.021**	**0.000**	**-**	**0.450**	**0.257**	**0.086**	**0.192**	**0.000**	**-**	**0.620**	**0.415**	**0.880**	**0.750**	**0.150**	**-**
GO-GARCH MM	48	**-**	**0.092**	**0.040**	**0.312**	**0.000**	**0.124**	**-**	**0.240**	**0.006**	**0.034**	**0.000**	**0.261**	**-**	**0.081**	**0.146**	**0.588**	**0.015**	**0.596**
GO-GARCH ICA	48	**0.262**	**-**	**0.575**	**0.261**	**0.000**	**0.023**	**0.665**	**-**	**0.818**	**0.715**	**0.000**	**0.251**	**0.106**	**-**	**0.578**	**0.227**	**0.000**	**0.188**
DCC	48	**0.050**	**0.721**	**-**	**0.446**	**0.000**	**0.001**	**0.030**	**0.233**	**-**	**0.435**	**0.000**	**0.001**	**0.116**	**0.749**	**-**	**0.399**	**0.000**	**0.387**
COPULA DCC	48	**0.489**	**0.627**	**0.309**	**-**	**0.000**	**0.037**	**0.196**	**0.574**	**0.448**	**-**	**0.000**	**0.012**	**0.728**	**0.211**	**0.257**	**-**	**0.005**	**0.997**
EWMA (0.03, 0.97)	48	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.028**	**0.000**	**0.000**	**0.013**	**-**	**0.003**
SAMPLE	48	**0.136**	**0.030**	**0.001**	**0.053**	**0.000**	**-**	**0.387**	**0.306**	**0.003**	**0.040**	**0.000**	**-**	**0.459**	**0.325**	**0.413**	**0.721**	**0.003**	**-**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.67 Statistical significance of monthly percentage EM BRIC weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.011**	**0.960**	**0.725**	**0.129**	**0.421**	**-**	**0.005**	**0.152**	**0.074**	**0.380**	**0.350**
GO-GARCH ICA	48	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**0.044**	**-**	**0.011**	**0.029**	**0.233**	**0.091**	**0.017**	**-**	**0.162**	**0.296**	**0.049**	**0.074**
DCC	48	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**0.919**	**0.069**	**-**	**0.740**	**0.134**	**0.449**	**0.203**	**0.236**	**-**	**0.736**	**0.547**	**0.650**
COPULA DCC	48	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**0.919**	**0.063**	**0.999**	**-**	**0.263**	**0.651**	**0.222**	**0.234**	**0.973**	**-**	**0.387**	**0.487**
EWMA (0.03, 0.97)	48	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**0.138**	**0.563**	**0.189**	**0.180**	**-**	**0.501**	**0.721**	**0.054**	**0.388**	**0.412**	**-**	**0.784**
SAMPLE	48	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.535**	**0.110**	**0.627**	**0.619**	**0.325**	**-**	**0.243**	**0.122**	**0.835**	**0.867**	**0.462**	**-**
GO-GARCH MM	48	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.008**	**0.538**	**0.508**	**0.030**	**0.216**	**-**	**0.002**	**0.016**	**0.033**	**0.145**	**0.069**
GO-GARCH ICA	48	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**1.000**	**0.011**	**-**	**0.023**	**0.022**	**0.387**	**0.106**	**0.004**	**-**	**0.330**	**0.241**	**0.046**	**0.079**
DCC	48	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**1.000**	**0.600**	**0.025**	**-**	**0.963**	**0.085**	**0.515**	**0.029**	**0.319**	**-**	**0.792**	**0.258**	**0.390**
COPULA DCC	48	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**1.000**	**0.499**	**0.029**	**0.880**	**-**	**0.085**	**0.540**	**0.048**	**0.262**	**0.861**	**-**	**0.406**	**0.617**
EWMA (0.03, 0.97)	48	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**1.000**	**0.022**	**0.496**	**0.048**	**0.057**	**-**	**0.315**	**0.246**	**0.036**	**0.220**	**0.316**	**-**	**0.738**
SAMPLE	48	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**-**	**0.257**	**0.106**	**0.497**	**0.580**	**0.225**	**-**	**0.046**	**0.157**	**0.691**	**0.850**	**0.347**	**-**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.68 Statistical significance of monthly percentage EM Europe weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.682**	**0.655**	**0.986**	**0.300**	**0.082**	-	**0.541**	**0.789**	**0.822**	**0.766**	**0.701**	-	**0.437**	**0.982**	**0.945**	**0.982**	**0.970**
GO-GARCH ICA	48	**0.955**	-	**0.387**	**0.655**	**0.551**	**0.159**	**0.518**	-	**0.727**	**0.739**	**0.739**	**0.776**	**0.669**	-	**0.427**	**0.427**	**0.427**	**0.447**
DCC	48	**0.346**	**0.330**	-	**0.678**	**0.162**	**0.043**	**0.473**	**0.974**	-	**0.994**	**0.957**	**0.933**	**0.527**	**0.920**	-	**0.994**	**0.994**	**0.970**
COPULA DCC	48	**0.734**	**0.702**	**0.557**	-	**0.300**	**0.082**	**0.477**	**0.994**	**0.979**	-	**0.970**	**0.921**	**0.384**	**0.770**	**0.831**	-	**0.970**	**0.945**
EWMA (0.03, 0.97)	48	**0.169**	**0.211**	**0.066**	**0.166**	-	**0.327**	**0.676**	**0.799**	**0.765**	**0.781**	-	**0.982**	**0.592**	**0.999**	**0.907**	**0.736**	-	**0.970**
SAMPLE	48	**0.148**	**0.187**	**0.060**	**0.151**	**0.322**	-	**0.593**	**0.337**	**0.293**	**0.290**	**0.428**	-	**0.668**	**0.515**	**0.367**	**0.257**	**0.407**	-
GO-GARCH MM	48	-	**0.647**	**0.588**	**0.964**	**0.349**	**0.151**	-	**1.000**	**0.591**	**0.575**	**0.299**	**0.104**	-	**0.557**	**0.061**	**0.056**	**0.516**	**0.481**
GO-GARCH ICA	48	**0.507**	-	**0.293**	**0.580**	**0.627**	**0.315**	**0.878**	-	**0.616**	**0.612**	**0.310**	**0.121**	**0.712**	-	**0.224**	**0.221**	**0.994**	**0.221**
DCC	48	**0.511**	**0.139**	-	**0.603**	**0.120**	**0.040**	**0.597**	**0.787**	-	**1.000**	**0.116**	**0.034**	**0.162**	**0.468**	-	**0.994**	**0.208**	**0.013**
COPULA DCC	48	**0.935**	**0.350**	**0.491**	-	**0.288**	**0.116**	**0.391**	**0.652**	**0.863**	-	**0.108**	**0.030**	**0.036**	**0.324**	**0.860**	-	**0.203**	**0.011**
EWMA (0.03, 0.97)	48	**0.203**	**0.446**	**0.027**	**0.069**	-	**0.599**	**0.451**	**0.519**	**0.258**	**0.096**	-	**0.550**	**0.242**	**0.854**	**0.423**	**0.188**	-	**0.182**
SAMPLE	48	**0.111**	**0.228**	**0.012**	**0.028**	**0.537**	-	**0.082**	**0.175**	**0.058**	**0.013**	**0.222**	-	**0.209**	**0.260**	**0.041**	**0.008**	**0.047**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.69 Statistical significance of monthly percentage EM Latin America weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	-	**0.327**	**1.000**	**1.000**	**1.000**	**1.000**	-	**0.687**	**0.016**	**0.034**	**0.467**	**0.039**	-	**0.061**	**0.006**	**0.002**	**0.059**	**0.800**
GO-GARCH ICA	48	**0.322**	-	**0.327**	**0.327**	**0.327**	**0.327**	**0.240**	-	**0.019**	**0.035**	**0.323**	**0.267**	**0.054**	-	**0.181**	**0.125**	**0.766**	**0.078**
DCC	48	**1.000**	**0.322**	-	**1.000**	**1.000**	**1.000**	**0.023**	**0.455**	-	**0.929**	**0.104**	**0.000**	**0.005**	**0.436**	-	**0.772**	**0.165**	**0.001**
COPULA DCC	48	**1.000**	**0.322**	**1.000**	-	**1.000**	**1.000**	**0.020**	**0.411**	**0.922**	-	**0.142**	**0.000**	**0.002**	**0.302**	**0.772**	-	**0.078**	**0.000**
EWMA (0.03, 0.97)	48	**1.000**	**0.322**	**1.000**	**1.000**	-	**1.000**	**0.415**	**0.600**	**0.136**	**0.119**	-	**0.010**	**0.134**	**0.564**	**0.143**	**0.085**	-	**0.031**
SAMPLE	48	**1.000**	**0.322**	**1.000**	**1.000**	**1.000**	-	**0.020**	**0.007**	**0.000**	**0.000**	**0.003**	-	**0.942**	**0.032**	**0.001**	**0.001**	**0.088**	-
GO-GARCH MM	48	-	**0.164**	**1.000**	**1.000**	**1.000**	**1.000**	-	**0.429**	**0.006**	**0.009**	**0.498**	**0.015**	-	**0.202**	**0.000**	**0.000**	**0.025**	**0.531**
GO-GARCH ICA	48	**0.245**	-	**0.164**	**0.164**	**0.164**	**0.164**	**0.772**	-	**0.004**	**0.002**	**0.198**	**0.260**	**0.145**	-	**0.089**	**0.029**	**0.501**	**0.359**
DCC	48	**1.000**	**0.245**	-	**1.000**	**1.000**	**1.000**	**0.006**	**0.006**	-	**0.544**	**0.081**	**0.000**	**0.000**	**0.045**	-	**0.744**	**0.081**	**0.000**
COPULA DCC	48	**1.000**	**0.245**	**1.000**	-	**1.000**	**1.000**	**0.013**	**0.012**	**0.631**	-	**0.111**	**0.000**	**0.000**	**0.014**	**0.648**	-	**0.034**	**0.000**
EWMA (0.03, 0.97)	48	**1.000**	**0.245**	**1.000**	**1.000**	-	**1.000**	**0.408**	**0.304**	**0.080**	**0.156**	-	**0.004**	**0.027**	**0.580**	**0.103**	**0.032**	-	**0.017**
SAMPLE	48	**1.000**	**0.245**	**1.000**	**1.000**	**1.000**	-	**0.006**	**0.036**	**0.000**	**0.000**	**0.001**	-	**0.943**	**0.088**	**0.000**	**0.000**	**0.008**	-

