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Modelling and Forecasting Financial Asset Return and Volatility Spillovers: Theory and Applications

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Research Outputs

From thesis

- *Aftab, Hira & Beg, Rabiul & Sun, Sizhong & Zhou, Zhangyue. (2019).* **Erratum to "Testing and Predicting Volatility Spillover—A Multivariate GJR-GARCH Approach" [Theoretical Economics Letters, 2019, 9, 83-99].** Theoretical Economics Letters. 09. 1393-1410. 10.4236/tel.2019.95090.

Conference Presentations

- *Aftab, Hira & Beg, Rabiul & Sun, Sizhong & Zhou, Zhangyue.* **Multivariate BEKK-TGARCH approach to testing and predicting volatility spillovers & leverage effects.** Asia-Pacific Conference on Economics & Finance, Singapore, 26-27 July 2018

Statement of the Contribution of Others

Name of Assistance	Contribution	Names, Titles and Affiliation of Contributors
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Abstract

This thesis presents a new methodology and evidence for the stochastic behaviour of financial asset returns and the relationship between return volatility and expected returns. This thesis deals with both univariate and multivariate financial volatility model specifications and modelling issues encountered in both theory and applications. Starting with univariate volatility models, this study estimates and predicts standard generalised autoregressive conditional heteroscedasticity (SGARCH) models. Extension of the univariate GARCH to Glosten–Jagannathan–Runkle (GJR) allows exploration of the effects of return shocks on volatility generally known as GJR-GARCH. The asymmetric effects of volatility risk premiums are investigated within GJR-GARCH-in-mean (GJR-GARCH-M) models allowing the asymmetric conditional volatility to be a determinant of expected returns. The parameters of the univariate models are estimated by the maximum likelihood (ML) method under the assumptions of a normal distribution and Student-t and skewed Student-t distributions with unknown degrees of freedom. Models are tested for adequacy using univariate Ljung–Box statistics. Asymmetric 'news' effects on the volatility, sign and size bias of asymmetry and the existence of risk premiums are tested in these models using the Student-t test and F tests. This study analyses the effects of long-run and short-run return shocks on conditional volatility models for policy decision analysis.

Since the univariate study is incomplete with respect to financial security markets, there is a need for multivariate models for the analysis of financial securities, for three main reasons. First, univariate models are incapable of assessing market interactions and causality in a Granger sense. Second, in the univariate case, it is not known explicitly how the movement of forecast error variance of an asset is due to its own shocks as opposed to shocks from other assets. Third, co-volatility, partial co-volatility and full co-volatility spillovers of return shocks on volatility cannot be assessed in general. To allow dynamic interdependence of assets across countries, I formulated conditional volatility models within a multivariate time series framework.

Multivariate volatility models commonly used in the literature include the full Baba–Engle–Kraft–Kroner (BEKK), the dynamic conditional correlation (DCC)-parameterised BEKK volatility model, and the diagonal vectorization (VEC) model. The univariate GARCH is not a special case of these multivariate models. These multivariate models have no underlying

stochastic process, regularity conditions or asymptotic properties. The quasi-likelihood estimates (QMLEs) for the above multivariate models have no asymptotic properties. Consequently, no valid test of co-volatility spillovers exists for these models. However, multivariate volatility models derived from multivariate random coefficient vector autoregression (VAR) of the return shocks of order one provides diagonal BEKK (DBEKK) have the required asymptotic properties of the QMLE and classical statistical tests of volatility spillovers derived from DBEKK are statistically valid.

This study analyses DBEKK-GARCH, DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M models to investigate volatility spillovers and develop Wald-type tests for asymmetric volatility spillovers. The definition of partial co-volatility is extended to DBEKK-GJR-GARCH models for testing and modelling financial volatilities within a multivariate framework for the stock returns of 12 countries grouped as developed, advanced emerging and emerging financial markets.

Dynamic interrelationships of stock returns and bond returns are investigated within classical VAR model with crash events, called VAR-X and panel VAR with the crash event, called PVAR-X models. The VAR-X is estimated by employing Cholesky's factorisation technique and the PVAR-X is estimated utilising the generalised method of moments. The estimated models are utilised to test for financial market crash events and a new severity index (SI) is created using Fisher's p-value for determining the degree of severity of events occurring during the financial crash of 1987, the Asian Financial Crisis (AFC) and the Global Financial Crisis (GFC). Variance decomposition and impulse response analyses are conducted to examine the effects of assets' own shocks, as well as shocks of other assets, on return volatility and prediction analysis. Model stability is tested using the eigenvalue approach to VAR-X and PVAR-X models. This study conducts nonparametric Kendall's tau correlation tests and Spearman's rank correlation tests on the return series to determine both linear and nonlinear dependence between asset returns. Pearson's linear correlation is also considered for comparison purposes with chi-square tests of covariance dependence calculated for all pairs jointly. Finally, the Gumbel copula with Student-t marginal distributions is utilised as an alternative to GARCH for volatility dependence analysis. In general, this thesis provides a wide range of methodologies for dynamic dependence of asset returns and volatilities of returns in the multivariate context.

This study finds evidence of asymmetric co-volatility spillovers, significant long- and short-run effects of return shocks on volatility, the existence of Granger type causality, co-volatility spillovers and significant risk premiums, with some reservations. Further, evidence suggests that the severity of the 1987 crash is the highest, followed by the GFC and Asian Financial Crisis (AFC) in the stock markets of the five selected countries, namely Australia, France, Japan, Singapore, and US. The severity of the GFC experienced by the five countries across Stock, Bond, and Money markets is in the order of $\text{Stock}_{Gfc} > \text{T-bill}_{Gfc} > \text{Bond}_{Gfc}$. Nonparametric correlation tests and covariance dependence tests find significant correlations and covariance dependence among returns in the stock market for US, UK, Japan, Australia and Hong Kong. A simulated copula reveals significant dependence in the conditional volatility of stock returns.

The approach employed in this thesis is expected to find the relationship between asset markets volatility, contagion and expected returns that best meet the objectives of researchers, investors and policy makers in the real world of business.

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List of Abbreviations

ADF	Augmented Dickey–Fuller
AIC	Akaike Information Criterion
APARCH	Asymmetric power autoregressive conditional heteroscedasticity
AR	Autoregression
ARCH	Autoregressive conditional heteroscedasticity
AARCH	Asymmetric ARCH
ARMA	Autoregressive moving average
BEKK	Baba Engle Kraft Kroner
BIC	Bayesian Information Criterion
BRICS	Brazil, Russia, India, China and South Africa (association)
CAPM	Capital asset pricing model
CCC	Constant conditional correlation
CEE	Central and Eastern Europe
DBEKK	Diagonal BEKK
DGP	Data generating processes
EARCH	Exponential ARCH
EGARCH	Exponential GARCH
EMH	Efficient market hypothesis
FTSE	Financial Times Stock Exchange
GARCH	Generalised ARCH
GED	Generalised error distribution
GFC	Global Financial Crisis
GJR	Glosten Jagannathan Runkle
GMM	Generalised method of moments

HK	Hong Kong
HQ	Hannan and Quinn
ICAPM	Intertemporal capital asset pricing model
IPS	Im, Pesaran and Shin
IRF	Impulse response function
LM	Lagrange multiplier
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LB	Ljung-Box
LR	Likelihood ratio
MA	Moving average
MGARCH	Multivariate generalised ARCH
ML	Maximum likelihood
MLE	Maximum likelihood estimate
MSCI	Morgan Stanley Capital International
OLS	Ordinary least squares
PP	Phillips-Perron
PVAR	Panel VAR
QML	Quasi-maximum likelihood
QMLE	Quasi-maximum likelihood estimate
RE	Rational expectation
SBC	Schwarz Bayesian Criterion
SGARCH	Standard generalised ARCH
SI	Severity index
SK	South Korea
SUR	Seemingly unrelated regression
TBEKK	Triangular BEKK

UK	United Kingdom
US	United States
VaR	Value-at-risk
VAR	Vector autoregression
VARMA	Vector autoregressive moving average
VC	Varying correlation
VEC	Diagonal vectorization
VMA	Vector moving average
vs	Versus

List of Formulae

$$r_t = \mu_t + \varepsilon_t = E\left(r_t \mid F_{t-1}\right) + \varepsilon_t \tag{3.1}$$

$$r_t \mid F_{t-1} = \phi_0 + \sum_{i=1}^{k} \phi_i r_{t-i} + \sum_{j=1}^{m} \psi_j \varepsilon_{t-j} + \varepsilon_t \tag{3.2}$$

$$\varepsilon_t = e_t h_t^{1/2} \tag{3.3}$$

$$h_t \mid F_{t-1} = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{3.4}$$

$$r_t \mid F_{t-1} \sim N(\mu_t, h_t) \tag{3.5}$$

$$h_t = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{3.6}$$

$$r_t = \mu_t + \delta g(h_t) + \varepsilon_t \tag{3.7}$$

$$\ln h_t = w_0 + \sum_{j=1}^{p} \beta_j \ln h_{t-1} + \sum_{i=1}^{q} \gamma_i e_{t-i} + \sum_{i=1}^{q} \delta_i \left[\mid e_{t-i} \mid - \sqrt{2/\pi} \right] \tag{3.8}$$

$$r_t \mid F_{t-1} = \mu_t + \varepsilon_t,$$

$$h_t \mid F_{t-1} = w_0 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i d_{t-i} \varepsilon_{t-i}^2 \tag{3.9}$$

$$r_t = \mu_t + \varepsilon_t, \ \varepsilon_t = H^{0.5} e_t \tag{3.10}$$

$$\mu_t = \sum_{i=1}^{k} \phi_i r_{t-i} + \sum_{j=1}^{m} \psi_j \varepsilon_{t-j} \tag{3.11}$$

$$E(\varepsilon_t \varepsilon_t' \mid F_{t-1}) = H_t \tag{3.12}$$

$$corr(\varepsilon_t \mid F_{t-1}) = \rho_t = D^{-1/2} H_t D^{-1/2} \tag{3.13}$$

$$H_t = D_t \rho_t D_t \tag{3.14}$$

$$H_t = L_t D_t * L_t' \tag{3.15}$$

$$H_t = W_0 + \sum_{i=1}^{q} A_i \odot (\varepsilon_{t-i}\varepsilon'_{t-i}) + \sum_{j=1}^{p} B_j \odot H_{t-j} \tag{3.16}$$

$$H_t = CC' + \sum_{i=1}^{q}\sum_{k=1}^{K} A_{ki}\varepsilon_{t-i}\varepsilon'_{t-i}A'_{ki} + \sum_{j=1}^{p}\sum_{k=1}^{K} B_{kj}H_{t-j}B'_{kj} \tag{3.17}$$

$$H_t = CC' + \sum_{i=1}^{q} A_i\varepsilon_{t-i}\varepsilon'_{t-i}A'_i + \sum_{j=1}^{p} B_j H_{t-j} B'_j \tag{3.18}$$

$$\left(H_{ij}\right)_t = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij},\ i \neq j \tag{3.19}$$

$$h_t = w + \sum_{i=1}^{q} A_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} B_j h_{t-j} \tag{3.20}$$

$$\rho_t = (1-\lambda_1-\lambda_2)\rho + \lambda_1\rho_{t-1} + \lambda_2\Pi_{t-1} \tag{3.21}$$

$$\rho_t = (1-\gamma_1-\gamma_2)G + \gamma_1 G_{t-1} + \gamma_2\rho_{t-1} \tag{3.22}$$

$$Q_t = (1-\gamma_1-\gamma_2)\bar{Q} + \gamma_1\varepsilon_{t-1}\varepsilon'_{t-1} + \gamma_2 Q_{t-1} \tag{3.23}$$

$$\rho_t = (I \odot Q_t)^{-1/2} Q_t (I \odot Q_t)^{-1/2} \tag{3.24}$$

$$r_t = E(r_t \mid F_{t-1}) + \varepsilon_t \tag{4.1}$$

$$r_t \mid F_{t-1} = \phi_0 + \sum_{i=1}^{k} \phi_i r_{t-i} + \sum_{j=1}^{m} \psi_j \varepsilon_{t-j} + \varepsilon_t \tag{4.2}$$

$$h_t \mid F_{t-1} \sim GARCH(p,q) \tag{4.3}$$

$$h_t \mid F_{t-1} \sim GJR-GARCH(p,q) \tag{4.4}$$

$$r_t \mid F_{t-1} = ARMA(\mathrm{k,m}) + \delta g(h_t) + \varepsilon_t \tag{4.5}$$

$$f(\varepsilon_t \mid F_{t-1}) = \frac{\Gamma[(v+1)/2]}{\pi^{1/2}\Gamma(v/2)}[(v-2)h_t]^{-1/2} \times \left[1 + \frac{\varepsilon_t^2}{(v-2)h_t}\right]^{-(1/2)(v+1)} \tag{4.6}$$

$$f(\varepsilon_t \mid F_{t-1}) = \frac{v \exp\left(-(1/2)\left|\frac{\varepsilon_t}{\sqrt{h_t}\ \lambda}\right|^v\right)}{\sqrt{h_t}\ \lambda 2^{(v+1)/2}\Gamma(1/v)} \tag{4.7}$$

where $\lambda = \sqrt{\frac{2^{-2/v}\Gamma(1/v)}{\Gamma(3/v)}}$

$$f(e_t \mid v, \lambda) = \begin{cases} bc\left[1 + (1/(v-2))\left(\frac{be_t + a}{1-\lambda}\right)^2\right]^{-((v+1)/2)} & \text{if } e_t < -a/b \\ bc\left[1 + (1/(v-2))\left(\frac{be_t + a}{1+\lambda}\right)^2\right]^{-((v+1)/2)} & \text{if } e_t \geq -a/b \end{cases} \tag{4.8}$$

$$l(\theta \mid r) = \sum_{t=1}^{T}\left\{-\frac{1}{2}\ln 2\pi - \frac{1}{2}\ln h_t - \frac{\varepsilon_t^2}{2h_2}\right\} \tag{4.9}$$

$$r_t \mid F_{t-1} = \Phi_0 + \Phi_1 r_{t-1} + \varepsilon_t, \text{ and } \varepsilon_t = \mathrm{H}^{1/2} z_t \tag{4.10}$$

$$\mathrm{H_t|F_{t-1}} = \mathrm{CC'} + \mathrm{A}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\mathrm{A}^{'} + \mathrm{BH_{t-1}B}^{'} + \Gamma \mathrm{D_{t-1}}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\Gamma' \tag{4.11}$$

$$\mathrm{H_t{=}CC'}+\begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix}\begin{pmatrix} \varepsilon_{1t}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} & \varepsilon_{1t-1}\varepsilon_{3t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon_{2t}^2 & \varepsilon_{2t-1}\varepsilon_{3t-1} \\ \varepsilon_{3t-1}\varepsilon_{1t-1} & \varepsilon_{3t-1}\varepsilon_{2t-1} & \varepsilon_{3t}^2 \end{pmatrix}\begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix}^{'} + \begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix}\begin{pmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t} & h_{33,t-1} \end{pmatrix}\begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix}^{'} +$$

$$\begin{pmatrix} \gamma_{11} & 0 & 0 \\ 0 & \gamma_{22} & 0 \\ 0 & 0 & \gamma_{33} \end{pmatrix}\mathrm{D_t}\begin{pmatrix} \varepsilon_{1t}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} & \varepsilon_{1t-1}\varepsilon_{3t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon_{2t}^2 & \varepsilon_{2t-1}\varepsilon_{3t-1} \\ \varepsilon_{3t-1}\varepsilon_{1t-1} & \varepsilon_{3t-1}\varepsilon_{2t-1} & \varepsilon_{3t}^2 \end{pmatrix}\begin{pmatrix} \gamma_{11} & 0 & 0 \\ 0 & \gamma_{22} & 0 \\ 0 & 0 & \gamma_{33} \end{pmatrix}^{'} \tag{4.12}$$

$$\operatorname{var} g(\hat{a}_{11}, \hat{a}_{22}) =$$

$$\left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{11}}\right]^2 \operatorname{var}(a_{11}) + \left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{22}}\right]^2 \operatorname{var}(a_{22}) + 2\left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{11}}\right]\left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{22}}\right]\operatorname{cov}(a_{11}, a_{22}) \tag{4.13}$$

$$= \left[\hat{a}_{22}\right]^2 \widehat{\operatorname{var}}(\hat{a}_{11}) + \left[\hat{a}_{11}\right]^2 \widehat{\operatorname{var}}(\hat{a}_{22}) + 2\hat{a}_{11} \times \hat{a}_{22} \operatorname{cov}(\hat{a}_{11}, \hat{a}_{22}).$$

$$\mathrm{W} = [g(\hat{\theta})]'[\widehat{\operatorname{cov}}(g(\hat{\theta}))]^{-1}[g(\hat{\theta})] \tag{4.14}$$

$$r_t = A_0 + \sum_{l=1}^{p} A(l) r_{t-l} + u_t \tag{4.15}$$

$$r_{it} = \sum_{l=1}^{p} A_i(l) r_{it-l} + u_i + \varepsilon_{it} \tag{4.16}$$

$$r_{it} = \sum_{l=1}^{p} A_i(l) r_{it-l} + \Pi_i X_t + u_i + \varepsilon_{it} \tag{4.17}$$

$$r_t \mid F_{t-1} = \Phi_0 + \Phi_1 r_{t-1} + \varepsilon_t \tag{6.1}$$

$$\mathrm{H_t|F_{t\text{-}1}} = \mathrm{CC'} + \mathrm{A}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\mathrm{A}^{'} + \mathrm{BH_{t\text{-}1}B}^{'} + \Gamma\, \mathrm{I_{t\text{-}1}}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\Gamma' \tag{6.2}$$

$$r_t \mid F_{t-1} = \Phi_0 + \sum_{i=1}^{k} \Phi_i r_{t\text{-}i} + D_t\delta + \varepsilon_t \tag{6.3}$$

$$H_t \mid F_{t-1} = CC' + \sum_{j=1}^{q} A_j(\varepsilon_{t-j}\varepsilon_{t-j}^{'})A_j^{'} + \sum_{l=1}^{p} B_l H_{t-1} B_l^{'} + \sum_{j=1}^{q} \Gamma_j I_{jt-j}(\varepsilon_{t-j}\varepsilon_{t-j}^{'})\Gamma_j^{'} \tag{6.4}$$

$$H_t \mid F_{t-1} = CC' + A(\varepsilon_{t-1}\varepsilon_{t-1}^{'})A' + BH_{t-1}B' + \Gamma(I_{t-1}\varepsilon_{t-1}\varepsilon_{t-1}^{'})\Gamma' \tag{6.5}$$

$$y_t = A_0 + \sum_{l=1}^{2} A_l y_{t-l} + \sum_{i=1}^{3} B_i X_{it} + \varepsilon_t \tag{6.6}$$

$$\Delta y_{it} = a_i + \rho_i y_{t-1} + \sum_{j=1}^{k} \phi_j \Delta y_{t-j} + \delta_i t + \gamma_t + \varepsilon_{it} \tag{6.7}$$

$$r_{it} = u_i + \sum_{l=l}^{p} A_l r_{it-l} + \delta x_{it} + \varepsilon_{it} \tag{6.8}$$

$$F_{XY}(x, y) = C\left(F_X(x), F_Y(y)\right) \tag{6.9}$$

Chapter 1: Introduction

1.1 Background of the Study

Stock market returns and volatility (risk) of returns has been a highly researched area in theoretical and empirical finance since the publication of the seminal paper 'Portfolio Selection' of Markowitz (1952). This is the basis of the development of the first capital asset pricing model, introduced by Sharpe (1964), Lintner (1965) and Mossin (1966) among others. Fama (1970) developed the efficient market hypothesis (EMH) and Black (1976) reported the existence of 'predictive asymmetry between stock returns and future volatility' in financial returns series. Further, Mandelbrot (1963) identified the heavy-tailed and non-normal properties of return series. The considered ideas of the efficient market hypotheses, asymmetry in volatility and heavy-tailed properties of financial returns attracted researchers to continue the journey of the original researchers in the hope of developing new ideas involving uncertainty in the volatility of financial returns. In finance, a return is the amount of money an investor receives from an investment and volatility of returns is a term that refers to fluctuations of returns over a period.

My main objective in this thesis is to present a new methodology and novel evidence on the stochastic behaviour of asset returns and the relationship between asset market volatility and expected returns, which led me to develop and apply econometric and statistical techniques for modelling and testing for causality and volatility spillovers among assets across countries in a multivariate context. The purpose of this analysis is to identify models that best meet the objectives of researchers, investors and policy makers in the real world of business.

Much of the finance literature describes various aspects of financial transactions; delayed transactions; and portfolio diversification and management issues. Most importantly, the time-varying conditional volatility (risk) of return models of Engle (1982) and Bollerslev (1986) have gained popularity with diverse applications in the fields of finance and elsewhere. These models are known as autoregressive conditional heteroscedasticity (ARCH) and generalised ARCH (GARCH) respectively, in the econometrics and finance literature. Engle and Ng (1993) incorporated a news impact curve in estimating and modelling risk. They suggested three new diagnostic tests for 'news' asymmetry, which are generally known as the sign (positive and negative) and size bias tests. These tests are widely used in financial data analysis to study the so-called news effects of asset returns volatility. Nelson (1991) and Glosten et al. (1993) provided a statistically testable form of asymmetric return shocks on volatility, and Beg and Anwar (2014) dealt with sources of volatility in exchange markets.

Schwert (1990) investigated the US stock market crash of October 1987 and raised the issue of financial market stability and economic surges. However, Officer (1973) had previously noticed that stock return variability was unusually high during the 1929–39 Great Depression. Schwert (1989) tried to establish a relationship between business cycles, financial crises and stock volatility in the US for the period 1834–1987 (known as the Industrialised Economic Period of the US). He observed that stock volatility increases after stock prices fall, during the recession and around major financial crises. The issue of stability after a crash is of great concern for future economic growth. He provided empirical evidence that crises in financial institutions are linked to economic activities. He applied linear autoregression (AR) for both the conditional mean and standard deviation of stock returns. He further used a nonlinear regime switching model for stock returns along the lines of Hamilton (1988). He observed that stock volatility was higher during financial crises; in the post-World War I recession of 1925–34; the 1937–38 depressions; and the 1973–74 OPEC (Organization of the Petroleum Exporting Countries) recession. This information is useful for financial decision making purposes.

Schwert (2011) further used monthly returns from 1802 to 2010, daily returns from 1885 to 2010 and intraday returns from 1982 to 2010 in the US to show how stock volatility changes over time. He found that the crisis of 2008 did not live longer, in contrast to the Great Depression of 1929. For the United Kingdom (UK) and Japan stock, volatility in the 2008 crisis was relatively short-lived. Hartman et al. (2001, 2004), by employing an extreme dependence measure, characterised asset return linkages during stress across five countries. They evaluated the degree of simultaneous crashes in bond and stock markets, both domestic and global.

To understand the interdependence among time series, Engle and Kroner (1995) proposed the Baba–Engle–Kraft–Kroner (BEKK) model and multivariate BEKK-GARCH-type model for volatility. Engle (2002) provided a re-parameterised BEKK-GARCH known as a dynamic conditional correlation (DCC) model and Bollerslev, Engle and Wooldridge (1988) proposed a diagonal vectorization (VEC) model of conditional volatility. The reviews of multivariate GARCH models by Silvennoinen and Terasvitra (2009) and of multivariate volatility models by Tsay (2006), and the multivariate survey of Bauwens et al. (2006) among others are useful references for multivariate volatility models. In applications, Akhtaruzzaman and Shamsuddin (2015) used dynamic volatility models to test and forecast financial returns, and volatilities of returns during normal and crisis periods. Dias (2017) proposed an estimation strategy for time-varying risk premium parameters and Alsalman (2016) developed a GARCH-in-mean (GARCH-M) model to examine the oil price uncertainty of US stock returns and found no significant effect of oil price volatility in stock returns. A variety of modifications and extensions of the theory of returns and volatility of returns have opened up further research opportunities in the flourishing field of financial volatility modelling and testing. Very recently, Chang et al. (2018), Chang et al. (2017), Chang and McAleer (2018), Caporin and McAleer (2013), Chang and McAleer (2014), McAleer et al. (2009) and Massimillano and McAleer (2006) have shown that the standard stated full BEKK of Engle and Kroner (1995) and the DCC of Engle (2002) have no valid statistical properties for estimation and statistical hypothesis tests of volatility spillovers.

Despite the vast literature dealing with domestic and global financial market interactions, three key issues remain largely unsolved. The first is the specification of conditional volatility models and modelling issues such as estimation and statistical hypothesis testing. This is important because a misspecified model can lead to mistaken conclusions from both theoretical and statistical points of view. Second, the dynamics of returns and co-volatility of returns spillovers issues require further investigation to examine whether causality and spillovers change during financial crises. It is important for policy makers to understand the sources of asymmetric effects of return shocks on volatility; differences in patterns of volatility spillovers from one market to another; and return volatility from one country to another. Third, the severity of market crash events and crash dependence require deeper investigation as it is important to know whether big asset markets are prone to the more severe crisis than are small ones in global financial markets, which can in turn influence asset holders' portfolio selection, allocation and management. Finally, it is useful to investigate whether a time-varying risk premium exists in international financial markets in a multivariate framework. This will help determine the applicability of the EMH theory in the multivariate context.

Motivated by the work of Caprion and McAleer (2013), Chang and McAleer (2014), Chang et al. (2017), Allan et al. (2018) and Hartman et al. (2014), among others, this thesis explores modelling and testing issues relating to conditional volatility for assessing interdependence, co-volatility spillovers and causality among stock, bond and money markets across countries. The thesis also examines dynamic interrelationships among multiple asset returns utilising Sims's (1982) vector autoregression (VAR) model and VAR-X framework, and Abrigo and Love's (2015) panel VAR-X (PVAR-X) model of financial crisis. Finally, I employ Kendall's tau, Spearman rank correlation and product moment correlation to investigate the covariance dependence among multiple stock returns series. The Gumbel copula with Student-t marginal distributions undertaken in this thesis provides another source of dependent analysis among stock returns.

This chapter is organised as follows. The research questions and research hypothesis are stated and discussed in Section 1.2. Data, models and methodology are outlined in Section 1.3. Contributions of this research are explained in Section 1.4. Section 1.5 discusses the key findings, and thesis structure is revealed in Section 1.6.

1.2 Research Questions

This study involves the money, bond and stock markets of Asia, Europe and the US to evaluate global asset market linkages in a multivariate context. This study focuses on understanding the dynamics of financial asset market movements caused by uncertain and rare events occurring in financial markets. Further, the study examines volatility spillovers, causality, contagion and interdependence and flight to quality (i.e. where a crash in one market leads to a boom in another) in relation to both domestic and international financial assets markets. To achieve the objectives of this study I address the following research questions in order.

RQ1: Do volatilities of returns spillover symmetrically?

Addressing this research question is important to understand how asymmetric (or leverage) effects change the pattern of co-volatility spillovers in international stock markets across countries for agents' asset allocation and diversification strategies.

RQ2: Do risk premiums hold in international financial markets?

Addressing this research question is important in regard to international asset diversification as it is important to understand how risk premiums work in dealing with cross-country asset allocations. This information is useful for investment decision making in international bond markets and to test for the applicability of the EMH in multiple bond markets.

RQ3: Does the severity of crisis affect asset markets globally?

This research question is vital for its role in global financial market stability and predictability. Stability is a major issue in the current era for two main reasons. First, if financial markets are not stable and crash jointly, this will have a more harmful (contagion) influence on those markets that hold widely diversifiable portfolios. Second, from a regularity point of view, a strong policy recommendation is required to tackle unstable situations.

RQ4: Are financial returns dependent across countries?

This research question is important because it is useful to know whether large or small asset markets are interlinked for portfolio management.

1.3 Data, Models and Methodology

In this section I briefly introduce the data, models and methodology used to address the research questions to achieve the objectives of this thesis, walking the reader through empirical determination of returns, volatilities of returns and dynamic dependence analysis.

1.3.1 Data

This study utilises data from US, European and Asian financial centres. The country selection process was based on FTSE Annual Country Classification Review report on the Global Equity Index Series. Seventeen countries are selected from three blocks of countries; these are America (North and South), Europe, and the Asia Pacific. Each of the 17 countries is individually analysed using univariate time series techniques. These countries are then categorised as developed, advanced emerging and emerging countries for multivariate time series analysis. Three financial market datasets namely the stock, bond, and money market Treasury-bill (T-bill) data series for 30 January 1985–30 December 2016 are analysed. The data are collected from the Bloomberg database. From the stock market I use stock index return; from the bond market I use the 5-year bond rate; and from the money market I use the 3-month T-bill rate. Continuously compounded returns of each of the financial securities are used. Returns rather than asset prices were chosen because (i) the return of an asset is a complete and scale-free summary of the investment opportunity, and (ii) a return series is easier to handle than is a price series because of the attractive statistical properties of return series. The selection of countries was made according to maximum availability of sample data.

1.3.2 Research models and methodology

The empirical analysis begins with calculations of basic statistics for the data, followed by univariate and multivariate Ljung–Box (LB)-Q tests (the Q test is a chi-square test) for serial dependence of the series and squared series. Next, I test the series for unit roots using the augmented Dickey–Fuller [ADF; Dickey and Fuller, (1979, 1981)], Phillips–Perron [PP; Phillips and Perror (1989)] and Kwiatkowski–Phillips–Schmidt–Shin [KPSS; Kwiatowski, Phillips, Schmidt, and Shin, (1992)] tests for financial returns series. Univariate GARCH-type volatility models, namely standard GARCH (SGARCH), Glosten–Jagannathan–Runkle (GJR; GJR-GARCH; Glosten, Jagannathan, and Runkle, 1993) and GJR-GARCH-in-mean (GJR-GARCH-M) models are estimated under normal, Student-t and skewed Student-t innovation distributions for the selected 17 countries. I conduct tests for asymmetric return shocks on volatility and for risk premiums utilising Student-t tests, and sign and size bias tests using the t and F tests, and provide predictions for return and volatility.

In the absence of normality, I estimate DBEKK-GJR-GARCH-type models for conditional volatility utilising quasi-maximum likelihood estimates (QMLE). McAleer (2008), Chang and McAleer (2014), and Allen et al. (2017) derived DBEKK models from vector random coefficient autoregressive process of order one of the vector return shocks. The QMLEs of DBEKK are asymptotically normal. Statistical tests are valid for inference and hypothesis tests. I extend the DBEKK-GARCH to DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M models for co-volatility spillovers and risk premium analysis. Partial dynamic interdependence of Sims's (1980) VAR with crash events denoted, VAR-X is estimated by Cholesky decomposition. The panel VAR with GFC event denoted, PVAR-X is estimated utilising generalised method of moments (GMM) estimation. The severity of crisis is measured by employing the modified Fisher's p-value. The tools employed by VAR-Granger causality, forecast error variance decomposition, and impulse response analysis are used to examine the dynamic interdependence of global stock markets. The covariance dependence test of the asset returns is conducted via chi-square tests based on the correlations computed by nonparametric Kendall's tau and Spearman rank correlation, and parametric correlation by Pearson product moment correlation of the return series. Another approach used for the dependence of stock returns is the Gumbel copula with Student-t marginal distribution of the financial returns series.

1.3.3 Econometric packages used in the empirical analysis

The models are estimated and tested using the STATA, RATS and R econometric and statistical packages whenever required for empirical data analysis.

1.4 Key Findings

I examined the stochastic behaviour of asset returns of stock, bond and T-bill series for 17 countries. Most of the return series were found to be negatively skewed, heavy-tailed and non-normal. The return series were also found to be serially dependent in both level and squared return series. The series exhibit volatility clustering as confirmed by the LB-Q and kurtosis tests. I established relationships between return volatility and expected return in univariate and multivariate frameworks utilising the GARCH-type models of Bollerslev (1986) within a univariate time series framework. I found a significant effect of return shock on volatility in all of the series, with the exception of those for the China, Indonesia and Malaysia stock returns. This implies that any return shock persists in these stock markets for the sample periods. In other countries, shocks were found to be statistically transitory. I predicted volatility under normal, Student-t and skewed Student-t innovation and found skewed Student-t return shock dominating the other two which is a reflection of the heavy-tailed data property.

I fitted the GJR-GARCH model and found significant asymmetric volatility in the stock returns series. Both the SGARCH and GJR-GARCH models provided significant short- and long-run return shocks in almost all the series considered in this study. The asymmetric significance of news effects was found in all series except the China and Indonesia stock returns. I found the half-life of return shocks on volatility for the GJR-GARCH-M model was between 0.29 and 0.47 days for the daily returns. The risk premiums were found to be positive but not significant in most cases. A similar result was documented by Panayiotis and Lee (1995), Schewert (1989, 1990, 2011) using GARCH-M models.

Multivariate derivation of GARCH (1,1) using a vector random coefficient autoregressive model produced the DBEKK-GARCH of Chang and McAleer (2017). I extended this approach to DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M. These models were estimated utilising a QMLE with data from the developed, advanced emerging and emerging countries. The partial co-volatility spillover within the DBEKK-GJR-GARCH models was defined along the lines of Chang and McAleer (2017). I found significant partial co-volatility in the multivariate volatility models using the new Wald test, and significant Granger causality in the multivariate return models. Specifically, I found bi-directional causality running between the US and UK stock markets. Significant short-run and long-run volatility exists and was found to be significant in multiple stock markets. Significant asymmetric volatility spillovers exist in multiple stock markets. Interestingly, I found a significant volatility risk premium in the US and Japan bond markets but not the Australian bond market, which indicates EMH theory does not hold in general. This information is useful for investment decision making regarding asset allocation strategies in international bond markets.

The Sims (1980) VAR-X model was estimated using Cholesky decomposition for the 10 countries selected on the basis of availability of maximum number of data values. I found a significant effect of the 1987 crash, Asian Financial Crisis (AFC) and GFC in VAR-X. A significant effect of GFC was documented for 9 of the 10 selected countries; the Asian crisis was experienced by only 4 of these 10 countries (Canada, Hong Kong [HK], Indonesia and Malaysia). The 1987 crash was experienced by 7 of these 10 countries: Australia, Canada, Germany, HK, Malaysia, UK and US. Causal dependence was checked individually by the t test and jointly by the F test. The variance decomposition within the VAR framework revealed the proportion of movements in a sequence because of its own shocks, versus shocks in response to the other variables in the VAR-X. For example, the three principal factors driving the two-step forecast error variance for Australia were Australia (84.0%) itself, Canada (9.9%) and Germany (5.1%). Using the new severity index based on Fisher's p-value, majority of the stock markets experienced higher severity in the 1987 crash and the GFC than the AFC. This is an important finding for both domestic and international stock market investors and decision makers in financial markets. I also estimated the stock, bond and T-bill markets within the PVAR specification for the selected five countries. The PVAR-X model was estimated using the GMM and evaluated the effects of GFC only. I found that the GFC most severely affected the stock market, followed by the T-bill. Less severely affected were the bond markets for the sample of five countries jointly. Dependence among global stock returns was investigated utilising parametric and nonparametric correlation tests, which revealed significant dependence of pairwise stock returns in the lists of Australia, HK, Japan and US. Chi-square tests showed that significant contemporaneous covariance exists among the assets returns jointly. I examined the dependence of returns volatilities of the selected countries utilising the Gumbel copula and Student-t margins. I found significant dependence of the returns series by copula simulation. This thesis reports significant volatility spillovers, significant risk premiums, significant effects of financial crises, partial co-volatility spillovers and dependence among financial assets across countries in multivariate assets markets for the sample period. These are the main contributions of this thesis.

1.5 Significance of the Thesis

This research has important implications for investors, managers, stock market regulators, policy makers and forecasters in local and global financial markets for efficient policy decision analysis. In particular, it examines the transmission of returns and co-volatilities of returns shocks from one market's return shocks to another, as well as the cross-market volatilities and correlations of volatilities. These are essential issues for financial market participants, both individuals and agents, in terms of domestic and international asset pricing, portfolio allocation and diversification strategies. Most importantly, understanding how one asset market transmits returns shocks and volatilities to other markets during stress is important for future decision making purposes. This will provide information for investors about ways to monitor and manage portfolio diversification among markets across countries. Therefore, financial market crash event analysis is important to investigate dependencies, stability and contiguity effects among financial markets locally and globally to uncover how systematic risks are related to stocks, bonds and money markets during crisis and non-crisis periods. This will determine the severity of crisis experienced by these markets during the crisis and peace times. Further, how returns and volatilities spill over among different markets across countries will indicate the role played by news information during a crisis in those markets to enable evaluation of convergence of returns and volatilities globally. These are useful issues for portfolio allocation, diversification and management for future asset trading strategies under uncertainty.

1.6 Thesis Structure

This thesis consists of seven chapters. This first chapter introduces the study; discusses the background to the study; and identifies research questions and methodological contributions to fulfil the research objectives, and the significance, main findings and structure of the thesis.

Chapter 2 presents an extensive review of the literature relevant to the objectives of the thesis. This includes theoretical and empirical findings on risk and return in global financial markets specifically, the dependence of asset returns and returns volatilities spillovers across countries. It reviews all statistical and econometric approaches to financial data analysis. The chapter ends by identifying gaps in the literature and research questions that need addressing.

Chapter 3 deals with the theory of conditional volatility and modelling issues in a univariate and multivariate context. Further estimation methods are discussed in the context of conditional volatility models.

Chapter 4 deals with methodological approaches, which include the theory of VAR and PVAR, to model the financial returns jointly. Multivariate volatility models such as multivariate generalised autoregressive conditional heteroscedasticity (MGARCH), MGJR-GARCH, MGARCH-in-mean (MGARCH-M) and MGJR-GARCH-in-conditional mean are implemented within the multivariate DBEKK volatility spillovers and risk premium analysis. The models are estimated by employing ordinary least squares (OLS), GMM, maximum likelihood (ML) with normal, Student-t and skewed Student-t innovation, and QMLE in the absence of normality assumption. These methods have desirable statistical properties under the regularity conditions for valid statistical inference.

Chapter 5 deals with empirical univariate volatility model estimation, prediction and statistical tests for model adequacy.

Chapter 6 reports empirical results for the returns and volatility spillovers of different financial markets across countries under various specifications within the multivariate framework. The chapter reports the empirical findings highlighting the importance of the methodologies proposed by the research.

Chapter 7 presents a summary of the major findings, implications and limitations of this thesis, along with directions for future research.

Chapter 2: A Review of Literature on Modelling Financial Asset Returns and Volatility of Returns Spillovers

2.1 Introduction

The theme of this research is linkages between asset markets volatility and expected returns in various financial markets across countries. It is important to study these linkages because the turmoil that occurs in some financial markets might have a corrupting influence on the prices of various assets among markets across countries. One such turmoil, the 1987 crash was not limited to the US stock market, but transmitted shock waves to the US bond and money market and further to other countries around the world (Ro 2013). Another turmoil, the Asian Financial Crisis (AFC) of 1997-1998, originated in Thailand and had similar impacts on many other emerging markets in Asia, Latin America and Eastern Europe. This resulted from the liberalisation of capital movements, together with advances in computer technology and the improved worldwide processing of 'news'. It is clear in the modern era of technology that national and international financial markets react rapidly to new information coming from global stock exchange markets. Another crisis widely known as the global financial crisis (GFC) originated in the mortgage sector of the US dragged to collapse many large institutions in US. Thus, the purpose of this study is to investigate how dynamic interrelationships across different financial markets have evolved since 1985 because three major financial crises, namely 1987 Crash, AFC, and GFC had severely affected global markets.

This study attempts to investigate the dependencies and stability of stock, bond and money markets jointly across countries. The main aim of the study is to investigate dependence among different financial market returns, volatilities of returns spillovers, contagion and convergence during the global crisis and non-crisis periods for effective forecasts and policy decision purposes. The study focuses on determining the causes and dynamic dependence of financial asset market crashes, and explores linkages between domestic and global financial markets both jointly and separately. Further, the study examines the severity of crisis in relation to the assets and locations of markets.

This chapter provides a detailed literature review on theoretical and empirical linkages among asset markets across countries. This includes an overview of the risk-return nexus in Section

2.2. Section 2.3 examines international evidence regarding the issue of financial asset returns and volatility spillovers, and finally, Section 2.4 highlights research gaps in the literature.

2.2 Overview of the Risk-return Nexus

In traditional portfolio selection, investor behaviour was important to understand the pricing of assets in financial markets. Markowitz (1959) conjectured that assets' expected returns should not only reflect their own risk because part of the risk could be diversified away. Therefore, the expected returns should reflect only the part of the risk that is non-diversifiable. Non-diversifiable risk is generally known as systematic risk as it is linked with market risk. Asset selection strategies were first introduced in the finance literature by Markowitz (1952) within utility maximisation theory. Modifying his own work, Markowitz (1959) then developed a testable form of asset allocation utilising the mean variance approach. The principle of the mean variance lies in the following optimisation rules:

- minimise the variance of portfolio return given expected return.
- maximise expected return, given variance.

Thus, mean variance analysis is the core process in asset pricing, VaR calculations, asset allocation and asset diversification. Motivated by the work of Markowitz (1959), Sharpe (1964) and Lintner (1965) independently developed a model of 'dependence' between expected returns and risk in dealing with the risk-return nexus. Sharpe (1964) and Lintner (1965) introduced a model with an additional two key assumptions:

- All investors are assumed to follow the mean variance rule; that is, they choose mean variance efficient portfolios.
- There is unlimited lending and borrowing at the risk-free rate, r_f, which does not depend on the amount borrowed or lent.

This model is known as the capital asset pricing model (CAPM). The theory of CAPM states that the risk premium on a security is proportional to the risk premium on a market portfolio. That is, $r_i - r_f \propto (r_m - r_f)$, where r_i and r_f are the returns on security i and the risk-free rate, respectively, r_m is the return on the market portfolio, and the proportionality constant of the model is denoted by β_i, the $i-$th security's 'beta' value. A stock's beta is important to investors and policy makers because it reveals the stock's volatility. This model has been extensively used in empirical finance.

Although theoretically, the CAPM is sound, some of its assumptions are questionable. Results based on the theory are mixed in practice, perhaps because of its specification. Recent studies have not found support for the CAPM in observed phenomena in return series. Poor empirical performance of the traditional static CAPM has given rise to modifications of the CAPM. Basu (1977, 1983) gave evidence that when common stocks are sorted on earnings–price (E/P) ratios, the future returns on high E/P stocks are higher than predicted by the traditional CAPM. Banz (1981) documented a size effect when stocks are sorted by market capitalisation (price × shares outstanding), in which average returns on small stocks are higher than predicted by the CAPM. Stattman (1980) and Rosenberg et al. (1985) documented that stocks with high book-to-market equity ratios have high average returns that are not captured by their betas. Fama and French (1992) updated and synthesised the evidence on the empirical failures of the CAPM. Using the cross-sectional regression approach, Fama and French confirmed that size, E/P and debt-to-equity and book-to-market ratios added to the explanation of expected stock returns provided by market betas. Fama and French (1996) reached the same conclusion using time series regression applied to portfolios of stocks sorted by price ratios.

Jaganathan and Wang (1996) included additional risk factors to Fama and French (1992), such as return on human capital, and found some support for the theory and practice of CAPM. Specifically, they found some improvements in the model for monthly rather than annual data. The Fama–French (1992) model is known as the three-factor asset pricing model in finance. They further extended the model by including several other exogenous variables. The resulting model is known as the Fama–French (2015) five-factor asset pricing model. This model is directed at capturing the size, value, profitability and investment patterns in average stock returns, and performs better than the three-factor model. The five-factor model's main problem is its failure to capture the low average returns on small stocks whose returns behave like those of firms that invest a lot despite low profitability. Ratios involving stock prices have information about expected returns that are missed by market betas. Such ratios are thus prime candidates to expose shortcomings of asset pricing models in the case of the CAPM, and of the prediction, that market betas suffice to explain expected returns. These observations may be regarded as misspecifications of the traditional CAPM caused by omitted variables, with the consequence that the traditional CAPM might suffer from bias and inconsistency.

Another important issue in the lack of empirical support for CAPM might be the linearity assumption of expected returns. The linear model may perform badly in empirical applications if the linearity assumption is violated. It is well known that most asset returns exhibit stylised facts; for example, limit cycles, sudden jumps, amplitude frequency dependencies and nonlinearity. The inherent nonlinearity of the traditional linear CAPM may be a model specification problem. Therefore, the assumption of linearity in the CAPM needs to be tested before adopting such a model for policy decision analysis. One of the sources of inherent nonlinearity may enter into the model through the conditional second moment of a financial returns series. If linearity does not hold then the use of correlation as a measure of dependence between different financial assets is not appropriate for optimal portfolio selection by the CAPM. The linearity, however, implies normality. Therefore, the traditional static CAPM approach founded on the assumption of multivariate normality may not be appropriate. This could be regarded as functional misspecification of the traditional CAPM. The nonlinear dependence might be additive, multiplicative or both.

Merton (1973) proposed the intertemporal capital asset pricing model (ICAPM), suggesting that the conditional expected excess return on the stock market is positively and linearly related to the market's conditional variance. However, that ICAPM is not supported empirically, which makes the risk-return trade-off one of the main puzzles in finance. Specifically, empirical evidence about the risk aversion coefficient sign is mixed. Early studies conducted by French et al. (1987), Baillie and DeGennaro (1990) and Campbell and Hentschel (1992) among others showed a positive but mostly insignificant relationship between the conditional expected return and conditional variance, while Campbell (1987) and Nelson (1991) discovered a significantly negative relationship. Both a positive and a negative relationship were found by Turner et al. (1989), Glosten et al. (1993) and Harvey (2001). Recently, Jingzhen Liu (2019) investigated the impacts of lagged returns on the relationship between the conditional mean and conditional variance in the Chinese stock market. The results suggest that the risk-return trade-off is time varying and affected by lagged returns; however, the results are sensitive to the data frequency.