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.70 Statistical significance of monthly percentage EM Asia weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	**-**	**0.565**	**0.897**	**0.298**	**0.027**	**0.006**	**-**	**0.266**	**0.020**	**0.044**	**0.029**	**0.750**	**-**	**0.101**	**0.033**	**0.018**	**0.080**	**0.694**
GO-GARCH ICA	48	**0.117**	**-**	**0.434**	**0.764**	**0.007**	**0.002**	**0.301**	**-**	**0.569**	**0.518**	**0.997**	**0.484**	**0.107**	**-**	**0.669**	**0.380**	**0.802**	**0.060**
DCC	48	**0.333**	**0.295**	**-**	**0.252**	**0.046**	**0.012**	**0.027**	**0.364**	**-**	**0.837**	**0.503**	**0.042**	**0.024**	**0.591**	**-**	**0.598**	**0.454**	**0.006**
COPULA DCC	48	**0.058**	**0.869**	**0.256**	**-**	**0.004**	**0.001**	**0.097**	**0.584**	**0.750**	**-**	**0.448**	**0.078**	**0.016**	**0.460**	**0.820**	**-**	**0.241**	**0.003**
EWMA (0.03, 0.97)	48	**0.045**	**0.042**	**0.040**	**0.010**	**-**	**0.327**	**0.026**	**0.478**	**0.723**	**0.963**	**-**	**0.023**	**0.071**	**0.972**	**0.577**	**0.437**	**-**	**0.027**
SAMPLE	48	**0.031**	**0.040**	**0.034**	**0.009**	**0.322**	**-**	**0.767**	**0.404**	**0.040**	**0.137**	**0.039**	**-**	**0.595**	**0.033**	**0.005**	**0.003**	**0.018**	**-**
GO-GARCH MM	48	**-**	**0.567**	**0.905**	**0.255**	**0.082**	**0.044**	**-**	**0.022**	**0.000**	**0.001**	**0.000**	**0.191**	**-**	**0.091**	**0.002**	**0.000**	**0.012**	**0.776**
GO-GARCH ICA	48	**0.588**	**-**	**0.436**	**0.587**	**0.020**	**0.009**	**0.009**	**-**	**0.891**	**0.864**	**0.752**	**0.061**	**0.059**	**-**	**0.780**	**0.354**	**0.705**	**0.036**
DCC	48	**0.586**	**0.248**	**-**	**0.156**	**0.068**	**0.032**	**0.000**	**0.258**	**-**	**0.556**	**0.925**	**0.000**	**0.001**	**0.320**	**-**	**0.432**	**0.100**	**0.000**
COPULA DCC	48	**0.210**	**0.480**	**0.050**	**-**	**0.003**	**0.001**	**0.001**	**0.811**	**0.292**	**-**	**0.574**	**0.004**	**0.000**	**0.143**	**0.521**	**-**	**0.034**	**0.000**
EWMA (0.03, 0.97)	48	**0.033**	**0.008**	**0.034**	**0.001**	**-**	**0.797**	**0.000**	**0.296**	**0.930**	**0.345**	**-**	**0.000**	**0.014**	**0.929**	**0.215**	**0.063**	**-**	**0.000**
SAMPLE	48	**0.008**	**0.002**	**0.004**	**0.000**	**0.555**	**-**	**0.376**	**0.033**	**0.000**	**0.004**	**0.000**	**-**	**0.638**	**0.010**	**0.000**	**0.000**	**0.000**	**-**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.71 Statistical significance of monthly percentage EMF Africa weight of mean-variance long-only portfolios between models for the 72-month estimation period

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	48	**-**	**0.786**	**0.629**	**0.111**	**0.454**	**0.023**	**-**	**0.312**	**0.480**	**0.159**	**0.113**	**0.010**	**-**	**0.174**	**0.300**	**0.147**	**0.709**	**0.011**
GO-GARCH ICA	48	**0.494**	**-**	**0.873**	**0.196**	**0.307**	**0.012**	**0.015**	**-**	**0.729**	**0.885**	**0.864**	**0.509**	**0.007**	**-**	**0.589**	**0.662**	**0.259**	**0.529**
DCC	48	**0.088**	**0.186**	**-**	**0.281**	**0.255**	**0.012**	**0.115**	**0.347**	**-**	**0.525**	**0.471**	**0.133**	**0.118**	**0.135**	**-**	**0.875**	**0.475**	**0.208**
COPULA DCC	48	**0.015**	**0.037**	**0.433**	**-**	**0.027**	**0.001**	**0.047**	**0.527**	**0.729**	**-**	**0.890**	**0.536**	**0.078**	**0.153**	**0.904**	**-**	**0.339**	**0.601**
EWMA (0.03, 0.97)	48	**0.764**	**0.422**	**0.079**	**0.014**	**-**	**0.082**	**0.046**	**0.442**	**0.809**	**0.902**	**-**	**0.598**	**0.402**	**0.034**	**0.439**	**0.351**	**-**	**0.077**
SAMPLE	48	**0.057**	**0.196**	**0.050**	**0.009**	**0.266**	**-**	**0.072**	**0.136**	**0.676**	**0.387**	**0.434**	**-**	**0.257**	**0.022**	**0.369**	**0.269**	**0.973**	**-**
GO-GARCH MM	48	**-**	**0.730**	**0.552**	**0.085**	**0.586**	**0.129**	**-**	**0.382**	**0.764**	**0.314**	**0.400**	**0.209**	**-**	**0.314**	**0.449**	**0.279**	**0.737**	**0.134**
GO-GARCH ICA	48	**0.618**	**-**	**0.833**	**0.180**	**0.360**	**0.061**	**0.523**	**-**	**0.692**	**0.683**	**0.742**	**0.443**	**0.347**	**-**	**0.850**	**0.873**	**0.233**	**0.509**
DCC	48	**0.441**	**0.821**	**-**	**0.227**	**0.230**	**0.026**	**1.000**	**0.465**	**-**	**0.348**	**0.319**	**0.096**	**0.553**	**0.642**	**-**	**0.770**	**0.125**	**0.373**
COPULA DCC	48	**0.088**	**0.244**	**0.311**	**-**	**0.018**	**0.001**	**0.384**	**0.857**	**0.304**	**-**	**1.000**	**0.492**	**0.365**	**0.877**	**0.717**	**-**	**0.068**	**0.530**
EWMA (0.03, 0.97)	48	**0.384**	**0.168**	**0.076**	**0.007**	**-**	**0.307**	**0.466**	**1.000**	**0.380**	**0.830**	**-**	**0.443**	**0.484**	**0.080**	**0.130**	**0.060**	**-**	**0.009**
SAMPLE	48	**0.043**	**0.014**	**0.003**	**0.000**	**0.160**	**-**	**0.207**	**0.574**	**0.130**	**0.670**	**0.494**	**-**	**0.177**	**0.798**	**0.384**	**0.622**	**0.014**	**-**

Notes: The sample runs from 30 June 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The top (bottom) part represents the results for absolute (rank-based) performance. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.