The nonlinearity that may enter returns series was first cleverly modelled by the Nobel Laureate Robert Engle in 1982. The resulting ARCH model is widely used in finance and elsewhere. Engle showed that it is possible to model the conditional mean and conditional variance of a series of observations jointly. This theory makes a stronger additional contribution to the traditional static CAPM. Engle (1982) showed that the unconditional forecast of a random process has greater variance than its conditional variance. This statistical property motivated a large number of researchers to model asset returns along this line. The model captures various stylised facts exhibited by financial asset returns, such as volatility clustering, asymmetry and a high degree of persistence. Bollerslev (1986) extended Engle's (1982) ARCH by developing a technique that allows the conditional variance to be an autoregressive moving average (ARMA) process. This expanded conditional variance is widely known as the GARCH model. These two models are widely used in empirical finance for volatility modelling.

The univariate ARCH and GARCH models of volatility, developed by Engle (1982) and Bollerslev (1986) respectively, form the basis of many extensions to conditional volatility models in the literature. Although popular, both ARCH and GARCH models are incapable of capturing asymmetric news arriving in the market during periods of the transaction and delayed transaction. Since news is unobservable and random, various proxies have been reported in the literature to tackle the unobservable. Since financial returns and volatility are news dependent, it is of interest to create a variable that can be used as a proxy for news. In this context, various extensions of ARCH/GARCH have appeared in the literature to overcome some inherent nonlinearity problems with the GARCH class of models. Since volatility clustering is a likely characteristic of financial returns, which are nonlinear by nature, they can be modelled using the asymmetric t-distribution, generalised error distribution (GED) and extreme value theory among others. A popular nonlinear extension of ARCH/GARCH is Nelson's (1991) exponential generalised autoregressive conditional heteroscedasticity (EGARCH) model. It attempts to include the asymmetric impact of return shocks on volatility. In addition, this model does not require non-negativity restrictions on the parameters, unlike the ARCH/GARCH conditional volatility models.

Another popular extension of the GARCH is the Glosten, Jagannathan and Runkle (1993) extension, known as the GJR volatility model in financial econometrics. These latter two models (EGARCH and GJR) allow for leverage effects (the tendency of volatility to decline when returns rise and to rise when returns fall), contrary to classical ARCH and GARCH models. The GJR is centred on ε_{t-1} (shocks), but the slope is asymmetric about zero; that is, there are different slopes on the positive and negative sides of $\varepsilon_{t-1} = 0$. Both the GJR and EGARCH models capture an interesting feature of asset prices, that so-called 'bad news' seems to have a more pronounced effect on volatility than does 'good news'. This phenomenon is often called the ‘leverage effect’. Both the GJR and EGARCH capture asymmetric effects of return shocks on volatility but their model specification is different. Other asymmetric models include the ‘news impact curves’ of Engle and Ng (1993), and the nonlinear asymmetric GARCH (NAGARCH) and vector AGARCH (VAGARCH) of Engle (1990). These models have different centres from the EGARCH and GJR. It is important to note that if a negative return shock causes more volatility than a positive shock of the same size, the classical GARCH model under predicts the amount of volatility following bad news and over predicts the amount of volatility following good news. Ding et al. (1993) investigated the ‘long-memory’ property of stock market returns, finding that the power transformation of the absolute return has quite a high autocorrelation for long lags, which argues against the use of ARCH-type volatility. The conditional volatility specification of Ding at al. (1993) is known as the asymmetric power ARCH (APARCH) model. Both the GJR and EGARCH models are special cases of APARCH model of Ding et al. (1993).

Asset pricing theories agree that a high risk has to be compensated for by higher expected returns. It is, therefore, reasonable to include variance in an expected return model, to take account of risk premiums. The resulting models are known as ARCH-M and GARCH-M models in the ARCH/GARCH context. The ARCH-M model was introduced by Engle et al. (1987) and may be considered an extension of the CAPM. By employing this model one can estimate and test for the existence of a time-varying risk premium in financial markets. The presence of a risk premium is an issue that weakens the rational expectation (RE) hypothesis (see Shiller, 1978, 1981; Shiller, Campbell & Schoenholtz, 1983 and Campbell, 1986 among others in the univariate case). However, the above univariate volatility models are not capable of capturing returns and volatilities of returns spillovers and causality effects.

2.3 International Evidence

Over the years a vast literature has developed, reflecting the different objectives related to returns and volatilities of returns spillovers among financial markets across countries. Stock market returns and volatility spillovers have been a highly researched area in the theory and practice of finance. This has always been a focus of financial regulators, policy makers and scholars in relation to the issue of assets spillovers. Many researchers have studied the movements of aggregate stock market volatility. Studies on volatility in US and Japanese stock markets tend to dominate the literature. However, the literature on the volatility co-movement of stock, bond and money markets within and across markets is sparse. The limited nature of such work prompted the current investigation of asset market linkages and volatility co-movement in different financial markets and across countries.

GARCH-M models have been widely used for identifying the risk-return relationship, including the research by Engle et al. (1987), French et al. (1987), Campbell and Hentschel (1992) and Glosten et al. (1993). All these studies estimated the model using monthly data. However, Glosten et al. (1993) considered different impacts of negative and positive lagged returns on the conditional variance and indicated that positive and negative innovations in returns have different influences on conditional volatility. One advantage of using GARCH family models is that the conditional returns and volatilities can be estimated simultaneously and 1-step-ahead forecasts for the conditional mean and variance are readily obtained. Moreover, the GARCH-M framework allows for an extension of the model by including extra regressors to control for any incremental information of implied volatility beyond the GARCH parameterisations in modelling variance (Blair et al., 2001). Lundblad (2007) used GARCH, EGARCH, quadratic ARCH (QARCH) of Sentana (1995), Threshold GARCH (TGARCH) of Zakoian (1994) and used the specifications of the conditional variance to investigate risk-return trade-offs in US and UK equity markets by using a large set of monthly data. He reported a significant positive risk-return trade-off for the above markets, although the relationship between risk and return is time varying. Skintzi and Refenes (2006) examined the dynamic linkages among European bond markets using an EGARCH model, which allowed for a dynamic correlation structure. The results suggest significant volatility spillovers exist from both the aggregate euro area and US bond markets to individual European markets. A negative correlation between current return and the future volatility of many stocks is often called the leverage effect. This concept of a leverage or threshold effect on volatility may be explored by utilising a threshold or asymmetric GARCH model.

Recently, researchers have considered that the relationship between risk and return may be time varying and dependent on markets state. Cheng and Parvar (2014) used the bi-normal GARCH and several volatility estimators to examine the risk-return trade-off in the 14 Pacific Basin stock markets. Their results show significant positive risk-return relationship for 11 of the 14 markets studied. Salvador et al. (2014) investigated the risk-return trade-off in 11 European markets and discovered significant evidence for a positive risk-return trade-off for low volatility states. However, this risk-return relationship is weak and may be insignificant during periods of high volatility. Kinnunen (2014) proposed a model that captures the dynamic relevance of the risk-return trade-off and autocorrelation and applied it to study the relationship between the conditional mean and conditional variance of US aggregate stock returns. The result suggests a positive risk-return trade-off which depends on the level of information flow, measured by volatility. Specifically, during low volatility periods, the autocorrelation in returns increases, which creates a weak relationship between expected returns and conditional volatility. Christensen et al. (2015) applied the fractionally integrated exponential GARCH-M (FIEGARCH-M) model to daily US stock return data. They found a significant positive risk-return trade-off during financial crises, but this was insignificant during non-crisis periods. Malik (2015) used Monte Carlo simulations and real US stock market data to show that structural breaks and sample size as two important factors determining the estimation of the risk-return trade-off.

Chang (2016) proposed a time series return state varying (TSV)-GARCH, risk-return model to capture the state dependent trade-off between risk and return in the Standard and Poor (S&P) 500 stock index. The result shows that the driving forces in mean and volatility are distinct and the risk-return trade-off is significantly positive in different market states. Specifically, risk-return tradeoff is significantly higher during periods of a bear market. Wang and Khan (2017) used a new mixed data sampling method to re-examine and estimate conditional variance in risk-return trade-off in the US stock market. Their results show that the risk-return trade-off in the US stock market and the six other G7 countries (Canada, France, Germany, Italy, Japan and the UK) is dynamic and dependent on market state. Further, the lagged market return was found to be the best indicator of market state. Guo (2006) using monthly data found a significant positive relationship between risk and return of the US market. Kanas (2012) highlighted that an implied volatility index (VIX) may carry important forward-looking information to explain the risk-return relationship. He found a significant positive relationship between risk-return for the S&P 100 market index. Kanas (2013) also found a significantly positive risk-return relationship for the S&P 500 market index for different data frequencies using GARCH (1,1) model. Huang et al. (2016) investigated 25 individual stocks traded on the Taiwan Stock Exchange and provided evidence that the herding behaviour of institutional investors strengthens the positive risk-return relationship.

Significant literature relates to theoretical and empirical issues involved with intermarket linkages among national and international asset markets. Early investigations of intra-continental linkages among different capital markets were analysed using correlation analysis (see Hilliard 1979; Robichek, Cohn and Pringle 1972 and Solnik, Boucrelle, and Fur 1996 among others). Empirical results have frequently indicated that cross-country correlations are low, while certain countries in proximate geographical areas generally exhibit more substantive co-movement than do countries farther apart. Several early studies considered lead–lag relationships among world stock exchanges. Analysing monthly data, Agmon (1972) found that share prices in three non-US countries respond immediately to price changes in the US market index. Hilliard (1979) examined high-frequency daily data on the stock index prices of 10 countries during the energy crisis of 1973 and 1974. His spectral analysis indicated that stock markets sharing the same continent tend to move simultaneously, while markets located in different geographical areas are usually not related.

Bertoneche (1979) performed spectral and co-spectral analysis on the weekly index of seven stock markets Germany, France, Italy, Netherlands, Belgium, the UK and the US from January 1969 to December 1976. He found evidence suggesting some leads and lags among the weekly returns, but found little relationship between any of these countries with the US. Koch and Koch (1991) used a dynamic simultaneous model to investigate contemporaneous and lead–lag relationships among eight national stock markets. The results highlight growing regional interdependence over time and an increasing influence of the Tokyo market at the expense of the New York market. However, Miyakoshi (2003) examined the magnitude of return and volatility spillovers from Japan and the US to seven Asian equity markets and found that Asian markets' returns were influenced only by the world factor of the US market, not by the regional factor of the Japanese market. He found that Asian returns increase when the US returns increase, but that this was totally the opposite in the case of volatilities. Wang et al. (2005) examined returns and volatility spillovers from the US and Japanese stock markets to three South Asian capital markets using a univariate EGARCH spillover model. He studied local shock, a regional shock from Japan and a global shock from the US to identify the most influential market-driven shocks for any particular South Asian market. The study discovered returns spillovers in all three markets; and volatility spillovers from the US to the Indian and Sri Lankan markets, and from the Japanese to the Pakistani market. Further, they highlighted there were no volatility spillovers during the Asian Financial Crisis, whereas spillovers of great intensity were identified during the post-crisis period. Additionally, a sub-period analysis revealed that before the crisis, regional factors were more important than their world factor counterparts. However, after the crisis, world factors dominated regional factors; that is, the US stock market had a larger impact on small South Asian stock markets. Krause and Tse (2013) used a VAR model and found significant lead–lag relationships among US and Canadian firms. Further, by using a bi-variate EGARCH, they found that spillovers occur only from the US to Canada.

Marinela et al. (2017) studied contemporaneous volatility spillover effects focusing on the US and UK stock markets. They used a structural VAR model and compared its dynamic relationships, impulse responses and variance decomposition with those of a reduced-form VAR model. They provided evidence of asymmetric contemporaneous spillover effects and demonstrated that ignoring contemporaneous relationships led to different conclusions regarding the magnitude and direction of volatility spillovers between the two stock markets. Xiaoye Jin (2015) compared return and volatility spillover effects between China's interbank and exchange T-bond markets. The empirical findings suggested that good news originating in the exchange market leads to higher interbank returns while bad news has no significant impact. In contrast, both good and bad news from the interbank market leads to higher exchange returns, albeit in different sizes. Tolikas (2017) examined the relative informational efficiency of bonds and underlying stocks through the lead–lag relationship between their daily returns and found that stock returns lead the returns of high yield bonds but not those of investment grade bonds, which indicates that the stock market is relatively more information efficient than the bond market. This finding implies trading opportunities for bonds are highly sensitive to the release of new information.

Another branch of research has focused on the transmission of international equity movements by studying the spillover of return and volatility across markets. Empirical research on volatility spillovers largely began by examining spillovers across markets trading the same asset class. The phenomenon of financial market crises spilling over to other countries was first systematically studied by Morgenstern (1959). He examined the effects of 23 stock market panics on foreign markets and explicitly referred to the 'statistical extremes' of stock market movements. Schwert (1990) analysed data from 1857 to 1987 and found that stock volatility remained very high for weeks after the 1987 crash. He observed that stock volatility increases when the stock price falls; that is, during the recession. His research also highlighted weak evidence that macroeconomic volatility can help to predict stock and bond return volatility.

Hamao et al. (1990) studied three major stock markets (London, New York and Tokyo) using univariate GARCH-M models. They identified volatility spillovers from New York to Tokyo and London, and from London to Tokyo. Baillie and Bollerslev (1991) found little evidence in favour of volatility spillovers between the US dollar exchange rate and the (British) pound sterling, German mark, Swiss franc and Japanese yen. A natural extension, therefore, is to examine the degree of interdependence between stock returns and exchange rates, with early studies including those of Smith (1992) and Ajayi and Mougoué (1996). Further research in this vein includes that of Laopodis (1998), who reported significant volatility spillovers among a range of Deutsche mark exchange rates prior to Germany's reunification, while also noting asymmetric spillover effects, whereby a bad news spillover has a greater impact than a comparable good one. Hong (2001) found evidence of simultaneous interactions between the German mark and the Japanese yen. Huang and Yang (2002) reported that volatility in London and New York causes volatility in Tokyo, with volatility in New York causing only slight volatility in London. Bubák et al. (2011) reported the presence of significant volatility spillovers among the Central European (Czech, Hungarian and Polish) foreign exchange markets. Further, Malik (2005) found that the euro is considerably more volatile than the pound sterling, while Nikkinen et al. (2006) pointed out that the volatility of the euro significantly affects the expected volatility of the pound sterling and the Swiss franc.

Kanas (2000) analysed interdependencies between exchange rate and stock return volatilities for six industrialised countries. Evidence of such spillovers arising from stock return to exchange rate return variations was reported for five of these countries (US, UK, Japan, France and Canada), with the exception being Germany. This finding is consistent with the growing integration of international financial markets. Similarly, Kanas (2002) found that stock return volatility is a significant determinant of exchange rate volatility in the US, UK and Japan. In contrast, Apergis and Rezitis (2001) reported spillovers from the foreign exchange market to the stock market, but not in the reverse direction. Meanwhile, Wu (2005), studying seven developed and emerging Asian countries, reported the presence of a two-way feedback relationship between stock return and exchange rate volatility. Yau and Nieh (2006) noted that Taiwanese and Japanese stock prices interact with each other but there is no comparable relationship between exchange rates and stock prices. Fu et al. (2011) reported significant volatility transmission between Japanese stock and foreign exchange markets. Antonakakis (2012) and Kitamura (2010) reported the presence of volatility spillovers running from the euro to the pound sterling. In a study of three euro exchange rates (against the US dollar, Japanese yen and pound sterling), McMillan and Speight (2010) reported that the US dollar rate dominates the other two rates in terms of volatility spillovers.

Following the analysis of exchange rate spillovers, researchers examined stock markets for the presence of similar effects. Bonfiglioli and Favero (2005) detected no long-term interdependence between German and US stock markets; however, there are short-term fluctuations in the spillover of US share prices to German ones. Caporale et al. (2006) found evidence of volatility spillovers in all cases for US, European, Japanese and South-east Asian daily stock market returns and Chinzara and Aziakpono (2009) revealed the presence of both return and volatility transmission between South African and major world equity markets. In turn, Beirne et al. (2013) identified volatility spillovers from mature to emerging stock markets.

Susmel and Engle (1994) examined price and volatility spillovers between New York and London using hourly returns and established the short duration of these spillovers using nonlinear GARCH. The results highlighted minimum evidence for volatility spillovers between these markets, with a duration of only an hour or so. Using multivariate EGARCH (1,1), Andrew and Higgs (2004) examined the transmission of equity returns and volatility among Asian equity markets and investigated the differences in this regard between developed and emerging markets. The results generally indicate the presence of large and predominantly positive mean and volatility spillovers. Diebold and Kamil (2009) studied the interdependence of asset returns and volatilities using VAR variance decomposition. They measured financial asset return and volatility spillovers, with application to global equity markets. Nineteen global equity markets were studied and striking evidence for divergent behaviour in the dynamics of return spillovers versus volatility spillovers was reported. Priyanka et al. (2010) examined price and volatility spillovers across North American, European and Asian stock markets. They found that return spillover takes place from US to the Japanese markets; Korean markets to Singapore; Taiwan markets to HK; and HK to European markets and the US. Volatility spillovers were estimated by Liu and Pan (1997) using a two-step AR-GARCH model and the same-day effect was captured using the same method as used in return spillovers.

Karunanayake et al. (2010) studied the effects of financial crises on international stock market volatility transmission. Using an MGARCH model, they showed that country-specific past shocks (lagged ARCH effects) have a stronger effect on their own future volatility than do past volatility shocks arising from other markets. Syllignakis and Kouretas (2011) applied the DCC multivariate GARCH model of Engle (2002) to examine time-varying conditional correlations in the weekly index returns of seven emerging stock markets in Central and

Eastern Europe (CEE). The main finding was a significant increase in conditional correlations between the US and the German stock returns and the CEE stock returns, particularly during the 2007–09 financial crisis, implying that these emerging markets are exposed to external shocks with a substantial regime shift in conditional correlation. Duncan and Kabundi (2014) studied volatility co-movement in world equity markets between 1994 and 2008. They arrived at two conclusions: first, developed markets have a higher degree of average volatility co-movement than do emerging markets; and second, peaks in volatility co-movement are correlated with the timing of financial crises. Lyócsa et al. (2019) studied the connectedness of a sample of 40 stock markets across five continents using daily closing prices and return spillovers based on Granger causality. The possible 1,560 return spillovers among the 40 markets create a complex network of relationships between equity markets around the world. Results show that the temporal proximity between closing hours is important for information propagation; therefore, choosing markets that trade during similar hours creates additional risk for investors because of the probability of return spillovers increases.

A number of researchers have addressed the question of whether the quantity of news (i.e. the size of innovation) and the quality of the information (i.e. the sign of an innovation) are important determinants of the degree of volatility spillover across markets. This question has been motivated by the findings of an 'asymmetric' or 'leverage' effect associated with equity returns. This asymmetric effect has been examined in studies of volatility spillovers across markets. Bae and Karolyi (1994) examined the joint dynamics of overnight and daytime return volatility for the New York and Tokyo stock markets over the period 1988–92. They found that the magnitude and persistence of shocks that originated in stock markets transmitted to other markets is significantly understated if this asymmetric effect is ignored. However, bad news from domestic and foreign markets appears to have a much larger impact on subsequent return volatility than does good news. Koutmos and Booth (1995), using multivariate EGARCH on daily open-to-close returns across the New York, Tokyo and London markets, found strong evidence for an association between news and volatility spillovers. They revealed linkages among these three country-specific markets before, during and after the crash of 1987 and concluded that the quantity and quality of news could be important determinants of the degree of volatility spillovers across markets. In all instances, the volatility transmission mechanism was asymmetric; that is, negative innovations in one market increased volatility in the other market considerably more than their positive counterparts.

Booth et al. (1997) analysed four Scandinavian markets and found asymmetric volatility spillovers among Swedish, Danish, Norwegian and Finnish securities using an EGARCH model. They further reported that spillovers were more pronounced for bad than for good news. Similar evidence was found for other European markets (London, Paris and Frankfurt) by Kanas (1998). Andersen et al. (2003) pointed out that US macroeconomic news in particular has a significant effect on the US dollar–euro exchange rate. Jondeau and Rockinger (2006) investigated the dependency structure between daily returns of major stock market indices. They found a negative return has a stronger effect on subsequent volatility than a positive return of the same magnitude; and a crash is more likely to be followed by a subsequent large return (of either sign) than by a boom. The Student-t copula fit the data very well in that study. Andersen et al. (2007) measured cross-market linkages and spillovers between the US, UK and German stock markets using a high-frequency dataset. Their result qualified earlier work suggesting that bond markets react most strongly to macroeconomic news; in particular, when conditioning on the state of the economy, the equity and foreign exchange markets appear equally responsive. Adrangi et al. (2014) investigated the daily volatility spillovers between the S&P 500 and equity indices of Brazil, Argentina and Mexico from August 2007 to August 2012. Bi-variate GARCH estimation indicated bi-directional spillovers and there was evidence of a leverage effect as positive and negative shocks to each market have unequal impacts on the volatility of the other market. Further, the effects of negative shocks are much more intense than those of positive shocks.

Financial contagion receives considerable attention throughout the literature. The term emerged from the Asian Financial Crisis, triggered by the flotation of the Thai baht in 1997. Thereafter, the subject gained attention as more crises occurred that caused negative repercussions across nations. The presence of contagion as a threat to the stability of the global economy was highlighted during the sub-prime mortgage crisis of 2007. This financial market turbulence, like previous crises, produced strong price movements in securities markets worldwide. This directly affected the general reassessment of credit risk and then dried the liquidity even of some of the largest and most mature securities markets. As a result, cross-market return correlations temporarily underwent dramatic changes, challenging portfolio allocation and risk management strategies, which rely on constant historical co-movements of asset prices.

Against this background, researchers have been interested in exploring linkages across countries to determine whether there exists financial contagion during crises. Domanski and

Kremer (2000) measured the dynamics of international asset price linkages by employing bi-variate GARCH models to analyse the co-movements between weekly stock and bond market returns across US, Japan and the Eurozone. Their results show that if the US market switches to a high volatility regime (while Germany remains in the low volatility state), the correlation between German government bonds and US Treasury bonds almost doubles, irrespective of the maturity of the former. Kristin and Roberto (2002) examined stock market co-movements and contagion during financial crisis. In each of these cases, tests based on unadjusted correlation coefficients provided evidence for contagion in several countries, while tests based on adjusted for bias of coefficients found virtually no contagion. Hartmann et al. (2004) studied asset return linkages during periods of crisis. Their estimates for the five countries (Brazil, China, India, Mexico and South Africa) suggest that simultaneous crashes in stock markets are around two times more likely than in bond markets. Moreover, stock–bond contagion is about as frequent as a flight to quality, where a crash in the stock market is accompanied by a boom in the government bond market.

Dungey and Martin (2007) studied financial market linkages during crisis. Their results provide strong evidence that cross-market links are important and spillovers have a larger effect on volatility than does contagion, although both were significant in their study. The results also show that US financial markets can act as a conduit in transmitting crises across countries, implying particularly for Australia that there are both direct and indirect channels for contagion from the US. By applying EGARCH, Choi et al. (2009) studied volatility spillovers between stock market returns and exchange rates to investigate volatility behaviour in New Zealand stock returns and currency movements. They reported significant volatility spillovers from exchange rate changes to stock market returns, while volatility spillovers from the stock market return to exchange rate were marginally significant and changed from negative before the 1987 stock crash to positive after the crash.

Further, leverage effects have been identified in the stock market. Go and Hamori (2016) studied co-movements and volatility spillovers among financial sectors in the UK. They found contagion among three sector credit default swap indices, evidenced by sharp increases in the DCCs for all pairs following the Lehman Brothers bankruptcy. They examined the dataset for the DCCs using the DCC–GARCH model developed by Engle (2002). Dua and Tuteja (2016) investigated contagion across the stock and currency markets of China, the Eurozone, India, Japan and the US during the GFC and the Eurozone Sovereign Debt Crisis. The results indicate significant contagion as well as the flight to quality effects both across and within asset classes. A DCC–GARCH model was used to estimate conditional correlation among the assets and test for contagion/flight to quality effects during the crises.

Akhtaruzzaman and Shamsuddin (2016) studied international contagion (the spread of market disturbances from one country to the other) through financial versus nonfinancial firms using the DCC–GARCH model introduced by Engle (2002). Monthly data were analysed from January 1990 to March 2014. Results include a positive spillover effect from the US market to developed, emerging and frontier markets, and that nonfinancial firms play a more prominent role in the transmission of information across countries than do financial firms. Kenourgios et al. (2016) investigated the contagion effects of the GFC and Eurozone Sovereign Debt Crisis on Islamic equity and bond markets utilising the asymmetric dynamic conditional correlation (A-DCC) model developed by Cappiello et al. (2006). The results fail to provide strong evidence of contagion between conventional and Islamic equity and bond indices, supporting the decoupling hypothesis for Islamic securities.

The above issues of interdependence and contagion among assets across countries may be fruitfully explored utilising the PVAR approach. Luchtenberg and Vu (2015) provided strong evidence using logistic regression suggesting that during a crisis contagion can be transmitted among nations, regardless of the level of development. Jin and An (2016) employed the volatility impulse response approach for addressing the extent of contagion effects between the stock markets of Brazil, Russia, India, China and South Africa association (BRICS) and the US. The empirical results show that during the period of the GFC there are significant contagion effects from the US to the BRICS stock. However, the degree of stock market reactions to such shocks differs from one market to another, depending on the level of integration with international economy markets. BenMim and BenSaïda (2019) used a regular vine copula approach to model the dependence dynamics between major US and European stock markets by distinguishing effects during crisis and tranquillity periods. The empirical results include a significant change in the connectedness and shock transmissions during both periods, providing strong evidence for financial contagion with the Eurozone at its origin.

Very recently, Chang et al. (2018) in modelling volatility spillover between energy and agricultural markets, drew attention to the use of commonly applied full BEKK specification for estimating conditional volatility. They argued that QMLE-based parameter estimates of the full BEKK model have no asymptotic properties and hence there are no valid statistical tests for volatility spillover effects in the full BEKK. This is similar in the case of DCC volatility models. A DCC represents the dynamic conditional covariances of standardised residuals and has no moments or any testable regularity conditions. Further, a DCC has no asymptotic properties and the two step procedure of estimation of DCC is not consistent. Chang et al. (2018) argued for the use of a DBEKK rather than a full BEKK because DBEKK models have stochastic validity for the likelihood function and QMLEs have desirable statistical properties for developing statistical inferences and tests. Chang et al. (2018) suggested that the existence of multivariate eighth moments cannot be verified for the existence of distributional properties of the full BEKK specification. Hence, there are no valid tests for volatility spillover effects. McAleer et al. (2008) showed that the QMLEs of the parameters are consistent and asymptotically normally distributed. Chang et al. (2017, 2018a, 2018b), McAleer (2014, 2019) and Allen and McAleer (2018) are only a few of the important articles discussing statistical distributional issues for estimating and testing full BEKK, DBEKK and triangular BEKK (TBEKK) models for volatility spillovers. It is stated in the above papers that the full BEKK and TBEKK have no verifiable asymptotic properties.

As financial markets have become increasingly integrated, both domestically and internationally, the nature of this integration and the transmission channels through which shocks dissipate are, however, still not well understood. Michael et al. (2005), presented a framework to analyse the degree of financial transmission between money, bond, equity markets and exchange rates within and between the US and the euro area. They found that asset prices react most strongly to other domestic asset price shocks and that there are substantial international spillovers both within and across asset classes. They show that spillovers are stronger from the US to the euro area market, but that spillovers in the opposite direction have been present since the introduction of the euro in 1999. They highlighted US as the main driver of global financial markets spillovers. Further, they explained the US markets on average accounts for 30% movement in euro markets, while euro markets explain only 6% in US market.

Beirne and Bricco (2014) assessed interdependence and contagion across three asset classes (bonds, stocks and currencies) over 60 economies from 1998 to 2011. Using global VAR, they tested for changes in the transmission mechanism within and across markets during periods of global financial turbulence. Within-market contagion effects are notable in Latin American and emerging Asian equities. In addition, Beirne and Gieck (2014) found that in times of financial crisis, US equity shocks lead to risk aversion by investors in equities and currencies globally, as well as bonds in some emerging markets. Euro area shocks were significant mainly within the bond market. Bienkowski et al. (2014) examined co-movements of stock markets in the CEE3 (Poland, the Czech Republic and Hungary) countries using the VAR-GARCH-BEKK model over the period 2005–13. Their research indicates that in the CEE3 countries, volatility spillovers play a dominant role and that the stock exchanges in Poland, the Czech Republic and Hungary did not react similarly to the global shocks from the subprime mortgage crisis. They used a dynamic version of the Diebold–Yilmaz (2009) volatility spillover index to examine the evolution of volatility transmission over time. The results show that the CEE3 countries are volatility takers in the period under analysis and that the volatility spillovers are extremely high during periods characterised by market uncertainty.

Clements et al. (2015) studied the transmission of volatility in global foreign exchange, equity and bond markets. Using a multivariate GARCH framework, significant volatility and news spillovers were found to occur on the same trading day between Japan, Europe and the US. All markets exhibit significant degrees of asymmetry in terms of the transmission of volatility associated with good and bad news. Ehrmann and Fratzscher (2017) analysed the integration of euro area sovereign bond markets during the Eurozone Sovereign Debt Crisis. They tested for contagion (i.e. intensification in the transmission of shocks across countries), fragmentation (a reduction in spillovers) and flight to quality patterns, exploiting the heteroscedasticity of intraday changes in bond yields for identification. They found that euro area government bond markets were well integrated prior to the crisis, but there was substantial fragmentation from 2010 onwards. Flight to quality was present at the height of the crisis, but has largely dissipated following the European Central Bank's announcement of its *Outright Monetary Transactions* program in 2012.

2.4 Research Gaps and Contributions

Comparatively, little attention has been given to exploring the linkage between stock, bond and money markets within individual nations and across countries at regional levels. This is somewhat puzzling as the nature of the linkage provides an important and rich information source for financial practitioners in terms of arbitrage opportunity, financial risk management, capital market regulation and portfolio management. Nonetheless, very little is known about the dynamic linkage between these three markets. The purpose of this study is to fill this void by investigating the interdependence of stock, bond and money markets across 17 countries. No study has investigated the stock, bond and money market linkages jointly within the context of VAR-DBEKK-GJR-GARCH, VAR-DBEKK-GJR-GARCH-M, VAR-X, PVAR-X.

Transmission of returns and volatilities of returns among three financial markets (stock, bond and money) across countries and their predictions are mostly silent within these specifications. One empirical result was provided by Aftab et al. (2019), who analysed stock, bond and money market interactions in the case of Australia. They found pairwise significant co-volatility in stock, bond and T-bill returns. Specifications of the conditional volatility and prediction thereof are important for various reasons. Any conclusion based on a misspecified model will be misleading. Most importantly, how the different asset market returns and volatilities of returns spillover to another financial market will provide information for investors and institutions about the ways to monitor and manage portfolio diversification.

The contribution of this study is threefold. First, while most previous studies have focused on the relationships between equity markets and bond markets, I investigate the interaction between stock, bond and money markets within and across countries using DBEKK. The multivariate empirical covolatiltity analysis within DBEKK-GJR-GARCH is not presented in the literature. I develop a Wald-type test for covolatility and asymmetry within DBEKK-GJR-GARCH. Second, this study provides fresh evidence to support the rationale for financial contagion, risk-return trade-off, lead–lag relationships, the leverage effect and asymmetric news effect that may be used to explain financial market interdependence. Third, this study employs a range of methodological approaches including non-parametric correlation and copula links to identify linkages between financial markets.

Chapter 3: Theory of Conditional Volatility and Modelling Issues

3.1 Introduction

In the finance area, asset price volatility is an important concern among researchers. As such, estimation and prediction of price volatility are useful in financial decision making for pricing securities; measurement of value-at-risk (VaR); allocation and diversification of assets; and assistance for financial regulators in policy implementation. There are three main areas of volatility modelling: (i) implied volatility, (ii) realised volatility and (iii) conditional volatility (Tsay, 2010).

These areas can be understood first if prices are governed by an econometric model such as the Black–Scholes formula (Tsay, 2010); one can then compute the conditional standard deviation (σ_t) by solving the Black–Scholes formula for σ_t. This value of σ_t is called the implied volatility of the underlying stock. The implied volatility is derived under the assumption that the price of the asset follows a geometric Brownian motion (Ross, 2010). Second, when high-frequency data such as intraday log returns, r_{it}, are available they can be used to compute the daily log returns of an asset, as $r_t = \sum_{i=1}^{n} r_{it}^2$, where n is the equally spaced intraday log return. The quantity $\sum_{i=1}^{n} r_{it}^2$ is called the realised volatility and is in fact a quadratic variation of r_t. Finally, the volatility of returns can be modelled conditionally on all available information on past returns within the mean variance framework.

The basic idea behind a conditional volatility model relies on the fact that the return series is either serially uncorrelated, or has minor low order serial correlations but the return series is dependent. This form of conditional volatility modelling is popular in economics and finance. There are two strands of modelling volatilities: univariate and multivariate financial return volatility modelling. In this chapter, I discuss conditional volatility models in the univariate and multivariate context.

This chapter is organised as follows. Section 3.2 deals with the econometrics of univariate volatility models and Section 3.3 discusses multivariate approaches to conditional volatility models. Estimation approaches are discussed with their statistical properties in Section 3.4.

Finally, Section 3.5 outlines the empirical analysis of the proposed volatility models in Chapter 4.

3.2 Univariate Conditional Volatility Models

A special feature of stock volatility is that it is not directly observable. The four most popular univariate conditional volatility models are the autoregressive (generalised) conditional heteroscedasticity (ARCH/GARCH) models of Engle (1982) and Bollerslev (1986); the GJR (often alternatively termed as asymmetric or threshold) GARCH of Glosten, Jaganathan and Runkle (1993); the EGARCH of Nelson (1991); and quality and quantity effects of the news volatility model of Engle and Ng (1993). Note that the data properties determine the choice of different variants of the GARCH model. I treat GARCH as the base model and continue searching for appropriate models for return volatility. Various univariate volatility models have been used to evaluate the risk, size and sign effects of volatility and to compute VaR in economics and finance. I use the following notations in the next sections:

r_t : return or log return of an asset over time t

F_{t-1} : set of information available at time *t-1*

ε_t : innovation or returns shock variable

$E(.|.)$: conditional expectation of the argument.

3.2.1 The ARCH model of volatility

Engle (1982) developed the ARCH model to capture time-varying conditional volatility of a series of observations. Let us assume that a financial return series is generated as:

$$r_t = \mu_t + \varepsilon_t = E\left(r_t \mid F_{t-1}\right) + \varepsilon_t \tag{3.1}$$

We usually assume that the conditional mean (μ_t) of r_t in Equation (3.1) follows an autoregressive moving average (ARMA) process of order, say k and m, denoted by ARMA (*k,m*). The conditional mean may include past values of r_t, current and past values of the innovation and other exogenous variables. Under this description the specification of r_t can be expressed as:

$$r_t \mid F_{t-1} = \phi_0 + \sum_{i=1}^{k} \phi_i r_{t-i} + \sum_{j=1}^{m} \psi_j \varepsilon_{t-j} + \varepsilon_t \tag{3.2}$$

The unknown order of ARMA can be determined by utilising the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), Hannan and Quinn information criterion (HQ) and ML methods, among others. The parameters ϕ_0, ϕ_i and ψ_i are the intercept, autoregressive (AR) and moving average (MA) parameters, respectively. The second and third terms on the right-hand side of Equation (3.2) are known as autoregressive and MA processes, respectively.

The stationarity of the return series r_t can be tested by a series of unit root tests including the ADF, PP and KPSS tests. Herman Ole Andreas Wold (1938) established a link between the autoregressive of order k denoted AR (k), and moving average of order m denoted MA (m). This link is generally known as the Wold decomposition theorem, which states that any covariance stationary process can be decomposed into two mutually uncorrelated component processes; one that is purely deterministic and one that is purely indeterministic. The innovation or returns shock ε_t in Equation (3.2) is assumed to be conditionally heteroscedastic as:

$$\varepsilon_t = e_t h_t^{1/2} \tag{3.3}$$

where e_t is an independent identically distributed (iid) random variable with mean 0 and variance 1 and h_t is the conditional variance of order q, which takes the following form:

$$h_t \mid F_{t-1} = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{3.4}$$

Equation (3.4) requires that $w_0 > 0$, $\alpha_1, \alpha_2, ..., \alpha_q \geq 0$ while $\sum_{i=1}^{q} |\alpha_i| < 1$ and is generally known as an ARCH model of order q, denoted ARCH(q) (see Engle, 1982). If we assume that the e_t are iid and normal, then the conditional distribution of $\varepsilon_t \mid F_{t-1}$ is a Gaussian process with mean 0 and conditional variance h_t. The standardised residual can be obtained from Equation (3.3) as $e_t = \varepsilon_t / \sqrt{h_t}$. Tsay (1987) derived the ARCH (1) model of Engle (1982) from the random coefficient autoregressive process of order one of the return shock ε_t. Equations (3.2) and (3.4) are collectively known as the conditional mean and conditional volatility models of the random variable r_t. The conditional distribution of r_t can be expressed under normality as follows:

$$r_t \mid F_{t-1} \sim N(\mu_t, h_t) \tag{3.5}$$

Equation (3.4) cannot be estimated independently of Equation (3.2). Therefore, Equations (3.2) and (3.4) need to be estimated jointly by the ML or quasi-maximum likelihood (QML) method in the absence of normality. The prediction of Equation (3.4) provides volatility prediction, which is useful for financial asset allocation and portfolio management.

The financial return series has a variety of characteristics including thick tails, leptokurtosis, variance change over time and the property that large/small changes tend to follow large(small) changes of either sign (volatility clustering). Therefore, the usual assumption of iid for the r_t is violated for financial returns data. These characteristics make conditional volatility models complicated but attractive for real applications in economics and finance. Although popular, ARCH models cannot distinguish between the effects of positive and negative return shocks on volatility. Further, they cannot identify the source of volatility of a financial time series.

3.2.2 The GARCH model of volatility

The next milestone was the development of Bollerslev's (1986) GARCH model, which is famously popular among researchers, financial analysists and decision makers trading securities in financial markets, for modelling volatility of financial security returns. The conditional innovation, $\varepsilon_t \mid F_{t-1}$ is assumed to be distributed normally with mean 0, and the conditional variance is assumed to be generated by:

$$h_t = w_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{3.6}$$

where $w_0 > 0$, $\alpha_i \geq 0$, and $\beta_j \geq 0$ are required for positivity of variance and $\sum_{i=}^{q} \alpha_i < 1$, $\sum_{j=1}^{p} \beta_j < 1$, and $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$ for invertibility and stability of the conditional variance function.

If $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j = 1$, then the GARCH model is called an integrated GARCH (or IGARCH) model. In this case, return shocks persist. Although the conditional innovation distribution is normal, the unconditional distribution of the innovation has been found to be non-normal in empirical finance; for example, by Mandelbrot (1963) and Black (1976) among others. The volatility Equation (3.6) is known as GARCH (*p,q*). The choice of the order p and q in a GARCH model can be determined by utilising AIC, SBC, HQ and ML approaches. Equation (3.6) has an ARMA interpretation (see Bollerslev, 1986). In this form, volatility is generated by both short- and long-run return shocks. Various forms of the mean model can be used on the grounds that the investor's expected future income changes. On this basis I treat the returns as a random variable and volatile.

ARMA-ARCH/GARCH models of asset returns and volatility of returns are widely used in modelling of the mean variance relationships of financial asset returns for low-, medium- and high-frequency data (see, e.g., French et al., 1987 and Engle et al., 1987). The advantage of GARCH is that the returns are not assumed to be independent, and unconditionally they are not Gaussian, because volatility clustering generates leptokurtosis. GARCH has the same advantages and weaknesses as does ARCH. However, one additional advantage with GARCH is that it describes the volatility evaluation. A list of GARCH class models is available in Bollerslev (2008) and Silvennoinen and Terasvitra (2009). In finance, the GARCH model can be treated as the base model with respect to any variant of GARCH and can be compared with the SGARCH as is done universally with the normal distribution in the statistics.

3.2.3 The GARCH-M model of risk premium

A widely used extension of ARCH is the ARCH-M model proposed by Engle et al. (1987); see also Bollerslev et al. (1992), Bera and Higgins (1993). The (G)ARCH-M model allows the conditional mean to depend on its own conditional variance. This model is suitable for studying the asset markets' time-varying risk premiums. The basic intent of this model is to consider situations where risk-averse agents require compensation for holding a risky asset. Engle et al. (1987) assumed that the risk premium is an increasing function of the conditional variance of innovation. Engle et al. (1987) provided a novel approach by which one can estimate and test for a time-varying risk premium. Mathematically, if h_t is the conditional variance (see Equation 3.6) of innovation, the risk premium can be expressed as:

$$r_t = \mu_t + \delta g(h_t) + \varepsilon_t \tag{3.7}$$

The function $g(h_t)$ is a monotonically increasing function of the conditional variance with $g(w_0) = 0$; μ_t can take the form of (3.2). The Equation (3.7) can be treated as the volatility risk premium model. In finance, $\delta g(h_t)$ represents the risk premium. The parameter δ measures the increase in the expected rate of return due to an increase in the variance of the return. A significant δ supports the existence of a risk premium. In most applications, $g(h_t) = \sqrt{h_t}$ has been used; see, for example, Domowitz and Hakio (1985) and Bollerslev et al. (1988). There are, however, some issues relating to the form of the specification $g(h_t)$. Pagan and Hong (1988) argued against using $g(h_t) = \log(h_t)$ because for $h_t < 1$, $g(h_t)$ will be negative and when $h_t \to 0$ the effect of volatility on r_t will be infinite; see Bera and Higgins (1993).

Asymmetric volatility models provide a rich class of volatility models. There are a number of asymmetric volatility model available in the literature: for example, the asymmetric GARCH model of Engle (1990), asymmetric power ARCH (APARCH) model of Ding et al. (1993), threshold ARCH model of Zakoian (1994) and Nelson (1991) and the GJR model of Glosten et al. (1993). Among many variations of GARCH specification, the next sections describe the two most popular models of asymmetric GARCH.

3.2.4 The EGARCH model of volatility

Although ARCH/GARCH models are popular and extensively used in the finance literature, they are restricted to use with symmetric information. Various extensions of ARCH/GARCH have appeared in the literature to overcome some inherent nonlinearity problems with ARCH and GARCH models. This is because volatility clustering is the likely characteristic of financial returns that are nonlinear and can be modelled by Student-t distribution, skewed

Student-t distribution, GED and extreme value distribution, among others. A popular nonlinear extension of ARCH/GARCH is Nelson's (1991) EGARCH model, which attempts to include the asymmetric impact of return shocks on volatility. In addition, this model does not require non-negativity restrictions on the parameters, unlike ARCH/GARCH conditional volatility models. The univariate EGARCH model takes the following form:

$$\ln h_t = w_0 + \sum_{j=1}^{p} \beta_j \ln h_{t-1} + \sum_{i=1}^{q} \gamma_i e_{t-i} + \sum_{i=1}^{q} \delta_i \left[| e_{t-i} | - \sqrt{2/\pi} \right] \tag{3.8}$$

The coefficient γ_i of e_{t-i} measures the sign effect and the coefficient δ_i measures the magnitude (or size) effect on the conditional asymmetric variance shift. Under the formulation (3.8), the variance h_t remains positive as required by a variance function. Therefore, the forecasts of the conditional variance are non-negative. Note that for the Gaussian random variable $e_t, E|e_t| = \sqrt{2/\pi}$. The term in |.| represents the absolute value function, and e_t is the standardized residuals.

3.2.5 The GJR-(asymmetric)-GARCH model of volatility

Another popular asymmetric extension of GARCH is Glosten, Jagannathan and Runkle's (1989) GARCH volatility model, GJR-GARCH, which takes the following form:

$$r_t | F_{t-1} = \mu_t + \varepsilon_t,$$

$$h_t | F_{t-1} = w_0 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i d_{t-i} \varepsilon_{t-i}^2 \tag{3.9}$$

where μ_t is as defined in (3.2) and $d_{t-i} = \begin{cases} 1 & if \;\; \varepsilon_{t-i} < 0 \\ 0 & otherwise \end{cases}$. Order selection can be achieved by employing the AIC, SBC, HQ or likelihood ratio test, among others. The EGARCH and GJR-GARCH models allow for leverage effect (the tendency of volatility to decline when returns rise and to rise when returns fall), in contrast to classical ARCH and GARCH models. ARCH/GARCH themselves cannot capture asymmetric information. The GJR is centred at ε_{t-1} but the slope is asymmetric about 0; that is, there are different slopes on the positive and negative sides of $\varepsilon_{t-1} = 0$. We expect $\gamma_i > 0$, which implies that a negative return shock increases the conditional volatility more than does a positive shock. Therefore, negative return shock increases volatility by $\alpha_i + \gamma_i$ while positive return shock increases volatility by α_i. Thus, a test for the asymmetry effect of return shocks on volatility may be based on the null hypothesis that $\gamma_i = 0$, versus the alternative hypothesis $\gamma_i > 0$. A comparison of EGARCH and GJR-GARCH can be made by applying the tests provided by Engle and Ng (1993). Both models are asymmetric volatility models but their specifications are different.