Table 6.72 Mean realised monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	-0.014	0.107	0.215	0.230	0.001	0.010
EWMA (4) smoothing	47	-0.021	0.049	0.097	0.098	-0.042	-0.005
EWMA (8) smoothing	47	-0.007	0.031	0.049	0.047	-0.047	-0.003
EWMA (12) smoothing	47	0.003	0.053	0.038	0.034	-0.045	0.003
No smoothing	47	-0.115	-0.257	-0.051	-0.113	-0.062	0.011
EWMA (4) smoothing	47	-0.158	-0.147	-0.189	-0.200	-0.170	-0.058
EWMA (8) smoothing	47	-0.177	-0.092	-0.262	-0.244	-0.243	-0.105
EWMA (12) smoothing	47	-0.186	-0.045	-0.288	-0.258	-0.281	-0.126
No smoothing	47	-0.347	-0.496	-0.412	-0.324	-0.175	-0.174
EWMA (4) smoothing	47	-0.321	-0.325	-0.397	-0.378	-0.268	-0.199
EWMA (8) smoothing	47	-0.344	-0.242	-0.447	-0.432	-0.362	-0.243
EWMA (12) smoothing	47	-0.360	-0.189	-0.473	-0.456	-0.414	-0.268

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

Table 6.73 Mean realised cumulative monthly percentage returns of mean-variance long-only portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	-14.283	-11.594	-6.690	-6.343	-9.814	-12.797
EWMA (4) smoothing	47	-14.694	-12.966	-11.669	-11.503	-12.467	-13.602
EWMA (8) smoothing	47	-14.498	-12.987	-13.910	-13.920	-13.401	-13.760
EWMA (12) smoothing	47	-14.279	-12.091	-14.584	-14.715	-13.680	-13.683
No smoothing	47	-18.722	-24.454	-16.657	-18.739	-14.699	-14.639
EWMA (4) smoothing	47	-21.013	-20.749	-22.708	-22.750	-20.155	-17.437
EWMA (8) smoothing	47	-21.835	-18.454	-26.053	-25.120	-23.531	-19.075
EWMA (12) smoothing	47	-22.111	-16.485	-27.305	-25.894	-25.060	-19.731
No smoothing	47	-23.231	-29.823	-27.401	-24.376	-18.360	-18.723
EWMA (4) smoothing	47	-24.440	-25.100	-28.569	-27.557	-23.527	-20.444
EWMA (8) smoothing	47	-25.880	-22.569	-31.302	-30.500	-27.798	-22.483
EWMA (12) smoothing	47	-26.590	-20.689	-32.651	-31.762	-29.995	-23.529

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

Table 6.74 Mean monthly percentage standard deviation of mean-variance long-only portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	48	5.437	12.980	4.971	4.939	6.116	5.270
EWMA (4) smoothing	48	5.437	12.980	4.971	4.939	6.116	5.270
EWMA (8) smoothing	48	5.437	12.980	4.971	4.939	6.116	5.270
EWMA (12) smoothing	48	5.437	12.980	4.971	4.939	6.116	5.270
No smoothing	48	6.327	15.508	5.854	5.782	6.985	6.118
EWMA (4) smoothing	48	6.327	15.508	5.854	5.782	6.985	6.118
EWMA (8) smoothing	48	6.327	15.508	5.854	5.782	6.985	6.118
EWMA (12) smoothing	48	6.327	15.508	5.854	5.782	6.985	6.118
No smoothing	48	7.896	19.827	7.422	7.340	8.707	7.642
EWMA (4) smoothing	48	7.896	19.827	7.422	7.340	8.707	7.642
EWMA (8) smoothing	48	7.896	19.827	7.422	7.340	8.707	7.642
EWMA (12) smoothing	48	7.896	19.827	7.422	7.340	8.707	7.642

Notes: The sample runs from 30 June 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

Table 6.75 Mean monthly conditional Sharpe ratio of mean-variance long-only portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	-0.046	-0.020	-0.022	-0.012	-0.093	-0.072
EWMA (4) smoothing	47	-0.049	-0.027	-0.037	-0.038	-0.097	-0.075
EWMA (8) smoothing	47	-0.047	-0.030	-0.048	-0.052	-0.096	-0.076
EWMA (12) smoothing	47	-0.046	-0.029	-0.052	-0.057	-0.095	-0.075
No smoothing	47	-0.092	-0.052	-0.078	-0.071	-0.121	-0.076
EWMA (4) smoothing	47	-0.093	-0.045	-0.090	-0.080	-0.133	-0.089
EWMA (8) smoothing	47	-0.095	-0.043	-0.100	-0.086	-0.140	-0.098
EWMA (12) smoothing	47	-0.096	-0.041	-0.104	-0.088	-0.145	-0.102
No smoothing	47	-0.123	-0.060	-0.114	-0.082	-0.141	-0.099
EWMA (4) smoothing	47	-0.115	-0.051	-0.102	-0.081	-0.147	-0.104
EWMA (8) smoothing	47	-0.116	-0.046	-0.104	-0.083	-0.154	-0.110
EWMA (12) smoothing	47	-0.117	-0.044	-0.106	-0.084	-0.159	-0.114

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics.