Thus far I have considered univariate analysis of returns and volatility of returns. The univariate ARCH, GARCH, GARCH-M, EGARCH and GJR-GARCH models cannot provide information about causality among the portfolio of assets returns and cannot capture full co-volatility and partial co-volatility as recently defined by Chang et al. (2018). To capture interdependence among assets returns and volatility of returns, modelling volatility must be undertaken within a multivariate framework. Multivariate volatility models are useful for exploring spillovers and causal effects of the returns and volatilities of returns among assets across countries. The linkages among multiple asset markets give more detailed joint information on the asset trading behaviour of financial markets. This information is vital for asset allocation and portfolio diversification strategies.

3.3 Multivariate Conditional Volatility Models

In general, by multivariate volatility, I refer to the conditional variance–covariance matrix of multiple asset returns. Multivariate volatility jointly examines the linkages among multiple asset markets domestically and globally. These models have many important financial applications such as in volatility spillover, co-volatility and causality among multiple financial assets. These are useful pieces of information informing agents' strategic decision making tools for asset pricing, asset allocation and diversification to achieve optimal returns. In this section I describe multivariate models dealing with the data inherent phenomenon; that is, volatility clustering, asymmetry, leverage effects, sudden jump, time-varying dynamic co-volatility and DCC, and nonlinearity. I use the same notations as used in the descriptions of univariate volatility models as above, but here the components are now vectors and matrix representations of the conditional mean and volatility models. Let $r_t = (r_{1t}, r_{2t}, ..., r_{Nt})'$ be an ($N \times 1$) vector of N returns or log returns for the time index $t = 1, 2, ..., T$ generated by the following structure:

$$r_t = \mu_t + \varepsilon_t \,,\ \varepsilon_t = H^{0.5} e_t \tag{3.10}$$

where $\mu_t = E(r_t | F_{t-1})$ is the conditional expectation of the vector r_t given the past information F_{t-1}; $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{Nt})'$ is an $(N \times 1)$ vector of shock, or innovation or noise at time t; H_t is an ($N \times N$) covariance matrix of the innovation vector ε_t of order ($N \times 1$); e_t = ($e_{1t}, e_{2t}, ..., e_{Nt}$)' is a vector of ($N \times 1$) iid random variables with an ($N \times 1$) vector of mean 0 and covariance matrix I_N of order ($N \times N$).

The probability distribution of e_t is G$(0, I_N)$, where G is assumed to be a continuous probability density function. The information set may contain past values of returns and past innovations, or some exogenous vector of variables. The conditional mean is assumed to have the following form:

$$\mu_t = \sum_{i=1}^{k} \phi_i r_{t-i} + \sum_{j=1}^{m} \psi_j \varepsilon_{t-j} \tag{3.11}$$

where each ϕ_i and ψ_j is an ($N \times N$) matrix of the mean model. In this form, Equation (3.11) is generally known as a VARMA model. Note that Equation (3.11) may include other exogenous vectors of variables (*X*), in this situation I call the resulting process a mixed VARMA-X process. Equation (3.11) is a multivariate VAR if it does not have the lagged errors vectors; that is, if ψ_j is a zero matrix for all $j = 1, 2, ..., m$. The conditional covariance matrix of ε_t given F_{t-1} is defined as follows:

$$E(\varepsilon_t \varepsilon_t' | F_{t-1}) = H_t \tag{3.12}$$

where H_t is an ($N \times N$) unknown but symmetric positive definite matrix. I refer to Equation (6.12) as a multivariate volatility model, which is needed to be specified for the multivariate vector of return series r_t. The multivariate relationship between the univariate ε_t and e_t is as $\varepsilon_t = \sqrt{D_t}\, e_t$ and the conditional correlation matrix of ε_t is expressed as:

$$corr(\varepsilon_t | F_{t-1}) = \rho_t = D^{-1/2} H_t D^{-1/2} \tag{3.13}$$

where $D_t = \text{diag}(h_{ii,t})$ and $h_{ii,t}$ is the *ii*-th diagonal element of the matrix H_t and the *ij*-th element of $\rho_t = \rho_{ij} (i = 1, 2, ..., N; j = 1, 2, ..., N)$. An ideal multivariate volatility model should allow covariance spillovers and feedback. Equation (3.13) can be expressed equivalently as:

$$H_t = D_t \rho_t D_t \tag{3.14}$$

Equation (3.14) expresses the relationship between the time evolution of H_t and ρ_t. Further, the relationship between the conditional variances $h_{ii,t}$ and correlations $\rho_{ij,t}$ of ρ_t can be estimated directly or by applying the exponential smoother. Because H_t is a symmetric and positive definite matrix, there exists a lower triangular matrix L with unit diagonal matrix and a diagonal matrix D_t* with positive diagonal elements, such that the following equality holds:

$$H_t = L_t D_t * L_t ' \tag{3.15}$$

This decomposition of H_t in (3.15) is known as Cholesky decomposition (Tsay, 2010). Equations (3.14) and (3.15) are a kind of reparameterisation of the matrix H_t. This reparameterisation is required for manageable statistical inference of the covariance matrix H_t, which is the main purpose of volatility modelling. I discuss below some common specifications for H_t.

3.3.1 Approaches to multivariate conditional volatility

There are a few approaches to modelling the conditional covariance in the multivariate context. These approaches can be distinguished as follows:

1. direct generalisation of the univariate GARCH model
2. linear combinations of the univariate GARCH model
3. nonlinear combinations of the univariate GARCH model.

Among these classifications, the direct generalisation of GARCH is popular among researchers. Under this generalisation, I describe the volatility specification as the VEC-GARCH model of Bollerslev et al. (1988); the BEKK model proposed in Engle and Kroner (1995); and factor models, which are motivated by economic theory. The factor-GARCH (F-GARCH) model was introduced by Engle et al. (1990). It is motivated by the fact that the arbitrage pricing theory states that returns are generated by a number of common unobserved components, or factors; see Silvennoinen and Terasvitra (2008) for a general exposition.

3.3.2 The VEC-GARCH model

The VEC-GARCH model of Bollerslev et al. (1988) is a diagonal vectorisation of the multivariate H_t, and takes the following form:

$$H_t = W_0 + \sum_{i=1}^{q} A_i \odot (\varepsilon_{t-i}\varepsilon'_{t-i}) + \sum_{j=1}^{p} B_j \odot H_{t-j} \tag{3.16}$$

where W_0, A_i and B_j are symmetric matrices of order $N \times N$ and $\odot$ represents Hadamard product matrices (i.e. an element-by-element multiplication of the matrices). Because of the success of GARCH (1,1) in univariate analysis, I assume the multivariate GARCH (p = 1, q = 1) holds. However, the order of a multivariate GARCH can be chosen using the multivariate AIC, Bayesian Information Criterion (BIC) or likelihood criteria. Since H_t is a symmetric matrix I consider the lower triangular part of H_t and the associated right-hand side terms of the matrices. In this form, each element of H_t follows a univariate GARCH-type model that depends only on its past value and the corresponding product term in the lower triangular matrix $\varepsilon_{t-1}\varepsilon_{t-1}'$. In this general form the multivariate conditional GARCH (MGARCH) is simple, but has the vital drawback that it may suffer from a loss of positive definiteness of the H_t matrix. Another drawback is that the H_t does not allow for dynamic dependence between multiple asset class; that is, no spillovers and causality analysis is possible under the VEC specification of multivariate GARCH or MGARCH. The model is very flexible but has severe disadvantages. The number of parameters in the variance function appears to be $(p+q)(N+(N+1)/2)^2 + N(N+1)/2$. This number increases with N, the number of assets.

Bollerslev et al. (1988) further presented a simplified version of (3.16) by restricting A_i and B_j to diagonal matrices. In this form the estimation is less difficult, with only $(p+q+1)(N(N+1)/2$ parameters to estimate. Also, the positivity of H_t may be maintained, although it lacks spillovers as a consequence of financial market interactions. This model is known as diagonal VECH (DVECH).

3.3.3 The BEKK-GARCH model

Engle and Kroner (1995) proposed the BEKK model, which overcomes the non-positive definiteness of the VEC-GARCH. The model has the following form:

$$H_t = CC' + \sum_{i=1}^{q}\sum_{k=1}^{K} A_{ki}\varepsilon_{t-i}\varepsilon_{t-i}^{'}A_{ki}^{'} + \sum_{j=1}^{p}\sum_{k=1}^{K} B_{kj}H_{t-j}B_{kj}^{'} \tag{3.17}$$

where C is a lower triangular matrix and both A_{ki} and B_{kj} are $N \times N$ matrices. The first term on the right-hand side of Equation (3.17) ensures the positive definiteness of H_t. The BEKK model is covariance stationary only if the modulus of the $\sum_{i=1}^{q}\sum_{k=1}^{K} A_{ki} \otimes A_{ki}^{'} + \sum_{j=1}^{p}\sum_{k=1}^{K} B_{kj} \otimes B_{kj}^{'} < 1$ and $\otimes$ denotes the Kronecker product of two matrices. For $K > 1$, an identification problem arises; see Silvennoinen and Terasvitra (2008). Engle and Kroner (1995) gave conditions for eliminating redundant, observationally equivalent representations. The restricted version of the DBEKK model is the scalar BEKK with *A = a1 and B =b1*, where I is the identity matrix. A simpler form of BEKK obtained from (3.17) by setting $K = 1$ is the following:

$$H_t = CC' + \sum_{i=1}^{q} A_i\varepsilon_{t-i}\varepsilon_{t-i}^{'}A_i^{'} + \sum_{j=1}^{p} B_j H_{t-j} B_j^{'} \tag{3.18}$$

The number of parameters increases rapidly with *p* and *q*. Tsay (2010) showed that many of the estimates of BEKK parameters are insignificant in applications. Reparameterisation by the use of correlations and Cholesky decomposition as described above may be adopted for feasible multivariate volatility models.

3.3.4 The constant conditional correlation model

Bollerslev (1990) considered the special case of $H_t = D_t \rho_t D_t$ (see Equation [3.14]), which assumes that $\rho_t = \rho$; that is, the conditional correlation is assumed to be time invariant. This model is generally known as the constant conditional correlation (CCC) model of volatility. Note that $\rho = (\rho_{ij}) = \begin{cases} 1 \text{ for } i = j\,(i, j = 1, 2, ..., N) \\ -1 < \rho_{ij} < +1,\ i \neq j \end{cases}$. Therefore, the off-diagonal elements of the conditional covariance matrix are as follows:

$$\left(H_{ij}\right)_t = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij}, \; i \neq j \tag{3.19}$$

The h_t in (3.19) is usually modelled as univariate GARCH (p,q). In that case the conditional volatility model takes the following form:

$$h_t = w + \sum_{i=1}^{q} A_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} B_j h_{t-j} \tag{3.20}$$

where h_t, ε_t^2 and w are vectors of order ($N \times 1$) and $A_i = (\alpha_{ij})$ and $B_j = (\beta_{ij})$ are matrices of order ($N \times N$). The existence of $E\varepsilon_t^2$ requires that the eigenvalues of $A+B$ are positive but <1 and the ε_t^2 is weakly stationary. If $\alpha_{ij} + \beta_{ij} = 0$, then the volatility of ε_{it} does not depend on the ε_{jt} ($i \neq j$). If A_i and B_j are diagonal, then the model reduces to N volatility models that are not dynamically related.

A major drawback of the CCC model is that the correlation coefficient tends to change over time in real applications (see Tsay, 2010). Parsimonious models for ρ_t in Equation (3.19) to describe the time-varying correlations are generally known as DCC models. Two such models were developed by Tse and Tsui (2002) and Engle (2002).

3.3.5 DCC models

For N dimensional returns, Tse and Tsui (2002) assumed that the conditional correlation matrix ρ_t (see Equation [3.14]) follows the model:

$$\rho_t = (1 - \lambda_1 - \lambda_2)\rho + \lambda_1 \rho_{t-1} + \lambda_2 \Pi_{t-1} \tag{3.21}$$

where λ_1 and λ_2 are scalar parameters and ρ is an ($N \times N$) diagonal positive definite matrix with unit diagonal elements. Π_{t-1} is an ($N \times N$) sample correlation matrix using shocks or innovations from $t-n, \ldots\ldots, t-1$ for a pre-specified n. The assumptions $0 \leq \lambda_i < 1$, $\lambda_1 + \lambda_2 < 1$ and $p = q = 1$ are required for the matrix ρ_t to be positive definite. Retaining the previous decomposition, Tse and Tsui (2002) assumed that the conditional correlation matrix is time varying. In this case the positive definiteness of H_t follows if ρ_t is positive definite at each point in time. To overcome the difficulties inherent in this situation, Tse and Tsui (2002) imposed GARCH-type dynamics on the conditional correlations. The conditional correlations in their varying correlation (VC)-GARCH model are functional correlations of the previous period (see Silvennoinen & Terasvitra, 2008). The estimated correlations can be obtained from the following:

$$\rho_t = (1-\gamma_1-\gamma_2)G + \gamma_1 G_{t-1} + \gamma_2 \rho_{t-1} \tag{3.22}$$

where G is a constant positive definite matrix with values of 1 on the main diagonals; γ_1 and γ_2 are non-negative scalar parameters such that $\gamma_1+\gamma_2 \leq 1$; G_{t-1} is the sample correlation matrix of the past *n* standardised residuals $\varepsilon_{t-j}, j=1,2,....,n$; and $\hat{\varepsilon}_{t-j} = \hat{D}_{t-j}^{-1} r_{t-j}, j=1,2,....,m$. Engle (2002) introduced a DCC-GARCH, the specification of which is similar to the VC of Tse and Tsue (2002). Engle's DCC takes the following form:

$$Q_t = (1-\gamma_1-\gamma_2)\bar{Q} + \gamma_1 \varepsilon_{t-1}\varepsilon_{t-1}^{'} + \gamma_2 Q_{t-1} \tag{3.23}$$

where γ_1 and γ_2 are non-negative scalar parameters such that $\gamma_1+\gamma_2 < 1$; $\bar{Q}$ is the unconditional correlation of the standardised error ε_t; and Q_t is positive definite for a valid correlation:

$$\rho_t = (I \odot Q_t)^{-1/2} Q_t (I \odot Q_t)^{-1/2} \tag{3.24}$$

Very recently Chang et al. (2018) and Chang and McAleer (2018) have shown that the full BEKK, CCC and DCC multivariate volatility models estimated by QMLEs do not have the asymptotic statistical properties required for valid statistical tests of volatility spillover effects. Chang et al. (2017) showed that the full, triangular and Hadamard BEKK models cannot be derived from any known underlying stochastic processes. This means that there are no valid asymptotic properties of the QMLEs of the parameters of the above multivariate models. The only valid multivariate extension of univariate volatility model is the DBEKK derived from a vector random coefficient autoregressive process of order one has asymptotic validity of the QMLE (see Chang et al., 2018). I deal with multivariate volatility model specification issues in Chapter 4.

3.3.6 Estimation and inference in conditional volatility models

Univariate model estimation is comparatively easy to undertake jointly for the conditional mean and the conditional volatility specification by the likelihood function approach under the assumption of normality, Student-t, skewed Student-t, skewed normal and generalised error of the innovation distribution. However, for the multivariate case the estimation is not so simple and a good model requires statistical properties to hold at least asymptotically. In most of the multivariate volatility models, some conditions are put on the model parameters to make the estimation manageable and feasible. In most nonlinear cases the estimation involves using the normal distribution. However, under misspecification, the MLEs based on normality do not have standard statistical properties. In the absence of normality, the QMLEs of DBEKK-GARCH parameters are asymptotically normally distributed, under regularity conditions; see McAleer et al. (2008), Ling and McAleer (2003), Chang et al. (2017). The tests related to the specifications, co-volatility and partial co-volatility of the multivariate DBEKK model and its variation models have valid regularity conditions and asymptotic properties for statistical estimation and inference.

3.4 Conclusion

This chapter provides an overview of the univariate and multivariate time series models of financial volatility and volatility spillovers. Autoregressive (AR) and moving average (MA) processes are usually entertained for time series analysis in general. In this context the Wold (1938) decomposition theorem is a useful technique which describes that an infinite order autoregressive process can be approximated by smaller order ARMA process. The advantage of this theory is to unify the unobserved stochastic dynamics with observed dynamics. This concept is applied to larger order autoregressive conditional heteroskedastic (ARCH) model to arrive at a lower order generalized autoregressive conditional heteroscedastic (GARCH) model of financial volatility. However, the order selection of GARCH is an empirical issue, can be resolved by AIC, BIC, HH or other criteria. In the empirical finance GARCH (1,1) is the most popular for modelling and forecasting volatility. Although popular, GARCH cannot capture asymmetric information of the financial markets. Consequently, various extensions of ARCH/GARCH have appeared in the finance literature to cope with asymmetric information. Most notably the GJR-GARCH and EGARCH models are widely used in finance. Another model, quite popular in measuring and predicting volatilty, is generally known as GARCH-in-mean (GARCH-M) model which measures the risk premium in financial markets with various specifications of conditional volatility. The univariate conditional volatility models are simple and have closed-form solutions.

However, the univariate conditional volatility models are incapable of capturing the interrelationship among financial markets, both domestic and international. This motivates researchers to explore the multivariate asset market analyses. Multivariate study is useful for extracting joint information on the trading behavior of financial assets, volatility of return shocks and spillover effects. This provides useful information for financial strategic decision making, asset allocation and diversifications issues. Since the univariate GARCH cannot be directly generalized to multivariate GARCH, the multivariate GARCH has been derived from the random coefficient autoregressive processes of multivariate return shocks. In this context the multivariate GARCH and GJR-GARCH are introduced within the diagonal BEKK (DBEKK) framework. The estimation of the univariate model has the desirable statistical properties under the conditional normality. However, the estimation of Full BEKK multivariate volatility model does not have asymptotic statistical properties. The quasi-maximum likelihood estimates (QMLE) of the DBEKK are consistent and asymptotically normal. This information is useful for statistical inference. The next chapter describes the methodology and data used for empirical analyses of the research questions of this thesis.

Chapter 4: Data and Methodology

4.1 Introduction

This chapter develops the research methodologies required to address the research questions stated in Chapter 1 of this thesis. I use both univariate and multivariate financial return volatility modelling approaches as discussed in Chapter 3. In addition to those developed in Chapter 3, my research methodology includes econometric techniques within the multivariate VAR originally developed by Sims (1980). The VAR is extended to include the qualitative variables VAR-X and PVAR-X to gain insights into financial market crash events such as the 1987 crash, the AFC and the GFC. I undertake nonparametric correlation analysis and copula-based dependence between assets returns and volatility of returns to explore asset dependence across countries. Because of some specification issues with multivariate GARCH volatility models, I extend the multivariate GARCH methodologies to understand the dynamics of partial co-volatility spillovers, Granger causality, impulse response functions (IRFs), variance decomposition, nonparametric dependence and copula dependence approaches. These approaches extract information about the sources of volatility generated by data generating processes (DGPs). Under impulse response and forecast error variance decomposition, I am able to determine the proportion of volatility movements in a series because of its 'own' shocks versus shocks to other variables. This rich class of forecast error variance decomposition is an important and useful source of volatility spillovers and causality issues among securities traded in the local and global financial markets.

In this chapter, I provide a detailed description of the methodologies employed in the data analyses to fulfil the objectives of this thesis. Within the univariate and multivariate context I formulate model specification and modification; and develop tests for co-volatility spillovers and the existence of contemporaneous correlation among financial assets across countries. This chapter is organised as follows. In the next section, I outline sources of data, variable descriptions and data transformation. Section 4.3 describes the univariate models of returns volatility, estimation and volatility predictions, model adequacy, strength and weakness of the univariate models and methodology. Multivariate models of volatility, specification issues, estimation, test strategies, model adequacy and prediction are discussed in Section 4.4.

4.2 Univariate Financial Return Model

I assume that the conditional mean in 'return', r_t, generated by the DGP F_{t-1} can be described by the following stochastic process:

$$r_t = E(r_t \mid F_{t-1}) + \varepsilon_t \tag{4.1}$$

I assume that $\varepsilon_t \mid F_{t-1} = \sqrt{h_t} e_t$, where F_{t-1} is the set of information available at time *t* and the random variable e_t is an iid random variable with mean 0 and variance 1. Specifically, model (4.1) can be expressed as:

$$r_t \mid F_{t-1} = \phi_0 + \sum_{i=1}^{k} \phi_i r_{t-i} + \sum_{j=1}^{m} \psi_j \varepsilon_{t-j} + \varepsilon_t \tag{4.2}$$

Model (4.2) is an autoregressive moving average process of order *k* and *m* denoted ARMA (*k*,*m*). The parameters $\phi = (\phi_0, \phi_1, \ldots\ldots, \phi_k)'$ and $\psi = (\psi_1, \psi_2, \ldots\ldots, \psi_m)'$ are respectively the AR and MA vectors of parameters. The stability condition of the process (4.1) requires that $\sum_{i=1}^{k} |\phi_i| < 1$ and $\sum_{j=1}^{m} |\psi_j| < 1$. These two conditions are respectively known as the stationarity and invertibility conditions of the stochastic process r_t. The random variable ε_r is a conditionally heteroskedastic error term, known as return shock in finance. In this study the univariate return volatility models take the following forms:

$$h_t \mid F_{t-1} \sim GARCH(p,q) \tag{4.3}$$

$$h_t \mid F_{t-1} \sim GJR-GARCH(p,q) \tag{4.4}$$

where F_{t-1} is the information set available at time *t*–1. The extended condition mean model (4.1) is:

$$r_t \mid F_{t-1} = ARMA(\text{k,m}) + \delta g(h_t) + \varepsilon_t \tag{4.5}$$

Since GJR is popular in empirical finance, I use GJR-type asymmetry in conditional volatility models in both univariate and multivariate analysis in this thesis. Equation (4.5) is generally known as the GARCH-M model. The term $\delta g(h_t)$ is called risk premium in finance. To study the statistical properties of the risk-return (r_t, h_t) relationship I jointly model both the mean and variance of the return series. Under the assumption of conditional normality of the innovation distribution, the mean variance model parameters can be jointly estimated using the nonlinear MLE method. In the absence of normality, I use QMLEs.

I define a generic set of parameters as θ, which includes all the parameters of the mean variance model. Under the conditional normality assumption of the return shock distribution, the MLEs of the parameters are strongly consistent. Further, under the correct specification the MLEs are efficient and normal. Note that different probability distributions of the return shock ε_t are possible for example, Student-t, skewed Student-t, Cauchy, GED and Laplace distributions among others depending on the data property. Since the Gaussian GARCH model as stated in (4.1 and 4.3) cannot explain the inherent stylised fact of leptokurtosis in financial data, Bollerslev (1987) suggested replacing conditional normality by the conditional Student-t distribution. The univariate distribution of the t-innovation takes the following form:

$$f(\varepsilon_t \mid F_{t-1}) = \frac{\Gamma[(v+1)/2]}{\pi^{1/2}\Gamma(v/2)}[(v-2)h_t]^{-1/2} \times \left[1+\frac{\varepsilon_t^2}{(v-2)h_t}\right]^{-(1/2)(v+1)} \tag{4.6}$$

This distribution is always fat-tailed and produces a better fit than the normal distribution for most asset return series. The distribution is well defined only if $v > 2$. Note that the variance of a Student-t distribution with $v \leq 2$ is infinite. The distribution of the GED innovation is also useful in modelling the stylised facts of return series, which has the following form:

$$f(\varepsilon_t \mid F_{t-1}) = \frac{v\exp\left(-(1/2)\left|\frac{\varepsilon_t}{\sqrt{h_t}\ \lambda}\right|^v\right)}{\sqrt{h_t}\ \lambda 2^{(v+1)/2}\Gamma(1/v)} \tag{4.7}$$

where $\lambda = \sqrt{\frac{2^{-2/v}\Gamma(1/v)}{\Gamma(3/v)}}$

This is a fat-tailed distribution when $v < 2$ and is thin-tailed when $v > 2$. The variance is infinite when $v < 1$. Another useful distribution introduced by Hansen (1994) is the skewed Student-t distribution, which allows for skewness (third moment) in the returns. This distribution, in fact, allows for both time-varying shapes and skewness in financial data. Let

e_t be the standardised innovation (i.e. $e_t = \varepsilon_t / \sqrt{h_t}$); thus the skewed Student-t takes the following form:

$$f(e_t \mid v, \lambda) = \begin{cases} bc\left[1 + (1/(v-2))\left(\dfrac{be_t + a}{1-\lambda}\right)^2\right]^{-((v+1)/2)} & \text{if } e_t < -a/b \\ bc\left[1 + (1/(v-2))\left(\dfrac{be_t + a}{1+\lambda}\right)^2\right]^{-((v+1)/2)} & \text{if } e_t \geq -a/b \end{cases} \tag{4.8}$$

Where $2 < v < \infty$ and $-1 < \lambda < 1$. The constants a, b, c are as follows: $a = 4\lambda c\left(\dfrac{v-2}{v-1}\right)$, $b^2 = 1 + 3\lambda^2 - a^2$, and $c = \dfrac{\Gamma(v+1)/2}{\sqrt{\pi(v-2)}\,\Gamma(v/2)}$. This density of e_t has mean 0 and variance 1. If $\lambda = 0$ we have the usual Student-t distribution. The skewed Student-t density (see [4.8]) is continuous and has a single mode at $-a/b$. If $\lambda > 0$ then the model is on the left of 0 (implying a right-skewed density) and when $\lambda < 0$, the density is left-skewed. In my empirical analysis of stock returns in Chapter 5, I employ normal, Student-t and skewed Student-t distributions.

4.2.1 Univariate model estimation

Under the normality assumption, I estimate the unknown parameter θ by maximising the log-likelihood function of T independent observations as follows:

$$l(\theta \mid r) = \sum_{t=1}^{T}\left\{-\frac{1}{2}\ln 2\pi - \frac{1}{2}\ln h_t - \frac{\varepsilon_t^2}{2h_2}\right\} \tag{4.9}$$

where $l(\theta \mid r)$ is the log-likelihood function of the parameters. The maximisation principle involves the following two conditions: $\dfrac{\partial l(\theta \mid data)}{\partial \theta} = 0$ and $\dfrac{\partial^2 l(\theta \mid Data)}{\partial \theta \partial \theta'} < 0$. The MLE is consistent when the first moment of the likelihood is $\theta < \infty$ and the first derivative of the first moment $< \infty$. If the variance is finite and the likelihood is well behaved then the MLE is asymptotically normal. The QMLE is, however, consistent and asymptotically normal under the assumption of iid z_t, where z_t is the standardised return shock (see Lamsdaine, 1991).

4.3 The Multivariate Volatility Models

In this section, I explore the BEKK proposed by Engle and Kroner (1995) for the multivariate GARCH model.

4.3.1 The BEKK-GARCH model for multivariate conditional volatility

Engle and Kroner (1995) proposed the BEKK model for modelling multivariate conditional volatility. The QMLEs of the full BEKK do not have stochastic properties; see Chang et al. (2018), Chang and McAleer (2017). Moreover, the full BEKK method requires additional parameter estimation and the number of parameters increases as the number of assets increases. Many of the parameter estimates of the full BEKK are not significant in real applications and the estimates have no interpretation (see Tsay, 2010).

I utilise the DBEKK model, a variant of the full BEKK for volatility estimation as suggested in a series of papers by Chang et al. (2018), McAleer et al. (2009), Allen et al. (2017) and Allen and McAleer (2018) (see also McAleer, 2005). The QMLEs of a DBEKK model are consistent and asymptotically normally distributed. The normality of the estimates means that I can test a variety of linear and nonlinear hypotheses regarding co-volatility spillovers with valid statistical properties of the tests. The determination of co-volatility spillovers is important for risk management and asset diversification in financial markets in general.

4.3.2 The DBEKK-GARCH volatility model

I start with the DBEKK-GJR-GARCH model because in the univariate analysis (see Chapter 5) I found that significant GJR-type leverage exists for return volatility. For the empirical analysis of the relationship between stock market volatility and expected returns, I consider the following model specifications.

4.3.2.1 *Multivariate conditional mean model*

I use the following multivariate return model

$$r_t \mid F_{t-1} = \Phi_0 + \Phi_1 r_{t-1} + \varepsilon_t, \tag{4.10}$$

where r_t is an $(N \times 1)$ vector of asset returns, F_{t-1} is the set of information available at time *t*-1; The parameters Φ_0 and Φ_1 are to be estimated; The $(N \times 1)$ vector ε_t is the vector of return shock assumed to be a vector random coefficient autoregressive process of order one. The multivariate standardized residuals $e_t = \frac{\varepsilon_t}{\sqrt{h_t}}$ or $\varepsilon_t = h_t^{1/2} e_t$, where the $(N\times 1)$ random vector e_t is assumed to be iid with zero mean and covariance matriz CC' and h_t is the $(\mathrm{N}\times\mathrm{N})$ diagonal matrix comprising the univariate conditional volatilities. Let $\mathrm{H_t}$ be the conditional covariance matrix of ε_{t}.

4.3.2.2 *Conditional variance–covariance model*

I use the following multivariate extension of GJR-GARCH(1,1) obtained from the vector random coefficient autoregressive process of order one of the return shocks

$$\mathrm{H_t|F_{t-1}} = \mathrm{CC'} + \mathrm{A}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\mathrm{A}^{'} + \mathrm{BH_{t-1}B}^{'} + \Gamma\mathrm{D_{t-1}}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\Gamma' \tag{4.11}$$

where A, B and Γ are each $(N\times N)$ diagonal matrices; C is an $(N\times N)$ lower triangular matrix; ε_t is an $(N\times 1)$ vector of return shocks; and $\mathrm{D_{t-1}}$ is an indicator matrix that determines the asymmetric effect of return shocks on volatility. The matrix variable $\mathrm{D_{t-1}}$ is defined as:

$$\mathrm{D_{t-1}} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} \le 0 \\ 0 & \text{if } \varepsilon_{t-1} > 0 \end{cases}$$

Equation (4.11) is known as the DBEKK-GJR-GARCH (model of conditional volatility). In my analysis I use the stock indices from developed, advanced emerging and emerging markets and transform the series into log returns. Equations (4.10) and (4.11) are estimated jointly by the QML method. The QMLE has the desirable statistical properties for developing tests for the co-volatility spillover effects of return shocks on volatility.

4.3.3 Volatility spillovers, estimation and tests

Three definitions of volatility spillovers are provided in the literature (see Chang et al., 2017): (i) full volatility spillovers, (ii) full co-volatility spillovers, and (iii) partial co-volatility spillovers. I extend the partial co-volatility spillover definition of Chang et al. (2018) to the multivariate DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M models. I estimate the asymmetric effect of return shocks on volatility and develop a novel Wald-type test for co-volatility spillover effects of return shocks on conditional volatility models. I noted in the multivariate context that the number of parameters increases as the number of assets increases. For this reason, I limit the co-volatility analysis to three assets to optimise computation and ease interpretation of the multivariate volatility model parameter estimates. Multivariate DBEKK-GJR-GARCH volatility model specification takes the following form:

$$\mathrm{H_t{=}CC'}+\begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix}\begin{pmatrix} \varepsilon_{1t}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} & \varepsilon_{1t-1}\varepsilon_{3t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon_{2t}^2 & \varepsilon_{2t-1}\varepsilon_{3t-1} \\ \varepsilon_{3t-1}\varepsilon_{1t-1} & \varepsilon_{3t-1}\varepsilon_{2t-1} & \varepsilon_{3t}^2 \end{pmatrix}\begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix}^{'}+\begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix}\begin{pmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t} & h_{33,t-1} \end{pmatrix}\begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix}^{'}+$$

$$\begin{pmatrix} \gamma_{11} & 0 & 0 \\ 0 & \gamma_{22} & 0 \\ 0 & 0 & \gamma_{33} \end{pmatrix}\mathrm{D_t}\begin{pmatrix} \varepsilon_{1t}^2 & \varepsilon_{1t-1}\varepsilon_{2t-1} & \varepsilon_{1t-1}\varepsilon_{3t-1} \\ \varepsilon_{2t-1}\varepsilon_{1t-1} & \varepsilon_{2t}^2 & \varepsilon_{2t-1}\varepsilon_{3t-1} \\ \varepsilon_{3t-1}\varepsilon_{1t-1} & \varepsilon_{3t-1}\varepsilon_{2t-1} & \varepsilon_{3t}^2 \end{pmatrix}\begin{pmatrix} \gamma_{11} & 0 & 0 \\ 0 & \gamma_{22} & 0 \\ 0 & 0 & \gamma_{33} \end{pmatrix}^{'} \qquad (4.12)$$

where matrix $A = \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix}$ reflects the short-run effects of return shock on volatility; C =

Where the matrix A = reflects the short-run effects of return shock on volatility.

$C = \begin{pmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{pmatrix}$ is a lower triangular matrix; B = $B = \begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix}$ is a weight matrix that represents the long-run volatility persistence; and matrix $\Gamma = \begin{pmatrix} \gamma_{11} & 0 & 0 \\ 0 & \gamma_{22} & 0 \\ 0 & 0 & \gamma_{33} \end{pmatrix}$ reflects news effects. I apply the QML method to Equations (4.10) and (4.11) jointly and compute the QMLEs of the matrix parameter of Equation (4.12).

4.3.3.1 *Partial co-volatility spillovers*

I have extended the partial co-volatility definition of Chang et al. (2018) to DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M models. It is to be noted that Chang et al. (2018) used DEBKK-GARCH. The use of the DBEKK-GJR-GARCH model here thus extends the risk premium model. The partial co-volatility is computed as follows:

$$\frac{\partial \mathrm{H}_{ij,t}}{\partial \varepsilon_{k,t-1}} = a_{ii}a_{jj}\varepsilon_{it-1} + \lambda_{ii}\lambda_{jj}\varepsilon_{it-1}, \; i,j = 1,2,3; \; i \neq j, \;\; k = \text{either } i \text{ or } j.$$

$$\frac{\partial \mathrm{H}_{12,t}}{\partial \varepsilon_{1,t-1}} = a_{11}a_{22}\varepsilon_{2t-1} + \lambda_{11}\lambda_{22}\varepsilon_{2t-1} \;\text{ or, }\; \frac{\partial \mathrm{H}_{12,t}}{\partial \varepsilon_{2,t-1}} = a_{11}a_{22}\varepsilon_{1t-1} + \lambda_{11}\lambda_{22}\varepsilon_{1t-1}$$

$$\frac{\partial \mathrm{H}_{13,t}}{\partial \varepsilon_{1,t-1}} = a_{33}a_{11}\varepsilon_{3t-1} + \lambda_{11}\lambda_{22}\varepsilon_{3t-1} \;\text{ or, }\; \frac{\partial \mathrm{H}_{13,t}}{\partial \varepsilon_{3,t-1}} = a_{33}a_{11}\varepsilon_{1t-1} + \lambda_{11}\lambda_{22}\varepsilon_{1-1}$$

$$\frac{\partial \mathrm{H}_{23,t}}{\partial \varepsilon_{2,t-1}} = a_{33}a_{22}\varepsilon_{3t-1} + \lambda_{11}\lambda_{22}\varepsilon_{3t-1} \text{ or } \frac{\partial \mathrm{H}_{23,t}}{\partial \varepsilon_{3,t-1}} = a_{33}a_{22}\varepsilon_{2t-1} + \lambda_{11}\lambda_{22}\varepsilon_{2t-1}$$

The co-volatility spillovers are evaluated at the average return shocks. For a simple multivariate DBEKK-GARCH volatility specification, 'pure' co-volatility spillover tests are of interest. Thus, I develop a Wald-type test of co-volatility spillover:

1. $\mathrm{H}_0:\ a_{11}a_{22} = 0$

If the null hypothesis is rejected then there is volatility spillover from the return shock of stock (bond) to the co-volatility between stock and bond return:

2. $\mathrm{H}_0:\ a_{11}a_{33} = 0$

If the null hypothesis is rejected then there is volatility spillover from the return shock of stock (T-bill) to the co-volatility between stock and T-bill:

3. $\mathrm{H}_0:\ a_{22}a_{33} = 0$

If the null hypothesis is rejected, then there is spillover from the return shock of bond (T-bill) to the co-volatility between bond and T-bill.

The above definitional theory of co-volatility is extended to the multivariate DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M models. In the absence of normality, the DBEKK-GARCH type model is estimated by the QML method. The QMLEs are consistent and asymptotically normally distributed. Asymptotic normality means that in general, I can test H_0 consistently using classical statistical test approaches.

4.3.3.2 *Wald-type test*

I perform the Wald-type test for the existence of co-volatility spillover of return shocks. I test the null hypothesis against the alternative in a multivariate DBEKK-GARCH model in which $\mathrm{H}_0: g(a_{ii}, a_{jj}) = a_{ii} \times a_{jj} = 0$ and $\mathrm{H}_1: g(a_{ii}, a_{jj}) = a_{ii} \times a_{jj} \neq 0$. I estimate $\widehat{g}(a_{ii}, a_{jj}) = \widehat{a}_{ii} \times \widehat{a}_{jj}$ by the QMLE. Let $H_0: g(a_{11}, a_{22}) = a_{11} \times a_{22} = 0$ (a case of single nonlinear combination of parameters) be a regular function of parameters. Then, the variance of $g(a_{11} \times a_{22})$ can be computed using the delta method as follows:

$$\operatorname{var} g(\hat{a}_{11}, \hat{a}_{22}) =$$

$$\left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{11}}\right]^2 \operatorname{var}(a_{11}) + \left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{22}}\right]^2 \operatorname{var}(a_{22}) + 2\left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{11}}\right]\left[\frac{\partial g(a_{11}, a_{22})}{\partial a_{22}}\right]\operatorname{cov}(a_{11}, a_{22}) \tag{4.13}$$

$$= \left[\hat{a}_{22}\right]^2 \widehat{\operatorname{var}}(\hat{a}_{11}) + \left[\hat{a}_{11}\right]^2 \widehat{\operatorname{var}}(\hat{a}_{22}) + 2\hat{a}_{11} \times \hat{a}_{22} \operatorname{cov}(\hat{a}_{11}, \hat{a}_{22}) .$$

The derivatives are evaluated at the solution points and similarly computed for all other pairwise cases. In general, when $g(\theta)$ is a vector of nonlinear functions of parameters, when testing for $H_0 : g(\theta) = 0$ versus $H_1 : g(\theta) \neq 0$, the Wald test statistic takes the following form in matrix notations:

$$\mathrm{W} = [g(\hat{\theta})]'[\widehat{\operatorname{cov}}(g(\hat{\theta}))]^{-1}[g(\hat{\theta})] \tag{4.14}$$

where $g(\theta)$ is a nonlinear function of unknown parameter vector θ; ‘ ' ’ is transposed notation; $\hat{\theta}$ is a QMLE-estimated parameter vector under the alternative hypothesis; and $\widehat{\operatorname{cov}}(.)$ is the estimated variance–covariance matrix evaluated under the alternative hypothesis. The QML method is used to estimate the objective function. The test statistic, W, follows an asymptotic χ^2 distribution with k (number of restrictions under the null hypothesis) degrees of freedom. In Chapter 6, I apply the QML method of estimation for Equation (4.10) and (4.11) parameters jointly for computing return spillover effects in the Granger sense and the asymmetric news effect in the Glosten et al. (1993) sense; and evaluate the short- and long-run effects of return shocks on volatility. Conditional return volatility models are popular in the field of finance because they have data-relevant statistical properties: for example, heavy tails, volatility clustering, limit cycle and sudden jumps. Thus, I employ conditional volatility models for computations in relation to various issues related to policy decision objectives.

I categorise financial markets as (i) developed, (ii) advanced emerging and (iii) emerging markets (following the FTSE 100 Index) for estimation and empirical analysis of multivariate VAR-DBEKK-GJR-GARCH models (4.10) and (4.11) jointly. I then estimate an extended form of Engle et al.'s (1987) univariate risk premium model for the multivariate VAR-DBEKK-GJR-GARCH-M framework. Further, I extend Sims's VAR to VAR-X and PVAR-X to take account of exogenous variables (X) (financial crash events), and finally utilise nonparametric dependence using Kendall's tau, Spearman rank correlations, and Gumbel copula with Student-t margins to explore the financial asset return dependence.

4.3.4 VAR and PVAR models

In the multivariate formulation, I consider more than one asset and treat them as a vector of variables. The vector $r_t = (r_{1t}, r_{2t}, \ldots\ldots.., r_{Nt})'$ is an $(N \times 1)$ vector of financial asset returns. The VAR model of Sims (1980) treats all variables as endogenous and interdependent. To formulate a VAR, let r_t be an $(N \times 1)$ vector of endogenous variables say asset returns. Then the VAR for r_t takes the following form:

$$r_t = A_0 + \sum_{l=1}^{p} A(l) r_{t-l} + u_t \tag{4.15}$$

where $E(u_{it}) = 0$, $E(u_{it}u_{it}^{'}) = \Sigma_u$ and $E(u_{it}u_{is}^{'}) = 0$ for all $t > s$; $A(l)$ is the matrix of parameters at lag l; u_t is an $(N \times 1)$ vector of errors; Σ_u is the variance–covariance matrix of the error vector u_t; and A_0 is an $(N \times 1)$ vector of intercept parameters. Only the time dimension is considered in this formulation. Under the assumption of linearity, stationarity and invertibility, the Wold (1938) decomposition theorem provides an MA representation of the VAR process. In this form it is useful to analyse the IRF and forecast error variance decomposition of the time series of returns. The IRF visually represents the behaviour of the $\{r_{it}\}$ in response to various shocks. The forecast error variance decomposition tells us the proportion of movements in a sequence due to its 'own' shocks rather than shocks due to other factors. The estimation can be based on the ML method under the iid normal or QML method. The QMLEs and MLEs are consistent and asymptotically normally distributed. Order selection for VAR is conducted using the multivariate AIC, BIC, and HQ and lilelohood ration (LR) criteria. Model adequacy tests are conducted for further statistical inference and policy decision purposes. When a cross-sectional dimension is added to the VAR representation (4.15), the resulting model is known as a PVAR model, which takes the following form:

$$r_{it} = \sum_{l=1}^{p} A_i(l) r_{it-l} + u_i + \varepsilon_{it} \tag{4.16}$$

where the index i could indicate countries, sectors, markets and so on, and t is the time index. The variable r_{it} is an $(N \times 1)$ vector of dependent variables; u_i and ε_{it} are $(N \times 1)$ vectors of dependent variable-specific panel fixed effects and idiosyncratic errors, respectively. The $\varepsilon_{it} = (\varepsilon_{1t}, \varepsilon_{2t}, \ldots\ldots, \varepsilon_{Nt})'$ is such that $E(\varepsilon_{it}) = 0, E\varepsilon_{it}\varepsilon_{it}^{'} = \Sigma$ and $E(\varepsilon_{it}\varepsilon_{is}^{'}) = 0$ for all $t > s$. Further extension of Equation (4.16) would be useful to include other exogenous variables; for example, dummy variables capturing specific events, which may take the following form:

$$r_{it} = \sum_{l=1}^{p} A_i(l) r_{it-l} + \Pi_i X_t + u_i + \varepsilon_{it} \tag{4.17}$$

where r_{it} is a vector of N variables for each unit $i = 1, 2, \ldots., N$; Π_i are $N \times K$ matrices and X_t is a $K \times 1$ vector of exogenous variables common to all unit i. In this form Equation (4.17) is known as a PVAR-X model. In both Equations (4.16) and (4.17), the ε_{it} values are generally correlated across i (situation of static dependence), and the ε_{it} values are correlated with lags of all endogenous variables entering the model for unit i (situation of dynamic interdependence). Equation (4.17) could be useful for testing the existence of international CAPM within a system equations (seemingly unrelated regression [SUR]) framework. Equation (4.17) is useful for investigating contemporaneous dependence among financial returns.

I further utilise the nonparametric Kendall's tau and Spearman rank correlation for dependence analysis among the asset returns and perform a covariance dependence test to examine the contemporaneous dependence between the covariances among the asset returns jointly. I also conduct dependence in volatility tests utilising the Gumbel copula with Student-t margins.

4.4 Data

This study utilises data from 17 countries from America (North and South), Europe, and Asia Pacific financial centres. The selection process for countries is based on the FTSE Global Equity Index Series report. The data series from three financial markets, namely stock, bond and money markets are collected for the period 30 January 1985–30 December 2016 from the Bloomberg database. From the stock market I use stock index; from the bond market I use the 5-year bond rate; and from the money market I use the 3-month T-bill rate. The continuously compounded returns of each of the financial securities are used for this study. I chose to use returns instead of prices of assets because (i) the return of an asset is a complete and scale-free summary of the investment opportunity; and (ii) a return series is easier to handle than a price series because of its attractive statistical properties. Table 4.1 shows the selected countries, chosen on the basis of data availability.

Table 4.1: Selected countries for data collection

Developed	Advanced emerging	Emerging
US	Brazil	China
Japan	Mexico	India
UK	Malaysia	Indonesia
Germany		Thailand
France		
Canada		
South Korea		
Australia		
HK		
Singapore		
10	3	4

4.5 Methodology

The research questions for this thesis posed in Section 1.3 are addressed here as follows.

RQ1. Do volatilities of returns spillover symmetrically?

RQ1 is addressed by jointly estimating the conditional returns and conditional volatilities of returns in the multivariate context. I allow the multivariate conditional DBEKK volatility of the VAR model to include the conditional asymmetric volatilities, constituting a multivariate DBEKK-GJR-GARCH model. This model is suitable for revealing the asymmetric volatility spillover effects and causality tests. The model is estimated by the QML method of estimation for the data from the developed, advanced emerging and emerging market stock returns. The QMLEs are consistent and asymptotically normally distributed. These statistical properties are useful for developing valid statistical tests. The estimated model is used to test for model adequacy and causality in the vector of returns series, via t and F tests. The partial co-volatility spillovers tests are conducted using Wald tests. This adds a novel methodological development to the literature.