Table 6.76 Mean monthly percentage turnover of mean-variance long-only portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	31.275	61.233	58.427	49.288	10.816	2.417
EWMA (4) smoothing	47	10.855	24.083	23.386	22.426	6.153	1.804
EWMA (8) smoothing	47	6.096	14.267	13.427	13.631	4.494	1.603
EWMA (12) smoothing	47	4.388	10.634	9.494	9.944	3.480	1.498
No smoothing	47	55.974	83.758	82.459	76.715	32.026	19.663
EWMA (4) smoothing	47	22.090	34.196	32.227	31.548	15.614	10.163
EWMA (8) smoothing	47	13.090	20.512	18.546	18.413	10.668	7.511
EWMA (12) smoothing	47	9.626	14.928	13.312	13.339	8.525	6.276
No smoothing	47	63.800	85.925	77.669	76.327	38.304	25.603
EWMA (4) smoothing	47	26.316	34.407	28.974	30.311	19.309	12.540
EWMA (8) smoothing	47	15.507	19.858	16.990	17.645	13.295	8.850
EWMA (12) smoothing	47	11.439	14.132	12.445	12.822	10.535	7.256

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean values of portfolio monthly statistics. Values are expressed in percentages.

Table 6.77 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-short portfolios between models for the 72-month estimation period based on no weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.000**	**0.928**	**0.701**	**0.000**	**0.000**	-	**0.000**	**0.451**	**0.851**	**0.000**	**0.000**	-	**0.000**	**0.460**	**0.792**	**0.000**	**0.000**
GO-GARCH ICA	47	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.615**	**0.000**	-	**0.451**	**0.000**	**0.000**	**0.909**	**0.000**	-	**0.284**	**0.000**	**0.000**	**0.858**	**0.000**	-	**0.230**	**0.000**	**0.000**
COPULA DCC	47	**0.327**	**0.000**	**0.575**	-	**0.000**	**0.000**	**0.526**	**0.000**	**0.408**	-	**0.000**	**0.000**	**0.462**	**0.000**	**0.317**	-	**0.000**	**0.000**
EWMA (0.03, 0.97)	47	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.011**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.006**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.016**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$. *The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.78 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-short portfolios between models for the 72-month estimation period based on EWMA (4) weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.000**	**0.964**	**0.940**	**0.001**	**0.000**	-	**0.000**	**1.000**	**0.868**	**0.001**	**0.000**	-	**0.000**	**0.821**	**0.851**	**0.001**	**0.000**
GO-GARCH ICA	47	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.689**	**0.000**	-	**0.988**	**0.000**	**0.000**	**0.773**	**0.000**	-	**0.928**	**0.000**	**0.000**	**0.663**	**0.000**	-	**0.816**	**0.001**	**0.000**
COPULA DCC	47	**0.717**	**0.000**	**0.965**	-	**0.000**	**0.000**	**0.654**	**0.000**	**0.863**	-	**0.001**	**0.000**	**0.456**	**0.000**	**0.746**	-	**0.002**	**0.000**
EWMA (0.03, 0.97)	47	**0.007**	**0.000**	**0.009**	**0.008**	-	**0.000**	**0.008**	**0.000**	**0.009**	**0.012**	-	**0.001**	**0.011**	**0.000**	**0.021**	**0.034**	-	**0.003**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.010**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$. *The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.79 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-short portfolios between models for the 72-month estimation period based on EWMA (8) weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.000**	**0.816**	**0.982**	**0.015**	**0.000**	-	**0.000**	**0.928**	**0.934**	**0.030**	**0.000**	-	**0.000**	**0.970**	**0.964**	**0.065**	**0.000**
GO-GARCH ICA	47	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	-	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.754**	**0.000**	-	**0.804**	**0.033**	**0.000**	**0.822**	**0.000**	-	**0.874**	**0.028**	**0.000**	**0.770**	**0.000**	-	**0.934**	**0.074**	**0.000**
COPULA DCC	47	**0.906**	**0.000**	**0.845**	-	**0.034**	**0.000**	**0.823**	**0.000**	**0.999**	-	**0.030**	**0.000**	**0.652**	**0.000**	**0.868**	-	**0.096**	**0.000**
EWMA (0.03, 0.97)	47	**0.111**	**0.000**	**0.171**	**0.131**	-	**0.001**	**0.146**	**0.000**	**0.190**	**0.195**	-	**0.003**	**0.195**	**0.000**	**0.280**	**0.347**	-	**0.006**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.011**	-	**0.000**	**0.000**	**0.000**	**0.000**	**0.018**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$. *The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.80 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-short portfolios between models for the 72-month estimation period based on EWMA (12) weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	**-**	**0.000**	**0.821**	**0.857**	**0.090**	**0.000**	**-**	**0.000**	**0.958**	**0.792**	**0.160**	**0.000**	**-**	**0.000**	**0.910**	**0.964**	**0.271**	**0.000**
GO-GARCH ICA	47	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**-**	**0.000**	**0.000**	**0.000**	**0.000**
DCC	47	**0.828**	**0.000**	**-**	**0.781**	**0.139**	**0.000**	**0.924**	**0.000**	**-**	**0.868**	**0.163**	**0.000**	**0.867**	**0.000**	**-**	**0.952**	**0.281**	**0.000**
COPULA DCC	47	**0.971**	**0.000**	**0.803**	**-**	**0.120**	**0.000**	**0.978**	**0.000**	**0.947**	**-**	**0.141**	**0.000**	**0.819**	**0.000**	**0.947**	**-**	**0.258**	**0.000**
EWMA (0.03, 0.97)	47	**0.342**	**0.000**	**0.442**	**0.334**	**-**	**0.004**	**0.443**	**0.000**	**0.485**	**0.459**	**-**	**0.008**	**0.531**	**0.000**	**0.625**	**0.672**	**-**	**0.008**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.008**	**-**	**0.001**	**0.000**	**0.001**	**0.001**	**0.023**	**-**	**0.002**	**0.000**	**0.003**	**0.004**	**0.033**	**-**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$. *The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.81 Mean realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-only portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	-11.961	-23.285	-22.104	-18.598	-4.130	-0.913
EWMA (4) smoothing	47	-4.167	-9.151	-8.837	-8.469	-2.393	-0.694
EWMA (8) smoothing	47	-2.336	-5.419	-5.080	-5.160	-1.764	-0.616
EWMA (12) smoothing	47	-1.673	-4.009	-3.589	-3.765	-1.374	-0.569
No smoothing	47	-21.497	-32.253	-31.550	-29.418	-12.296	-7.500
EWMA (4) smoothing	47	-8.596	-13.211	-12.499	-12.251	-6.134	-3.940
EWMA (8) smoothing	47	-5.177	-7.927	-7.346	-7.278	-4.318	-2.974
EWMA (12) smoothing	47	-3.863	-5.747	-5.373	-5.354	-3.538	-2.524
No smoothing	47	-24.719	-33.319	-30.082	-29.481	-14.807	-9.955
EWMA (4) smoothing	47	-10.374	-13.469	-11.465	-11.957	-7.644	-4.989
EWMA (8) smoothing	47	-6.268	-7.828	-6.937	-7.172	-5.440	-3.623
EWMA (12) smoothing	47	-4.730	-5.588	-5.227	-5.354	-4.439	-3.040