RQ2. Do risk premiums hold in international financial markets?

RQ2 is important to address because a vast number of researchers are involved in CAPM modelling of univariate financial returns on securities. The complexity of the traditional CAPM arises when I use a variant of the CAPM that allows a time-varying risk premium in the return generating process. This risk premium is governed by the DBEKK-GJR-GARCH-M model. The model is estimated by the QMLE and used to test for the presence of risk premiums in multimarket asset utilising student-t tests and Wald chi-square tests. This is a novel empirical addition to the literature.

RQ3. Does the severity of crisis affect asset markets globally?

RQ3 is addressed by investigating financial returns utilising VAR-X and PVAR-X models. However, before estimating and testing for VAR, it is useful to present basic descriptive statistics for the data and some preliminary tests on the time series of interest. The unit roots for the data series are tested for stationarity by applying the ADF, PP and KPSS tests. For PVAR models the corresponding panel unit root tests applied are (i) the Im, Pesaran and Shin (IPS) (2003) test; (ii) the Maddala and Wu (1999) Fisher-type test; and the Hadri (2000) Lagrange multiplier (LM) test. These are tests of the null hypothesis of panel unit root (i.e. panel nonstationarity) against the alternative of no panel unit root (i.e. panel stationarity). The only exception is the KPSS and Hadri LM tests which consider stationarity as the null versus nonstationarity as the alternative. The panel unit root tests are based on the ADF model; however the constructions of the tests are different. The return series are found to provide overwhelming support for stationarity using these unit root tests.

I analyse the return series using VAR-X and PVAR-X models. The estimated VAR-X and PVAR-X models are investigated for Granger causality, variance decomposition and impulse responses, as applied to VAR-type models. One important property of VAR and PVAR is that they only deal with short-run dynamic dependence of return series. Further, VAR allows for aggregation of spillover effects across markets; thus I apply statistical tests for market crashes based on the estimated VAR-X and PVAR-X to determine whether financial markets crash jointly across countries during crisis.

The VAR-X model is estimated using the ML method under the assumptions of normality, or by OLS estimation. The PVAR-X model is estimated using GMM estimation. The VAR-X model includes event-specific dummy variables indicating crisis periods. Three financial crashes the 1987 crash, AFC, and the GFC are considered to address this research question. However, for the PVAR-X model I examined only the GFC effect on the asset markets for a block of five countries jointly. The estimated model is tested for model adequacy using various tests including LB and ARCH tests. Model evaluation is based on Granger causality, variance decomposition and impulse response analysis. The return spillovers in the Granger sense are tested using Wald F tests. Further, I employ impulse responses or forecast error variance decomposition on the VAR-X model to identify interdependence among the securities across markets. In particular, variance decomposition provides information about the proportion of movements in a sequence that is due to its own shocks versus shocks to the other variables. Variance decomposition also determines the exogeneity status of variables under shocks. This research question addresses how many financial markets are in danger during crises, by utilising the SI. This makes an additional methodological contribution to the literature.

RQ4. Are financial returns dependent across countries?

RQ4 is important to address to understand how many financial markets are closely dependent on each other for asset management policy analysis purposes. This question is addressed by nonparametric test approaches employing Kendall's tau and Spearman rank correlation tests. These approaches can capture both linear and nonlinear dependencies between asset returns. I also perform covariance dependence tests utilising χ^2 test statistics. Tests for pairwise bi-variate GARCH-type volatility dependence are conducted by the Gumbel copula with Student-t margins. Application of this methodology is a novel addition to empirical dependence analysis in the finance literature.

The empirical analyses employing the proposed methodologies outlined in this chapter are described in Chapter 5 for univariate and Chapter 6 for multivariate cases.

4.6 Conclusion

This chapter discusses the methodologies used for empirical analyses of the research questions and the sources of data. I have discussed the full volatility spillover, full co-volatility spillover and partial co-volatility spillovers. I have also introduced a novel Wald-type test approach to test for partial co-volatility within DBEKK model demonstrated using three variables cases. Furthermore, in this chapter I have introduced the VAR, PVAR and PVAR-X models. The Granger causality, variance decomposition and impulse responses functions are the tools used for empirical analyses of the multivariate return volatility models. The DBEKK and DBEKK-GJR-GARCH-M models are estimated by the QMLE and the PVAR models are estimated by the GMM estimation. Nonparametric approaches to test for dependence among assets are also utilized in this thesis for empirical analysis.

For empirical analysis, seventeen countries' data have taken from Bloomberg database. The countries are classified as developed, advanced and emerging countries based on the FTSE Global Equity Index series report. The return series are constructed using logarithmic differenced series. This chapter links the methodology to the specific research questions of this thesis. The empirical results of the univariate and multivariate volatility models are provided in the next two chapters.

Chapter 5: Empirical Analysis of Univariate Asset Return and Volatility of Return

5.1 Introduction

In this chapter I present an empirical analysis of 17 global share markets' stock returns individually for three classes of volatility models: (i) the SGARCH, (ii) GJR-GARCH and (iii) the GARCH-M model of risk. These conditional volatility models have been found to be useful in real applications, with some reservations. Differences in the predictions from the normal GARCH, Student-t GARCH and skewed Student-t GARCH are investigated, as is the risk-averse behaviour of investors by GARCH-M, for each of the 17 countries individually.

This chapter also provides basic summary statistics and diagnostic tests for checking the data properties and evaluating each market's stylised facts in financial return series. To achieve a basic understanding of the markets I first analyse only the financial stock markets of all 17 countries. The stock, bond and money markets are jointly analysed in Chapter 6 using multivariate DBEKK-GJR-GARCH, DBEKK-GJR-GARCH-M, VAR-X and PVAR-X approaches to evaluate linkages.

5.2 Univariate Volatility Models

In finance, risk is measured as the standard deviation in financial asset returns. Since the volatility of returns is unknown, three measures of volatility are proposed in the literature: (i) realised volatility, (ii) implied volatility and (iii) conditional volatility. In the previous chapter I defined the theoretical basis of these definitions. In relation to these definitions a vast literature discusses the analysis of conditional volatility of the return generating process. In this chapter I take the opportunity to explore the conditional volatility definition. Since the volatility generating function is unknown, I consider important issues of conditional volatility to investigate the sources of volatility in different financial markets. Specifically I investigate 17 countries' stock returns empirically to determine suitability of the various functional forms of the unknown return volatility function for measuring and predicting the risk of holding and trading assets in financial markets. The models are estimated by the ML method under the assumption of (i) conditional normality, (ii) Student-t and (iii) skewed Student-t innovation distribution of the return generating process. In the absence of normality, however, the QML method was found to have asymptotic properties for statistical estimation and inference.

5.2.1 Descriptive statistics and data properties

In this section, I provide basic statistics for the stock return series of the 17 countries. Stationarity tests on the return series were conducted utilising ADF, PP, KPSS tests. I also performed LB-Q tests on the level series and the squared level series to examine serial correlation and presence of volatility. The Jarque–Bera (JB) test was conducted for the normality of series to evaluate stylised facts such as skewness, heavy tails, sudden jumps and volatility clustering of financial time series. Time plots of the stock returns of 17 countries are provided in appendix A. These properties provide vital information for modelling and predicting the first two moments jointly for policy decision analysis. The following tables describe the data properties as mentioned.

The sample size differs among countries depending on the availability of data. The basic statistics in Table 5.1 provide useful numerical information about the properties of the data. Means of the stock return series are mostly significant at the conventional level, with the exception of those for France, Japan and Thailand. Ten returns series are positively skewed and seven are negatively skewed. Fourteen out of the 17 stock returns series depart significantly from symmetry. The excess (with reference to normality) kurtosis of all the return series is significantly leptokurtic. The stock returns series were found to be non-normal by the JB test. These properties of stock returns are consistent with stylised facts for financial returns series such as volatility clustering, asymmetry and heavy tails. All of the series are serially correlated according to the LB-Q test, and LB-Q^2 tests confirmed significant dependence in the second moment of all series except for China. I further conducted stationarity tests on the return series using the ADF, PP and KPSS tests. The stationarity of the stock return series was confirmed by all three tests with the exception of Brazil, the stock returns are stationary according to both the ADF and PP test but not the KPSS test (see Table 5.2).

Table 5.1: Descriptive statistics and preliminary test results for global stock returns

Country	Sample start date	Sample size	Mean	SD	Min	Max	Skewness	Excess Kurtosis	LB-Q (10)	LB-Q^2 (10)	JB
Australia	1/1/1985	8099	0.030***	0.942	–24.995	6.257	–2.771***	66.908***	92.617***	415.870***	1520858.536***
Brazil	21/8/1991	6273	0.238***	2.745	–32.609	41.199	1.240***	29.511***	144.338***	2591.029***	229167.448***
Canada	2/1/1985	8051	0.031***	1.066	–12.401	18.821	–0.094***	23.618***	42.158***	4637.635***	187106.579***
China	19/2/1990	6367	0.089***	2.774	–27.170	104.173	9.379***	327.764***	40.345***	10.145	28588936.467***
France	9/7/1987	7465	0.026	1.458	–12.473	10.592	–0.285***	5.554***	60.260***	3031.535***	9695.170***
Germany	2/1/1985	8079	0.042***	1.393	–9.860	10.623	–0.248***	5.136***	35.765***	4079.805***	8960.492***
HK	2/1/1985	7907	0.050***	1.637	–33.330	14.817	–1.400***	31.827***	54.779***	656.004***	336269.318***
India	2/1/1985	7530	0.077***	1.816	–11.302	13.507	0.018	4.661***	28.757***	3450.920***	6821.741***
Indonesia	2/1/1985	7762	0.069***	1.637	–20.172	49.645	4.491***	132.139***	420.625***	1105.092***	5672508.229***
Japan	4/1/1985	7870	0.016	1.370	–14.871	13.234	0.009	6.882***	49.103***	2330.126***	15532.797***
Malaysia	2/1/1985	7878	0.031**	1.366	–22.121	21.519	0.309***	36.313***	119.065***	5923.750***	432912.147***
Mexico	19/1/1994	5734	0.062***	1.498	–13.139	13.471	0.270***	7.405***	68.962***	1269.338***	13169.723***
Singapore	10/6/1987	7270	0.038*	1.722	–11.029	14.248	0.076***	4.370***	33.488***	3027.127***	5790.736***
SK	2/7/1987	7236	0.037*	1.666	–15.961	13.543	0.008	7.343***	89.392***	1603.183***	16228.928***
Thailand	31/8/1999	4554	0.014	1.264	–13.135	15.944	0.156***	14.041***	46.471***	2447.937***	34954.806***
UK	1/4/1986	7774	0.025*	1.149	–13.797	10.956	–0.253***	9.263***	72.307***	2648.561***	27871.081***
US	2/1/1985	8068	0.041***	1.081	–13.420	10.949	–0.294***	11.535***	40.894***	3701.731***	44843.084***

Note 1. Returns are in percentages.
Note 2. '***', '**', '*' indicate significance at the 1%, 5% and 10% levels respectively.
Note 3. 'LB-Q(*m*) 'and, 'LB-Q2 (*m*)' are the *m*-th lag Ljung–Box test statistics applied to the original and squared series.
Note 4. JB is the 1987 Jarque-Bera chi-square test with 2 degrees of freedom for normality tests of the original series.
Note 5. The data end date for all series is 30/12/2016, except for Brazil, which has a data end date of 29/12/2016.

Table 5.2: Stationarity test for the stock returns series

Country	Size	ADF	PP	KPSS
Australia	8099	–36.057**	–83.390**	0.173
Brazil	6273	–33.379**	–80.572**	5.833**
Canada	8051	–37.969**	–92.323**	0.053
China	6367	–31.566**	–81.758**	0.303
France	7765	–37.688*	–93.107**	0.081
Germany	8079	–38.599**	–88.627**	0.068
HK	7907	–36.497**	–85.763**	0.229
India	7530	–36.608**	–87.581**	0.202
Indonesia	7762	–37.056**	–74.186**	0.828
Japan	7870	–37.765**	–84.764**	0.140
Malaysia	7878	–35.541**	–81.346**	0.059
Mexico	5734	–31.314**	–68.607**	0.081
Singapore	7270	–36.547**	–82.042**	0.052
SK	7236	–34.538**	–78.547**	0.124
Thailand	4554	–27.687**	–68.150**	0.081
UK	7774	–38.690**	–91.199**	0.096
US	8068	–37.945**	–92.642**	0.210

Note 1. KPSS tests the null hypothesis of stationarity *versus* the alternative hypothesis of nonstationarity.
Note 2. '**', '*' indicate significance at the 1%, and 5% levels respectively.
Note 3. 5 lags used for the tests.

I also evaluated the basic statistical properties of the bond return series, as provided in Table 5.3. The mean of bond returns is significantly different from zero for all cases. The skewness of the Japan series is not significant, and non-significant excess kurtosis was encountered in the Brazil, France, India and Indonesia bond returns. Serial correlation up to lag 10 exists in each of the series. All of the bond return series were found to be fat-tailed as indicated by the LB-Q^2 statistic and excess kurtosis. Each of the series is non-normal according to the JB test. I further tested stationarity of the bond returns using ADF, PP and KPSS tests. Table 5.4 displays these test results.

Table 5.3: Descriptive statistics and preliminary tests results for global bond returns

Country	Sample start date	Sample size	Mean	SD	Min	Max	Skewness	Excess kurtosis	LB-Q (10)	LB-Q^2(10)	JB
Australia	2/01/1985	7727	6.6328***	3.310	1.467	15.600	0.9291***	0.1189**	77104.764***	77036.973***	1116.2302***
Brazil	5/01/2007	1684	12.090***	2.011	8.444	19.004	0.4341***	0.1093	16282.178***	16141.604***	53.7465***
China	8/6/2005	2575	3.1637***	0.577	1.780	4.5700	0.3353***	–0.7886***	25048.601***	25081.300***	114.9739***
France	6/08/1990	6799	3.9517***	2.493	–0.456	10.570	0.4888***	–0.08201	67902.062***	67869.642***	272.7114***
Germany	7/08/1990	6789	3.6646***	2.369	–0.623	9.1370	0.2210***	–0.3464***	67814.551***	67788.944***	89.2204***
HK	11/06/2012	1127	97.459***	3.593	89.059	104.535	–0.1457**	–0.9000***	10810.107***	10812.139***	42.0198***
India	24/05/2001	3560	7.3755***	1.055	4.582	9.734	–0.7358***	0.0624	34904.671***	34813.004***	321.8518***
Indonesia	6/01/2003	3361	8.9079***	2.472	4.475	20.058	0.4934***	–0.0540	32940.54***	32292.317***	136.7827***
Japan	4/04/1988	7067	1.7672***	2.004	–0.370	8.4900	1.4325	0.9816***	70597.767***	70521.055***	2700.8762***
Malaysia	3/08/1998	4526	3.8422***	0.821	2.444	9.9430	2.4957***	7.9084***	43123.898***	42100.800***	16493.2179***
Mexico	22/03/2011	1495	5.2254***	0.525	3.943	7.2520	0.9000***	1.8528***	13858.084***	13899.938***	415.6778***
Singapore	2/01/1988	4762	2.1559***	1.091	0.305	5.2600	0.2252***	–0.8884***	47125.547***	46872.483***	196.8595***
US	2/01/1985	8271	4.7844***	2.557	0.543	11.706	0.1333***	–0.9224***	82487.856***	82353.031***	317.7055***

Note 1. Returns are in percentages.
Note 2. '***', '**', '*' indicate significance at the 1%, 5% and 10% levels respectively.
Note 3. 'LB-Q(*m*) 'and, 'LB-Q2 (*m*)' are the *m*-th lag Ljung–Box test statistics applied to the original and squared series.
Note 4. JB is the 1987 Jarque-Bera chi-square test with 2 degrees of freedom for normality tests of the original series.
Note 5. The data end date for all series is 30/12/2016, except for Brazil, which has a data end date of 29/12/2016.

Table 5.4: Stationarity test for the bond returns series

Country	Size	ADF	PP	KPSS
Australia	7727	–37.396**	–92.186**	0.347
Brazil	1684	–17.913**	–40.552	0.122
Canada	62	–2.886(.)	–7.104**	0.106
China	2575	–18.002**	–51.259**	0.070
France	6799	–37.750**	–92.633**	0.064
Germany	6789	–38.994**	–108.688**	0.025
HK	1127	–13.471**	–32.318**	0.110
India	3560	–25.282**	–62.728**	0.173
Indonesia	3361	–22.749**	–52.418**	0.120
Japan	7068	–36.753**	–111.272**	0.060
Malaysia	4526	–31.655**	–102.184*	0.196
Mexico	1495	–15.681**	–30.296**	0.439
Singapore	4762	–28.892**	–61.408**	0.900
Thailand	118	–5.152**	–8.993**	0.036
UK	112	–13.427**	–32.318**	0.110
US	8271	–38.482**	–96.664**	0.036

Note 1. KPSS tests the null hypothesis of stationarity *versus* the alternative hypothesis of nonstationarity.
Note 2. '**', '*' indicate significance at the 1%, and 5% levels respectively.
Note 3. 5 lags used for the tests

Based on the stationarity test results for the bond returns series, shown in Table 5.4, all series are stationary. However, in some cases, such as Thailand, Canada and UK, the reliability of the test is questionable because of the small sample size; in these cases, robust conclusions cannot be drawn. In general, I conclude that bond returns series are stationary but suffer from serial correlation and non-normality. These observations and tests indicate that appropriate modelling for bond returns volatility should consider these issues to ensure a good volatility prediction model for financial asset pricing. Finally, I considered the money market activities in the financial market. The results are based on the 3-month T-bill returns for 15 countries as shown in Table 5.5.

The mean returns for the short-term T-bill are significant in some cases and not significant in others. This may be due to volatility and tranquillity in financial markets. However, all of the series have significant skewness. There is significant serial correlation in the series, except those of Japan and Thailand. Excess kurtosis indicates return distributions are heavy-tailed. Further, each of the series wasfound to be dependent by the LB-Q^2 test, with the exception of Thailand and Canada. All series are significantly non-normal according to the JB test. I also tested each of the T-bill series for stationarity by the ADF, PP and KPSS tests. The test results are displayed in Table 5.6.

Table 5.5: Descriptive statistics and preliminary tests results for global T-bill returns

Country	Sample start date	Sample size	Mean	SD	Min	Max	Skewness	Excess Kurtosis	LB-Q(10)	LB-Q_2(10)	JB
Australia	1/10/1996	5220	–0.022*	0.847	–10.089	12.970	–0.640***	26.798***	26.830***	164.946***	156517.569***
Brazil	28/3/2007	2282	0.006	0.922	–13.621	9.279	–1.793***	56.220***	161.950***	109.926***	301618.343***
Canada	25/8/2016	92	0.002**	0.008	–0.016	0.029	0.682***	2.283***	18.935**	2.434	26.548***
China	20/12/2005	2531	0.175	5.690	–50.495	81.166	1.994***	30.787***	488.234***	461.645***	101593.815***
France	15/6/1989	6872	–0.016	22.237	–405.000	993.023	20.221***	915.668***	312.329***	76.030***	237393347.41***
India	11/5/2000	3947	0.010	1.848	–23.522	42.151	4.545***	121.238***	41.760***	91.807***	2430303.776***
Indonesia	31/3/2003	270	–0.128	3.894	–13.554	47.592	7.068***	88.630***	236.105***	40.314***	90284.703***
Japan	5/10/1995	4343	8.807	486.453	–1.15e+03	3.18e+04	64.501***	4215.776***	5.465	1.789e–03	3210247083.588***
Malaysia	10/12/1996	3164	0.049	3.918	–58.333	76.923	4.673***	130.973***	519.467***	408.553***	2272264.345***
Mexico	19/11/1999	4122	–0.008	1.974	–17.422	25.647	0.649***	20.204***	198.374***	471.773***	70379.009***
Singapore	2/1/1998	4645	0.127*	5.097	–58.333	80.952	2.306***	47.775	155.480***	1240.925***	445777.890***
SK	28/5/1999	2825	0.764***	15.561	–87.507	260.441	9.720***	136.104***	278.410***	82.506***	2224158.194***
Thailand	13/1/2012	1171	0.059*	1.163	–11.730	9.016	–1.414***	20.346***	6.696	14.277	20569.644***
UK	7/10/2008	2077	–0.107*	2.582	–24.973	42.960	1.440***	54.231***	60.600***	187.788***	255114.732***
US	2/1/1985	8268	0.841**	35.655	–700.000	1166.667	9.021***	335.618***	121.088***	57.437***	38902356.569***

Note 1. Returns are in percentages.
Note 2. '***', '**', '*' indicate significance at the 1%, 5% and 10% levels respectively.
Note 3. 'LB-Q(m) 'and, 'LB-Q2 (m)' are the m-th lag Ljung–Box test statistics applied to the original and squared series.
Note 4. JB is the 1987 Jarque-Bera chi-square test with 2 degrees of freedom for normality tests of the original series.
Note 5. The data end date for all series is 30/12/2016, except for Brazil, which has a data end date of 29/12/2016.

Table 5.6: Stationarity test for the T-bill returns series

Country	Size	ADF	PP	KPSS
Australia	5220	–28.114**	–75.221**	0.372
Brazil	2282	–18.785**	–60.729**	0.501*
Canada	91	–5.152**	–8.871**	0.055
China	2531	–26.129**	–97.395**	0.064
France	6872	–33.181**	–112.751**	0.047
India	3947	–26.758**	–66.679**	0.088
Indonesia	270	–5.995**	–30.708**	0.031
Malaysia	3164	–25.580**	–89.188**	0.129
Mexico	4122	–25.376**	–77.295**	0.294
Singapore	4646	–29.409**	–63.370**	0.055
Thailand	1171	–13.376**	–35.517**	0.107
UK	2077	–17.875**	–49.476**	1.029**
US	8268	–48.813**	–114.885**	0.017

Note 1. KPSS tests the null hypothesis of stationarity *versus* the alternative hypothesis of nonstationarity.
Note 2. '**', '*' indicate significance at the 1%, and 5% levels respectively.
Note 3. 5 lags used for the tests

From Tables 5.1-5.6 it is clear that the stock, bond and T-bill returns of most of the countries are stationary but serially dependent. The JB tests revealed that the return series are non-normal. Similar properties of financial series are reported in the literature. To develop good volatility models these properties of financial returns series must be considered. In the following section, I provide univariate volatility model fitting for the stock returns series of 17 countries.

5.2.2 Univariate conditional mean and conditional variance in stock returns

In this section, I evaluate the three most popular models of volatility for the 17 global stock returns. The estimated univariate volatility models are reported in the following tables.

5.2.2.1 *Univariate ARMA-GARCH model*

The univariate ARMA-GARCH model estimated by the normal log-likelihood method is reported below. The standard ARMA (1,1)-GARCH(1,1) is as follows:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \psi_1 \varepsilon_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid h_{t-1} = \sqrt{h_t}\, z_t$$

In $h_t \mid F_{t-1} = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$, F_{t-1} is the set of information available at time $t-1$.

Table 5.7: Univariate ARMA(1,1)-GARCH(1,1) model estimation and model adequacy tests

Parameter	Australia	Brazil	Canada	China	France	Germany	HK	India
ϕ_0	0.080***	0.116**	0.051***	$0.008^{(.)}$	0.047**	0.078**	0.071***	0.097**
	(5.553)	(2.840)	(4.528)	(1.766)	(2.824)	(2.723)	(4.126)	(3.270)
ϕ_1	–0.306*	–0.038	–0.012	0.738***	0.087	–0.025	0.117	–0.210
	(–2.136)	(–0.126)	(–0.088)	(20.608)	(0.354)	(–0.074)	(0.822)	(–0.732)
ψ_1	0.410**	0.069	0.096	–0.752***	–0.139	0.049	–0.031	0.246
	(2.983)	(0.229)	(0.698)	(–22.211)	(–0.571)	(0.146)	(–0.214)	(0.862)
ω	0.034***	0.056***	0.012***	0.047***	0.045***	0.027***	0.057***	0.044***
	(7.761)	(5.757)	(6.870)	(7.260)	(7.693)	(7.532)	(8.406)	103.118
α_1	0.171***	0.097***	0.093***	0.169***	0.107***	0.091***	0.117***	0.116***
	(15.866)	(12.725)	(13.749)	(15.064)	(13.789)	(14.041)	(15.494)	(14.229)
β_1	0.799***	0.894	0.897***	0.852***	0.872***	0.895***	0.862***	0.873***
	(60.996)	(114.033)	(125.179)	(101.932)	(97.147	(124.675)	(102.919)	(103.118)
LL	–9772.842	–13340.96	–10084.28	–12979.62	–12357.2	–12859.97	–13602.61	–13915.99
AIC	2.415	4.256	2.506	4.079	3.312	3.185	3.442	3.696
BIC	2.420	4.262	2.512	4.086	3.318	3.190	3.447	3.702
HQ	2.416	4.258	2.508	4.081	3.314	3.187	3.444	3.698
LB-Q(10)	22.727	30.773	11.009	91.764	7.435	16.895	22.099	24.163
χ^2 test	[0.012]	[0.0006]	[0.356]	[2.442×10^{-15}]	[0.683]	[0.076]	[0.014]	[0.007]
LB-Q^2(10)	8.217	20.036	10.350	2.398	9.769	8.235	209.514	25.428
χ^2 test	[.607]	[0.028]	[0.410]	[0.992]	[0.461]	[0.605]	[0]	[0.004]
ARCH(10)	8.424	22.464	11.563	3.111	12.422	9.537	218.471	26.127
LM test	[0.751]	[0.032]	[0.481]	[0.994]	[0.412]	[0.656]	[0]	[0.010]
JB-(2)	27906.91	454.129	7038.756	148968.4	1788.207	4627.85	9538.851	446.2351
χ^2 test	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]
Mean prediction Step 1	0.031	0.166	0.065	0.042	0.044	0.082	0.165	0.077
Step2	0.070	0.110	0.050	0.039	0.051	0.076	0.091	0.081
Step5	0.061	0.112	0.050	0.035	0.052	0.076	0.081	0.080
Volatility prediction Step 1	0.658	1.493	0.581	0.956	0.757	0.773	1.006	0.964
Step 2	0.674	1.505	0.588	0.992	0.779	0.786	1.024	0.982
Step 5	0.719	1.542	0.610	1.094	0.839	0.821	1.075	1.033

Parameter	Indonesia	Japan	Malaysia	Mexico	Singapore	South Korea	Thailand	UK	US
ϕ_0	0.008	0.063***	0.021**	0.085***	0.039(.)	0.043***	0.009	0.003**	0.013*
	(0.856)	(3.579)	(2.763)	(4.475)	(1.787)	(3.813)	(1.400)	(2.744)	(2.0780
ϕ_1	0.209**	–0.055	0.269***	–0.090	–0.080	0.514***	0.665***	0.932***	0.773***
	(2.648)	(–0.260)	(3.906)	(–0.772)	(–0.185)	(5.568)	(3.859)	(42.382	(7.332)
ψ_1	–0.042	0.111	–0.114	0.195(.)	0.098	–0.429***	–0.639***	–0.950***	–0.791***
	(–0.517)	(0.526)	(–1.609)	(1.697)	(0.227)	(–4.395)	(–3.608)	(–50.119)	(–7.542)
ω	0.015***	0.035***	0.016***	0.019***	0.014***	0.064***	0.009***	0.020***	0.017***
	(9.359)	(6.697)	(6.785)	(5.024)	(5.028)	(7.563)	(3.813)	(6.530)	(7.436)
α_1	0.138***	0.127***	0.138***	0.097***	0.070***	0.166***	0.097***	0.100***	0.083***
	(19.318)	(14.439)	(13.367)	(11.312)	(11.825)	(15.096)	(11.656)	(13.897)	(13.503)
β_1	0.879***	0.862***	0.866***	0.897***	0.926***	0.823***	0.902***	0.885***	0.902***
	(179.196	(95.775)	(93.387)	(103.826)	(154.578)	(76.375)	(117.386)	(108.820)	(127.987)
LL	–12070.16	–12713.18	–10938.33	–9414.376	–12932.3	–12730.69	–6152.553	–10864.04	–10680.23
AIC	3.112	3.232	2.778	3.286	3.559	3.525	2.829	2.796	2.649
BIC	3.117	3.238	2.784	3.293	3.565	3.531	2.838	2.802	2.654
HQ	3.114	3.234	2.780	3.288	3.561	3.527	2.832	2.798	2.651
LB-Q(10)	53.518	13.455	19.008	13.553	17.284	24.919	12.518	14.382	14.587
χ^2 test	[5.965×10^{-8}]	[0.199]	[0.040]	[0.194]	[0.068]	[0.005]	[0.251]	[0.156]	[0.147]
LB-Q^2(10)	9.392	10.282	5.707	17.992	18.635	12.825	19.009	13.180	11.803
χ^2 test	[0.495]	[0.416]	[0.839]	[0.055]	[0.045]	[0.233]	[0.040]	[0.213]	[0.298]
ARCH(10)	10.063	11.752	6.2623	22.161	20.330	13.561	22.495	19.031	12.700
LM test	[0.610]	[0.466]	[0.902]	[0.035]	[0.061]	[0.329]	[0.032]	[0.087]	[0.391]
JB-(2)	241872.1	12045.53	118442.5	982.748	1281.081	7259.249	577.589	2236.109	6743.346
χ^2 test	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]
Mean prediction Step 1	0.343	–0.029	0.106	0.142	0.0362	0.175	0.037	0.012	0.070
Step 2	0.080	0.064	0.050	0.072	0.0364	0.134	0.034	0.014	0.067
Step 5	0.011	0.059	0.030	0.078	0.0364	0.095	0.029	0.021	0.064
Volatility prediction Step 1	1.289	0.960	0.517	0.863	0.673	0.778	0.596	0.629	0.567
Step 2	1.306	0.973	0.534	0.872	0.682	0.815	0.602	0.641	0.578
Step 5	1.358	1.012	0.581	0.898	0.709	0.914	0.622	0.674	0.607

Note 1. Value in parentheses ( ) is the Student-t test statistic.
Note 2. Value in [ ] is the significance level of the LB-Q, ARCH and JB tests.
Note 3. 'LB-Q(m)' and 'LB-Q^2(m)' are the m-th lag Ljung–Box test statistics applied to the original and squared standardised residuals.

Note 4. JB is the 1987 Jarque–Bera chi-square test with 2 degrees of freedom for normality of the original series.
Note 5. LL is the log-likelihood function evaluated at the maximum.
Note 6. ARCH(m) is the Engle (1982) LM test, which tests for the remaining ARCH effect.

The estimated ARCH/GARCH parameters namely $\hat{\alpha}_1$ and $\hat{\beta}_1$ are significant at the 1% level and have a positive sign for all returns series. Stability conditions ($\hat{\alpha}_1 > 0$, $\hat{\beta}_1 > 0$ and $\hat{\alpha}_1 + \hat{\beta}_1 < 1$) are satisfied by all series except those for China, Indonesia and Malaysia. The JB test results indicate that the residuals are non-normal. The model diagnostic LB-Q test identifies no serial correlation in the standardised residuals of the ARMA-GARCH models for Canada, France, Japan, Mexico, Thailand, UK and US at any conventional significance level. The LB-Q^2 tests show no significant serial correlation in the standardised squared residuals of the models for Australia, Canada, China, France, Germany, Indonesia, Japan, Malaysia, South Korea, UK or US at any conventional significance level. Thus, I conclude that the standard ARMA-GARCH model for US, UK, JAPAN, Canada and France adequately describes the return series individually at conventional significance levels. There is no remaining ARCH effect revealed by the LM test in the conditional volatility model, at least at the 2% level of significance except for India and HK. For other countries there are mixed responses on the issue of model adequacy. For example, in the case of Australia, the variance function is correctly specified and the LR test indicates no remaining ARCH effect in the model, while the mean function suffers from serial correlation in the standardised residuals at the 1% level of significance.

The prediction of the conditional volatility increases as the forecast horizon increases. This finding is consistent with properties of the prediction function of conditional volatility. For the model section, I employed the minimum AIC (or BIC or HQ), maximum log-likelihood and the $\min \sum_{t=1}^{T} \hat{h}_t$ criteria. However, the univariate analyses above do not account for the conditional volatility of correlation between stock returns across countries, which is the subject of Chapter 6.

5.2.2.2 *Univariate ARMA-GJR-GARCH model*

An important issue in financial asset markets is so-called news information. The above SGARCH model cannot distinguish between asymmetric news information and the leverage effect. I now consider commonly used latent news information measured by utilising the Glosten et al. (1993) GJR-GARCH model.

The first order ARMA conditional mean and first order conditional volatility GJR-GARCH model takes the following forms respectively.

$$r_t = \phi_0 + \phi_1 r_{t-1} + \psi_1 \varepsilon_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid F_{t-1} = \sqrt{h_t}\, z_t$$

$$h_t \mid F_{t-1} = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}; d_{t-1} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0 \\ 0 & \text{if } \varepsilon_{t-1} \geq 0 \end{cases}$$

The parameters are described in Chapters 3 and 4. For example, γ measures the asymmetric (or leverage) effect of return shocks on conditional volatility. Information about γ is vital for investors' decision making purposes. In this case, I explore the effect of the latent variable on predicting financial risk. To test the asymmetric/leverage effect, I test $H_0 : \gamma \leq 0$ versus $H_1 : \gamma > 0$. I used one-sided t tests on the coefficient γ for asymmetric effects of return shocks on conditional volatility. All the econometric and statistical packages by default reports two-tailed test values. Thus, care is needed in interpreting the test results for one-tailed tests as required in the current case. Table 5.8 provides results for the upper, that is the right-tailed test, of the parameter γ. The parameters α_1, β_1 and w are restricted to $\alpha_1 > 0$, $\beta_1 > 0$ and $w > 0$ because of non-negativity of the h_t function (see Chapters 3 and 4).

Table 5.8 shows the empirical values of various statistics for the ARMA-GJR-GARCH models of returns and volatilities of returns, for the 17 countries. The short- and long-run volatility parameters are significantly positive for all series except for the short-run parameter α_1 for the Thailand returns. The leverage effect tests conducted by the t test are all significantly positive except that for Indonesia. The LB-Q^2 tests on the squared standardised residuals revealed that the conditional volatility function is correctly specified for all series except those of HK, India and Thailand. The LB-Q tests on the standardised residuals of the models reveal that the mean model adequately describes the first moment for the US, UK, Singapore, Mexico, Japan, France and Canada series. No remaining ARCH effect exists in the volatility models, with the exception of Thailand, India and HK by the ARCH-LM test. The prediction of conditional volatility increases as the forecast horizon increases. These tests reveal the correctness of the ARMA-GJR-GARCH model for estimation and prediction. A model comparison could be undertaken by utilising the LL, AIC, BIC, HQ and $\min \sum_{t=1}^{T} \hat{h}_t$

criteria. However, these statistics do not take account of the conditional correlation between series. In this chapter I evaluate specification issues within univariate conditional volatility models only.

Table 5.8: ARMA(1,1)-GJR-GARCH(1,1) model estimation and model adequacy tests

Parameter	Australia	Brazil	Canada	China	France	Germany	HK	India
ϕ_0	0.043***	0.068*	0.029**	0.007	0.017	0.038	0.039**	0.076**
	(3.323)	(2.276)	(3.024)	(1.539)	(1.404)	(1.531)	(2.737	(2.883)
ϕ_1	–0.261	0.098	0.051	0.736***	0.007	0.196	0.221	–0.195
	(–1.617)	(0.356)	(0.390)	(20.214)	(0.035)	(0.425)	(1.544)	(–0.688)
ψ_1	0.365*	–0.061	0.037	–0.751***	–0.052	–0.167	–0.134	0.233
	(2.342)	(–0.221)	(0.283)	(–21.879)	(–0.238)	(–0.362)	(–0.920)	(0.826)
ω	0.036***	0.0491***	0.014***	0.048***	0.048***	0.031***	0.067***	0.045***
	(8.861)	(5.379)	(7.860)	(7.307)	(8.606)	(8.440)	(9.591)	(6.768)
α_1	0.126***	0.094***	0.073***	0.171***	0.076***	0.072***	0.103***	0.117***
	(13.004)	(12.501)	(11.303)	(15.205)	(10.187)	(11.708)	(13.797)	(14.540)
β_1	0.816***	0.897***	0.905***	0.852***	0.882***	0.899***	0.862***	0.871***
	(69.306)	(116.057)	(132.221)	(102.331)	(106.124)	(132.605)	(103.108)	(103.621)
γ	0.354***	0.162***	0.292***	0.014	0.446***	0.369***	0.264***	0.092***
	(10.783)	(6.963	(7.546)	(0.773)	(8.640)	(8.880)	(8.356)	(4.156)
LL	–9676.649	–13316.37	–10038.13	–12979.32	–12270.73	–12789.96	–13554.98	–13907.25
AIC	2.391	4.248	2.495	4.079	3.289	3.168	3.431	3.694
BIC	2.397	4.256	2.502	4.087	3.296	3.174	3.436	3.701
HQ	2.393	4.251	2.497	4.082	3.292	3.170	3.433	3.696
LB-Q(10)	20.897	30.819	11.041	94.706	7.976	18.531	22.270	24.716
χ^2 test	[0.0218]	[0.0006]	[0.354]	[6.661×10^{-15}]	[0.631]	[0.046]	[0.014]	[0.006]
LB-Q^2(10)	6.750	13.905	6.170	2.347	6.343	9.720	108.599	21.208
χ^2 test	[0.748]	[0.177]	[0.801]	[0.992]	[0.785]	[0.465]	[0.0]	[0.019]
ARCH(10)	6.998	16.449	6.986	3.046	10.173	11.609	112.068	21.676
	[0.857]	[0.171]	[0.858]	[0.995]	[0.601]	[0.477]	[0.0000]	[0.041]
JB-(2)	12724.52	390.9262	4313.566	154572.5	1242.339	3109.656	6755.355	422.119
χ^2 test	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]
Mean prediction Step 1	0.013	0.1427	0.047	0.038	0.008	0.051	0.138	0.061
Step 2	0.039	0.082	0.031	0.036	0.018	0.048	0.069	0.064
Step 5	0.034	0.076	0.031	0.032	0.018	0.047	0.051	0.064
SD prediction Step 1	0.598	1.528	0.586	0.960	0.739	0.735	1.070	0.952
Step 2	0.616	1.541	0.593	0.995	0.762	0.749	1.087	0.971
Step 5	0.664	1.576	0.613	1.098	0.824	0.788	1.132	1.025

Parameter	Indonesia	Japan	Malaysia	Mexico	Singapore	South Korea	Thailand	UK	US
ϕ_0	0.017$^{(.)}$	0.023	0.015 $^{(.)}$	0.046*	0.015	0.020*	-1.66×10^{-3}	0.008	0.034
	(1.796)	(1.606)	(1.876)	(2.564)	(1.019)	(2.312)	(–0.795)	(1.257)	(0.933)
ϕ_1	0.205**	0.071	0.278***	–0.096	0.017	0.573***	-5.498×10^{-2}***	0.584$^{(.)}$	0.117
	(2.584)	(0.247)	(4.084)	(–0.768)	(0.046)	(6.686)	(–3.638)	(1.955)	(0.126)
ψ_1	–0.038	–0.009	–0.121$^{(.)}$	0.207$^{(.)}$	0.004	–0.484***	-9.978×10^{-1}***	–0.607*	–0.116
	(–0.475)	(–0.034)	(–1.732)	(1.688)	(0.011)	(–5.234)	(–2190.871)	(–2.073)	(–0.125)
ω	0.013***	0.038***	0.017***	0.020***	0.014***	0.069***	7.456×10^{2}	0.020***	0.021***
	(8.831)	(7.958)	(6.818)	(5.484)	(5.070)	(8.065)	(0.887)	(7.537)	(8.655)
α_1	0.139***	0.106***	0.139***	0.080***	0.067***	0.161***	1.000×10^{-8}	0.070***	0.065***
	(19.520)	(13.418)	(13.191)	(10.150)	(11.308)	(15.433)	(NA)	(11.019)	(10.341)
β_1	0.879***	0.864***	0.862***	0.904***	0.926***	0.819***	7.675×10^{-1}**	0.901***	0.902***
	(183.780)	(107.629)	(88.883)	(110.589)	(153.625)	(78.290)	(0.003)	(127.962)	(126.801)
γ	–0.106	0.381***	0.062**	0.346***	0.189***	0.192***	3.438×10^{-2}	0.408***	0.434***
	(–6.315)	(11.397)	(3.207)	(9.653)	(6.750)	(8.620)	(0.793)	(9.489)	(8.637)
LL	–12050.17	–12607.36	–10933.09	–9346.327	–12906.75	–12690.01	–23747.46	–10779.19	–10602.87
AIC	3.107	3.206	2.777	3.262	3.553	3.514	10.914	2.775	2.630
BIC	3.113	3.212	2.784	3.271	3.559	3.521	10.924	2.781	2.636
HQ	3.109	3.208	2.779	3.265	3.555	3.517	10.917	2.777	2.632
LB-Q(10)	53.139	15.545	18.545	11.028	15.797	22.798	8060.123	6.753	11.418
χ^2 test	[7.013×10^{-8}]	(0.113)	[0.046]	[0.355]	[0.105]	[0.011]	[0]	[0.748]	[0.325]
LB-Q^2(10)	9.081	10.819	4.873	7.095	15.047	10.769	9926.007	13.742	11.803
χ^2 test	[0.524]	[0.371]	[0.899]	[0.716]	[0.130]	[0.375]	[0]	[0.185]	[0.298]
ARCH(10)	9.706	12.136	5.323	10.270	17.204	11.897	3349.887	18.849	12.800
LM test	[0.642]	[0.434]	[0.946]	[0.592]	[0.142]	[0.453]	[0]	[0.092]	[0.384]
JB-(2)	199370.7	6308.532	138536.9	757.851	1171.989	5002.046	378.521	1647.593	6127.524
χ^2 test	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]
Mean prediction Step 1	0.350	–0.073	0.101	0.112	0.014	0.147	–69.110	0.006	0.0388
Step 2	0.089	0.018	0.043	0.035	0.016	0.105	3.798	0.012	0.0389
Step 5	0.022	0.025	0.021	0.042	0.016	0.058	–0.002	0.018	0.0390
SD prediction Step 1	1.344	1.027	0.525	0.908	0.686	0.765	56.631	0.594	0.566
Step 2	1.363	1.038	0.542	0.916	0.695	0.804	56.631	0.606	0.578
Step 5	1.418	1.072	0.592	0.941	0.722	0.909	56.631	0.639	0.612

Note 1. Value in parentheses ( ) is the Student-t test statistic.

Note 2. Value in [ ] is the significance level of the LB-Q, ARCH and JB tests.
Note 3. ‘LB-Q(*m*)’ and ‘LB-Q^2(*m*)’ are the *m*-th lag Ljung–Box test statistics applied to the original and squared standardised residuals.
Note 4. JB is the 1987 Jarque–Bera chi-square test with 2 degrees of freedom for normality of the original series.
Note 5. LL is the log-likelihood function evaluated at the maximum.
Note 6. ARCH(*m*) is the Engle (1982) LM test, which tests for the remaining ARCH effect.

In the next section, I deal with risk premium modelling in the univariate context using the Engle et al. (1987) GARCH-M model extended to univariate GJR-GARCH-M. This model is useful for determining the effect of risk premiums on generating financial returns.

5.2.2.3 *Univariate ARMA-GJR-GARCH-M model*

The first order conditional volatility GJR-GARCH in first order ARMA mean model ARMA(1,1)-GJR-GARCH-M takes the following form:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \psi_1 \varepsilon_{t-1} + \delta \sqrt{h_t} + \varepsilon_t, \quad \varepsilon_t = \sqrt{h_t}\, z_t$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1};\ d_{t-1} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0 \\ 0 & \text{if } \varepsilon_{t-1} \geq 0 \end{cases}$$

The parameter δ measures the risk premium demanded by agents for holding risky assets. I expect δ >0. Table 5.9 presents the estimated ARMA-GJR-GARH-M model including results of sign and size bias tests, and some diagnostics for model adequacy and volatility prediction.

The model was estimated by the ML method. The short- and long-run return shocks are all significantly positive, satisfying the positivity requirement for the conditional volatility function for all models. The LB-Q and LB-Q^2 tests conducted on the standardised residuals and squared standardised residuals respectively show that not all of the models adequately describe the first and second moments of the series jointly, as is evident from the significance levels for the LB-Q and LB-Q^2 tests. Only the Canada, France, Mexico and US risk premium models adequately describe the first and second model jointly. Thus I do not reject the null hypothesis of no ARCH effect at the 1% level of significance for the series. I tested whether heteroscedasticity depends on both the sign and size of previous shocks, utilising the Engle and Ng (1993) test. I found significant positive shocks in France, Germany, Thailand, UK and US models at the 10% level of significance. However, significant negative effects were found for Australia, Brazil, Canada, Germany, HK, Indonesia and Singapore at the 10% level of significance. In addition to the above discussion (the conditional volatility model specification, stochastic behaviour of stock returns, and the relationship between stock market volatility and expected returns) I am required to check whether the return shocks are persistent or transitory. This can be checked using the summary provided in Table 5.10.