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high-risk portfolios. This table shows mean realised monthly portfolio returns adjusted for the approximated mean monthly portfolio transaction costs i.e. $Mean\ realised\ return - Mean\ transaction\ costs$*. The approximated mean monthly portfolio transaction costs are calculated as the mean monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points.*[12,13] *Values are expressed in percentages.*

[12] The approximated mean monthly portfolio transaction costs can be found in the appendix in Table 6.87.

[13] There are a number of different estimates of transaction costs. For example, Sun *et al.* (2006) find that the transaction costs are 60 basis points for emerging markets, 40 basis points for developed markets and 30 basis points for US equity. French (2008) estimates the trading costs on US market to be 11 basis points. DeMiguel *et al.* (2009a) use 50 basis points as transaction costs. The estimated 38.2 basis points is the average of these values.

Table 6.82 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-only portfolios between models for the 72-month estimation period based on no weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	**-**	**0.027**	**0.006**	**0.043**	**0.001**	**0.000**	**-**	**0.056**	**0.009**	**0.043**	**0.001**	**0.000**	**-**	**0.184**	**0.227**	**0.271**	**0.009**	**0.000**
GO-GARCH ICA	47	**0.003**	**-**	**0.970**	**0.537**	**0.000**	**0.000**	**0.016**	**-**	**0.976**	**0.701**	**0.000**	**0.000**	**0.087**	**-**	**0.679**	**0.603**	**0.001**	**0.000**
DCC	47	**0.003**	**0.782**	**-**	**0.493**	**0.000**	**0.000**	**0.009**	**0.883**	**-**	**0.641**	**0.000**	**0.000**	**0.228**	**0.521**	**-**	**0.928**	**0.000**	**0.000**
COPULA DCC	47	**0.033**	**0.249**	**0.343**	**-**	**0.000**	**0.000**	**0.028**	**0.538**	**0.599**	**-**	**0.000**	**0.000**	**0.279**	**0.444**	**0.893**	**-**	**0.000**	**0.000**
EWMA (0.03, 0.97)	47	**0.002**	**0.000**	**0.000**	**0.000**	**-**	**0.098**	**0.004**	**0.000**	**0.000**	**0.000**	**-**	**0.089**	**0.014**	**0.000**	**0.000**	**0.000**	**-**	**0.194**
SAMPLE	47	**0.000**	**0.000**	**0.000**	**0.000**	**0.083**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.075**	**-**	**0.000**	**0.000**	**0.000**	**0.000**	**0.128**	**-**