Table 5.9: ARMA(1,1)-GJR-GARCH(1,1)-M model estimation and model adequacy tests

Parameter	Australia	Brazil	Canada	China	France	Germany	HK	India
ϕ_0	0.030	–0.247***	0.001	0.026	–0.046	0.038	0.070	0.064
	(0.879)	(–3.577)	(0.033)	(0.258)	(–1.088)	(1.000)	(1.244)	(1.356)
ϕ_1	–0.258	0.091	0.058	0.066	–0.039	0.316	0.196	–0.197
	(–0.933)	(0.403)	(0.455)	(0.494)	(–0.240)	(0.545)	(1.148)	(–0.743)
ψ_1	0.362	–0.055	0.031	–0.123	–0.002	–0.288	–0.109	0.234
	(1.346)	(–0.242)	(0.242)	(–0.786)	(–0.016)	(–0.492)	(–0.620)	(0.887)
δ	0.005	0.199***	0.042	0.006	0.059	0.008	–0.016	–0.0003
	(0.116)	(4.998)	(1.269)	(0.088)	(1.616)	(0.256)	(–0.367)	(–0.009)
ω	0.036***	0.058***	0.014***	0.069	0.051***	0.031***	0.066***	0.046***
	(3.262)	(3.959)	(3.452)	(1.534)	(4.900)	(4.456)	(3.539)	(4.322)
α_1	0.053***	0.068***	0.037***	0.143**	0.023**	0.028***	0.056***	0.096***
	(3.473)	(7.689)	(4.205)	(2.195)	(2.264)	(3.353)	(5.284)	(8.735)
β_1	0.816***	0.895***	0.904***	0.852***	0.879***	0.898***	0.862***	0.871***
	(18.708)	(72.247)	(49.809)	(16.951)	(61.818)	(81.431)	(36.885)	(68.133)
γ	0.179***	0.054***	0.085***	0.007	0.135***	0.107***	0.109***	0.043***
	(2.824)	(3.523)	(3.287)	(0.180)	(6.561)	(5.471)	(2.981)	(2.752)
LL	–9676.68	–13301.83	–10037.59	–13008.81	–12269.57	–12790.35	–13555.17	–13907.24
AIC	2.3919	4.244	2.495	4.089	3.289	3.168	3.431	3.694
BIC	2.3988	4.253	2.502	4.098	3.297	3.175	3.438	3.702
HQ	2.3942	4.247	2.498	4.092	3.292	3.171	3.433	3.697
LB-Q(5)	11.670	4.254**	1.605	49.32***	1.501	3.829	4.899***	5.970***
χ^2 test	[0.0000]	[0.034]	[0.995]	[0.0000]	[0.998]	[0.101]	[0.004]	(0.000)
LB-Q^2(5)	3.328	6.971*	1.375	0.356	2.584	6.928*	101.37***	9.008**
χ^2 test	[0.350]	[0.053]	[0.771]	[0.977]	[0.488]	[0.054]	[0.000]	[0.016]
ARCH(5)	1.516	5.557*	1.131	0.658	1.208	1.895	1.325	1.235
	[0.587]	[0.076]	[0.694]	[0.835]	[0.672]	[0.494]	[0.639]	[0.664]
Sign bias	1.674*	0.936	0.546	0.291	1.546	2.571**	0.980	1.169
	[0.094]	[0.349]	[0.585]	[0.770]	[0.122]	[0.001]	[0.326]	[0.242]
–ve sign	2.683***	1.744*	2.204**	1.015	1.336	2.346**	2.783***	0.079
	[0.007]	[0.081]	[0.027]	[0.309]	[0.181]	[0.002]	[0.005]	[0.936]
+ve sign	1.204	0.305	0.885	1.195	1.750*	2.188**	1.425	0.297
	[0.228]	[0.760]	[0.376]	[0.232]	[0.080]	[0.003]	[0.154]	[0.766]
Joint test	8.674**	9.066**	7.005*	2.553	11.380***	23.150***	11.341**	2.340
	[0.033]	[0.028]	[0.072]	[0.465]	[0.009]	[0.0000]	[0.010]	[0.504]

Parameter	Australia	Brazil	Canada	China	France	Germany	HK	India
JB	3538100***	267820***	219470***	3263100***	11732***	9658.1***	883300	6852
	$[2.2\times10^{-16}]$	$[2.2\times10^{-16}]$	$[2.2\times10^{-16}]$	$[2.2\times10^{-16}]$	$[2.2\times10^{-16}]$	$[2.2\times10^{-16}]$	$[2.2\times10^{-16}]$	$[2.2\times10^{-16}]$

Parameter	Indonesia	Japan	Malaysia	Mexico	Singapore	South Korea	Thailand	UK	US
ϕ_0	–0.038	0.102**	–0.032	–0.025	–0.042	0.126**	–0.001	–0.022	–0.013
	(–1.062)	(2.338)	(–0.890)	(–0.596)	(–1.121)	(2.241)	[–0.028]	(–0.777)	(–0.441)
ϕ_1	0.219**	–0.016	0.282***	–0.063	0.015	0.509***	0.750***	0.320	0.727***
	(2.260)	(–0.044)	(4.446)	(–0.529)	(0.044)	(6.132)	(6.635)	(0.568)	(19.895)
ψ_1	–0.056	0.074	–0.125*	0.176	0.005	–0.419***	–0.720***	–0.344	–0.730***
	(–0.597)	(0.203)	(–1.892)	(1.463)	(0.016)	(–4.762)	(–6.141)	(–0.615	(–19.278)
δ	0.081***	–0.076	0.074*	0.067*	0.052*	–0.066	0.009	0.050	0.067*
	(2.685)	(–1.912)	(1.911)	(1.734)	(1.688)	(–1.493)	(0.250)	(1.543)	(1.880)
ω	0.019	0.034***	0.019**	0.022***	0.015*	0.066***	0.007**	0.021***	0.022***
	(0.973)	(3.058)	(2.326)	(3.194)	(1.928)	(3.386)	(2.493)	(4.867)	(4.518)
α_1	0.138***	0.040***	0.120***	0.034***	0.044***	0.105***	0.039***	0.024***	0.021***
	(4.629)	(3.816)	(4.293)	(3.591)	(3.319)	(6.152)	(3.518)	(2.575)	(2.771)
β_1	0.883***	0.867***	0.862***	0.901***	0.925***	0.820***	0.913***	0.898***	0.899***
	(24.424)	(35.389)	(32.352)	(53.539)	(47.325)	(28.572)	(75.175)	(70.411)	(65.490)
γ	–0.045***	0.166***	0.0326	0.109***	0.049***	0.125***	0.087***	0.115***	0.110***
	(–1.602)	(3.843)	(0.832)	(4.441)	[3.414]	(3.201)	(4.852)	(5.980)	(4.818)
LL	–12065.87	–12605.03	–10931.02	–9344.938	–12905.4	–12691.81	–6124.009	–10778.45	–10601.22
AIC	3.111	3.205	2.777	3.262	3.553	3.515	2.817	2.775	2.630
BIC	3.118	3.212	2.784	3.272	3.560	3.523	2.829	2.782	2.637
HQ	3.113	3.208	2.779	3.266	3.555	3.518	2.821	2.777	2.632
LB-Q(5)	16.688***	0.5591	12.294***	2.368	2.046	8.208*	2.839	1.763	1.993
χ^2 test	[0.000]	[1.000]	[0.0000]	[0.843]	[0.948]	[0.000]	[0.574]	[0.987]	[0.959]
LB-Q^2(5)	9.560**	7.122**	2.365	2.925	6.501*	5.796	7.223**	11.46***	2.846
χ^2 test	[0.012]	[0.048]	[0.535]	[0.420]	[0.068]	[0.100]	[0.0457]	[0.003]	[0.435]
ARCH(5)	0.3489	0.2860	0.869	1.628	4.132	2.203	8.195**	0.446	1.3362
	[0.927]	[0.944]	[0.772]	[0.559]	[0.162]	[0.427]	[0.018]	[0.899]	[0.636]
Sign bias	0.145	0.831	0.051	0.796	1.014	0.560	0.247	0.647	2.193**
	[0.884]	[0.405]	[0.959]	[0.425]	[0.310]	[0.575]	[0.804]	[0.517]	[0.028]
–ve sign	1.782*	0.351	0.719	0.805	1.738*	0.036	0.545	0.636	1.484

Parameter	Indonesia	Japan	Malaysia	Mexico	Singapore	South Korea	Thailand	UK	US
	[0.074	[0.724]	[0.471]	[0.420]	[0.082]	[0.971]	[0.585]	[0.524]	[0.137]
+ve sign	1.486	1.030	0.971	1.481	1.909*	0.464	1.999**	1.819*	2.157**
	[0.137]	[0.302]	[0.331]	[0.138]	[0.056]	[0.642]	[0.045]	[0.068]	[0.031]
Joint test	5.569	5.957	1.507	9.731**	9.045**	0.454	4.638	10.534**	19.158***
	[0.134]	[0.113]	[0.680]	[0.021]	[0.028]	[0.928]	[0.200]	[0.014]	[0.0002]
JB(2)	1171200	18031	673100	13124	5684.8	16714	35598	34100	50124
	[2.2×10^{-16}]	[2.2×10^{-16}]	[2.2×10^{-16}]	[2.2×10^{-16}]	[2.2×10^{-16}]	[2.2×10^{-16}]	[2.2×10^{-16}]	[2.2×10^{-16}]	[2.2×10^{-16}]

Note 1. Value in parentheses ( ) is the Student-t test statistic.
Note 2. Value in [ ] is the significance level of the LB-Q, ARCH and JB tests.
Note 3. 'LB-Q(m)' and 'LB-Q^2(m)' are the m-th lag Ljung–Box test statistics applied to the original and squared standardised residuals.
Note 4. JB is the 1987 Jarque–Bera chi-square test with 2 degrees of freedom for normality of the original series.
Note 5. LL is the log-likelihood function evaluated at the maximum.
Note 6. ARCH(m) is the Engle (1982) LM test, which tests for the remaining ARCH effect.
Note 7. $d_{t-1}^{-}=\begin{cases}1 & \text{if } \varepsilon_{t-1}<0\\ 0 & \text{otherwise}\end{cases}$ is the sign bias variable; $d_{t-1}^{+}=1-d_{t-1}^{-}$, $d_{t-1}^{-}\varepsilon_{t-1}$ is the negative size bias variable; and $d_{t-1}^{+}\varepsilon_{t-1}$ is the negative size variable,

$\hat{\varepsilon}_t^2=a_0+a_1d_{t-1}^{-}+a_2d_{t-1}^{-}\varepsilon_{t-1}+a_3d_{t-1}^{+}\varepsilon_{t-1}+\eta_t$, where η_t is the regression residuals

Table 5.10: Summary of the short- and long-run parameter effects of return shocks on volatility GARCH-M models

Country	GARCH $\alpha_1+\beta_1$	GJR-GARCH $\alpha_1+\beta_1+\frac{\gamma}{2}$	GJR-GARCH-M $\alpha_1+\beta_1+\frac{\gamma}{2}$	GJR-GARCH-M $\alpha_1+\gamma$	Half-life	GJR-GARCH-M γ	δ
Australia	0.971	1.119	0.958	0.232	0.47	√	×
Brazil	0.991	1.072	0.990	0.122	0.33	√	√
Canada	0.99	1.124	0.983	0.122	0.33	√	×
China	1.02	1.030	0.998	0.150	0.36	×	×
France	0.979	1.182	0.969	0.158	0.37	√	×
Germany	0.986	1.155	0.979	0.135	0.35	√	×
HK	0.979	1.097	0.972	0.165	0.38	√	×
India	0.989	1.034	0.988	0.139	0.35	√	×
Indonesia	1.02	0.965	0.998	0.093	0.29	√	√
Japan	0.989	1.400	0.990	0.206	0.44	√	×
Malaysia	1.00	1.030	0.998	0.153	0.37	×	√
Mexico	0.994	1.157	0.989	0.143	0.36	√	√
Singapore	0.996	1.087	0.994	0.093	0.29	√	√
South Korea	0.989	1.076	0.988	0.23	0.47	√	×
Thailand	0.999	0.780	0.996	0.126	0.33	√	×
UK	0.985	1.175	0.979	0.139	0.35	√	×
US	0.985	1.184	0.974	0.131	0.34	√	√

Note 1. The half-life of a volatility shock was computed using the formula $\log_e(0.5)/\log_e(\alpha_1+\gamma)$. The half-life of the return shock is the time required for half of the shock to decay.
Note 2. √ indicates significance at the 1% level and × indicates insignificance.

For the GARCH (1,1) model, $\alpha_1+\beta_1$ is fairly close to 1. This phenomenon is commonly observed in practice. However, $\alpha_1+\beta_1 \geq 1$ was documented for China, Indonesia and Malaysia, indicating return shocks to volatility persist for these countries. The GJR-GARCH model is violating convergence for all the return series except those of Indonesia and Thailand. The GJR-GARCH-M model, however, documented convergence for all returns. The risk premium parameter δ is mostly positive, but not significantly so (×). A significant δ was found for Brazil, Indonesia, Malaysia, Mexico, Singapore and US. Theodossiou and Lee (1995) reported an insignificant risk premium in their GARCH-M model for Australia, Belgium, Canada, France and Italy. The half-life of a volatility shock is 0.47 days for Australia and 0.29 days for Singapore and Indonesia. All the other country half-life values are bounded by these two values. I now present graphs of volatility persistence of return shocks for all 17 countries under three different volatility models. The graphs display volatility persistence with reference to GJR-GARCH, GJR-GARCH-M and GARCH models.

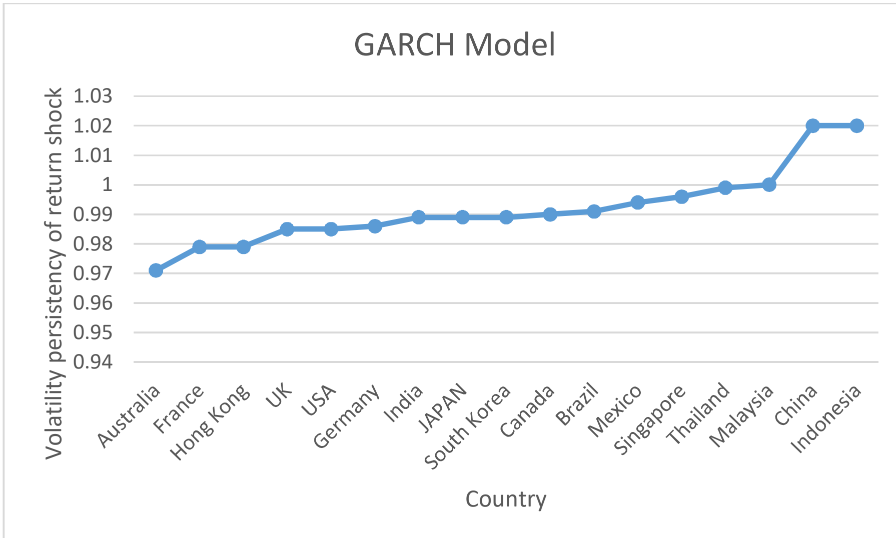


Figure 5.1: GARCH volatility persistence ordered according to country

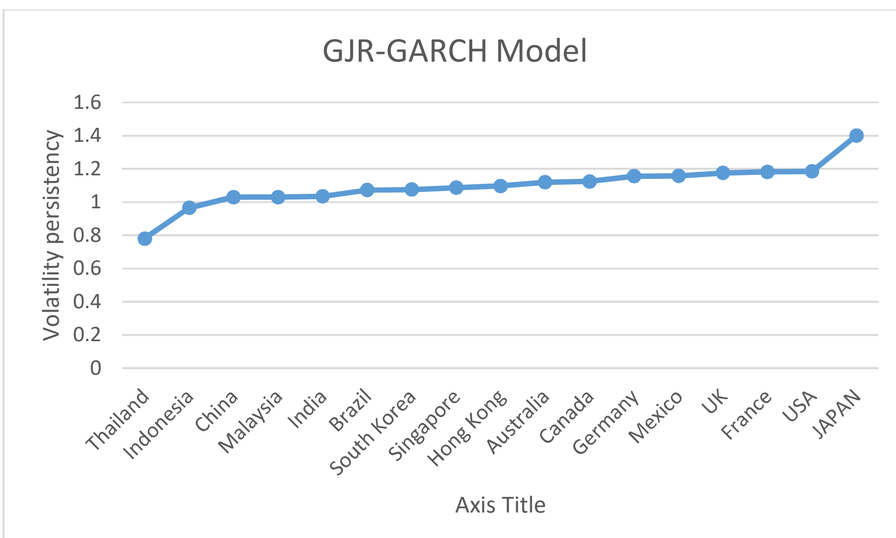


Figure 5.2: GJR volatility persistence ordered according to country

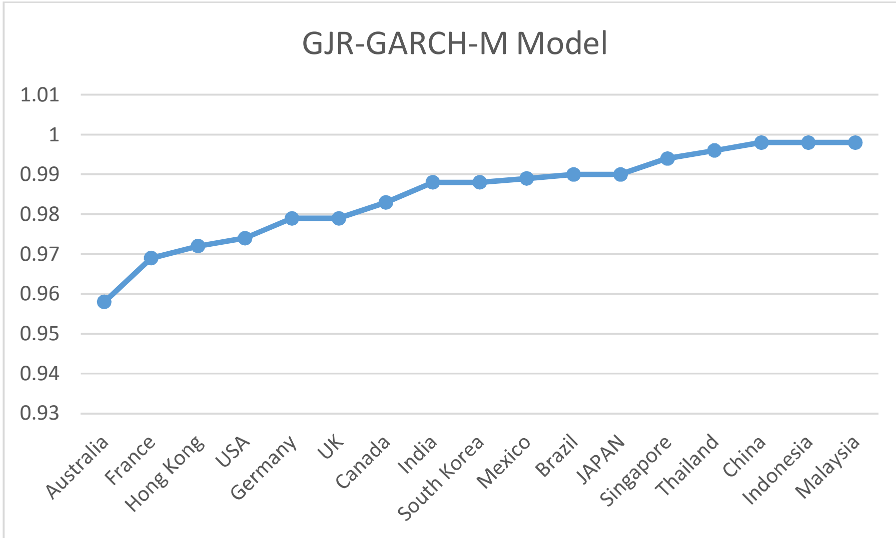


Figure 5.3: GJR-GARCH-M volatility persistence ordered according to country

Figure 5.1 show that Australia has the smallest volatility persistence of return shocks and Indonesia has the highest. UK and US show similar volatility persistence. Figure 5.2 shows that Thailand has the smallest volatility persistence and Japan has the highest, in the GJR-GARCH model of return shock. All other countries' volatility persistence lie between those of Thailand and Japan. Figure 5.3 displays volatility persistence patterns resulting from return shocks, which are the smallest for Australia and the largest for Malaysia in the GJR-GARCH-M model. The issue of volatility persistence could be used to explore trading options in financial markets.

So far I have discussed the results regarding univariate conditional volatility assuming normal innovation (shock) distribution. Bollerslev (1987) argued for the use of Student-t innovation for modelling the conditional volatility of stock returns series on the grounds that financial series often display thick-tailed distributions. Further to the choice of innovation distribution is consideration of both the skewness and kurtosis properties for volatility modelling of returns series. These two properties jointly can be modelled by the skewed Student-t distribution (see Hansen, 1994). In the following section I estimate ARMA-GARCH volatility models utilising Student-t and skewed Student-t innovation distributions and compare the predicted standard deviations for the three innovation distributions.

Table 5.11: ARMA-GARCH model estimation under Student-t innovation with unknown degrees of freedom

Parameter	Australia	Brazil	Canada	China	France	Germany	HK	India
ϕ_0	0.064***	0.134**	0.061***	0.011**	0.018*	0.113***	0.079**	0.095***
	(4.859)	(2.769)	(5.421)	(2.860)	(2.152)	(4.416)	(2.689)	(3.367)
ϕ_1	–0.066	–0.131	–0.086	0.824***	0.721***	–0.274	0.046	–0.160
	(–0.410)	(–0.375)	(–0.734)	(29.327)	(5.838)	(–1.146)	(0.147)	(–0.597)
ψ_1	0.156	0.160	0.174	–0.788***	–0.759***	0.301	0.008	0.199
	(0.979)	(0.460)	(1.502)	(–29.716)	(–6.548)	(1.265)	(0.027)	(0.746)
w	0.014***	0.055***	0.008***	0.055***	0.027***	0.014***	0.034***	0.038***
	(5.359)	(5.142)	(5.213)	(5.032)	(5.174)	(4.839)	(5.986)	(5.539)
α_1	0.083***	0.091***	0.072***	0.150***	0.090***	0.082***	0.078***	0.112***
	(10.146)	(10.828)	(10.046)	(10.050)	(10.894)	(11.951)	(10.603)	(12.513)
β_1	0.898***	0.899***	0.918	0.856***	0.898***	0.912***	0.906***	0.879***
	(91.363)	(9.163)	(117.607)	(71.026)	(100.378)	(130.893)	(109.380)	(96.805)
shape	7.797***	10.000***	7.133***	4.353***	7.404***	7.849***	6.623***	9.468***
	(13.260)	(9.163)	(13.633)	(17.971)	(12.838)	(12.727)	(14.601)	(10.412
LL	–9494.069	–13273.07	–9866.347	–12391.27	–12197.95	–12667.65	–13324.77	–13830.83
LB-Q(10)	18.609	32.552	10.899	33.588	17.838	16.748	31.593	23.231
	[0.045]	[0.000]	[0.365]	[0.000]	[0.057]	[0.080]	[0.000]	[.009]
LB-Q^2 (10)	10.398	23.956	17.483	1.622	13.563	8.240	348.250	27.328
	[0.406]	[0.007]	[0.064]	[0.998]	[0.194]	[0.605]	[0]	[0.002)
ARCH(10)	10.541	25.959	18.122	2.032	16.945	9.598	366.204	28.165
	[0.568]	[0.011]	[0.112]	[0.999]	[0.151]	[0.651]	[0]	[0.005]
AIC	2.346	4.234	2.453	3.895	3.270	3.138	3.372	3.673
BIC	2.352	4.242	2.459	3.902	3.276	3.144	3.378	3.680
HQ	2.348	4.234	2.455	3.897	3.272	3.140	3.374	3.676
Mean prediction								
Step 1	0.063	0.170	0.073	0.028	0.066	0.099	0.136	0.079
Step 2	0.060	0.112	0.055	0.034	0.066	0.086	0.085	0.083
Step 5	0.060	0.119	0.057	0.046	0.066	0.088	0.083	0.082
Volatility prediction								
Step 1	0.673	1.501	0.589	0.972	0.764	0.782	0.987	0.958
Step 2	0.678	1.513	0.594	1.003	0.777	0.789	0.997	0.974
Step 5	0.691	1.546	0.608	1.092	0.815	0.810	1.024	1.020

Parameter	Indonesia	Japan	Malaysia	Mexico	Singapore	South Korea	Thailand	UK	US
ϕ_0	0.022***	0.063**	0.032***	0.094***	0.046*	0.041***	0.014	0.004*	0.014*
	(4.244)	(3.261)	(4.115)	(4.914)	(2.032)	(3.631)	(0.5270	(2.215)	(2.412)
ϕ_1	0.422***	–0.107	0.192*	–0.159	–0.081	0.495***	0.660	0.914***	0.799***
	(5.579)	(–0.428)	(2.290)	(–1.442)	(–0.203)	(4.859)	(1.036)	(25.533)	(9.921)
ψ_1	–0.280***	0.149	–0.051	0.257*	0.103	–0.424***	–0.657	–0.934***	–0.825***
	(–3.488)	(0.596)	(–0.602)	(2.385)	(0.257)	(–4.012)	(–1.027)	(–29.394)	(–10.615)
w	0.004***	0.020***	0.016***	0.018***	0.013***	0.056***	0.008***	0.016***	0.011***
	(4.124)	(5.094)	(5.738)	(4.365)	(3.824)	(6.226)	(3.502)	(5.493)	(5.240)
α_1	0.286***	0.102***	0.151***	0.085***	0.078***	0.141***	0.088***	*0.086****	0.075***
	(10.618)	(12.544)	(10.995)	(9.602)	(9.837)	(11.815)	(8.795)	*(11.220)*	(10.580)
β_1	0.813***	0.892***	0.851***	0.907***	0.919***	0.844***	0.909***	*0.901****	0.915***
	(69.608)	(111.392)	(71.627)	(101.701)	(118.001)	(70.891)	(96.714)	*(105.996)*	(121.953)
$shape$	3.297***	7.643***	4.899***	6.736***	8.564***	6.142***	6.926***	7.867***	5.884***
	(23.181)	(13.116)	(18.516)	(11.596)	(11.314)	(14.671)	(10.008)	(12.319)	(15.185)
LL	–10949.1	–12495	–10373.69	–9292.6	–12811.73	–12473.38	–6066.577	–10706.14	–10409.46
LB-Q(10)	49.624	17.702	33.219	15.267	16.701	34.508	17.808	15.214	19.473
	[0.000]	[0.060]	[0.000]	[0.123]	[0.081]	[0.000]	[0.058]	[0.124]	[0.034]
LB-Q^2(10)	2.416	11.817	4.957	23.643	15.075	14.255	22.412	22.388	11.897
	[0.992)	[0.297]	[0.893]	[0.008]	[0.129]	[0.162]	[0.013]	[0.013]	[0.292]
ARCH(10)	2.755	12.968	5.542	27.273	17.253	14.795	26.073	28.334	12.917
	[0.997]	[0.371]	[0.937]	[0.007]	[0.140]	[0.253]	[0.010]	[0.005]	[0.375]
AIC	2.823	3.177	2.635	3.244	3.526	3.454	2.790	2.756	2.582
BIC	2.829	3.184	2.641	3.252	3.533	3.461	2.801	2.763	2.588
HQ	2.825	3.179	2.637	3.247	3.529	3.457	2.794	2.758	2.584
Mean prediction									
Step 1	0.377	–0.008	0.104	0.140	0.043	0.154	0.043	0.012	0.082
Step 2	0.181	0.064	0.053	0.071	0.043	0.117	0.042	0.016	0.079
Step 5	0.048	0.057	0.041	0.081	0.043	0.086	0.042	0.024	0.075
Volatility prediction									
Step 1	1.599	0.952	0.502	0.886	0.652	0.776	0.605	0.636	0.550
Step 2	1.678	0.959	0.518	0.894	0.661	0.806	0.611	0.645	0.558
Step 5	1.938	0.983	0.565	0.916	0.687	0.889	0.629	0.671	0.573

Note 1. Value in parentheses ( ) is the Student-t test statistic.

Note 2. Value in [ ] is the significance level of the LB-Q, ARCH and JB tests.

Note 3. 'LB-Q(m)' and 'LB-Q^2(m)' are the m-th lag Ljung–Box test statistics applied to the original and squared standardised residuals.

Note 4. JB is the 1987 Jarque–Bera chi-square test with 2 degrees of freedom for normality of the original series.
Note 5. LL is the log-likelihood function evaluated at the maximum.
Note 6. ARCH(*m*) is the Engle (1982) LM test, which tests for the remaining ARCH effect.

5.2.2.4 *ARMA-GARCH with Student-t innovation*

I use the following first order ARMA conditional mean and conditional volatility models under the Student-t innovation of the return series. The ARMA(1,1)-GARCH(1,1) model takes the following form:

$$r_t = \phi_0 + \phi_1 r_{t-1} + \psi_1 \varepsilon_{t-1} + \varepsilon_t \,,\ \varepsilon_t \mid F_{t-1} \sim \text{Student-}t \text{ with unknown shape parameter}$$

$$h_t = w + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

Table 5.11 provides the ARMA-GARCH model estimation under Student-t innovation with unknown degrees of freedom. The estimated ARCH/GARCH parameters $\hat{\alpha}_1$ and $\hat{\beta}_1$ are significant at the 1% level and have a positive sign for all returns series. Stability conditions, that is, $\hat{\alpha}_1 > 0$, $\hat{\beta}_1 > 0$ and $\hat{\alpha}_1 + \hat{\beta}_1 < 1$, are satisfied by all series except those for China, Indonesia and Malaysia. The JB test indicates that the residuals are non-normal. The t-innovation distribution produced similar findings to Gaussian innovation. The standardised residuals are serially uncorrelated for Japan, Mexico, Singapore, Thailand, UK and Canada. Also, the standardised squared residuals are serially uncorrelated for Indonesia, Japan, Thailand, UK, Australia, China, France and Germany. The volatility model adequately describes the conditional volatility. However noticeable differences were found in volatility prediction between the same models with different innovations. I consider the skewed-t innovation in the GARCH volatility model for all 17 countries in the next section.

5.2.2.5 *ARMA-GARCH with skewed Student-t distribution*

The skewed Student-t distribution was presented in Chapter 3. Table 5.12 describes the parameter estimates and diagnostic tests of the model.

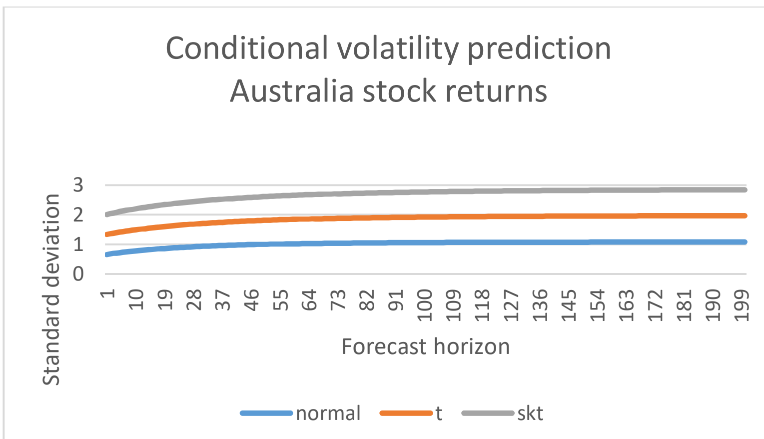
Table 5.12: ARMA-GARCH-*t* model estimation and diagnostics

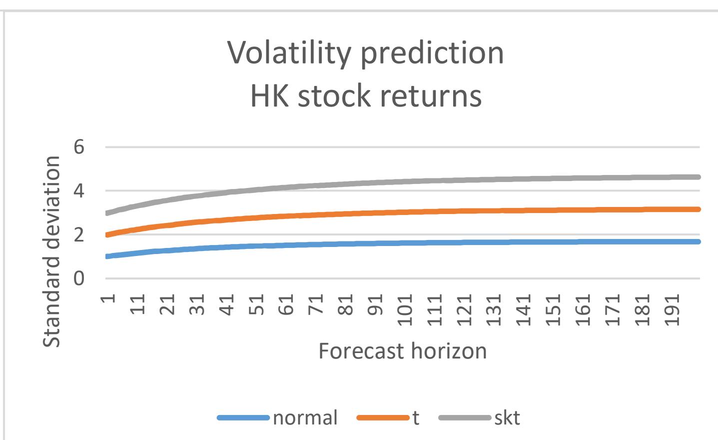
Country	Parameter									Diagnostic statistics				
	ϕ_0	ϕ_1	ψ_1	ω	α_1	β_1	Skewed Student -t λ	Student -t shape	ARCH	JB-Q (10)	LB-Q^2(10)	1-step mean	1-step SD	LL
Australia	0.06***	–0.17	0.26	0.01***	0.08***	0.90***	0.90**	8.2***	10.63	22.45	10.48	0.04	0.67	–9477.45
Brazil	0.13***	–0.26	0.28	0.05***	0.09***	0.90***	0.94***	10.0***	26.12	34.02	24.10	0.15	1.50	–13267.76
Canada	0.04**	–0.14	0.23	0.008***	0.07***	0.92***	0.9***	7.5	18.14	13.08	17.47	0.06	0.59	–9847.60
China	0.006	–0.82	–0.78	0.05***	0.15***	0.85***	.95***	4.36***	2.13	34.59	1.7	0.008	0.968	–12387.09
France	0.01**	0.74***	–0.79***	0.02***	0.08***	0.90***	0.87***	7.98***	17.96	29.77	14.59	0.03	0.77	–12167.93
Germany	0.09***	–0.34	0.36	0.01***	0.08***	0.91***	0.90***	8.37***	9.69	18.12	8.47	0.08	0.79	–12646.96
HK	0.08*	–0.06	0.12	0.03***	0.08***	0.90***	0.96***	6.7***	366.02	32.90	348.03	0.13	0.99	–13321.63
India	0.09**	–0.19	0.23***	0.04***	0.11***	0.88***	0.97***	9.53***	28.22	23.72	27.40	0.07	0.96	–13828.75
Indonesia	0.02***	0.42***	–0.28***	0.004***	0.28***	0.81***	0.99***	3.30***	2.76	50.16	2.42	0.37	1.60	–10948.92
Japan	0.06**	–0.22	0.26	0.02***	0.10***	0.89***	0.95	7.76	12.82	20.07	11.68	–0.008	0.95	–12490.27
Malaysia	0.04***	0.20*	–0.06	0.02***	0.15***	0.85***	1.02***	4.88***	5.48	32.16	4.89	0.11	0.50	–10372.00
Mexico	0.08***	–1.8	0.28*	0.02***	0.08***	0.90***	0.96***	6.85***	26.82	16.34	23.11	0.13	0.89	–9290.41
Singapore	0.04	–0.19	0.21	0.012***	0.079***	0.92***	0.94***	8.65***	17.11	17.63	14.89	0.03	0.65	–12805.18
SK	0.04***	0.48***	–0.41***	0.06***	0.14***	0.84***	0.97***	6.19***	14.71	36.61	14.18	0.14	0.78	–12471.87
Thailand	0.002	0.93***	0.93***	0.008***	0.08***	0.91***	0.90***	7.3***	26.68	23.80	23.10	0.03	0.60	–6055.498
UK	0.005*	0.86***	–0.89***	0.02***	0.08***	0.90***	0.90***	0.82***	30.01	25.80	24.14	–0.02	0.64	–10687
US	0.010**	0.81***	–084***	0.01***	0.07***	0.92***	0.93***	6.1**	13.34	25.87	12.36	0.07	0.55	–10396.87

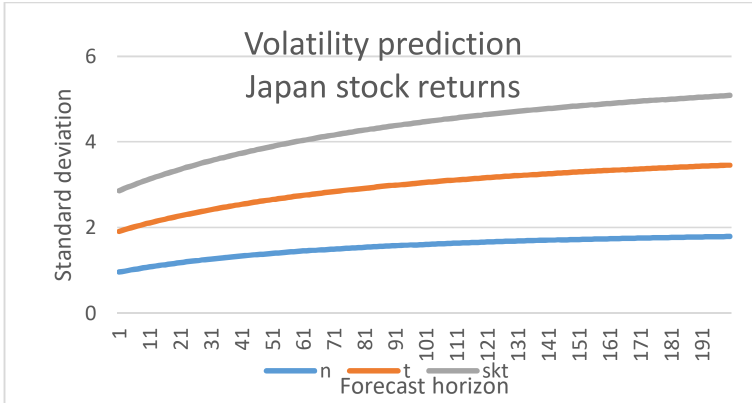
Note 1. Value in parentheses ( ) is the Student-t test statistic.
Note 2. Value in [ ] is the significance level of the LB-Q, ARCH and JB tests.
Note 3. ‘LB-Q(*m*)’ and ‘LB-Q^2(*m*)’ are the *m*-th lag Ljung–Box test statistics applied to the original and squared standardised residuals.
Note 4. JB is the 1987 Jarque–Bera chi-square test with 2 degrees of freedom for normality of the original series.
Note 5. LL is the log-likelihood function evaluated at the maximum.
Note 6. ARCH(*m*) is the Engle (1982) LM test, which tests for the remaining ARCH effect.

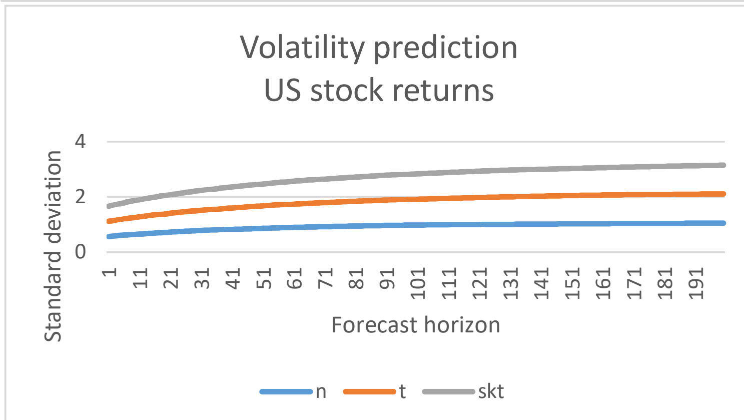
The estimated shape parameter is significant in all cases. Similar to the previous distributions, the skewed-t-innovation GARCH model $\hat{\alpha}_1 + \hat{\beta}_1$ is quite close to 1. This phenomenon is commonly observed in practice. However, those of China, Indonesia and Malaysia exceed 1 indicating volatility persistence, i.e. any return shock persists for these countries. The skewness parameter λ of the skewed-t innovation GARCH model is significant for all countries. The models adequately describe the data with some reservations. In the case of Japan the parameter λ is insignificant. However, a significant difference is evident in the volatility predictions. The graphs in Figure 5.4 compare the volatility prediction of the SGARCH under different innovation distributions.

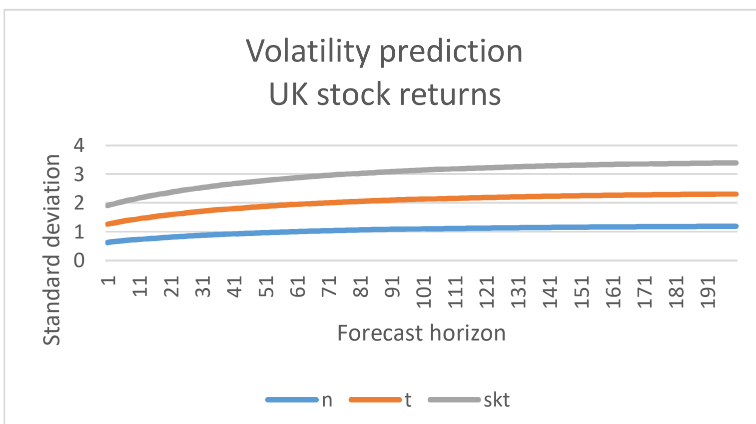
Figure 5.4: Forecast comparison GARCH models of stock returns under different innovations











Note 1: n indicate normal, t for student-t and skt indicate skewed student-t

Figure 5.4 compares the forecast volatility using GARCH with normal, Student-t and skewed Student-t innovation for stock returns series, which reveals the following characteristics.

Forecast volatility of the Australia stock returns captures most of the variation with skewed-t innovation. Volatility converges to approximately 3% for the chosen 200 forecast horizon, whereas under the normal innovation prediction, volatility converges to 1 as the forecast horizon increases. For the HK volatility prediction, skewed-t captures most of the tail thickness of the return series. Prediction volatility converges to approximately 4.5% as the forecast horizon increases, in the skewed Student-t distribution. For Japan, volatility prediction under skewed Student-t innovation increases as the forecast horizon increases and converges to approximately 5% as the forecast horizon increases. Volatility prediction for UK stock returns converges to around 3.5% as the forecast horizon increases. For US stock returns the prediction volatility converges to approximately 3.2% as the forecast horizon increases, according to skewed-t-innovation.

Among the five advanced stock markets, according to the return volatility predicted using the GARCH specification with skewed-t-innovation, Japan has the highest volatility as its forecast horizon increases, followed by HK, UK, US and then Australia. The other innovation distributions, such as the Gaussian and Student-t distributions capture comparatively less volatility. Financial volatility is an unobservable phenomenon and the return series have second and fourth moments with the highest concentration in the tail of the probability distribution with excess kurtosis, which indicates that the skewed Student-t distribution might have captured the volatility clustering and asymmetry of returns series by the GARCH skewed-t in all five advanced financial stock market volatilities. However, one important limitation with the GARCH is that leverage effects cannot be isolated by the GARCH skewed Student-t distribution. One could use GJR-GARCH for forecasting volatility considering leverage effects under a skewed Student-t innovation distribution. However, the results did not consider interactions among the stock markets. The interdependence among financial markets is discussed in Chapter 6.

5.3 Conclusion

This chapter dealt with univariate GARCH-type return volatility models. I considered three popular models of volatility: SGARCH, GJR-GARCH and GJR-GARCH-M models. I dealt with model specification issues including the functional form of unobservable volatility and modelling issues in joint description of the relationship between stock market volatility and expected stock returns for 17 stock markets. I estimated models using the ML method. In all cases I found volatility persistence. The implications of these findings are that any return shock on volatility persists. The short- and the long-run volatility parameters are statistically significant. The asymmetry or leverage parameter of the models was found to be significant, implying a significant leverage effect in the GARCH model. I tested for sign bias and size bias of the asymmetric volatility and found mixed results using F tests.

The leverage parameter γ in the GARCH-M model is significant for all countries except China and Malaysia. However, the risk premium parameter δ in the GARCH-M model is statistically non-significant; nevertheless, it has a positive sign (as volatility increases returns also increase), consistent with theory. The volatility predictions from each country's returns were found to be finite. I also compared the prediction volatility of GARCH specification with different return innovation distributions. The skewed Student-t captures more volatility than the Student-t and normal innovations. One drawback with the univariate analysis of financial markets is that the interdependence between volatilities and correlation of volatilities cannot be understood. This is the subject of Chapter 6.

Chapter 6: Multivariate Asset Returns and Volatility

6.1 Introduction

In this chapter, I extend the univariate financial asset to a multivariate set of assets and empirically investigate patterns of dependence among assets returns across financial markets locally and globally. Specifically, the first and second conditional moments of the DGP are of interest for joint investigation of the multivariate financial data for two reasons. First, at least the first two moments of a DGP are required to construct the probability distribution of a stochastic process statistically. Second, from the financial applications point of view, the first conditional moment determines a vector of 'returns' and the matrix of second central moments determines a measure of 'risk' of holding and trading assets in financial markets. Since variance is usually unknown, various types of measure of volatility are addressed in the literature. These include implied volatility, realised volatility and conditional volatility as mentioned in Chapter 4. Starting with the Engle–Kroner BEKK model developed in 1995 for the multivariate volatility (i.e. second central moment) and multivariate VARMA mean (i.e. first moment). This chapter specifies various forms of conditional expected returns and volatility of returns for addressing financial market issues for example, interdependence, causality, co-volatility and spillover effects, both locally and globally by applying valid statistical inference.

A range of methodological novelties are applied here to the multivariate context namely, conditional DBEKK volatility, VAR, PVAR, nonparametric dependence and copula links to specify and estimate multivariate risk-return (or mean variance) models in real applications. The models are estimated and hypotheses tested using highly sophisticated statistical methods for inferential purposes to address the research questions of interest as presented in Chapter 1. Various estimation techniques are utilised for estimation purposes; in particular the QML, GMM, OLS and SUR methods. I extend the definition of co-volatility to multivariate asymmetric volatility models. The volatility risk premium model of the conditional mean is tested for the applicability of the general concept of the RE hypothesis in finance. I develop a variant of the Wald test for partial co-volatility and asymmetric co-volatility spillover tests jointly by utilising a novel asymptotic chi-square test. I conduct covariance dependence tests using asymptotic chi-square tests. Granger causality-type return spillovers; aggregate forecast volatility spillover effects across markets; nonparametric correlation and covariance tests; and contagion effects tests are conducted in the multivariate framework.

This chapter is organised as follows. Section 6.2 addresses RQ1: 'Do volatilities of returns spillover symmetrically?' I address RQ2, 'Do risk premiums exist in international financial markets?' in Section 6.3. RQ3, 'Does the severity of crisis affect asset markets globally?' is discussed in Sections 6.4 and 6.5. Section 6.6 explores RQ4: 'Are financial returns dependent across countries?' and finally, Section 6.7 summarises the chapter.

6.2 The VAR-DBEKK-GJR-GARCH Model

To address RQ1, I specify a multivariate risk-return model as follows. The conditional mean model is:

$$r_t \mid F_{t-1} = \Phi_0 + \Phi_1 r_{t-1} + \varepsilon_t \tag{6.1}$$

where r_t is a vector of asset returns of order ($N \times 1$); F_{t-1} is the set of information available at time $t-1$; z_t is a vector of random variables of order ($N \times 1$) that are assumed iid with zero mean vector and identity variance–covariance matrix of order $(\mathrm{N}{\times}\mathrm{N})$; the parameters Φ_0 and Φ_1 are to be estimated along with the unknown parameters in the H_t; and ε_t is a random (Nx1) vector of variables often called the shock, noise or error variable is a vector of random coefficient autoregressive process of order one. Following Chang and McAleer (2017) and Engle and Kroner (1995), the multivariate extension of the univariate relationship between return shocks and standardised residuals $e_t = \frac{\varepsilon_t}{\sqrt{h_t}}$ (see Chapters 4 and 5) is a useful multivariate relationship given by $\varepsilon_t = [(diag(h_{1t}, h_{2t}, ..., h_{Nt})]^{1/2} e_t$. The random vector e is assumed is an iid process with mean zero and covariance matrix $\mathrm{CC'}$. Let the covariance matrix of ε_t be H_t.

Then I specify the conditional variance–covariance model as:

$$\mathrm{H_t|F_{t-1}} = \mathrm{CC'} + \mathrm{A}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\mathrm{A}^{'} + \mathrm{BH_{t-1}B}^{'} + \Gamma\,\mathrm{D_{t-1}}\varepsilon_{t-1}\varepsilon_{t-1}^{'}\Gamma' \tag{6.2}$$

where $\mathrm{D}_{\text{t-1}}$ is an indicator matrix that determines the asymmetric effect of return shocks on volatility, defined as $D = \begin{cases} 1 \;\; if \;\; \varepsilon_{t-1} < 0 \\ 0 \; if \;\; \varepsilon_{t-1} \leq 0 \end{cases}$; C is a ($N \times N$) lower triangular matrix; and A, B and Γ are each ($N\times N$) diagonal matrices. Model (6.2) is the DBEKK-GJR-GARCH model used here.