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$*. The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.83 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-only portfolios between models for the 72-month estimation period based on EWMA (4) weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	0.024	0.008	0.006	0.213	0.015	-	0.047	0.082	0.092	0.133	0.008	-	0.284	0.792	0.746	0.187	0.005
GO-GARCH ICA	47	0.012	-	0.940	1.000	0.001	0.000	0.040	-	0.707	0.619	0.001	0.000	0.224	-	0.358	0.498	0.028	0.000
DCC	47	0.010	0.880	-	0.982	0.000	0.000	0.079	0.766	-	0.964	0.002	0.000	0.661	0.454	-	0.804	0.133	0.004
COPULA DCC	47	0.019	0.744	0.850	-	0.000	0.000	0.093	0.683	0.915	-	0.002	0.000	0.507	0.557	0.846	-	0.064	0.001
EWMA (0.03, 0.97)	47	0.279	0.001	0.000	0.001	-	0.249	0.239	0.002	0.006	0.007	-	0.278	0.264	0.028	0.140	0.084	-	0.216
SAMPLE	47	0.026	0.000	0.000	0.000	0.271	-	0.016	0.000	0.000	0.000	0.266	-	0.017	0.001	0.008	0.003	0.255	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$. *The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.84 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-only portfolios between models for the 72-month estimation period based on EWMA (8) weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.054**	**0.049**	**0.038**	**0.593**	**0.187**	-	**0.103**	**0.295**	**0.271**	**0.542**	**0.116**	-	**0.465**	**0.880**	**0.707**	**0.684**	**0.149**
GO-GARCH ICA	47	**0.055**	-	**0.952**	**0.958**	**0.020**	**0.002**	**0.141**	-	**0.662**	**0.752**	**0.024**	**0.003**	**0.471**	-	**0.641**	**0.718**	**0.274**	**0.038**
DCC	47	**0.076**	**0.839**	-	**0.804**	**0.013**	**0.001**	**0.259**	**0.767**	-	**0.988**	**0.092**	**0.009**	**0.760**	**0.694**	-	**0.786**	**0.465**	**0.107**
COPULA DCC	47	**0.070**	**0.877**	**0.961**	-	**0.010**	**0.001**	**0.269**	**0.739**	**0.973**	-	**0.071**	**0.006**	**0.670**	**0.766**	**0.916**	-	**0.407**	**0.057**
EWMA (0.03, 0.97)	47	**0.697**	**0.024**	**0.034**	**0.031**	-	**0.382**	**0.645**	**0.061**	**0.126**	**0.131**	-	**0.366**	**0.703**	**0.289**	**0.510**	**0.433**	-	**0.312**
SAMPLE	47	**0.230**	**0.003**	**0.004**	**0.003**	**0.427**	-	**0.208**	**0.007**	**0.020**	**0.021**	**0.456**	-	**0.196**	**0.049**	**0.125**	**0.090**	**0.393**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$*. The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.85 Statistical significance of realised monthly percentage returns adjusted for approximated transaction costs of mean-variance long-only portfolios between models for the 72-month estimation period based on EWMA (12) weight smoothing

Model	Sample length	Low risk portfolio						Medium risk portfolio						High risk portfolio					
		MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL	MM	ICA	DCC	COP	EWMA	SMPL
GO-GARCH MM	47	-	**0.082**	**0.123**	**0.106**	**0.769**	**0.342**	-	**0.255**	**0.429**	**0.378**	**0.763**	**0.312**	-	**0.724**	**0.916**	**0.752**	**0.851**	**0.323**
GO-GARCH ICA	47	**0.118**	-	**0.781**	**0.904**	**0.051**	**0.012**	**0.288**	-	**0.729**	**0.910**	**0.125**	**0.039**	**0.678**	-	**0.810**	**0.880**	**0.567**	**0.182**
DCC	47	**0.192**	**0.784**	-	**0.763**	**0.073**	**0.021**	**0.408**	**0.839**	-	**0.976**	**0.320**	**0.073**	**0.813**	**0.867**	-	**0.886**	**0.724**	**0.252**
COPULA DCC	47	**0.157**	**0.874**	**0.908**	-	**0.047**	**0.016**	**0.410**	**0.829**	**0.992**	-	**0.278**	**0.065**	**0.761**	**0.911**	**0.953**	-	**0.593**	**0.236**
EWMA (0.03, 0.97)	47	**0.833**	**0.081**	**0.134**	**0.109**	-	**0.537**	**0.856**	**0.224**	**0.325**	**0.326**	-	**0.395**	**0.888**	**0.589**	**0.715**	**0.665**	-	**0.362**
SAMPLE	47	**0.429**	**0.021**	**0.039**	**0.030**	**0.566**	-	**0.430**	**0.063**	**0.110**	**0.109**	**0.559**	-	**0.394**	**0.212**	**0.292**	**0.254**	**0.495**	-

Notes: The sample runs from 31 July 2008 to 11 May 2012. The upper (lower) triangle represents the Wilcoxon rank sum (Welch t) test p-values. The results are for absolute performance. These realised monthly portfolio returns are adjusted for the approximated monthly portfolio transaction costs i.e. $Realised\ return - Transaction\ costs$. *The approximated monthly portfolio transaction costs are calculated as the monthly portfolio percentage turnover multiplied by the average transaction cost of 38.2 basis points. Blue indicates significant at 10%, Green indicates significant at 5%, Red indicates significant at 1%.*

Table 6.86 Approximated mean monthly percentage transaction costs of mean-variance long-short portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	65.491	151.374	61.593	57.780	28.892	10.611
EWMA (4) smoothing	47	23.604	51.300	22.323	22.369	14.539	5.161
EWMA (8) smoothing	47	13.355	28.257	12.555	12.848	9.621	3.560
EWMA (12) smoothing	47	9.433	19.758	8.831	9.163	7.392	2.853
No smoothing	47	77.137	177.178	77.918	71.075	36.504	19.432
EWMA (4) smoothing	47	28.728	61.328	27.486	26.887	18.017	8.941
EWMA (8) smoothing	47	16.354	33.846	15.533	15.463	12.102	6.131
EWMA (12) smoothing	47	11.594	23.792	11.065	11.131	9.437	4.895
No smoothing	47	94.408	210.489	96.020	85.586	48.017	29.041
EWMA (4) smoothing	47	35.827	74.007	33.557	32.249	23.152	13.136
EWMA (8) smoothing	47	20.349	41.237	19.114	18.607	15.602	8.959
EWMA (12) smoothing	47	14.496	28.864	13.669	13.462	12.202	7.146

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high risk portfolios. This table shows approximated mean monthly portfolio transaction costs i.e. the mean monthly portfolio percentage turnover is multiplied by the average transaction cost of 38.2 basis points. Values are expressed in percentages.