In model (6.2) I have used DBEKK because the QMLEs of the full BEKK parameters do not have asymptotic statistical properties. Hence the classical statistical tests are not valid in the full BEKK-GARCH for statistical inference model (Chang et al., 2018). However, the QMLEs of the DBEKK-GJR-GARCH parameter are consistent and asymptotically normally distributed. Models (6.1) and (6.2) are estimated jointly by the QML method for each block of countries; that is, developed, advanced emerging and emerging.

6.2.1 Developed markets

I considered the US, UK, HK, Japan and Australian stock markets to explore the dependence among stock markets for the block of developed markets. A sample of 5,767 useable observations for the period 2 April 1986–30 December 30 2016 was collected. I first tested the return series for stationarity using the ADF, PP and KPSS tests, with results as shown in Table 6.1. This is followed by descriptive summary statistics of the stock returns series for the developed countries in Table 6.2. I then tested for returns spillovers using the Granger causality test and tests for asymmetric partial co-volatility using a Wald-type test.

The test results shown in Table 6.1 indicate the return series are stationary, while the results in Table 6.2 show that all the return series have heavy-tailed distributions and are significantly negatively skewed. The normality of the series is rejected by the JB test. I estimated the model by QMLE. For analysis purposes I formed three groups of triplet countries returns. To address RQ1, I analysed the three triplet models for the developed markets followed by those for the advanced and emerging markets.

Table 6.1: Unit root test of stock returns for the developed countries

Country	ADF	PP	KPSS
US	–35.5064***	–78.2112***	0.152673
UK	–35.5735***	–78.2792***	0.112562
HK	–33.3865***	–76.4015***	0.226608
Japan	–35.0132***	–74.5989***	0.112724
Australia	–34.4008***	–70.6468***	0.066812

Note. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 6.2: Descriptive summary statistics

Country	Min	Max	Mean	SD	Skewness	Excess kurtosis	JB-statistic
US	–19.207	11.172	0.042**	1.266	–0.764***	16.363***	64889.958***
UK	–31.167	9.145	0.0250	1.346	–2.122***	53.448***	690670.793***
HK	–40.542	19.0415	0.045*	1.981	–1.826***	43.057***	448606.683***
Japan	–17.457	14.597	0.003	1.615	–0.607***	9.881***	23812.608***
Australia	–41.589	5.597	0.028*	1.185	–7.810***	266.025***	17061072.5***

Note. ***, ** and * indicate significance at the 1%, 5% and 10% level.

6.2.1.1 *Mean models for developed markets*

For multivariate analysis of developed markets, I jointly estimated models (6.1) and (6.2) using the QML method of estimation. The results are reported in Table 6.3.

Table 6.3: Mean model for developed markets

Dependent variable (stock returns)	**Independent variable (lagged returns)**			
	Constant	**Japan**	**UK**	**US**
US	0.04790***	0.00605	0.02423**	0.0004
	(0.0087)	(0.0075)	(0.01050)	(0.0104)
UK	0.0244**	–0.0089	–0.1712***	0.2790***
	(0.0100)	(0.0091)	(0.0119)	(0.0115)
Japan	–0.0067	–0.0114	0.0399***	0.1513***
	(0.0124)	(0.0137)	(0.0143)	(0.0128)
	Constant	**Australia**	**UK**	**US**
Australia	0.0178***	–0.0223**	0.1318***	0.1879***
	(0.0058)	(0.0110)	(0.0065)	(0.0101)
UK	0.0139	0.0186	–0.1087***	0.2026***
	(0.0096)	(0.0126)	(0.0130)	(0.0131)
US	0.0641***	0.0128	0.0562***	–0.0358***
	(0.0107)	(0.0114)	(0.0119)	(0.0130)
	Constant	**HK**	**Japan**	**US**
HK	0.0721***	0.0153	–0.0209**	0.0914***
	(0.0147)	(0.0102)	(0.0092)	(0.0140)
Japan	0.0002	0.0319***	–0.0038	0.1332***
	(0.0124)	(0.0077)	(0.0108)	(0.0113)
US	0.0582***	0.0116**	0.0168***	–0.0144
	(0.0086)	(0.0054)	(0.0059)	(0.0102)

Note 1. Values in parenthesis are the standard errors of the estimate.
Note 2. ***, ** and * indicate significance at the 1%, 5% and 10% level respectively.
Note 1 and Note 2 of significance apply in the following results unless stated otherwise.

In Table 6.3 for every block of developed markets significant causality is observed. Causality running from the UK to the US stock market and vice versa indicates bi-directional causality (interdependence; i.e. mutual dependence) between these two markets; whereas the Japan stock market shows unidirectional causality running from each of the US and UK stock markets. Similarly, there is significant causality running from both US and UK stock returns to the Australian stock market, but the Australian stock market does not influence UK or US stock markets. Both Japan and HK have a significant casual effect on the US stock market with varying degrees of significance. There is bi-directional causality running from HK to Japan and vice versa, and from Japan to the US and vice versa. This is an important finding in relation to portfolio diversification strategies for optimal expected stock returns.

Table 6.4: Conditional volatility models for developed markets

Conditional volatility model for Japan, US and UK

$$\hat{C}=\begin{pmatrix} \underset{(0.0051)}{0.1223^{***}} & 0 & 0 \\ \underset{(0.0050)}{0.0727^{***}} & \underset{(0.0039)}{0.0875^{***}} & 0 \\ \underset{(0.0068)}{0.0526^{***}} & \underset{(0.0084)}{0.0741^{***}} & \underset{(0.0075)}{0.1903^{***}} \end{pmatrix} \quad \hat{A}=\begin{pmatrix} \underset{(0.0087)}{0.1104^{***}} & 0 & 0 \\ 0 & \underset{(0.0014)}{0.1908^{***}} & 0 \\ 0 & 0 & \underset{(0.0184)}{0.1184^{***}} \end{pmatrix} \quad \hat{B}=\begin{pmatrix} \underset{(0.0012)}{0.9696^{***}} & 0 & 0 \\ 0 & \underset{(0.0005)}{0.9707^{***}} & 0 \\ 0 & 0 & \underset{(0.0016)}{0.9620^{***}} \end{pmatrix} \quad \hat{\Gamma}=\begin{pmatrix} \underset{(0.0079)}{0.2768^{***}} & 0 & 0 \\ 0 & \underset{(0.0040)}{0.1973^{***}} & 0 \\ 0 & 0 & \underset{(0.0085)}{0.3084^{***}} \end{pmatrix}$$

Conditional volatility model for Australia, US and UK

$$\hat{C}=\begin{pmatrix} \underset{(0.0061)}{0.1931^{***}} & 0 & 0 \\ \underset{(0.0061)}{0.0643^{***}} & \underset{(0.0099)}{0.1714^{***}} & 0 \\ \underset{(0.0053)}{0.0597^{***}} & \underset{(0.0084)}{0.0861^{***}} & \underset{(0.0056)}{0.1013^{***}} \end{pmatrix}, \quad \hat{A}=\begin{pmatrix} \underset{(0.0075)}{0.2338^{***}} & 0 & 0 \\ 0 & \underset{(0.0085)}{0.1211^{***}} & 0 \\ 0 & 0 & \underset{(0.0102)}{0.2080^{***}} \end{pmatrix} \quad \hat{B}=\begin{pmatrix} \underset{(0.0029)}{0.9241^{***}} & 0 & 0 \\ 0 & \underset{(0.0031)}{0.9526^{***}} & 0 \\ 0 & 0 & \underset{(0.0024)}{0.9627^{***}} \end{pmatrix} \quad \hat{\Gamma}=\begin{pmatrix} \underset{(0.0060)}{0.4286^{***}} & 0 & 0 \\ 0 & \underset{(0.0113)}{0.3648^{***}} & 0 \\ 0 & 0 & \underset{(0.0108)}{0.1757^{***}} \end{pmatrix}$$

Conditional volatility model for HK, Japan and US

$$\hat{C}=\begin{pmatrix} \underset{(0.0066)}{0.2720^{***}} & 0 & 0 \\ \underset{(0.0028)}{0.1555^{***}} & \underset{(0.0043)}{0.2006^{***}} & 0 \\ \underset{(0.0031)}{0.10267^{***}} & \underset{(0.0028)}{-0.0176^{***}} & \underset{(0.0019)}{0.1174^{***}} \end{pmatrix}, \quad \hat{A}=\begin{pmatrix} \underset{(0.0013)}{0.3058^{***}} & 0 & 0 \\ 0 & \underset{(0.0033)}{0.1235^{***}} & 0 \\ 0 & 0 & \underset{(0.0043)}{0.1578^{***}} \end{pmatrix} \quad \hat{B}=\begin{pmatrix} \underset{(0.0008)}{0.9401^{***}} & 0 & 0 \\ 0 & \underset{(0.0004)}{0.9542^{***}} & 0 \\ 0 & 0 & \underset{(0.0003)}{0.9590^{***}} \end{pmatrix}, \quad \hat{\Gamma}=\begin{pmatrix} \underset{(0.0063)}{0.1296^{***}} & 0 & 0 \\ 0 & \underset{(0.0034)}{0.3199^{***}} & 0 \\ 0 & 0 & \underset{(0.0047)}{0.2734^{***}} \end{pmatrix}$$

6.2.1.2 *Conditional volatility models for developed markets*

Estimation of the parameter matrices for the conditional volatility DBEKK-GJR-GARCH model is now described.

In the conditional volatility model for US, UK and Japan reported in Table 6.4, the weight matrix A represents the short-run effects of return shocks for US, UK and Japan on volatility and matrix B represents the long-run persistence of the shocks. The short- and long-run effects are all significant for the three models. The parameter $\widehat{\Gamma}$ represents the asymmetric effects of return shocks on volatility. The asymmetric return shocks are highly significant in all cases, indicating that asymmetric (leverage) effects of return shock exist in return volatility; that is, the return shocks asymmetrically influence the conditional volatility. This data-inherent information on the volatility-generating process is useful for determining the effects of the risk of holding assets in financial markets. The concept of risk premiums in multiple asset markets in multivariate asset return volatility is treated in the next section.

6.2.1.3 *Adequacy of mean and volatility models for developed markets*

Adequacy of the mean and volatility model was tested by the multivariate LB Q-statistic using the multivariate standardised residuals and squared standardised residuals. The null hypothesis was tested against the alternative hypothesis for the three variables jointly with 10 lags for serial dependence. The hypotheses tested were:

$$\mathrm{H}_0 : \rho_1 = \rho_2 = ... = \rho_{10}$$

$$\mathrm{H}_1 : \rho_1 \neq \rho_2 \neq .... \neq \rho_{10}$$

The LB-Q and LB-Q^2 statistics follow a multivariate χ^2 distribution with k^2m degrees of freedom. In the current application, $k = 3$ (number of assets) and m=10 (number of lagged serial correlations). The test results are provided in Table 6.5.

The joint multivariate mean variance model reported in Table 6.5 shows no serial dependence of the residuals according to the LB-Q test. The test result indicates that the mean and variance matrix functions are correctly specified. Note that for HK–Japan–US case, serial correlation of the standardised and standardised squared residuals is not significant at the 1% level. Similarly, for the Australia–US–UK case, serial correlation of the standardised residuals is not significant at the 1% level in the mean model. Therefore, models (6.1) and (6.2) jointly adequately describe the data for all the models, at least at the 1% level.

Table 6.5: LB-Q test

Model	Multivariate Q(10)	Sig. level (χ^2 (90))
Japan, US and UK		
Mean	106.21749	0.11664
Volatility	77.57355	0.8218
Australia, US and UK		
Mean	137.34423	0.02976
Volatility	86.32662	0.93829
HK, Japan and US		
Mean	134.82827	0.04115
Volatility	121.25550	0.01567

6.2.1.4 *Asymmetric partial co-volatility*

To test for asymmetric volatility spillovers, I tested the following hypotheses:

$$\mathrm{H}_0 : \gamma_{11} = \gamma_{22} = \gamma_{33} = 0$$

$$\mathrm{H}_1 : \gamma_{11} \neq \gamma_{22} \neq \gamma_{33} \neq 0$$

Table 6.6: Asymmetric volatility

Model	χ^2(3)
Japan, US and UK	15341.231 (0.000)
Australia, US and UK	6287.688 (0.000)
HK, Japan and US	1078.994 (0.000)

Significant asymmetric volatility spillovers were detected by the Wald chi-square tests reported in Table 6.6 for all three DBEKK-GJR-GARCH models.

6.2.1.5 *Asymmetric partial co-volatility*

Based on the definition of partial co-volatility (see Chapter 4), I estimated asymmetric partial co-volatility by estimating the asymmetric matrix coefficient $\hat{\Gamma}$ and the computed average co-volatility spillovers evaluated for the mean return shocks, as reported in Table 6.7.

Table 6.7: Asymmetric partial co-volatility

Partial co-volatility between countries	Average co-volatility spillovers
US and UK at average UK return shock	$\hat{\gamma}_{11}\hat{\gamma}_{22}\overline{\varepsilon}_{uk,t-1} = -0.000360$
US and Japan at average US return shock	$\hat{\gamma}_{11}\hat{\gamma}_{33}\overline{\varepsilon}_{usa,t-1} = -0.000605$
UK and Japan at average Japan return shock	$\hat{\gamma}_{22}\hat{\gamma}_{33}\overline{\varepsilon}_{Japan,t-1} = 0.00018$
Australia and UK at average Australian return shock	$\hat{\gamma}_{11}\hat{\gamma}_{22}\overline{\varepsilon}_{Aust,t-1} = -0.0000572$
UK and US at the average UK return shock	$\hat{\gamma}_{22}\hat{\gamma}_{33}\overline{\varepsilon}_{UK,t-1} = 0.000285$
Australia and US at average US return shock	$\hat{\gamma}_{11}\hat{\gamma}_{33}\overline{\varepsilon}_{USA,t-1} = -0.00168$
HK and Japan at average Japan return shock	$\hat{\gamma}_{11}\hat{\gamma}_{22}\overline{\varepsilon}_{Japan,t-1} = -0.00129$
HK and US at average HK return shock	$\hat{\gamma}_{11}\hat{\gamma}_{33}\overline{\varepsilon}_{HK,t-1} = -0.000577$
Japan and US at average US return shock	$\hat{\gamma}_{22}\hat{\gamma}_{33}\overline{\varepsilon}_{USA,t-1} = -0.0142$

Note 1. Partial co-volatility spillovers: $\dfrac{\partial H_{ijt}}{\partial \varepsilon_{kt}}, i \neq j,\ k =$ either i or j (see Chapter 4)

A negative sign indicates, for example, that a shock in US stock has a one-period delayed negative impact on the conditional co-volatility between the two markets concerned, and vice versa. A positive sign has the opposite effect. For example, the positive sign between UK and Japan co-volatility at the average Japan return shock indicates a one-period delayed positive impact on the conditional co-volatility between the two markets.

6.2.2 Advanced emerging markets

I considered the Brazil, Malaysia, Mexico, and Thailand stock markets to explore the dynamic dependence among the financial markets of advanced emerging markets using the mean model (6.1) and covariance matrix (6.2) jointly by utilising the QMLE. I used a tri-variate model for a sample of 5,011 useable observations for the sample period 19 January 1994–29 December 2016. I also tested the return series for stationarity, and the results are reported in Table 6.8. Descriptive summary statistics are provided in Table 6.9.

Table 6.8: Unit root test of stock returns of the advanced emerging countries

Country	ADF	PP	KPSS
Brazil	–34.8721**	–67.6960**	0.652551
Malaysia	–31.3276**	–67.8826**	0.138644
Mexico	–31.9973**	–66.0708**	0.083322
Thailand	–30.9666**	–66.6461**	0.457344

Note. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 6.9: Descriptive statistics of stock returns of the advanced emerging financial markets

Country	Min	Max	Mean	SD	Skewness	Excess kurtosis	JB-statistic
Brazil	–17.226	46.320	0.090**	2.495	2.216***	44.640***	420177.273***
Malaysia	–25.001	36.873	0.007	1.462	2.410***	109.585***	2512249.699***
Mexico	–14.086	12.638	0.057**	1.615	–0.107***	9.125***	17397.778***
Thailand	–14.029	27.145	0.001	1.727	0.644***	17.345***	63165.181***

Note. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 6.8 shows that the return series are stationary, while the results of Table 6.9 show that all the return series have a heavy-tailed distribution and are significantly negatively skewed. All the series exhibit volatility clustering. Normality of the series is rejected by the JB test. For analysis purposes I created three tri-variate groups of advanced emerging countries.

6.2.2.1 *Mean models for advanced emerging markets*

For multivariate analysis of developed markets, I jointly estimated models (6.1) and (6.2) using the QML method of estimation (see Table 6.10).

Table 6.10: Mean model for advanced emerging markets

Dependent variable (stock return)	**Independent variable (lagged returns)**			
	Constant	**Brazil**	**Malaysia**	**Mexico**
Brazil	0.0382*	0.0070	–0.0743***	0.1029***
	(0.0206)	(0.0125)	(0.0158)	(0.0163)
Malaysia	0.0042	0.0276***	0.0836***	0.0529***
	(0.0086)	(0.0057)	(0.0143)	(0.0082)
Mexico	0.0391***	0.0143*	–0.0182*	0.0641***
	(0.0142)	(0.0083)	(0.0100)	(0.0127)
	Constant	**Brazil**	**Malaysia**	**Thailand**
Brazil	0.0438*	0.0127	–0.0854***	0.6630***
	(0.0234)	(0.0137)	(0.0225)	(0.0876)
Malaysia	0.0087	0.0405***	0.0912***	0.0507***
	(0.0079)	(0.0053)	(0.0141)	(0.0075)
Thailand	0.0447***	0.0245***	0.0574***	0.0441***
	(0.0158)	(0.0074)	(0.0175)	(0.0143)
	Constant	**Malaysia**	**Mexico**	**Thailand**
Malaysia	0.0106	0.0775***	0.0666***	0.0524***
	(0.0100)	(0.0137)	(0.0076)	(0.0072)
Mexico	0.0416***	–0.0217	0.0767***	0.0288***
	(0.0125)	(0.0169)	(0.0135)	(0.0109)
Thailand	0.0378**	0.0328*	0.0813***	0.03657**
	(0.0164)	(0.0184)	(0.0111)	(0.0145

Table 6.10 shows significant bi-directional causality running from Mexico and Malaysia to Brazil, and vice versa. Similarly, there is bi-directional causality running from Brazil and Thailand to Malaysia, and from Brazil and Malaysia to Thailand. Negative causality running from Malaysia to Brazil and Malaysia to Mexico indicates a trade-off in the short run between these countries. It is interesting to observe that Malaysia returns shocks negatively spillover to Brazil. Further, bi-directional stock returns spillover from Mexico and Thailand to Malaysia. However, only Thailand stock returns influence Mexico returns. Estimates of the parameter matrices of the conditional volatility DBEKK-GJR-GARCH model are shown in Table 6.11.

Table 6.11: Conditional volatility models for advanced emerging markets

Conditional volatility model for Brazil, Malaysia and Mexico

$$\hat{C}=\begin{pmatrix} 0.2975^{***} & 0 & 0 \\ (0.0218) & & \\ 0.0066 & 0.0903^{***} & 0 \\ (0.0052) & (0.0069) & \\ 0.1146^{***} & 0.0222^{**} & -0.0855^{***} \\ (0.0094) & (0.0096) & (0.0115) \end{pmatrix}, \hat{A}=\begin{pmatrix} 0.2363^{***} & 0 & 0 \\ (0.0126) & & \\ 0 & 0.2311^{***} & 0 \\ & (0.0116) & \\ 0 & 0 & 0.0527^{***} \\ & & (0.0136) \end{pmatrix} \hat{B}=\begin{pmatrix} 0.9430^{***} & 0 & 0 \\ (0.0039) & & \\ 0 & 0.9578^{***} & 0 \\ & (0.0029) & \\ 0 & 0 & 0.9707^{***} \\ & & (0.0017) \end{pmatrix} \hat{\Gamma}=\begin{pmatrix} 0.2986^{***} & 0 & 0 \\ (0.0175) & & \\ 0 & 0.2449^{***} & 0 \\ & (0.0178) & \\ 0 & 0 & 0.3101^{***} \\ & & (0.0110) \end{pmatrix}$$

Conditional volatility model for Brazil, Malaysia and Thailand

$$\hat{C}=\begin{pmatrix} 0.3360^{***} & 0 & 0 \\ (0.0279) & & \\ 0.0497^{***} & 0.0987^{***} & 0 \\ (0.0083) & (0.00778) & \\ -0.0712^{***} & 0.0795^{***} & 0.2213^{***} \\ (0.0255) & (0.0191) & (0.0182) \end{pmatrix}, \hat{A}=\begin{pmatrix} 0.3134^{***} & 0 & 0 \\ (0.0124) & & \\ 0 & 0.1875^{***} & 0 \\ & (0.0117) & \\ 0 & 0 & 0.2946^{***} \\ & & (0.0129) \end{pmatrix} \hat{B}=\begin{pmatrix} 0.9336^{***} & 0 & 0 \\ (0.0056) & & \\ 0 & 0.9540^{***} & 0 \\ & (0.0027) & \\ 0 & 0 & 0.9345^{***} \\ & & (0.0047) \end{pmatrix} \hat{\Gamma}=\begin{pmatrix} -0.1615^{***} & 0 & 0 \\ (0.0316) & & \\ 0 & 0.3143^{***} & 0 \\ & (0.0156) & \\ 0 & 0 & 0.2186^{***} \\ & & (0.0230) \end{pmatrix}$$

Conditional volatility model for Malaysia, Mexico and Thailand

$$\hat{C}=\begin{pmatrix} 0.0905^{***} & 0 & 0 \\ (0.0072) & & \\ 0.0352^{***} & 0.1356^{***} & 0 \\ (0.0117) & (0.0111) & \\ 0.0501^{***} & 0.1058^{***} & 0.2266^{***} \\ (0.0159) & (0.0197) & 0.0144) \end{pmatrix}, \hat{A}=\begin{pmatrix} 0.2388^{***} & 0 & 0 \\ (0.0112) & & \\ 0 & 0.0625^{***} & 0 \\ & (0.0197) & \\ 0 & 0 & 0.3168^{***} \\ & & (0.0141) \end{pmatrix} \hat{B}=\begin{pmatrix} 0.9583^{***} & 0 & 0 \\ (0.0029) & & \\ 0 & 0.9674^{***} & 0 \\ & (0.0025) & \\ 0 & 0 & 0.9278^{***} \\ & & (0.0051) \end{pmatrix} \hat{\Gamma}=\begin{pmatrix} 0.2165^{***} & 0 & 0 \\ (0.0198) & & \\ 0 & 0.3328^{***} & 0 \\ & (0.0136) & \\ 0 & 0 & 0.2158^{***} \\ & & (0.0269) \end{pmatrix}$$

6.2.2.2 *Conditional volatility models for advanced emerging markets*

Estimated conditional volatility models are reported in Table 6.11. The weight matrix A represents the short-run effects of return shocks for Brazil, Mexico and Malaysia stock on volatility; matrix B represents the long-run persistence of the shocks, and vice versa. The short- and long-run effects are all significant for the three models. The leverage matrix $\widehat{\Gamma}$ shows that significant leverage (or asymmetric) effects are generated by bad news for stock markets in the case of Brazil, indicating that volatility decreases due to Brazil's own stock return shocks. This internal data-inherent information on the volatility-generating process is useful for determining the effects of the risk of holding assets in financial markets. The concept of the risk premium in multiple asset markets in terms of multivariate asset return volatility is treated in the next section.

6.2.2.3 *Adequacy of mean and volatility models for advanced emerging markets*

Adequacy of the mean and volatility model was tested by the multivariate LB Q-statistic using multivariate standardised residuals and squared standardised residuals displayed in Table 6.12. The null hypothesis was tested against the alternative hypothesis for the three variables jointly with 10 lags for serial dependence. The hypotheses tested were:

$$\mathrm{H}_0 : \rho_1 = \rho_2 = ... = \rho_{10}$$

$$\mathrm{H}_1 : \rho_1 \neq \rho_2 \neq .... \neq \rho_{10}$$

Table 6.12: LB-Q test

Model	**Multivariate Q(10)**	**Sig. level ($\chi^2(90)$)**
Brazil, Malaysia and Mexico		
Mean	59.6237	0.9943
Volatility	119.0673	0.0218
Brazil, Malaysia and Thailand		
Mean	75.1193	0.8700
Volatility	123.5696	0.0111
Malaysia, Mexico and Thailand		
Mean	67.0527	0.9665
Volatility	72.0556	0.9174

The joint multivariate mean variance model reported in Table 6.12 shows no serial dependence, at least at the 1% level, for the standardised squared residuals by the LB-Q test.

The test results indicate that the mean and variance matrix functions are correctly specified. Therefore, models (6.1) and (6.2) jointly adequately describe the data for all models.

6.2.2.4 *Asymmetric partial co-volatility*

I then tested for the effects of returns shocks on asymmetric partial co-volatility by testing the following hypotheses provided in Table 6.13:

$$H_0 : \gamma_{11} = \gamma_{22} = \gamma_{33} = 0$$

$$H_1 : \gamma_{11} \neq \gamma_{22} \neq \gamma_{33} \neq 0$$

Table 6.13: Asymmetric partial co-volatility

Model	**χ^2(3)**
Brazil, Malaysia and Mexico	951.440 (0.000)
Brazil, Malaysia and Thailand	693.265 (0.000)
Malaysia, Mexico and Thailand	722.582 (0.000)

I found significant asymmetric volatility spillovers by the Wald chi-square tests reported in table 6.13 for all three DBEKK-GJR-GARCH models.

6.2.2.5 *Asymmetric partial co-volatility*

Further, I computed asymmetric partial co-volatility (as defined in Chapter 4) (see Table 6.14). As outlined above, a negative sign indicates that a shock, for example in Thailand stock, has a one-period delayed impact on the conditional co-volatility between the two markets concerned. A positive sign has the opposite effect**.** The partial co-volatility was computed for the return shocks.

Table 6.14: Asymmetri partial co-volatility spillovers

Partial co-volatility between countries	Parameter and value
Brazil and Malaysia at average Malaysian return shock	$\hat{\gamma}_{11}\hat{\gamma}_{22}\overline{\varepsilon}_{Malaysia,t-1} = -0.000160$
Brazil and Mexico at average Brazil return shock	$\hat{\gamma}_{11}\hat{\gamma}_{33}\overline{\varepsilon}_{Brazil,t-1} = 0.00415$
Malaysia and Mexico at average Mexico return shock	$\hat{\gamma}_{22}\hat{\gamma}_{33}\overline{\varepsilon}_{Mexica,t-1} = 0.00100$
Brazil and Malaysia at average Malaysia return shock	$\hat{\gamma}_{11}\hat{\gamma}_{22}\overline{\varepsilon}_{Malaysia,t-1} = 0.000251$
Brazil and Thailand at average Brazil return shock	$\hat{\gamma}_{11}\hat{\gamma}_{33}\overline{\varepsilon}_{Brazil,t-1} = -0.001554$
Malaysia and Thailand at average Thailand return shock	$\hat{\gamma}_{22}\hat{\gamma}_{33}\overline{\varepsilon}_{Thailand,t-1} = -0.00318$
Malaysia and Mexico at average Mexico return shock	$\hat{\gamma}_{11}\hat{\gamma}_{22}\overline{\varepsilon}_{Mexico,t-1} = 0.000813$
Malaysia and Thailand at average Malaysian return shock	$\hat{\gamma}_{11}\hat{\gamma}_{33}\overline{\varepsilon}_{Malaysia,t-1} = -0.000318$
Mexico and Thailand at average Thailand return shock	$\hat{\gamma}_{22}\hat{\gamma}_{33}\overline{\varepsilon}_{Thailand,t-1} = -0.00299$

6.2.3 Emerging financial markets

I considered the China, India and Indonesia stock markets to study the dependence among emerging financial markets by estimating models (6.1) and (6.2) jointly utilising the QMLE. I used a tri-variate model for a sample of 5,565 useable observations, for the sample period 19 December 1990–30 December 2016. I tested the return series for stationarity (see Table 6.15).

Table 6.15: Unit root test of stock returns for the emerging countries

Country	ADF	PP	KPSS
China	–31.5399**	–76.0380**	0.326351
India	–32.8299**	–76.5831**	0.099538
Indonesia	–33.4691**	–65.2908**	0.129427

Note. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 6.16: Descriptive statistics for the stock returns of the emerging countries

Country	Min	Max	Mean	SD	Skewness	Excess Kurtosis	JB-statistic
China	–31.703	74.968	0.062*	2.778	4.005***	111.184**	2881295.115***
India	–11.383	16.153	0.057**	1.914	0.012	5.629***	7349.234***
Indonesia	–12.893	18.830	0.046**	1.619	–0.022	11.849***	32557.776***

Note. ***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 6.15 indicates that the return series are stationary while the results in Table 6.16 show that all the return series have heavy-tailed distributions and are significantly skewed. Only the China stock returns series is negatively skewed. Neither the India nor Indonesia stocks are skewed but both are heavy-tailed. All the series exhibit volatility clustering. The normality of the series is rejected by the JB test. For analysis purposes I created one tri-variate group of advanced emerging countries.

6.2.3.1 *Mean models for emerging markets*

For multivariate analysis of China, India and Indonesia, I jointly estimated models (6.1) and (6.2) by the QML method of estimation and the results are reported in Table 6.17.

Table 6.17: Mean model for emerging markets

Dependent variable	**Independent variable (lagged returns)**			
	Constant	**China**	**India**	**Indonesia**
China	0.0447***	–0.0427**	0.0124	0.0078
	(0.0155)	(0.0136)	(0.0117)	(0.0110)
India	0.0608***	0.0010	–0.0077	0.0428***
	(0.0175)	(0.0063)	(0.0116)	(0.0108)
Indonesia	0.0471***	–0.0059	0.0478***	0.1763***
	(0.0143)	(0.0042)	(0.0079)	(0.0135)

The mean model results in Table 6.17 show there are no return spillovers from India and Indonesia to China. However, there exists bi-directional causality between India and Indonesia. This result for the emerging stock markets of China, India and Indonesia indicates that participants in these markets should carefully consider their investment decisions.

6.2.3.2 *Conditional volatility models for emerging markets*

The conditional volatility DBEKK-GJR-GARCH model parameter matrices are provided in Table 6.18.

Table 6.18: Conditional volatility models for emerging markets

$$\widehat{C} = \begin{pmatrix} 0.2436^{***} & 0 & 0 \\ (0.0146) & & \\ 0.0608^{***} & 0.1575^{***} & 0 \\ (0.0139) & (0.0146) & \\ 0.0562^{***} & 0.0077^{***} & 0.2134^{***} \\ (0.0133) & (0.0145) & (0.0145) \end{pmatrix}, \quad \widehat{A} = \begin{pmatrix} 0.3560^{***} & 0 & 0 \\ (0.0097) & & \\ 0 & 0.2253^{***} & 0 \\ & (0.0121) & \\ 0 & 0 & 0.2274^{***} \\ & & (0.0142) \end{pmatrix}$$

$$\widehat{B} = \begin{pmatrix} 0.9387^{***} & 0 & 0 \\ (0.0030) & & \\ 0 & 0.9613^{***} & 0 \\ & (0.0027) & \\ 0 & 0 & 0.9424^{***} \\ & & (0.0051) \end{pmatrix} \quad \widehat{\Gamma} = \begin{pmatrix} -0.0695^{***} & 0 & 0 \\ (0.0254) & & \\ 0 & 0.2021^{***} & 0 \\ & (0.0229) & \\ 0 & 0 & 0.3018^{***} \\ & & (0.0191) \end{pmatrix}$$

The short- and long-run conditional volatility parameters are also highly significant, with variation in the size of the coefficient. The asymmetric news effects on volatility are positive and significant, indicating leverage of news on volatility.

6.2.3.3 *Adequacy of mean and volatility models for advanced emerging markets*

Adequacy of the mean and volatility model was tested by the multivariate LB Q-statistic using the multivariate standardised residuals and squared standardised residuals. The null hypothesis was tested against the alternative hypothesis for the three variables jointly with 10 lags for serial dependence. The hypotheses tested were:

$$H_0 : \rho_1 = \rho_2 = ... = \rho_{10}$$

$$H_1 : \rho_1 \neq \rho_2 \neq .... \neq \rho_{10}$$

Table 6.19: LB-Q test for emerging markets

Model for China, India and Indonesia	**Multivariate Q(10)**	**Sig. level ($\chi^2(90)$)**
Mean	87.3459	0.5596
Volatility	90.6380	0.4613

The joint multivariate mean variance model reported in Table 6.19 indicates no serial dependence of the standardised residuals and squared standardised residuals by the LB-Q and LB-Q^2 tests. The test results indicate that the mean and variance matrix functions are correctly specified. Therefore, models (6.1) and (6.2) jointly adequately describe the data for all the models.

6.2.3.4 *Asymmetric partial co-volatility*

I then tested for the effects of returns shocks on asymmetric partial co-volatility by testing the following hypotheses:

$$\mathrm{H}_0 : \gamma_{11} = \gamma_{22} = \gamma_{33} = 0$$

$$\mathrm{H}_1 : \gamma_{11} \neq \gamma_{22} \neq \gamma_{33} \neq 0$$

Table 6.20: Asymmetric partial co-volatility for emerging markets

Model	$\chi^2(3)$
China, India, Indonesia	468.359 (0.000)

The test results in Table 6.20 indicate that the China, India and Indonesia stock markets jointly explain significant asymmetric returns shocks effects that exist on conditional volatility.

6.2.3.5 *Asymmetric partial co-volatility*

I computed the partial co-volatility as reported in Table 6.21.

Table 6.21: Asymmetric partial co-volatility for emerging markets

Partial co-volatility between countries	**Parameter and value**
China and India at average India return shock	$\hat{\gamma}_{11}\hat{\gamma}_{22}\overline{\varepsilon}_{India,t-1} = 0.000058$
China and Indonesia at average China return shock	$\hat{\gamma}_{11}\hat{\gamma}_{33}\overline{\varepsilon}_{China,t-1} = -0.000354$
India and Indonesia at average Indonesia return shock	$\hat{\gamma}_{22}\hat{\gamma}_{33}\overline{\varepsilon}_{Indonesia,t-1} = -0.00068$

A negative sign indicates that, for example a shock in China stock will have a one-period delayed impact on the conditional co-volatility between the two markets concerned. A positive sign has the opposite effect. Partial co-volatility transmission provides additional information about volatility movement in stock markets.

6.2.4 Summary of DBEKK-GARCH model results

The above analyses revealed significant Granger causality-type stock returns spillovers. I also found significant asymmetric news volatility spillovers in developed, advanced emerging and emerging markets using chi-square tests. I also computed partial co-volatility spillovers across countries. This information is useful for portfolio management and asset diversification in global stock markets.

6.3 The VAR-DBEKK-GJR-GARCH-M Model

In this section, I develop the multivariate risk premium model by extending the univariate autoregressive ARCH-M to include the multivariate DBEKK-GJR-GARCH-M model volatility in the conditional mean return to address RQ2. In this form the mean model could be considered a multivariate extension of a time-varying CAPM-type model. The model is used for testing the appropriateness of the RE theory for financial markets. The VAR-DBEKK-GJR-GARCH-M model is estimated by the QML method using the 5-year government bond data of US, Japan and Australia for a sample of 5,862 useable observations, starting on 31 August 1990 and ending on 30 December 2016. The estimated model is used to identify the co-volatility spillover effect according to the extended co-volatility spillover definition (see Chapter 4) and tested for the existence of co-volatility using a novel Wald-type test for this context.

6.3.1 The VAR-DBEKK-GJR-GARCH-M model

The following form of the risk premium model is well established in the univariate case (see Engle et al., 1987). The multivariate counterpart (DBEKK-GJR-GARCH-M model) takes the following form:

$$r_t \mid F_{t-1} = \Phi_0 + \sum_{i=1}^{k} \Phi_i r_{t\text{-}i} + h_t \delta + \varepsilon_t \tag{6.3}$$

where $\varepsilon_t = h_t^{1/2} z_t$, $h_t = diag(h_{1t}, h_{2t}, ..., h_{Nt})$ (see Section 6 above), δ is an $(N \times 1)$ vector of risk premium parameters. The first-order DBEKK-GJR-GARCH model takes the following form:

$$H_t \mid F_{t-1} = CC' + A\varepsilon_{t-1}\varepsilon_{t-1}^{'} A' + B\ H_{t-1} B^{'} + \Gamma\ D_{t-1}(\varepsilon_{t-1}\varepsilon_{t-1}^{'})\Gamma^{'} \tag{6.4}$$

where matrices A, B and Γ are diagonal and matrix C is a lower triangular matrix.

6.3.2 Analysis of US, Japan and Australian bond data

I estimate the multivariate DBEKK-GJR-GARCH-M Equation (6.3) with $k=1$ jointly for the US, Japan and Australian bond data using QML method. The QMLE of the trivariate DBEKK-GJR-GARCH-M are as follows:

$$US_t = \text{-}0.0592^{**}\text{-}0.0329^{***}US_{t-1}\text{-}0.0068^{**}Japan_{t-1}{+}0.0306^{**}Aus_{t-1}+0.00905^{***}h_{1t}+\varepsilon_{1,t} \quad (6.5.1)$$
$$(s.e) \quad (0.0206) \quad (0.0126) \quad (0.0032) \quad (0.0138) \quad (0.0044)$$
$$Japan_t = \text{-}0.1244^{***}{+}0.2510^{***}US_{t-1}\text{-}0.0082Japan_{t-1}{+}0.0068Aus_{t-1}+0.0009^{**}h_{2t}+\varepsilon_{2,t} \quad (6.5.2)$$
$$(s.e) \quad (0.0270) \quad (0.0146) \quad (0.0132) \quad (0.0196) \quad (0.0004)$$
$$Australia_t = \text{-}0.0112+0.2495^{***}US_{t-1}\text{-}0.0010Japan_{t-1}\text{-}0.1060^{***}Aus_{t-1}\text{-}0.0031h_{3t}+\varepsilon_{3,t} \quad (6.5.3)$$
$$(s.e) \quad (0.0194)\ (0.0065) \quad (0.0017) \quad (0.0110) \quad (0.0111)$$

The above results indicate that the conditional mean process for US bond markets, see Equation (6.5.1), has a significant impact of return shock on its own return shock as well as the shocks of Japan and Australia bond markets. Return spillovers running from Japan and Australia to the US market. I found significant risk premium in the US bond market. For the Japan bond market, see Equation (6.5.2), I found significant return spillover running from US bond market to Japan bond market. Equations (6.5.1) and (6.5.2) indicate bidirectional return spillover exists between US and Japan. While Equation (6.5.3) indicates unidirectional spill over only running from US bond market to Australia bond market. Interestingly I found insignificant risk premium in the Australia bond market. This means that the full expectation theory does not hold for the US, Japan and Australia bond markets. This information is useful for investment decisions in international bond markets.

The components of the estimated conditional volatility model are as follows.

$$\widehat{\mathrm{C}} = \begin{pmatrix} \underset{(0.0109)}{0.0758^{***}} & 0. & 0. \\ \underset{(0.0732)}{0.0071} & \underset{(0.0209)}{0.1896^{***}} & 0. \\ \underset{(0.0111)}{-0.0024} & \underset{(0.0192)}{0.0398^{**}} & \underset{(0.0186)}{0.0501^{***}} \end{pmatrix}, \quad \widehat{\mathrm{A}} = \begin{pmatrix} \underset{(0.0103)}{0.0813^{***}} & 0 & 0 \\ 0 & \underset{(0.0162)}{0.4216^{***}} & 0 \\ 0 & 0 & \underset{(0.0076)}{0.1582^{***}} \end{pmatrix}$$

$$\widehat{\mathrm{B}} = \begin{pmatrix} \underset{(0.0013)}{0.9830^{***}} & 0 & 0 \\ 0 & \underset{(0.0032)}{0.9211^{***}} & 0 \\ 0 & 0 & \underset{(0.0014)}{0.9833^{***}} \end{pmatrix}, \quad \widehat{\Gamma} = \begin{pmatrix} \underset{(0.0012)}{0.2407^{***}} & 0 & 0 \\ 0 & \underset{(0.0743)}{0.1607^{***}} & 0 \\ 0 & 0 & \underset{(0.0147)}{0.1282^{***}} \end{pmatrix}$$

The results of the weight matrices $\hat{\mathrm{A}}$ and $\hat{\mathrm{B}}$ shows respectively that the short and long-run volatility parameters are all significant at the 1% level. Indicating significant return shocks on volatility. Note that there is a significant negative "news" effect in all three bond markets confirmed by the significant weight matrix $\hat{\Gamma}$. The news effect on volatility provides useful information for investors and agents regarding international investment strategies in bond markets.

Average return shocks for the US, Japan and Australia are –0.00131, 0.09844, and –0.00445 respectively. I computed the partial covolatility spillovers using the following formula.

$$\frac{\partial}{\partial \varepsilon_{k,t-1}} \mathrm{H}_{ij,t}, i \neq j, k = \text{either } i \text{ or } j;$$

i,j,k = 1,2,3; US = 1, Japan = 2 and Australia = 3

The pairwise partial co-volatilities at the average shocks are as follows:

$$\frac{\partial H_{12,t}}{\partial \varepsilon_{1,t-1}} = a_{11}a_{22}\varepsilon_{2t-1} + \lambda_{11}\lambda_{22}\varepsilon_{2t-1} = 0.00718, \text{ or } \frac{\partial H_{12,t}}{\partial \varepsilon_{2,t-1}} = a_{11}a_{22}\varepsilon_{1t-1} + \lambda_{11}\lambda_{22}\varepsilon_{1t-1} = 0.0000955$$

$$\frac{\partial H_{13,t}}{\partial \varepsilon_{1,t-1}} = a_{33}a_{11}\varepsilon_{3t-1} + \lambda_{11}\lambda_{22}\varepsilon_{3t-1} = -0.000194, \text{ or } \frac{\partial H_{13,t}}{\partial \varepsilon_{3,t-1}} = a_{33}a_{11}\varepsilon_{1t-1} + \lambda_{11}\lambda_{22}\varepsilon_{1-1} = -0.000057$$

$$\frac{\partial H_{23,t}}{\partial \varepsilon_{2,t-1}} = a_{33}a_{22}\varepsilon_{3t-1} + \lambda_{11}\lambda_{22}\varepsilon_{3t-1} = -0.0003884, \text{ or } \frac{\partial H_{23,t}}{\partial \varepsilon_{3,t-1}} = a_{33}a_{22}\varepsilon_{2t-1} + \lambda_{11}\lambda_{22}\varepsilon_{2t-1} = 0.00859$$

A negative sign indicates, for example, that a shock in US bond has a one-period delayed negative impact on the conditional co-volatility between US and Australia, and vice versa. A positive sign has the opposite effect. For example, the positive sign between US and Japan co-volatility at the average US return shock indicates a one-period delayed positive impact on the conditional co-volatility between US and Japan.

Using the risk premium concept within the DBEKK-GJR-GARCH-M framework, the risk premium is measured by the estimated coefficient vector δ. The empirical results here indicate that a risk premium exists in both the US and Japan bond markets, but not in the bond market of Australia. The severity of the risk premium is very high in both US and Japan; however the severity in Japan is the highest based on the degree of likelihood of rejection of the risk premium. I performed a Wald-type test of asymmetric co-volatility spillover using the newly developed Wald-type test as follows.

1. $\mathrm{H}_0 : \begin{cases} a_{11} \times a_{22} = 0 \\ \lambda_{11} \times \lambda_{22} = 0 \end{cases}$ versus $\mathrm{H}_1 : \begin{cases} a_{11} \times a_{22} \neq 0 \\ \lambda_{11} \times \lambda_{22} \neq 0 \end{cases}$

The value of the test statistic was W = 7.67, with a p-value of 0.0216. I thus reject the null hypothesis of no co-volatility and no asymmetry jointly; that is, I conclude that there exists co-volatility and asymmetric news spillovers.

2. $\mathrm{H}_0 : \begin{cases} a_{11} \times a_{33} = 0 \\ \lambda_{11} \times \lambda_{33} = 0 \end{cases}$ versus $\mathrm{H}_1 : \begin{cases} a_{11} \times a_{33} \neq 0 \\ \lambda_{11} \times \lambda_{33} \neq 0 \end{cases}$

The value of the test statistic was W = 76.23 with a p-value of 0.0000. I thus reject the joint null hypothesis of no co-volatility and no asymmetry jointly in the conditional volatility model. This shows that there is a significant spillover from the return shock.

3. $\mathrm{H}_0 : \begin{cases} a_{33} \times a_{22} = 0 \\ \lambda_{33} \times \lambda_{22} = 0 \end{cases}$ versus $\mathrm{H}_1 : \begin{cases} a_{11} \times a_{33} \neq 0 \\ \lambda_{11} \times \lambda_{33} \neq 0 \end{cases}$

The value of the test statistic was W = 269.12 with a p-value of 0.0000**.** I thus reject the null hypothesis of no co-volatility and no asymmetry jointly in the conditional volatility model and conclude that significant co-volatility and leveraged spillover effects exist for volatility, and hence risk premium.

These test results indicate that there is a significant co-volatility spillover and asymmetry jointly in the US, Japan and Australian bond markets. This finding indicates the existence of co-volatility and asymmetry jointly in these three bond markets. This is useful information for decision making in these dynamic financial bond markets. The Wald-type test is an additional contribution of this thesis to the literature.