Table 6.87 Approximated mean monthly percentage transaction costs of mean-variance long-only portfolios between models for the 72-month estimation period based on different weight smoothing

Weight smoothing	Sample length	Model					
		MM	ICA	DCC	COP	EWMA	SMPL
No smoothing	47	11.947	23.391	22.319	18.828	4.132	0.923
EWMA (4) smoothing	47	4.147	9.200	8.934	8.567	2.350	0.689
EWMA (8) smoothing	47	2.329	5.450	5.129	5.207	1.717	0.613
EWMA (12) smoothing	47	1.676	4.062	3.627	3.799	1.329	0.572
No smoothing	47	21.382	31.996	31.499	29.305	12.234	7.511
EWMA (4) smoothing	47	8.438	13.063	12.311	12.051	5.964	3.882
EWMA (8) smoothing	47	5.001	7.836	7.085	7.034	4.075	2.869
EWMA (12) smoothing	47	3.677	5.703	5.085	5.096	3.257	2.397
No smoothing	47	24.371	32.823	29.670	29.157	14.632	9.780
EWMA (4) smoothing	47	10.053	13.144	11.068	11.579	7.376	4.790
EWMA (8) smoothing	47	5.924	7.586	6.490	6.740	5.079	3.381
EWMA (12) smoothing	47	4.370	5.399	4.754	4.898	4.024	2.772

Notes: The sample runs from 31 July 2008 to 11 May 2012. The top, middle and bottom panels represent the low, medium and high risk portfolios. This table shows approximated mean monthly portfolio transaction costs i.e. the mean monthly portfolio percentage turnover is multiplied by the average transaction cost of 38.2 basis points. Values are expressed in percentages.

7 CONCLUSIONS, RECOMMENDATIONS AND FURTHER WORK

This last chapter of the PhD thesis describes the main conclusions and discusses the implications of the findings for professional portfolio managers. Finally, the chapter identifies the scope for potential future research.

7.1 THE IMPACT OF CRISIS AND ESTIMATION METHODOLOGY ON CORRELATION AND VOLATILITY

The main contributions of this PhD thesis to the academic body of knowledge are found in Chapters 4, 5 and 6.

In Chapter 4 I identify that conditional correlations estimated using the DCC model were influenced by the cyclical nature of financial markets. Prima facie evidence is presented to support the hypothesis that economic structural adjustment has resulted in long-term increases in the correlation between the US and other markets.

The second key finding is that the *magnitude* of the increase in correlation appears to be greater in respect to emerging/frontier markets. For example, from pre-crisis to post-crisis the correlation between the US and BRIC countries rose by 6.2% to 0.668 and between the US and emerging frontier Africa increased by 13% to 0.599. There is a prima facie case for the argument that the increases in correlation found are possibly a consequence of two interrelated factors. The global tightening of regulations and the deleveraging effects seen across much of the global financial sector in response to the crisis is the first possible factor. The second is the impact of the crisis on relative market conditional volatilities. It is found that, in most instances, post-crisis volatility *rose* in other developed markets relative to the US and that post-crisis volatility *fell* in emerging/frontier markets relative to the US. I would argue that this difference possibly explains the smaller increases in the correlation with the US in respect to developed markets than in respect to emerging/frontier markets.

In Chapter 5 I examine the impact of using different covariance methodologies on the estimates of correlations and volatilities.

From the tables in Chapter 5 it can be identified that GO-GARCH correlations *are higher* than both DCC and both MA correlations. The potential implications are that the diversification benefits *are lower* according to GO-GARCH methodologies than for DCC and MA methodologies. On this basis it was concluded that although the GO-GARCH methodologies have considerable drawbacks they had to be examined in the next stage of the thesis.

Conditional volatilities of GO-GARCH models (especially ICA and ML) *are generally higher* than those of the DCC and MA models. This implies that GO-GARCH portfolios will be less efficient because keeping correlations constant, high asset volatility implies high portfolio volatility.

In Chapter 6 I examine which estimation methods produce the most efficient portfolio. The main issue is how to deal with complexity of the task. In Figure 6.1 and Figure 6.2 I identify the main potential testing pathways. The actual pathways followed are shown using blue (Figure 6.1). In Figure 6.2 portfolio performance measures are shown in yellow and model comparison hypothesis tests are coloured in green. The output measures considered are: realised portfolio returns, realised cumulative portfolio returns and conditional Sharpe ratio. I also examine the issue of portfolio weightings and portfolio turnover. The main finding is that none of the time-varying covariance methodologies appreciably perform better than the others. In addition it is noted that PT rates were significantly greater for all the time-varying methods in comparison to the SMPL method. What implications do these findings have for portfolio management in practice?

7.2 IMPLICATIONS OF FINDINGS ON PORTFOLIO MANAGEMENT

The issue of turnover and how often portfolio should be rebalanced is frequently discussed by portfolio management practitioners. For example, John C. Bogle, the founder of the Vanguard Group, states:

‘As far as rebalancing goes, there is another option: hold off. Rebalancing is something I do not think anybody should follow slavishly.’ (Lim 2013)

Similar sentiments can be seen as been expressed elsewhere. For instance, Jaconetti *et al*. (2010) state:

‘…the risk-adjusted returns are not meaningfully different whether a portfolio is rebalanced monthly, quarterly, or annually; however, the number of rebalancing events and resulting costs (taxes, time and labour) increase significantly.’

I have identified that optimal portfolio rebalancing is extremely high for time-varying methods. I therefore have had to consider whether or not practitioners are correct in suggesting that rebalancing costs will outweigh their benefits. Table 6.24 identifies that after adjusting for transaction costs the returns from using all methodologies are negative.

7.3 FUTURE POTENTIAL WORK

The limited work on constrained optimisation shows that rebalancing has a major impact on the size of transaction costs associated with those covariance models. Future research would be to take this analysis further by looking at the impact of using different constrained optimisation techniques; these would include both smoothing-based methodologies and also threshold-based methods. It may be that under constrained techniques the time-varying techniques outperform the SMPL method. However, this would be a question to be looked at a future date.

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