6.3.3 Summary of VAR-DBEKK-GJR-GARCH-M model results

I found significant asymmetric risk premiums in both the US and Japan bond returns; however, this is not significant in the case of the Australian bond market. Notably, there is a significant negative news effect in all three bond markets, which provides useful information for investors and agents regarding their diversification strategies in bond markets.

6.4 VAR Models

In this section I investigate interdependence among the financial markets across countries. Sims's VAR is used to explore interrelationships within the set of assets by utilising Granger causality, variance decomposition and impulse response analysis. The variance decompositions allow me to aggregate spillover effects across markets. To explore the linkages among financial markets across countries during crises, the VAR model is extended to include market crash events (X), reflecting financial crises such as 1987 crash, the AFC and the GFC. I call this model a near VAR or VAR-X model. A measure of the severity of market crash events is developed here to address RQ3.

Table 6.22: Descriptive statistics for 10 countries' stock returns

Country	Mean	SD	Min	Max	Skewness	Excess kurtosis	JB
Australia	0.035**	1.141	–34.021	5.757	–4.86***	140.82***	4787113.22***
Canada	0.039**	1.252	–15.736	13.215	–0.51***	16.18***	63136.66***
Germany	0.049**	1.639	–18.183	11.213	–0.49***	8.03**	15718.40***
HK	0.065**	1.955	–33.330	20.975	–0.78***	27.14***	177555.62***
India	0.087***	2.035	–14.473	23.507	0.26***	7.73***	14440.19***
Indonesia	0.095***	1.981	–20.172	49.644	3.69***	90.14***	1965335.29***
Japan	0.016	1.609	–16.018	15.716	–0.34***	8.87**	19041.22***
Malaysia	0.051**	1.667	–32.181	44.590	2.20***	126.95***	3876731.04***
UK	0.034***	1.331	–26.777	9.577	–1.26***	32.54***	255873.22***
US	0.050***	1.262	–17.475	11.821	–0.45***	13.98***	47043.98***

Note. ***, ** and * indicate significance at the 1%, 5% and 10% level.

6.4.1 Estimation of the VAR-X model

I have selected 10 countries from developed, advanced emerging and emerging countries with 5,776 observations for the period 2 April 1986–30 December 2016. First I report descriptive statistics (Table 6.22), unit root test results for each of the series and then multivariate LB test results and applied multivariate AIC, BIC and HQ criteria for VAR lag order selection. I settled on HQ, which produces a lag length of 2 for the VAR-X estimation. The return series were tested for stationarity using the ADF, PP and KPSS tests. Multivariate serial correlation was tested by utilising the multivariate counterpart of the LB test. The X in the model indicates the set of exogenous variables in the extended multivariate VAR model and the variables in X include the 1987 crash, AFC and GFC. The model was estimated by the OLS using Cholesky factorisation.

Table 6.22 shows that the mean is statistically significant for all countries at the conventional (5%) level, with the exception of that for Japan stock returns. The log return series were found to be non-normal by the JB test. All the series are negatively skewed except those of India, Indonesia and Malaysia. All series have heavy-tailed distributions according to excess kurtosis tests. Table 6.23 reports the unit root test results for the stock returns series of each country.

Table 6.23: Unit root test

Country	ADF	PP	KPSS
	H_0 :Nonstationarity H_1: Stationarity	H_0: Nonstationarity H_1: Stationarity	H_0: Stationarity H_1: Nonstationarity
Australia	–34.6170***	–70.8212***	0.0932
Canada	–35.4875***	–74.8698***	0.0461
Germany	–34.7017***	–75.9860***	0.0429
HK	–33.7986***	–76.7160***	0.2960
India	–33.6831***	–77.5397***	0.1184
Indonesia	–34.0379***	–65.1605***	0.1405
Japan	–35.1660***	–74.6639***	0.1122
Malaysia	–34.2883***	–72.9430***	0.2459
UK	–35.7600***	–78.3590***	0.1182
US	–35.6770***	–78.5295***	0.1515

Note 1. ***, ** and * indicate significance at the 1%, 5% and 10% level.
Note 2. KPSS tests stationarity *vs* nonstationarity while both ADF and PP test nonstationarity *vs* stationarity.

Based on the results in Table 6.23, the log return series are stationary according to all three unit root tests. I further tested for multivariate serial dependence of the series for five lags using the multivariate LB test as follows:

$$H_0 : \rho_1 = \rho_2 = \rho_3 = \rho_4 = \rho_5 = 0$$

$$H_1 : \rho_i \neq 0 \text{ for all } i = 1,2,3,4,5$$

The test statistic is $Q_k(\mathrm{m}) = \mathrm{T}^2 \sum_{j=1}^{\mathrm{m}} \left(\frac{1}{\mathrm{T} - j} \right) trace(\widehat{\Gamma}'_j \widehat{\Gamma}_0^{-1} \widehat{\Gamma}_j \widehat{\Gamma}_0^{-1})$, where m is the number of lags; k is the number of experimental units; T is the sample size, $\widehat{\Gamma}_j$ is the sample cross-covariance matrix; and $Q_k(\mathrm{m})$ is the test statistic, which has a χ^2 distribution with $\mathrm{k}^2\mathrm{m}$ degrees of freedom.

Table 6.24: Multivariate Q-statistic at various lags

Lags *m*	***m* = 1**	***m* = 2**	***m* = 3**	***m* = 4**	***m* = 5**
$Q_{10}(m)$	2533.039	2961.654	3250.548	3459.580	3725.284
Degrees of freedom	100	200	300	400	500
p-value	0.000	0.000	0.000	0.000	0.000

Note. Where $m = 5$ and $k = 10$.

According to Table 6.24 the multivariate $Q_{10}(5)$ statistic displays significant serial correlation at each lag, indicating a lag–lead relationship among the 10 stock index returns. I conducted AIC, BIC and HQ criteria to select the lag length for the VAR model.

Table 6.25: Maximum lag selected by the information criteria

Criterion	**Lag**
AIC	5
SBC	1
HQ	2

I chose VAR lag 2 as suggested by the HQ criterion because it is lies the lags suggested by AIC and SBC criteria (Table 6.25). Thus I assume that VAR(2) captures the remaining serial correlations for the VAR system equations. After selecting the VAR order, I estimated the VAR-X model.

6.4.2 VAR-X model

I extend the Sims (1980) VAR model to include financial crisis events that are exogenously determined by the occurrence of market crash events. The nominal crash variables are time indicator vector of variables representing the 1987 crash, AFC, and the GFC, denoted by X. The VAR-X model takes the following form:

$$y_t = A_0 + \sum_{l=1}^{2} A_l y_{t-l} + \sum_{i=1}^{3} B_i X_{it} + \varepsilon_t \tag{6.6}$$

where $y_t = (Australia, Canada, Germany, Hong\ Kong, India, Indonesia, Japan, Malaysia, UK, US)'$ is a (10×1) vector of stock returns of the respective country; X_{it} includes the 1987 crash, AFC and GFC; A_0 is a (10×1) matrix of intercepts; A_l is a (10 × 10) matrix of parameters of the right-hand side vector of lag dependent variables y_{t-l}; B is a (10 × 3) matrix of parameters; X_t is a (3 × 1) vector of exogenous indicator variables reflecting crash events in the system equations; and ε_t is a random innovation vector of order (10 × 1).

Estimation of a VAR(2)-X model of stock returns for the selected countries in matrix form:

$$
\begin{pmatrix} Aust_t \\ Canada_t \\ Germany_t \\ HK_t \\ India_t \\ Indo_t \\ Japan_t \\ Malaysia_t \\ UK_t \\ USA_t \end{pmatrix}
=
\begin{pmatrix} 0.0365^{**} \\ (0.0145) \\ 0.0519^{***} \\ (0.0175) \\ 0.0552^{**} \\ (0.0229) \\ 0.0876^{***} \\ (0.0267) \\ 0.1035^{***} \\ (0.0286) \\ 0.0832^{***} \\ (0.0271) \\ 0.0221 \\ (0.0217) \\ 0.0554^{**} \\ (0.0231) \\ 0.0341^{*} \\ (0.0179) \\ 0.0667^{***} \\ (0.0175) \end{pmatrix}
+
\begin{pmatrix}
-0.1438^{***} & 0.1788^{***} & 0.1598^{***} & 0.0139 & 0.0223^{***} & 0.0052 & -0.0267^{***} & -0.0012 & 0.0329^{**} & 0.0264 \\
(0.0156) & (0.0142) & (0.0121) & (0.0090) & (0.0071) & (0.0074) & (0.0101) & (0.0092) & (0.0157) & (0.0165) \\
0.0376^{**} & -0.0461^{***} & 0.0409^{***} & -0.0245^{**} & 0.0039 & -0.0088 & -0.0151 & 0.0199^{*} & 0.0452^{**} & 0.02586 \\
(0.0188) & (0.01710) & (0.0145) & (0.0108) & (0.0085) & (0.0090) & (0.0121) & (0.0111) & (0.0189) & (0.0200) \\
-0.0991^{***} & 0.1626^{***} & -0.0088 & 0.0184 & 0.0096 & 0.0022 & -0.0254 & 0.0056 & -0.0365 & -0.0425 \\
(0.0246) & (0.0223) & (0.0190) & (0.0142) & (0.0112) & (0.0117) & (0.0158) & (0.0145) & (0.0247) & (0.0261) \\
0.1799^{***} & 0.2423^{***} & 0.1423^{***} & -0.1111^{***} & -0.0304^{**} & -0.0162 & -0.0923^{***} & 0.0783^{***} & 0.0523^{**} & -0.1636^{***} \\
(0.0286) & (0.0260) & (0.0221) & (0.0165) & (0.0130) & (0.0137) & (0.0185) & (0.0169) & (0.0287) & (0.03034) \\
0.0280 & 0.1739^{***} & 0.0495^{**} & -0.0073 & -0.0326^{**} & 0.0051 & -0.0007 & -0.0096 & -0.0363 & -0.1016^{***} \\
(0.0307) & (0.0278) & (0.0237) & (0.0177) & (0.0139) & (0.0146) & (0.0198) & (0.0181) & (0.0308) & (0.0325) \\
-0.0543^{*} & 0.2037^{***} & 0.1336^{***} & 0.0609^{***} & 0.0064 & 0.1134^{***} & -0.0212 & -0.0008 & -0.0533^{*} & -0.0656^{**} \\
(0.0291) & (0.0264) & (0.0225) & (0.0168) & (0.0132 & (0.0139) & (0.0187) & (0.0172) & (0.0292) & (0.0308) \\
-0.0073 & 0.2222^{***} & 0.2277^{***} & 0.0071 & 0.0179^{*} & 0.0059 & -0.0829^{***} & 0.0254^{*} & -0.0825^{***} & -0.0618^{**} \\
(0.0233) & (0.0212) & (0.0180) & (0.0134) & (0.0106) & (0.0112) & (0.0150) & (0.0138) & (0.0234) & (0.0247) \\
-0.0418^{*} & 0.1517^{***} & 0.0638^{***} & 0.0420^{***} & -0.0033 & 0.0418^{***} & -0.0235 & -0.0193 & -0.0218 & -0.0338 \\
(0.0247) & (0.0225) & (0.0191) & (0.0143) & (0.0113) & (0.0118) & (0.0159) & (0.0146) & (0.0248) & (0.0262) \\
-0.1219^{***} & 0.2292^{***} & 0.0831^{***} & 0.0474^{***} & 0.0130 & 0.0071 & -0.0313^{**} & -0.0251^{**} & -0.2023^{***} & 0.0674^{***} \\
(0.0192) & (0.0175) & (0.0148) & (0.0111) & (0.0087) & (0.0092) & (0.0124) & (0.0114) & (0.0193) & (0.0204) \\
0.0085 & 0.1450^{***} & 0.1129^{***} & -0.0223^{**} & -0.0035 & -0.0067 & -0.0090 & 0.0274^{**} & 0.0013 & -0.1979^{***} \\
(0.0187) & (0.0170) & (0.0145) & (0.0108) & (0.0085) & (0.0089) & (0.0121) & (0.0111) & (0.0188) & (0.0198)
\end{pmatrix}
\begin{pmatrix} Aust_{t-1} \\ Canada_{t-1} \\ Germany_{t-1} \\ HK_{t-1} \\ India_{t-1} \\ Indo_{t-1} \\ Japan_{t-1} \\ Malaysia_{t-1} \\ UK_{t-1} \\ USA_{t-1} \end{pmatrix}
$$

$$
+\begin{pmatrix}
-0.0477^{***} & 0.0366^{**} & -0.0009 & 0.0124 & -0.0014 & 0.0112 & 0.0013 & -0.0327^{***} & 0.0047 & 0.0160 \\
(0.0150) & (0.0145) & (0.0123) & (0.0089) & (0.0071) & (0.0074) & (0.0099) & (0.0092) & (0.0154) & (0.0166) \\
0.0242 & -0.0603^{***} & -0.0057 & -0.0295^{***} & -0.0152^{*} & 0.0060 & -0.00003 & 0.0165 & -0.0172 & 0.0133 \\
(0.0181) & (0.0174) & (0.0149) & (0.0107) & (0.0085) & (0.0089) & (0.0120) & (0.0111) & (0.0186) & (0.0200) \\
0.0491^{**} & 0.0142 & -0.0103 & 0.0039 & -0.0124 & -0.0047 & 0.0130 & -0.0241^{*} & -0.0036 & 0.0270 \\
(0.0236) & (0.0228) & (0.0195) & (0.0140) & (0.0112) & (0.0117) & (0.0157) & (0.0145) & (0.0243) & (0.0262) \\
0.0084 & -0.0149 & 0.0003 & -0.0219 & -0.0071 & -0.0076 & 0.0075 & -0.0486^{***} & 0.0033 & -0.0175 \\
(0.0275) & (0.0265) & (0.0226) & (0.0163) & (0.0130) & (0.0135) & (0.0183) & (0.0169) & (0.0283) & (0.0304) \\
0.0144 & -0.0464 & 0.0274 & -0.0079 & -0.0053 & -0.0021 & 0.0227 & -0.0168 & -0.0166 & 0.0789^{**} \\
(0.0295) & (0.0284) & (0.0243) & (0.0175) & (0.0140) & (0.0145) & (0.0196) & (0.0181) & (0.0303) & (0.0327) \\
0.0273 & -0.0027 & 0.0120 & -0.0282^{*} & -0.0208 & 0.1012^{***} & 0.0243 & -0.0300^{*} & -0.0135 & 0.0111 \\
(0.0279) & (0.0269) & (0.0230) & (0.0165) & (0.0132) & (0.0138) & (0.0185) & (0.0172) & (0.0287) & (0.0309) \\
0.0153 & 0.0986^{***} & 0.0113 & -0.0085 & -0.0065 & -0.0185^{*} & -0.0109 & 0.0044 & -0.0732^{***} & -0.0216 \\
(0.0224) & (0.0216) & (0.0184) & (0.0133) & (0.0106) & (0.0111) & (0.0149) & (0.0138) & (0.0230) & (0.0248) \\
0.0469^{**} & 0.0356 & 0.0097 & -0.0175 & -0.0085 & 0.0118 & -0.0079 & 0.0461^{***} & 0.0268 & -0.0054 \\
(0.0238) & (0.0229) & (0.0196) & (0.0141) & (0.0112) & (0.0117) & (0.0158) & (0.0146) & (0.0244) & (0.0263) \\
0.0118 & 0.0470^{***} & -0.0064 & 0.0149 & -0.0081 & -0.0005 & -0.0036 & -0.0401^{***} & -0.0414^{**} & 0.0381^{*} \\
(0.0184) & (0.0178) & (0.0152) & (0.0109) & (0.0087) & (0.0091) & (0.0122) & (0.0113) & (0.0190) & (0.0204) \\
0.0168 & -0.0435^{**} & -0.0045 & -0.0171 & -0.0133 & -0.0044 & 0.0153 & -0.0116 & 0.0126 & -0.0110 \\
(0.0180) & (0.0173) & (0.0148) & (0.0106) & (0.0085) & (0.0089) & (0.0119) & (0.0111) & (0.0185) & (0.0199)
\end{pmatrix}
\begin{pmatrix}
Aust_{t-2} \\ Canada_{t-2} \\ Germany_{t-2} \\ HK_{t-2} \\ India_{t-2} \\ Indo_{t-2} \\ Japan_{t-2} \\ Malaysia_{t-2} \\ UK_{t-2} \\ USA_{t-2}
\end{pmatrix}
$$

$$
+\begin{pmatrix}
-5.1735^{***} & -0.0652 & -0.2512^{***} \\
(0.4087) & (0.0753) & (0.0641) \\
-2.2963^{***} & -0.1521^{*} & -0.2267^{***} \\
(0.4920) & (0.0907) & (0.0772) \\
-2.9701^{***} & -0.0156 & -0.3229^{***} \\
(0.6440) & (0.1187) & (0.1011) \\
-5.6312^{***} & -0.3925^{***} & -0.3109^{***} \\
(0.7484) & (0.1380) & (0.1175) \\
0.0845 & -0.1965 & -0.3096^{***} \\
(0.8031) & (0.1481) & (0.1261) \\
0.5084 & -0.2794^{**} & -0.2080^{*} \\
(0.7608) & (0.1402) & (0.1194) \\
-0.8524 & -0.1319 & -0.248^{***} \\
(0.6103) & (0.1125) & (0.0958) \\
-3.8935^{***} & -0.2936^{**} & -0.1669 \\
(0.6478) & (0.1194) & (0.1017) \\
-3.6698^{***} & -0.0493 & -0.2302^{***} \\
(0.5028) & (0.0927) & (0.0789) \\
-2.3745^{***} & -0.0747 & -0.3300^{***} \\
(0.4899) & (0.0903) & (0.0769)
\end{pmatrix}
\begin{pmatrix}
\text{Crash 87} \\ \text{AFC} \\ \text{GFC}
\end{pmatrix}
$$

Note 1. Standard error of the estimate in parenthesis. Note 2. ***, ** and * indicate significance at the 1%, 5% and 10% level.

A significant GFC crash effect was documented for nine of the ten selected countries. While the AFC is experienced by only four of the ten selected countries (Canada, HK, Indonesia and Malaysia), the 1987 crash is experienced by seven of the ten selected countries: Australia, Canada, Germany, HK, Malaysia, UK, US. Causal dependences were checked individually by the t test and jointly by the F test (see appendix C for detailed test results). The parameter stability of the VAR-X model was tested using the eigenvalue approach.

According to Figure 6.1 all 20 eigenvalues (i.e. the characteristic roots of the determinant equation) for the VAR (2)-X lie inside the unit circle, which implies that the VAR(2) model is stable. Therefore, VAR (2)-X is a stationary stable specification. Documenting model stability is an important first step towards further inferences from the model. I developed a new severity index (SI) by which I can identify the severity (degree of contamination) of a financial market crash events. This criterion is based on the function of Fisher's *p*-value. I define a criterion index $\lambda = 1-\widehat{\alpha}$, where $\hat{\alpha}$ is the estimated level of significance of the coefficient of a crash event. Table 6.26 provides $\hat{\lambda}$ values for each country.

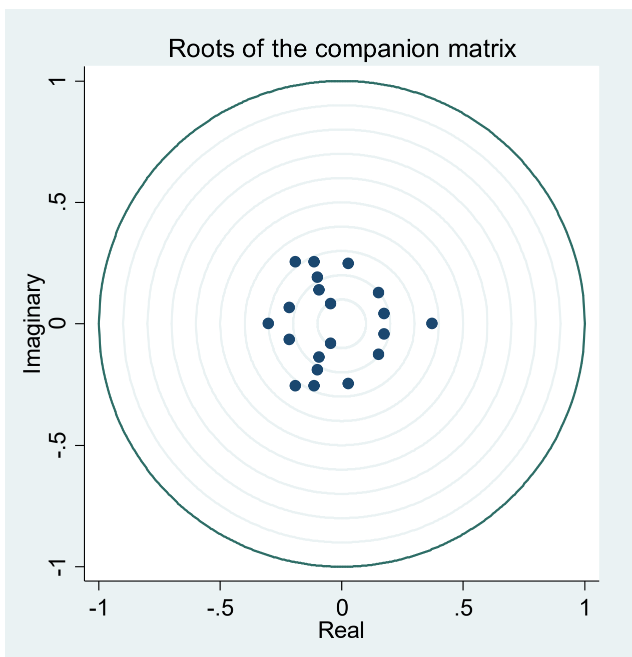


Figure 6.1: Eigenvalue plot of the VAR(2)

A value of λ closer to 1 indicates a strong market crash ; a value of λ near 0 is fairly safe stock market. Any value of λ between 0 and 1 explains the degree of severity. Thus, among the 10 selected countries seven of the stock markets experienced strong severity of 1987 crash. Six of the 10 countries experienced GFC crash and five countries experienced AFC crises.Analyst (2018) published research analysing data from Bloomberg, which highlighted that during the 1987 crash, UK, US, Germany and HK were affected the most. Further, Richardson (1998) showed that during the Asian Financial Crisis, Asian countries including HK, Japan, Malaysia and Indonesia were affected the most. Long et al. (2012) highlighted that during the GFC, major developed countries and European emerging market countries were affected relatively early, and that Asian emerging market countries were affected later.

The SI-based criteria support these findings. I found that during the 1987 crash UK, US, Germany, Canada and HK were affected the most. In the case of the GFC, the developed and developing countries were affected the most as this crisis was deeply rooted in developed countries. This is an important finding for both domestic and international stock market investors and decision markers. The SI developed in this thesis is an additional measure of severity for financial market crash events. This is an important information for the agent's financial decision making strategies. Next I evaluated Granger causality among the asset markets returns.

Table 6.26: Severity of crash events measured as λ

Crash	Country									
	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1987	1	1	1	1	0.90	0.5	0.84	1	1	1
Asia	.62	0.91	0.11	0.99	0.82	0.96	0.76	0.99	0.41	0.59
GFC	1	1	0.99	0.99	0.99	0.92	0.99	0.90	0.99	1

6.4.2.1 *Granger causality of the variables*

An important tool for VAR analysis is Granger causality. The importance of causality is that it improves the conditional forecast of returns due to their own shocks and the shocks of other returns series. When causality runs from one series to another it is called unidirectional causality. Unidirectional causality can be utilised to establish the existence of trade-offs between return series by applying t and F tests. When bi-directional causality exists among the returns of international series, those series are called interdependent (i.e. mutually dependent) at the global level. If a crash in a particular asset of a particular country spreads out and causally affects the other assets of other countries, we have a contagion (contamination transmission) effect. The effects of financial crah and contagion can be tested by creating a dummy variable of so-called 'crash events' involving the interaction of another country series in the VAR process, and testing the resulting interaction coefficient of this variable in the model of other variables.

The lagged dependent variables in the VAR equations were tested for Granger causality using a series of F tests (see Table 6.27). For example, India, Japan, Malaysia and UK do not influence Indonesia stock returns, according to F test. HK stock returns are influenced by all stock returns except those of UK and Indonesia. The Australian stock market is not affected by Indonesia, UK or US. Similar conclusions could be made with some variation regarding Granger causality, by comparing the F test values with their corresponding *p*-values. This causality information reveals the spillover effects of return shocks.

Table 6.27: Granger causality among the 10 countries' stock returns

Variable	F-statistic	*p*-value	Variable	F-statistic	*p*-value
Dependent variable Australia			**Dependent variable Canada**		
Canada	79.4775	0.0000	Australia	5.4287	0.0044
Germany	87.4500	0.0000	Germany	4.2984	0.0136
HK	3.2820	0.0376	HK	4.9725	0.0070
India	3.7973	0.0225	India	1.9398	0.1438
Indonesia	0.4396	0.6443	Indonesia	0.7578	0.4687
Japan	4.9283	0.0073	Japan	1.0207	0.3604
Malaysia	3.8573	0.0212	Malaysia	3.4528	0.0317
UK	2.2908	0.1013	UK	3.9174	0.0199
US	1.6374	0.1946	US	0.9862	0.3731
Dependent variable HK			**Dependent variable India**		
Australia	27.7951	0.0000	Australia	0.5084	0.6015
Canada	46.2908	0.0000	Canada	22.9721	0.0000
Germany	20.8990	0.0000	Germany	2.5636	0.0771
India	3.5321	0.0293	HK	0.1762	0.8385
Indonesia	1.7546	0.1731	Indonesia	0.0762	0.9266
Japan	13.9206	0.0000	Japan	0.7414	0.4765
Malaysia	15.4040	0.0000	Malaysia	0.5197	0.5947
UK	1.7102	0.1809	UK	0.8047	0.4473
US	14.5839	0.0000	US	9.4930	0.0001
Dependent variable Japan			**Dependent variable Malaysia**		
Australia	0.4556	0.6341	Australia	4.8994	0.0075
Canada	59.6861	0.0000	Canada	23.3674	0.0000
Germany	79.6987	0.0000	Germany	5.5796	0.0038
HK	0.4018	0.6691	HK	6.0574	0.0024
India	1.6429	0.1935	India	0.5468	0.5788
Indonesia	1.4844	0.2267	Indonesia	5.9854	0.0025
Malaysia	1.9547	0.1417	Japan	1.6178	0.1984
UK	9.7891	0.0001	UK	1.0621	0.3458
US	3.1889	0.0413	US	0.8418	0.4310

Dependent variable US			Dependent variable UK		
Australia	2.0395	0.1302	Australia	16.7223	0.0000
Canada	44.4305	0.0000	Canada	86.9083	0.0000
Germany	31.0951	0.0000	Germany	16.3392	0.0000
HK	2.5597	0.0774	HK	10.7405	0.0000
India	1.6327	0.1955	India	1.5106	0.2209
Indonesia	0.8351	0.4339	Indonesia	0.1511	0.8598
Japan	1.0903	0.3362	Japan	4.1351	0.0160
Malaysia	3.9009	0.0203	Malaysia	6.4803	0.0015
UK	0.1982	0.8202	US	6.4486	0.0016
Dependent variable Indonesia			**Dependent variable Germany**		
Australia	2.5100	0.0814	Australia	10.7009	0.0000
Canada	30.5821	0.0000	Canada	26.9741	0.0000
Germany	17.5232	0.0000	HK	1.0778	0.3404
HK	8.9100	0.0001	India	1.0930	0.3353
India	1.3114	0.2695	Indonesia	0.2025	0.8167
Japan	1.5984	0.2023	Japan	1.8779	0.1530
Malaysia	1.5332	0.2159	Malaysia	1.1512	0.3163
UK	1.7543	0.1731	UK	1.0292	0.3574
US	2.5551	0.0778	US	2.3176	0.0986

6.4.2.2 *Forecast error variance decomposition approach to modelling return volatility interdependence*

In this section I present forecast error variance decomposition as a second tool for VAR-X analysis.

Table 6.28: Decomposition of forecast error variance for Australia stock returns

Step	Standard error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.043	100.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	1.138	84.476	9.905	5.169	0.110	0.109	0.000	0.102	0.005	0.087	0.036
3	1.140	84.209	10.057	5.182	0.119	0.121	0.001	0.112	0.074	0.086	0.040
4	1.141	84.113	10.122	5.176	0.138	0.131	0.002	0.113	0.075	0.087	0.043
5	1.141	84.112	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
6	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
7	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
8	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
9	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
10	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
11	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
12	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
13	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
14	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
15	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
16	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
17	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
18	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
19	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
20	1.141	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043

I now discuss the implications of the empirical results. In Table 6.28, the first column shows the standard error of the forecast error variance for the Australia stock returns variable in the VAR-X model. This is the first variable in the set of VAR. The remaining columns provide the decomposition of the forecast error variance of the Australia stock returns at various lags, as shown by each row of the table for all other countries. The first row indicates that the Australian stock return explains all (100%) of its own 1-step-ahead forecast error variance and 84.11% of its 6–20-step-ahead forecast error variance. The four principal factors driving Australian returns volatility are itself, Canada, Germany and HK, up to 20-step-ahead forecasts. Similarly, at 15-steps ahead UK explains 45.22% of its own, 0.17% of the forecast error variance for the US and 19.59% for Australia respectively; the rest is due to the forecast error variances of others (see tables in appendices). In summary, I extracted information on the aggregate spillover effect across markets using forecast error variance decomposition in a series due to its 'own' shocks versus the shocks from other variables. If, for example, US shocks explain none of its forecast error variance for Australia at any forecast horizon, then Australian stock is exogenous; that is, Australia evolves independently of US return shocks. Conversely, if US shocks explain the entire forecast error variance in the Australian sequence at all forecast horizons, Australian stock is endogenous. Linkages among forecast error variance spillovers were detected (see appendix C for all other cases). The forecast error variance decomposition is important for investors' portfolios of asset management decisions based on the riskiness of an asset in the portfolios.

6.4.2.3 *Impulse response analysis*

Since the VAR process is stable according to the eigenvalue test, the Wold (1938) decomposition of the VAR into an infinite order vector moving average (VMA) can be derived. Using this dual relationship between multivariate VAR and multivariate VMA, it is possible to extract the impact (immediate) effect and 1-step multiplier, two-step multiplier and progressively all-step multiplier effects. The time path of all such multipliers is the IRF, which traces how the entire time path of a variable is affected by a stochastic return shock. The impulse responses of Australian stock tracing the effects of a return shock can be computed using the impulse responses computed as $\frac{\partial Aust_{t+j}}{\partial \varepsilon_t} = \frac{\partial Aust_t}{\partial \varepsilon_{t-j}}, j = 1, 2, ..., \propto$. When $j = 0$, we measure the immediate (or contemporaneous) effect. This is called the impact multiplier. Similarly, for all the stock returns in the VAR, impulse response analysis can be utilised for portfolio diversification policy decision purposes. The impulses for shocks in Australia are shown in Table 6.29 below for periods 1-20 for each of 10 return shocks. Note that for other stock markets, similar calculations produced the IRFs provided in the appendices.

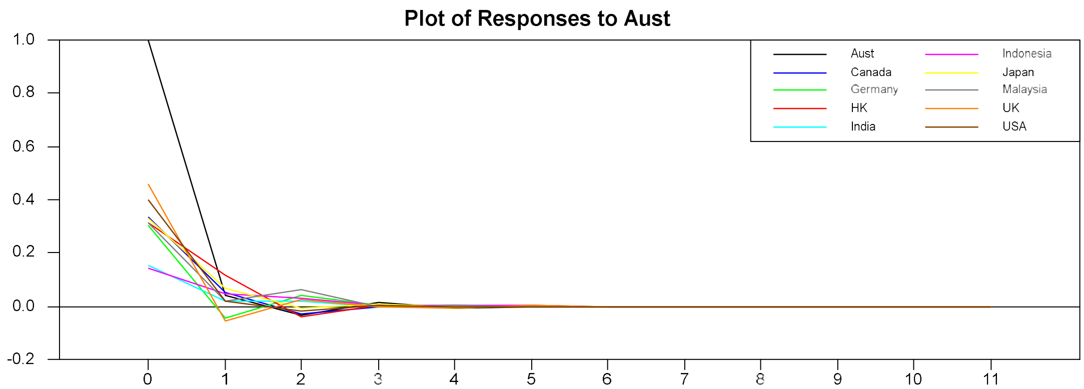


Figure 6.2: Impulse response function

Figure 6.2 shows responses to Australian stock return shocks: One standard deviation shock in Australian stock returns induces an increase of approximately 0.50 standard deviations in US returns for period 1. After period 1, UK induces a decrease of around 0.04; after period 2 all responses decay towards zero. The decay of the coefficients of the impulse function indicates that the effects of changes in the various shocks are of short-term duration. In the above IRF I have compared all other responses to the Australian return shocks. It is clear that Australian shocks transmit to all others up to lag 2; thereafter the Australian shock effect diminishes. Thus, risk-taking investors may hold Australian stocks for the short term. This information is important for investor’s decision making purposes regarding the holding of an asset in the short term.

Table 6.29: Impulse responses to shocks for Australian returns

No	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.043	0.424	0.504	0.619	0.311	0.268	0.506	0.522	0.594	0.501
2	0.076	0.081	–0.058	0.258	0.037	0.089	0.110	0.062	–0.044	0.037
3	0.000	–0.016	0.083	–0.027	0.042	0.056	0.001	0.133	0.055	–0.007
4	0.018	0.0028	0.004	0.016	–0.003	0.0143	0.022	0.005	–0.001	0.006
5	–0.005	0.002	–0.007	–0.005	0.000	0.003	–0.005	0.009	–0.010	–0.001
6	0.000	0.000	0.003	0.000	0.001	0.002	0.000	0.001	0.003	0.000
7	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
12	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
14	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
17	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
18	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
19	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

I analysed linkages among the stock returns of 10 countries for the 1987 crash, AFC and GFC. I tested the severity of these crisis events. The severity criteria revealed that the 10 stock markets experienced a higher severity from the 1987 crash and GFC crashes than from AFC. This is an important finding for both domestic and international stock market investors and decision markers regarding portfolio allocation and diversification strategies. I further utilised Granger causality tests to uncover directional causality among the sampled countries. The impulse response analysis traced out the time path of various return shocks. Next I test the effect of GFC crash considering both time and country effects using PVAR-X.

6.5 PVAR–X

Since the VAR only considers the time dimension, it does not capture cross-sectional effects when considering the time paths of the DGP. To consider jointly the time and cross-sectional effects I employed the PVAR approach to analyse interrelationships among stock, bond and money markets. The PVAR is a rich class of models that deals with panel heterogeneity and panel serial correlations jointly among the variables of interest. The panel model provides more information, more variability, less collinearity and more degrees of freedom and is thus an important statistical technique for data analysis purposes. The PVAR model was estimated by the GMM. The GMM estimates are consistent and asymptotically normally distributed. The stock, bond and money market returns of Australia, France, Japan, Singapore and US were analysed for a period of almost 17 years starting on 31 August 1999 and ending on 30 December 2016, with 3,311 useable observations, using the PVAR approach of Abrigo and Love (2016). I extend their approach in the finance area to identify linkages among asset markets across countries allowing financial market ‘crash’ events. This is a new application of the PVAR approach to modelling dynamic interdependence among financial markets specifically during financial crisis. The market ‘crash’ events are determined by the time of occurrence of the events. To apply the PVAR I tested each of the three return series for panel unit root by utilising Im, Pesaran and Shin (2003) called IPS panel unit root test, Fisher-type Maddala–Wu (1999) panel unit root and Hadri (2000) nonparametric LM unit root tests. The IPS and Fisher-type Maddala–Wu test consider the null hypothesis of nonstationarity, whereas Hadri has stationarity as its null hypothesis (similar to the univariate KPSS test). I applied the PVAR-X approach to address RQ4.

6.5.1 Panel unit root tests

I used the following model for the panel unit root tests of Im,Pesaran and Shin (IPS) and Maddala and Wu (*m*). Let r_{it} be the *i*-th variable of interest at time *t* in the first difference generated by the following process:

$$\Delta r_{it} = a_i + \rho_i r_{t-1} + \sum_{j=1}^{k} \phi_j \Delta r_{t-j} + \delta_i t + \gamma_t + \varepsilon_{it} \qquad (6.7)$$

where a_i is the i-th panel fixed effect; ρ_i is the panel-specific parameter indexed by i; δ_i is the time trend parameter; γ_t is a time-fixed effect; ε_{it} is random disturbance of the *i*-th panel at time *t*; and Δ represents the difference operator of the variable.

For Hadri (2000) test, I use $r_{it} = m_{it} + \varepsilon_{it}$, where $m_{it} = m_{it-1} + u_{it}$. The random variable $u_{it} \sim iid(0, \sigma_u^2)$ and ε_{it} is a stationary process. If $\sigma_u^2 = 0$, then m_{it} is a constant and r_{it} is a stationary process. A test for σ_u^2=0 is equivalent to $\lambda = 0$, where $\lambda = \dfrac{\sigma_u^2}{\sigma_\varepsilon^2}$.

The following hypotheses were of interest.

- IPS. $H_0 : \rho_i = 0$ for all i *vs.* $H_1 : \rho_i < 0$ for some panels are stationary
- Fisher-type Maddala–Wu. $H_0 : \rho_i = 0$ *vs.* $H_1 : \rho_i < 0$ for at least one i
- Hadri. $H_0 : \lambda = 0$ for all i *vs.* $H_1 : \lambda > 0$

The following test statistics were used:

- $t = \dfrac{\bar{t} - E(\bar{t} \mid H_0)}{\sqrt{\mathrm{var}(\bar{t} \mid H_0)}}$, where $\bar{t} = \dfrac{1}{N}\sum_{i=1}^{N} \tau_{\hat{\rho}}$ for the IPS test, where $\tau_{\hat{\rho}}$ is the ADF statistic for panel i.
- $m = -2\sum_{i=1}^{N} \ln \pi_i$ for Maddala–Wu, where π_i is the *p*-value for the Dickey-Fuller statistic for panel i obtained by the bootstrap procedure. The test statistic *m* follows a χ^2 distribution with $2N$ degrees of freedom.

- $\text{LM} = \dfrac{(1/N)\sum_{i=1}^{N}[(1/T^2)\sum_{t=1}^{T}S_{it}^2}{\hat{\sigma}_{\varepsilon}^2}$, where the partial sum of the residuals is $S_{it} = \sum_{j=1}^{t}\hat{\varepsilon}_{ij}$ and $\hat{\sigma}_{\varepsilon}^2 = \dfrac{1}{NT}\sum_{i}^{N}\sum_{t}^{T}\hat{\varepsilon}_{it}^2$. The limiting distribution of $\hat{\text{LM}}$ follow normal distribution with mean zero and variance 1, Hadri (2000).

Table 6.30: Stationarity test outcomes

Variable	IPS unit root test ($\bar{t}$)	Fisher-type test	Hadri–LM test
Stock returns	–62.5922(0.000)	360.4365(0.000)	–2.0785(0.981)
Bond returns	–57.7085(0.000)	360.4365(0.000)	–1.9117(0.972)
T-bill returns	–57.7936(0.000)	360.4365(0.000)	–2.0510(0.979)

Note 1. The *p*-value is in parentheses.
Note 2. The lag length k was selected by the AIC for IPS tests.

The test results shown in Table 6.30 indicate that all of the three returns series (stock, bond and T-bill) are stationary for all of the five countries according to the ADF, PP and KPSS tests.

6.5.2 Estimation and analysis of the PVAR-X model

The PVAR-X model takes the following form:

$$r_{it} = u_i + \sum_{l=l}^{p} A_l r_{it-l} + \delta x_{it} + \varepsilon_{it} \tag{6.8}$$

where r_{it} is an $(N \times 1)$ vector of dependent variables; x_{it} is a $(k \times 1)$ vector of exogenous variables reflecting stock market crash events; u_i is an $(N \times 1)$ vector of fixed or random effects; ε_{it} is an $(N \times 1)$ vector of idiosyncratic errors; A_l are $(N \times N)$ parameter matrices to be estimated; and δ is an $(N \times k)$ parameter matrix of exogenous variables.

In the current empirical application, r_{it} is a (3 × 1) vector of endogenous variables and x_{it} ($\text{d}_t \times \text{stock}_{\text{USA}_{t-1}}$, where d_t is the time dummy for the GFC) is a single variable measuring the (GFC) contagion effect of the US stock market and its spread to the stock, bond and T-bill markets of Australia, France, Japan and Singapore for the study period. The sample period starts from 31 August 1999-30th December 2016 with 16,549 number of observations in Panel VAR.

The fixed-effects mean-corrected PVAR model was estimated by the GMM. The GMM estimators are consistent and asymptotically normally distributed (see Hansen, 1982). The estimation result is provided below**:**

$$\begin{pmatrix} st\dot{o}ck_{it} \\ b\dot{o}nd_{it} \\ T-\dot{b}ill_{it} \end{pmatrix} = \begin{pmatrix} 0.3587^{***} & 0.0878^{***} & -0.1256^{***} \\ (0.0695) & (0.0326) & (0.0336) \\ 0.7967^{***} & 0.6094^{***} & 0.06359 \\ (0.1352) & (0.0755) & (0.07050) \\ 0.9214^{***} & 0.4874^{***} & -0.0715^{***} \\ (0.1169) & (0.0597) & (0.0540) \end{pmatrix} \begin{pmatrix} st\dot{o}ck_{it-1} \\ b\dot{o}nd_{it-1} \\ T-\dot{b}ill_{it-1} \end{pmatrix} + \begin{pmatrix} 0.1174^{***} \\ (0.0430) \\ 0.2470^{*} \\ (0.1373) \\ 0.3217^{**} \\ (0.0883) \end{pmatrix} x_{it}$$

Note. Standard errors in parentheses.

The results show significant US stock market contagion transmission to the stock, bond and T-bill markets of Australia, France, Japan, Singapore, and US jointly. However, the degree of contamination transmission to stocks, bonds and T-bills differs for different markets. The severity of contamination of the three asset markets among the five countries jointly can be ordered from most severe to least severe as $\mathrm{GFC}_{stock} > GFC_{T-bill} > \mathrm{GFC}_{bond}$ using the severity criterion developed in Section 6.4.2. The results of the PVAR-X model stability test and impulse response analysis are reported in the next section. The stability of the estimated PVAR was tested by the eigenvalue criterion, which is shown below.

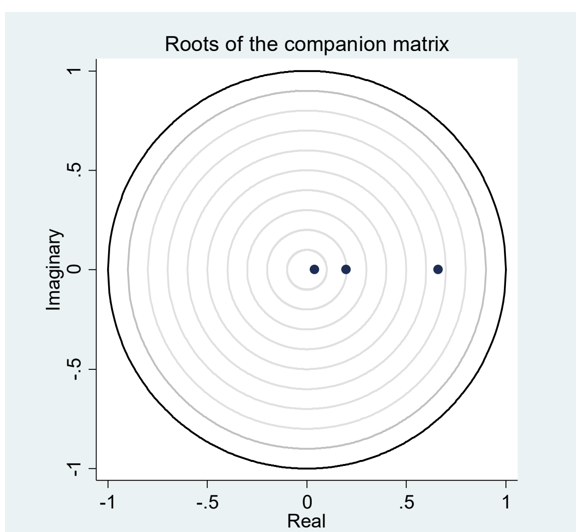


Figure 6.3: Location of panel unit roots

All the roots of the PVAR lie in the unit circle shown in Figure 6.3. Therefore, PVAR is stable and I can form the MA representation of the PVAR for impulse response analysis.

6.5.3 The impulse response analysis of the PVAR-X model of a set of asset returns

The impulse responses derived from the PVAR-X show that most markets rapidly transmit shocks across markets, but the most dramatic response is usually for one period (i.e. 1 day because the data are daily data) and later responses die out quickly. All are significant and lie within the 95% confidence band. The forecast error variance decomposition and IRF analysis are reported below.

From the forecast error variance decomposition in Table 6.31, it can be seen that stock explains all of its 1-step ahead forecast variance and approximately 99% of its 3-step ahead forecast variance, and the trend is flat from 3 steps onwards. The bond explains 95% of its 5-step ahead forecast variance and stock and T-bill explains approximately 46% and 0.02% of forecast error variance. A similar explanation applies to shocks for other variables. The impulse response analysis indicates that 1 standard deviation shock to stock is around 36%; this induces a contemporaneous increase in bond of approximately 9% and a contemporaneous decrease in T-bill of approximately 13%. Responses to shock to one variable in relation to others can be checked accordingly. The impulse response graphs in Figure 6.4 can be used to visualise the time path of return shocks.

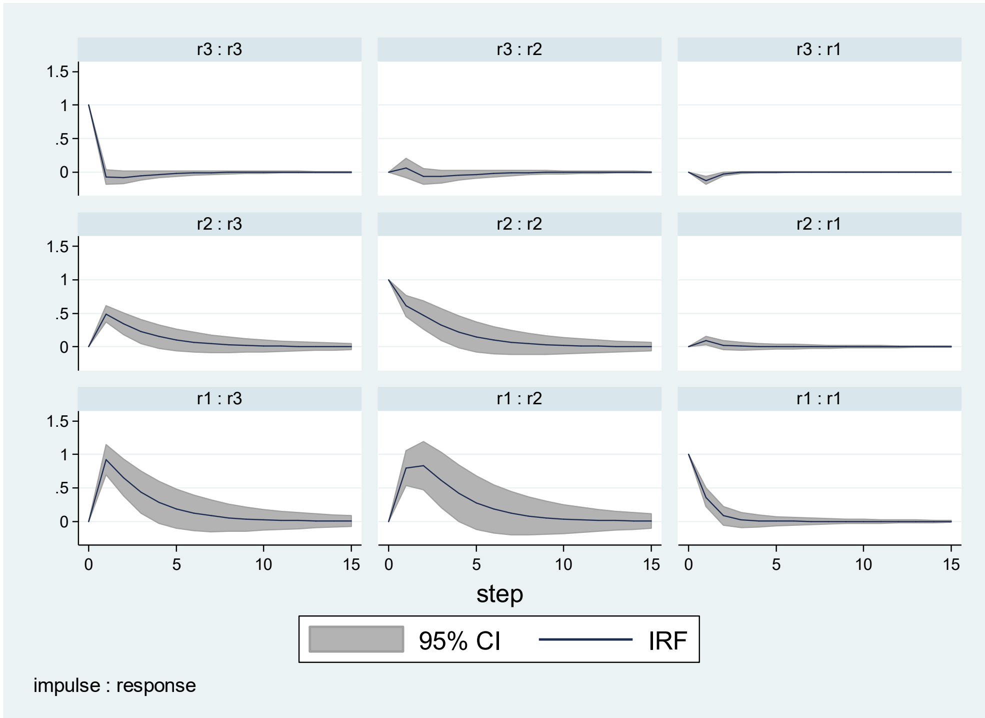


Figure 6.4: Impulse response functions of returns with a 2 standard deviation limit

Note. r1 = stock, r2 = bond and r3 = T-bill

Table 6.31: Forecast error variance decomposition and impulse response function (IRF)

Forecast error variance decomposition				IRF			
Response variable	**Impulse variable**			**Response variable**	**Impulse variable**		
Stock	**Stock**	**Bond**	**T-bill**	**Stock**	**Stock**	**Bond**	**T-bill**
0	0.0000	0.0000	0.0000	0	1.0000	0.0000	0.0000
1	1.0000	0.0000	0.0000	1	0.3587	0.0878	–0.1257
2	0.9903	0.0001	0.0096	2	0.0829	0.0238	–0.0305
3	0.9897	0.0001	0.0101	3	0.0206	0.0069	–0.0067
4	0.9897	0.0002	0.0101	4	0.0067	0.0028	–0.0017
5	0.9897	0.0002	0.0102	5	0.0031	0.0015	–0.0005
6	0.9897	0.0002	0.0102	6	0.0018	0.0009	–0.0003
7	0.9897	0.0002	0.0102	7	0.0011	0.0006	–0.0001
8	0.9897	0.0002	0.0102	8	0.0007	0.0004	–0.0001
9	0.9897	0.0002	0.0102	9	0.0005	0.0002	–0.0001
10	0.9897	0.0002	0.0102	10	0.0003	0.0002	0.0000
Bond	**Stock**	**Bond**	**T-bill**	**Bond**	**Stock**	**Bond**	**T-bill**
0	0.0000	0.0000	0.0000	0	0.0000	1.0000	0.0000
1	0.0538	0.9462	0.0000	1	0.7967	0.6094	0.0636
2	0.2999	0.6994	0.0007	2	0.8300	0.4724	–0.0659
3	0.4041	0.5947	0.0011	3	0.6134	0.3287	–0.0695
4	0.4426	0.5558	0.0016	4	0.4178	0.2203	–0.0512
5	0.4578	0.5405	0.0018	5	0.2782	0.1460	–0.0348
6	0.4640	0.5341	0.0019	6	0.1841	0.0965	–0.0232
7	0.4667	0.5314	0.0019	7	0.1215	0.0637	–0.0153
8	0.4679	0.5302	0.0019	8	0.0802	0.0420	–0.0101
9	0.4684	0.5297	0.0020	9	0.0529	0.0277	–0.0067
10	0.4686	0.5295	0.0020	10	0.0349	0.0183	–0.0044

T-bill	Stock	Bond	T-bill	T-bill	Stock	Bond	T-bill
1	0.1126	0.4683	0.4190	0	0.0000	0.0000	1.0000
2	0.4142	0.3649	0.2210	1	0.9215	0.4874	–0.0716
3	0.4783	0.3403	0.1814	2	0.6529	0.3431	–0.0797
4	0.4997	0.3320	0.1683	3	0.4342	0.2276	–0.0545
5	0.5081	0.3287	0.1632	4	0.2869	0.1503	–0.0362
6	0.5116	0.3273	0.1611	5	0.1893	0.0992	–0.0239
7	0.5131	0.3267	0.1602	6	0.1249	0.0654	–0.0158
8	0.5137	0.3265	0.1598	7	0.0824	0.0432	–0.0104
9	0.5140	0.3264	0.1596	8	0.0543	0.0285	–0.0069
10	0.5141	0.3263	0.1596	9	0.0358	0.0188	–0.0045

6.6 Measuring Dependence

Analysing covariance is one of the ways to understand the dependence of risk in financial asset returns. A number of measures can be utilised to understand the dependence of financial market volatility. I address RQ 4 further without considering severity issues but undertaking dependence analysis by using a nonparametric approach and copula dependence. This includes the Pearson product moment correlation, Spearman rank correlation, Kendal's tau and copulas. The product moment correlation is invariant to affine transformation of the variables of interest. However, Pearson correlation is not invariant to nonlinear transformation. As it is well known that the conditional volatility of financial returns is nonlinearly dependent on the return shock, linear correlation is insufficient for measuring the dependence of multiple series. The Spearman rank correlation is robust to certain nonlinear transformations and can assess the strength of a relationship nonparametrically. Kendall's tau can also measure nonlinear dependence based on the idea of concordance and discordance. Both the Spearman and Kendal correlations are nonparametric statistics, whereas Pearson correlation is a parametric statistic. Copulas are useful to study dependence among series of interest. The copula is a link function linking the joint distribution function with its one-dimensional margins. Based on information on the marginal the joint distributions of variables can be obtained by copula links. I focus on Spearman rank correlation, Kendall's τ and copula for pairwise dependence analysis of returns. Note that Kendall's τ and copulas are linked. However, this relationship depends on the choice of the copula. In this study I use the Gumbel copula. The sample includes Australia, HK, US, UK and Japan with 5765 observations for the period 2nd April 1986-30th December 2016.

6.6.1 Kendall's τ

Kendall's τ is a measure of dependence computed based on concordance and discordance.
The pairs (x_i, y_i) and (x_j, y_j) are concordant if $\operatorname{sgn}(x_i, y_i) = \operatorname{sgn}(x_j, y_j)$, where

$$\operatorname{sgn}(.) = \begin{cases} -1 & \text{for negative value} \\ 0 & \text{if } x_i - x_j = 0 \\ 1 & \text{if } x_i - x_j > 0 \end{cases} .$$

The population τ is defined as $\tau = E[\mathrm{sgn}(X_i - X_j)\mathrm{sgn}(Y_i - Y_j)]$. The sample counterpart of τ is $\hat{\tau} = \frac{2}{n(n-1)}\sum_{i,j=1}^{n}\mathrm{sgn}(x_i - x_j)\mathrm{sgn}(y_i - y_j)$, where n is the sample size.

Table 6.32: Pairwise Kendall's τ on stock returns

	Australia	HK	Japan	UK	US
Australia	1.000	0.195	0.223	0.254	0.189
HK	0.195***	1.000	0.274	0.283	0.316
Japan	0.223***	0.274***	1.000	0.262	0.274
UK	0.254***	0.283***	0.262***	1.000	0.346
US	0.189***	0.316***	0.274***	0.346***	1.000

Note. *** significant at the 1% level

The results in Table 6.32 indicate significant dependence between pairs of returns by the z test. I also conducted nonparametric Spearman's rank correlation ρ_s test and Pearson's parametric correlation ρ test and found significant by both the tests at varying degrees of significance. The tests are in the appendix D.

6.6.2 Multiple dependence using the copula

The main idea of the copula is that it is a function that joins or links one-dimensional distributions in multivariate distribution functions. This is achieved by applying cumulative distribution function (cdf) transformation to all random variables in a common domain. The dependence analysis then takes place in the common domain and the random variables can be transformed back to their original distribution by inverse cdf transformation (see Nelson R.B., 1999). Sklar's (1959) theorem provides a connection between the copula and joint distribution of a number of random variables. The random variables *X* and *Y* with cdf $F_X(x)$ and $F_Y(y)$ are joint by copula *C* if their joint distribution can be written as:

$$F_{XY}(x, y) = C\left(F_X(x), F_Y(y)\right) \tag{6.9}$$

For continuous cdf, *C* is unique. Note that $X = F_X^{-1}(U)$ and $U = F_X(X)$; we have $F_X(x) = u$ and $F_Y(y) = v$, where u and v are the realisation of uniform random variables U and V respectively. Then $C_{UV}(u, v) = F\left(F_X^{-1}(u), F_Y^{-1}(y)\right)$. A link function C is defined in the two-dimensional space. $C:[0,1]^2 \to [0,1]$ is a copula if it satisfies (a) $C(0,0) = 0$ for $u = 0$ or

$v = 0$; (b) $\sum_{i}^{2}\sum_{j}^{2}(-1)^{i+j}C(u_i, v_j) \geq 0$, for all (u_i, v_j) in $[0,1]^2$ with $u_1 < u_2$ *and* $v_1 < v_2$; and (c) $C(u,1) = u$, $C(1,v) = v$ for all u, v in [0,1].

For the construction of the copula function from joint multivariate distribution functions, various families of copulas are available in the literature; see for example, Joe (1997), Nelson (1999) and Kurowicka and Cooke (2006). To model stochastic dependence in the common domain I used the following steps:

- rank correlation calculated from the dataset;
- a copula with given rank correlation was used as a dependence function between ranks of the random variable;
- inverse cdf; the correlated ranks were transformed into the given marginal distributions.

I used pairwise stock returns for dependence analysis by employing a bi-variate Gumbel copula with t margins. The rank correlation was computed from the univariate GJR-GARCH-t estimated standardised residuals. The choice of the Gumbel and t distributions was justified by the facts that the return series are non-normal and asymmetry is captured by the Gumbel distribution. The Gumbel parameter $\theta(\geq 1)$ and Kendall' τ are related according to $\tau(\theta) = \frac{\theta - 1}{\theta}$. Table 6.33 provides measures of dependence for the pairs of returns in terms of Kendall's τ.

Table 6.33: Pair of returns

Pair of returns	$\tau(\hat{\theta})$
HK *vs* Australia	0.14
Japan *vs* US	0.15
UK *vs* US	0.17

I found some dependence between the pairs used in the analysis as reported in Table 6.33. Note that there is significant dependence for the pair of returns (see Table 6.33) according to the Kendall's tau function.

Figures 6.5, 6.6 and 6.7 display simulated dependence between returns using Gumbel copula with t margins. Specifically, the returns for the pairs US and UK, and Australia and HK are both tail dependent. Conversely, the Japan–US pair does not display tail dependence.

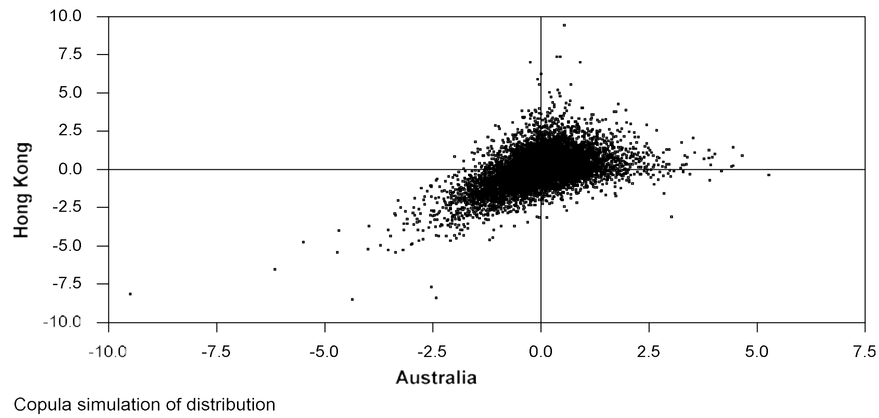


Figure 6.5: Australia *vs* HK copula simulation distribution

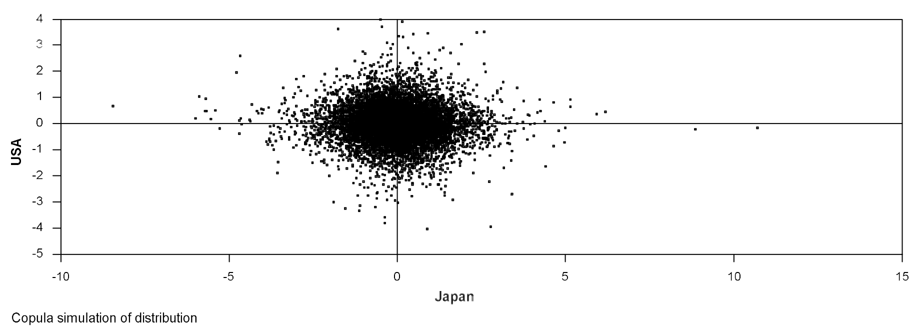


Figure 6.6: US *vs* Japan copula simulation distribution

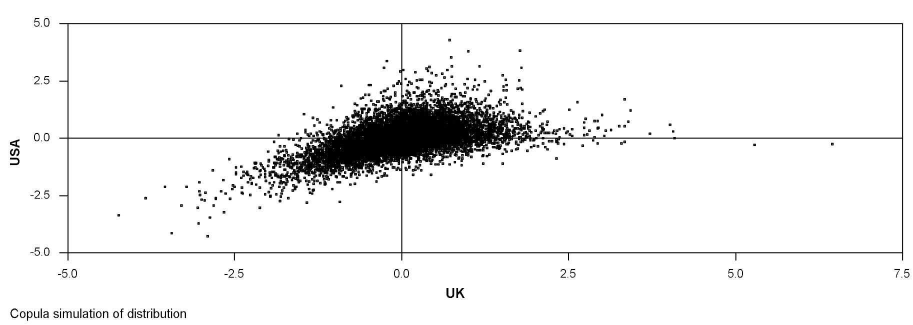


Figure 6.7: US *vs* UK copula simulation distribution

6.6.3 Tests for covariance dependence (or spatial dependence) between financial asset market returns

The dependence of global financial markets was investigated using the correlation coefficients computed by the three methods: Kendall's tau, Spearman rank correlation and Pearson product moment correlation. Squares of the correlations for the pairs were used to form asymptotic tests for the joint significance of the covariance matrix. I developed an asymptotic LM test to explore the existence of covariance jointly among the pairs of the sets of stock returns for Australia, HK, Japan, UK and US by testing the following null hypothesis versus the alternative hypothesis:

$$H_0 : \sigma_{21} = \sigma_{31} = \sigma_{32} = ... = \sigma_{N,N-1} = 0$$

$$H_1 : \sigma_{21} \neq \sigma_{31} \neq \sigma_{32} \neq .... \neq \sigma_{N,N-1} \neq 0$$

Test statistic is $\lambda = T\sum_{i=2}^{N}\sum_{j=1}^{i-1} r_{ij,k}^2$. The test statistic λ is asymptotically distributed as a χ^2 distribution with $N(N-1)/2$ degrees of freedom; N is the number of variables (stock returns of Australia, HK, Japan, UK and US); T is the sample size and k ={Kendall, Spearman, Pearson}.

The test statistic used for testing H_0 versus H_1 was:

$$\lambda(Kendall) = T\sum_{i=2}^{N}\sum_{j=1}^{i-1} r_{ij,k}^2 = 5767 \times 0.7063 = 4073.2321(0.00000)$$

$$\lambda(Spearman) = T\sum_{i=2}^{N}\sum_{j=1}^{i-1} r_{ij,k}^2 = 5767 \times 1.427 = 8229.509(0.00000)$$

$$\lambda(Pearson) = T\sum_{i=2}^{N}\sum_{j=1}^{i-1} r_{ij,k}^2 = 5767 \times 1.9171 = 11055.9157(0.00000)$$

Note. P value are in parenthesis

The value of the test statistic computed was based on the correlations computed by each of the methods (Kendall, Spearman, Pearson; see appendix D). The results provide strong evidence for covariance dependence between pairs of return series jointly by the LM-type chi-square test. This covariance dependence indicates co-volatility spillovers.

6.7 Summary

This chapter analysed the theory and application of an econometric methodology for modelling and predicting financial asset returns. The main aim was to jointly model the first and second moments of the return generating process. The returns of the financial markets (stock, bond and money) are of great interest. Here, the returns were constructed from price series and/or indices. The return is the main variable of interest to model for many financial decision making applications. In Chapter 5, univariate analysis was conducted for stock, bond and money markets for 17 countries individually. Based on this analysis alone, the interdependence of stock market volatility cannot be understood. To determine volatility spillover among assets across countries, the current chapter extended the univariate arena to multivariate analysis of financial market interactions. The theoretical development of the extended definition of asymmetric partial co-volatility and the Wald test for partial co-volatility was reported in Chapter 4. In the multivariate case, a model of conditional volatility of assets return is quite popular, and is developed by BEKK as proposed by Engle and Kroner (1995).

In Chapter 5, the univariate analysis revealed that 'news' in financial markets plays a very important role in dealing with volatility. It is to be noted that volatility is a measure of the risk of holding assets in financial markets. A significant effect of the presence of asymmetric news was found in the univariate volatility models. The stated Engle and Kroner (1995) full BEKK volatility model itself has an important statistical drawback as recently raised by Chang et al. (2018). The QMLE of the full BEKK model parameters do not have a statistical asymptotic distribution because BEKK is not derived from a stochastic process (see Chang et al., 2017). Therefore, the full BEKK is not valid for statistical inference in volatility spillover hypothesis testing. An operational form of full BEKK is the DBEKK derived from vector random coefficient autoregressive process of order one of the vector of return shocks, in which both the short and long run weight matrices are diagonal as shown by Chang and McAleer (2017). In the absence of normality, the QMLEs are asymptotically normally distributed. Asymptotic normality means that statistical inferences on the estimated parameters and/or functions of parameters are valid for estimating co-volatility spillover effects and testing for asymmetric co-volatility spillover. The returns and volatility of returns were tested for causality and asymmetric partial co-volatility spillovers.

As indicated previously, the role of news has extended the model for volatility, which is of great interest for analysis and decision making purposes. This model is commonly known as the DBEKK-GJR-GARCH conditional volatility model. The conditional mean model is taken as a VAR along the lines of Box and Jenkins (1978). The conditional mean model is based on the multivariate asset returns of one kind (say stock) or of a mix of assets (say stock, bond, money).

The vector conditional mean model, DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M models require estimation jointly for statistical inference. As mentioned in Chapters 4 and 5, the validity of the normality is in question; therefore, the QML method is an alternative for estimation. In the absence of normality, QMLEs are consistent and asymptotically normally distributed. This chapter contains five sections that deal with dependence analysis of returns in general.

Section 6.2 dealt with jointly fitting VAR mean and DBEKK-GJR-GARCH conditional volatility models. The resulting estimated model provided tests for causality and spillover effects of return shocks on volatility, thereby addressing the research hypotheses. Here I extended the existing definitions of co-volatility within the DBEKK-GJR-GARCH model and developed a Wald-type test for co-volatility spillover effects. In this section I grouped financial markets into developed, advanced emerging and emerging financial market categories based on the classification of the FTSE 100 Index. I found significant short and long-run effects of return shocks on volatility and asymmetric volatility. For all three groups, I found significant causality including uni-directional and bi-directional causality or interdependence among the stock markets, signifying the existence of spillover effects of return shocks among these markets during the sample period. The test results are provided in Section 6.2. The significance of the leverage effect indicated the effect of return shock on volatility from two sources: its own effect and that due to the news effect. A news effect might be due to a market crash, government intervention policy and so on.

In Section 6.3, I discussed an important issue relating to the international CAPM that helped to determine the existence of a risk premium in the multivariate asset market. This model is an extension of the previous mean model. The model is generally known as MGARCH-M model. In this context I called it the DBEKK-GJR-GARCH-M model and estimated it by QMLE. The estimated model parameters have the desirable asymptotic statistical properties for jointly testing leverage effect and volatility spillovers, as well as the existence of effects of return shocks on volatility. I computed the leverage effects and tested the risk premium by estimating the model by QMLE. The test results indicate a significant risk premium exists in US and Japan bond markets, while no significant risk premium was documented in the Australian bond market during the sample period. However, I reported, in chapter 5, the presence of a risk premium in the bond market in the univariate analysis. The reason for this difference may be the vector of the series in the multivariate case. The applicability of the EMH is mixed. Therefore, the full rational expectation (RE) hypothesis does not hold in the bond market, which is a violation of the full EMH. This information is important for portfolio diversification and portfolio allocation strategies.

In Section 6.4, I described the VAR approach to analysing dynamic dependence among a set of asset returns using Sims's (1980) methodology. I extended the methodology to allow the model to include financial crash events. Crash events were identified by the calendar date of the occurrence of rare events. These events do not occur frequently but are very important and their effects last longer in the financial market. I classified these market crash events as 1987 crash, AFC and the GFC. I modelled the return series using VAR-X, an extended form of Sims's VAR. The X-variables are exogenously determined but their occurrence depends on unknown sources of information.

The model was estimated by the OLS. The SUR of Zellner (1962) did not improve the efficiency because each equation in the system has the same right-hand-side variables. The estimated VAR coefficients were found to be stable by the eigenvalue of the determinantal equation. All roots of the VAR lie within the unit circle confining the stability of the VAR model. VAR order selection was conducted using multivariate AIC, BIC and HQ criteria. I used the estimated model and developed criteria to determine the severity of each crash event. The likelihood of rejection of the null hypothesis of no crash was used to compute an index $0 \leq \lambda \leq 1$, where is the value of the test statistic. A value of closer to 1 indicates a strong crash due to news (unknown but estimable by the return shock variable). Based on the newly developed criteria I found that most global financial stock markets experienced more severe crash effects from the 1987 crash and GFC than from AFC. This is consistent with reality. Causality and variance decomposition were investigated within the context. This criterion can be used for decision making purposes to choose the optimal portfolio during a crash period.

In Section 6.5, I extended the VAR to include both the time and cross-section dimension of global financial asset markets. I analysed five countries, each with three assets namely stock, bond and T-bill using the Panel VAR (PVAR) approach to explore the interrelationships among asset classes. All series were found to be stationary using the IPS, Maddala–Wu and Hadri panel unit root tests. I considered the fixed-effects PVAR because fixed-effects estimates are consistent. The model was estimated by GMM estimation. The GMM method does not require distributional assumptions for estimation and GMM estimators are consistent and asymptotically normally distributed (see Hansen, 1982). The forecast error variance decomposition and IRF were examined by Monte Carlo simulation as in Abrigo and Love (2015). The estimated model produced stable PVAR solutions. The test was conducted on the parameter vector for the effect of a market crash on the return series. The test results indicated a significant effect of the GFC on bond, stock and T-bill markets for the sample periods.

In Section 6.6, I further extended the dependence analysis by employing nonparametric approaches to the ranked correlation of Spearman, and Kendall's tau criteria. I developed an asymptotic χ^2 test for the existence of contemporaneous covariance dependence. The asymptotic χ^2 test revealed the existence of covariance dependence among the assets. Finally, I examined the dependence of multiple stock markets (pairwise) utilising the copula links that connect the multivariate joint distribution functions with their marginal. The copula link depends on the choice of copula function. I used the Gumbel copula with GJR-GARCH t-errors to generate copula dependence for the Australia–HK, Japan–US and UK–US market pairings respectively. I used the ranked residuals obtained from the GJR-GARCH with t-error to form the bi-variate Gumbel distribution. The Gumbel parameter and Kendall's tau (τ) are related by $\tau(\theta) = \frac{\theta - 1}{\theta}$, where $\theta \geq 1$. Therefore, $0 \leq \tau(\theta) < 1$. Values closer to 1 indicate the maximum dependence and those closer to 0 indicate non-dependence. I found some form of dependence between the pairs examined in the analysis.

This chapter has provided novel methodological innovations in the area of financial volatility modelling, estimation of co-volatility spillovers, partial co-volatility tests, aggregate volatility spillover effects, causality, contagion effects and dependence analysis. These methodologies are the main contributions of this thesis. Future research may be undertaken by applying the novel methodologies of this thesis to global financial markets in general, and the methodologies can be adopted for other branches of research.

Chapter 7: Conclusion

7.1 Introduction

Volatility is a term that refers to fluctuations in a time series over a period. In the finance area, asset price volatility is an important concern among researchers, agents and academics. As such, estimation and prediction of price volatility are useful in financial decision making for pricing of securities; measurement of VaR; allocation and diversification of assets; and assisting financial regulators with policy implementation. There are three main areas of volatility modelling: (i) implied volatility, (ii) realised volatility and (iii) conditional volatility. Of these, the ARCH of Engle (1982) and GARCH of Bollerslev (1986) have been the most well researched among financial volatility models.

Within the conditional volatility framework, this thesis proposes a new methodology and provides new evidence for the stochastic behaviour of asset returns and relationships between return volatility and expected returns. To provide a basic understanding I examined univariate volatility models utilising classical statistical distribution theories. In light of the recently developed theory of Chang and McAleer (2017) and McAleer (2019) among others, I extended the univariate situation to a multivariate analysis of financial asset returns and volatilities of returns across countries. I examined the daily return data of global stock, bond and money markets for 17 countries from 2 January 1985 to 30 December 2016. I investigated various methodologies and modelling issues to establish a good volatility model for effective policy decision making purposes.

7.2 Summary of Key Findings

Since the true specification of the DGP is never known completely, for a basic understanding of the DGP I first examined the basic properties of all 17 countries' asset return series. The majority of the return series were found to be skewed, heavy-tailed and non-normal. The return series were also found to be serially dependent in the level and squared series. These findings directed me to then apply theory and data-inherent properties jointly to search for a tentative model of the DGP under study. The two properties of serial dependence and asymmetry of the data directed me to develop a model of the first and second moments of a financial time series jointly to examine the stochastic behaviour of asset returns and to establish the relationship between return volatility and expected return. I introduced three probability distributions, namely the normal, Student-t and skewed Student-t distribution of return shock, to capture the volatility clustering encountered in the individual asset return series of the stock, bond and T-bill of 17 countries. Univariate and multivariate empirical results are reported in Chapters 5 and 6 respectively.

In Chapter 5, the basic descriptive statistics and preliminary tests of the returns of stock, bond and market-bill series were examined. Overwhelming support for the stylised facts of volatility clustering of a typical financial series were documented. Overall, the return series for stock, bond and T-bill were found to be serially dependent. These series exhibit volatility clustering as confirmed by LB-Q^2 and Kurtosis tests. Considering this fact of the data properties, I utilised the GARCH model of Bollerslev (1986) to model volatility clustering of the return series. It is to be noted that GARCH is a generalisation of the pioneering work represented by Engle's (1982) ARCH volatility model. The ARCH/GARCH model lacks the asymmetric news effect that is a common phenomenon often encountered in financial markets. Consequently, I utilised the popular GJR-GARCH model (Glosten, Jaganathan, & Runkle, 1993) of asymmetric volatility to understand the asymmetric behaviour of financial markets. There are, however, other asymmetric models available in the literature.

For a basic understanding, I examined univariate time series models of volatility and asymmetric volatility in Chapter 5. Both the GARCH and GJR models uncovered significant short- and long-run return shocks in almost all the series considered in this study. One additional piece of information extracted utilising the GJR-GARCH model was the news effects found to be significantly asymmetric in all series except the China and Indonesia stock returns. This information is useful for policy decision purposes in that an agent can distinguish 'good' and 'bad' news to trade assets effectively in global financial markets. So-called unobserved good and bad news can be a proxy related to positive and negative return shocks, respectively. Theoretically, it is true that negative shocks have a larger effect than positive shocks of the same magnitude. With the GARCH volatility model, I found a significant effect of return shock on volatility in all of the series, with the exception of the China, Indonesia and Malaysia stock returns. This implies that any shock persisted in these stock markets in the sample periods. In other cases, shocks were found to be statistically transitory.

I found the long-run effect of shock on volatility. This phenomenon is commonly observed in practice in GARCH volatility models. Volatility prediction under normal, Student-t and skewed Student-t innovation showed that the skewed Student-t distribution had the largest standard deviation for prediction, followed by Student-t. The normal innovation GARCH model had the lowest standard deviation for prediction of volatility. I computed the half-life of return shocks on volatility for the GJR-GARCH-M model. In this model, the risk premiums were found to be positive but not significant in most cases. A similar result was documented by Panayiotis and Lee (1995) using the GARCH-M model. I found that the half-life of a return shock on volatility of GJR-GARCH-M model was the highest (0.47 days) for Australia and South Korea, and lowest (0.29 days) for Singapore and Indonesia.

The inability of univariate volatility models to deal with interdependence and volatility spillovers among assets domestically or globally is of concern for investors. Information about interdependence, causality and volatility spillovers is vital for asset allocation and diversification strategies. I discussed modelling issues for multivariate specifications in Chapter 6.

In Chapter 6, I modelled and tested for causality in returns and volatility spillovers between financial assets across countries. In the literature, multivariate volatility models have been typically based on the BEKK and DCC of Engle (2002). The QMLEs of the full BEKK and DCC have no asymptotic properties, as shown by Chang and McAleer (2017). The multivariate extension of GARCH (1,1) derived from a vector random coefficient autoregressive process of order one has a DBEKK representation (McAleer et al., 2008; Chang & McAleer, 2017). Following Chang and McAleer (2017) and McAleer (2019) among others, I formulated the VAR-DBEKK-GARCH, VAR-DBEKK-GJR-GARCH and DBEKK-GJR-GARCH-M models for modelling multivariate conditional mean and volatility jointly for analysis of the return series for 12 countries categorised as developed, advanced emerging and emerging financial markets. The models were estimated utilising the QML method for data from the developed, advanced emerging and emerging countries. I extended the definition of partial co-volatility spillovers within the DBEKK-GJR-GARCH models. I estimated the co-volatility spillover effects and tested for co-volatility spillovers utilising a new quasi-Wald-type test. I found significant partial co-volatility in the multivariate volatility models and significant causality in the multivariate return models. I found significant causality running in the multiple stock markets with some reservations. Specifically, I found causality running from the UK to the US stock market and vice versa; that is, bi-directional causality between these two countries. Both Japan and HK have significant causal effects on the US stock market. Significant short and long-run volatility, and significant asymmetric volatility spillovers, exist in multiple stock markets. I allowed the multivariate returns to include the multivariate DBEKK-GJR-GARCH specification for measuring risk premiums in the multivariate context. The DBEKK-GJR-GARCH-M model was estimated by the QMLE for the 5-year bond market data. I found that a significant risk premium exists in the bond markets of the selected countries. This result indicates that the full EMH does not hold for the global bond markets in the sample. The conditional mean return of US bond markets has significant Granger causality of its own shocks as well as those of the Japan and Australia bond markets. Importantly, I found a significant volatility risk premium for the US and Japan bond markets but not for the Australian market. This means that the full expectation theory does not hold for the Japan and US markets. This information is useful for investment decision making in international bond markets.

I extended Sims's (1980) classical VAR to include financial crash events to evaluate the impact of these events on volatility spillovers using forecast error variance decomposition and impulse responses. The VAR-X allowed the inclusion of more dimensions for example, country and time dimensions to examine the tastes of the PVAR-X model and evaluate the effects of the GFC. These specifications extract information contained in the data, revealing the contributions of the forecast error variance of the multiple financial asset returns series across countries. A significant GFC crash effect was documented for 9 of the 10 selected countries; while the Asian crisis was experienced by only 4 of the 10 countries (Canada, HK, Indonesia and Malaysia). The 1987 crash was experienced by 7 of the 10 countries: Australia, Canada, Germany, HK, Malaysia, UK and US.

Causal dependence was checked individually by the t test and jointly by the F test. Variance decomposition within the VAR framework revealed the proportion of movements in a sequence that were due to its own shocks versus shocks to other variables. For example, in the sample, I found that 84.0% of the variance in the two-step forecast error was due to innovation in the Australia stock return itself. The three principal factors driving the two-step forecast were Australia (84.0%) itself, Canada (9.9%) and Germany (5.1%).

A new SI was constructed to determine the severity of crash events and contagion effects of volatility spillovers among assets returns. The stock markets experienced higher severity from the 1987 and GFC crashes than from the 1997–98 Asian Financial Crisis. This is an important finding for both domestic and international stock market investors and decision makers. I also estimated the stock, bond and T-bill markets within the PVAR specification for five selected countries using by the GMM to evaluate the effect of the GFC alone. I found that the GFC most severely affected the stock market, followed by T-bills and finally, bond markets in the sample of five countries jointly. Dependence among global stock returns was investigated utilising parametric and nonparametric correlation tests and revealed significant dependence of stock returns between two pairs of countries: Australia and HK; and Japan and US. Pairwise copula links were used to examine the dependence of returns volatilities of the selected countries by combining joint distribution functions with their marginals utilising the Gumbel copula and Student-t margins. I found significant dependence of the series via copula simulation. Application of the covariance dependence test of asset returns jointly revealed that there is significant contemporaneous covariance dependence among assets returns. Overall, this thesis has revealed significant volatility spillovers, significant risk premiums, effects of financial crisis, partial co-volatility spillovers and dependence among financial assets across countries within multivariate assets markets.

7.3 Implications of the Findings

Based on the research findings of this thesis, I realise that the univariate analysis of financial asset markets cannot provide any interaction effects between stock markets. Interactions among assets across countries are important for investment policy decision purposes. Therefore, there is a need to model multivariate asset markets domestically and internationally. However, multivariate conditional volatility model specification requires extra care to develop an adequate model that is valid for statistical inference and hypothesis testing of issues such as co-volatility spillovers and causality. This thesis provides the assets market dependence models that can be used for asset allocation and diversification.

The overall implication of the research findings of this thesis is that investors, agents and policy makers would benefit from utilising a range of econometric techniques to develop good volatility models for effective and efficient policy decision analysis.

7.4 Limitations and Recommendations for Future Research

No research is complete on its own and this is also true for this thesis. This research may be extended by considering the microstructure of financial markets to evaluate specific individual market interaction effects. The spatial dependence of markets may be structured to examine spatial effects in the pattern of asset trading. Dependence analysis using the copula may be extended by employing other copulas and additional assets because the choice of copula distributions and marginals can change the pattern of asset volatility dependence. The statistical validity of the tests for volatility spillover effects requires further investigation for correct statistical decision making purposes in financial markets.

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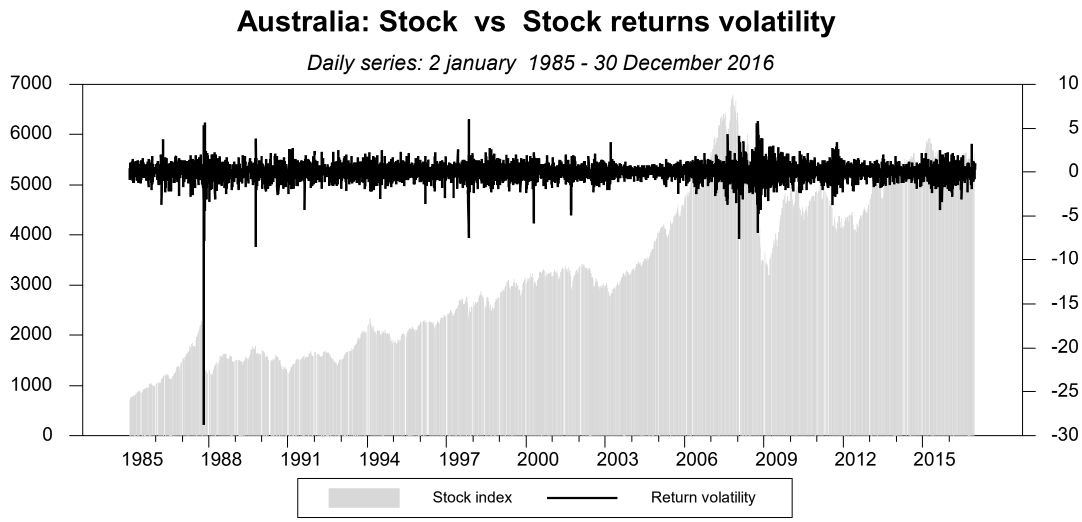
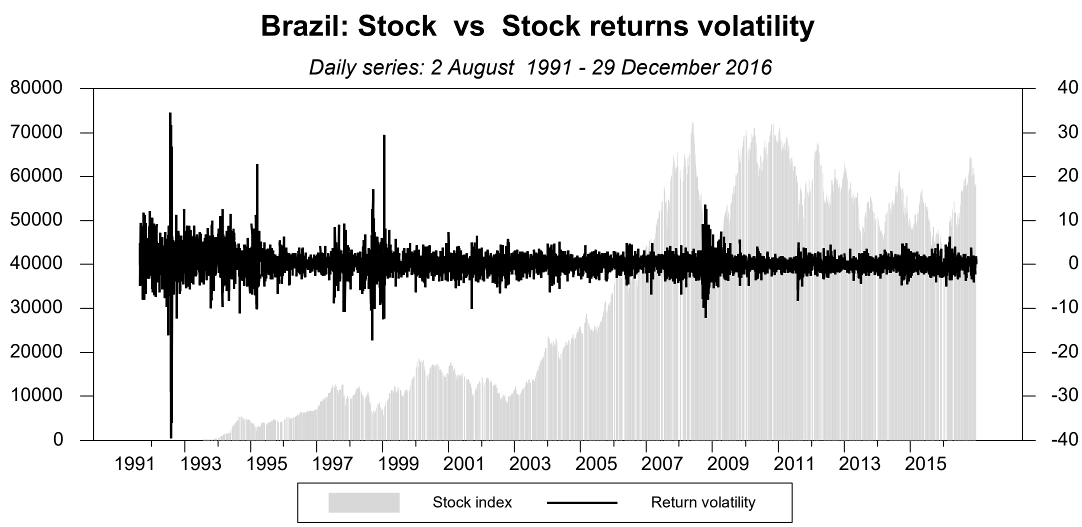
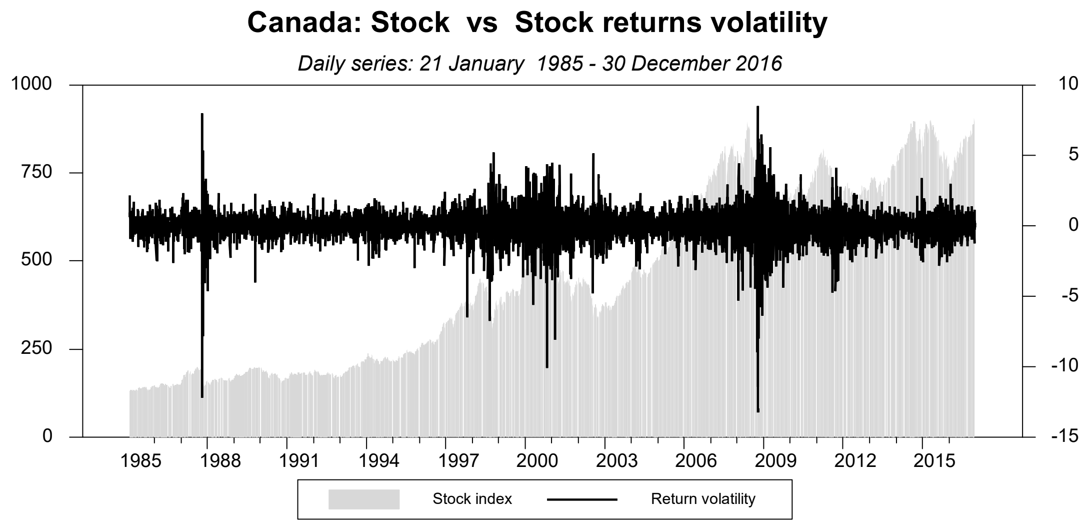
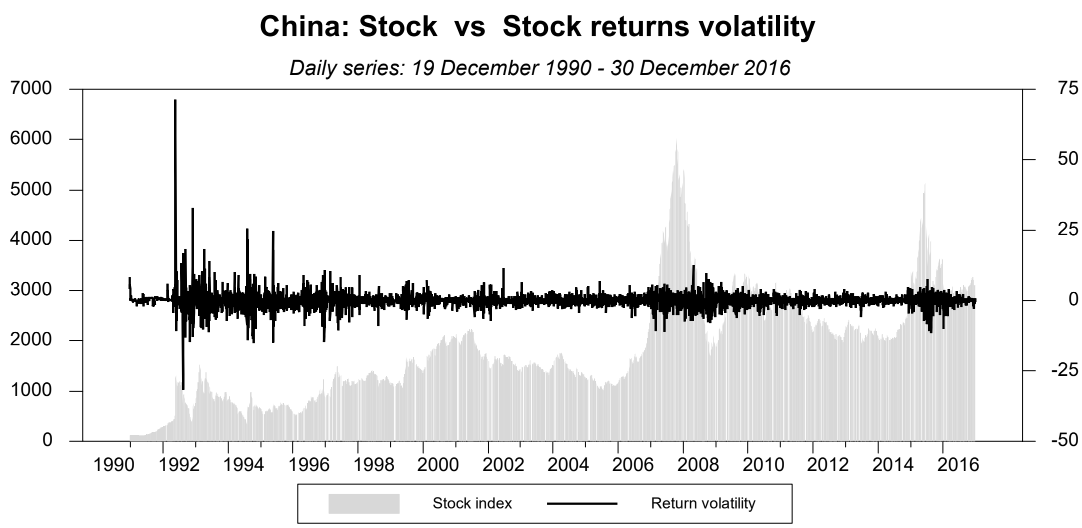
Appendix A

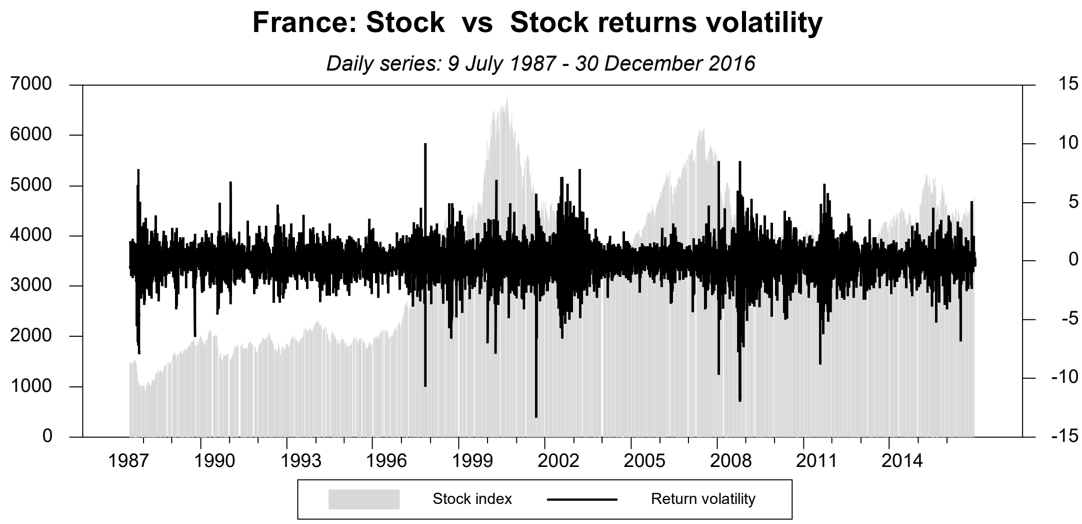
A1. Time plot of Stock of the selected countries

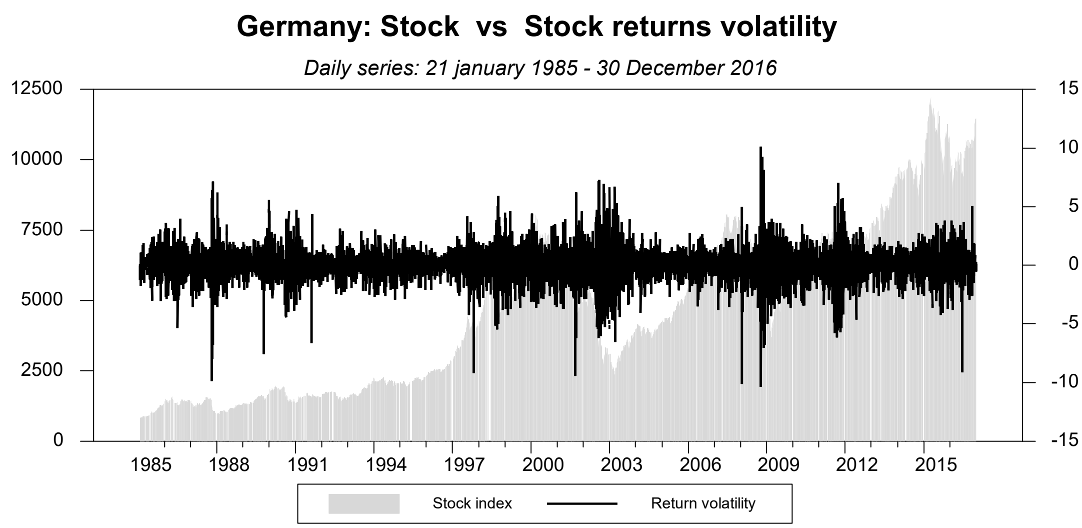


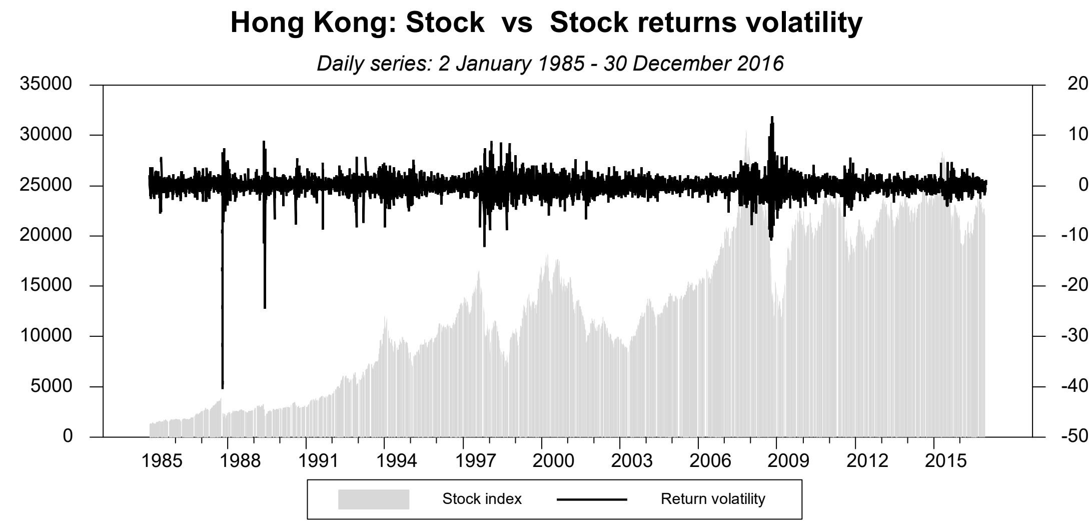


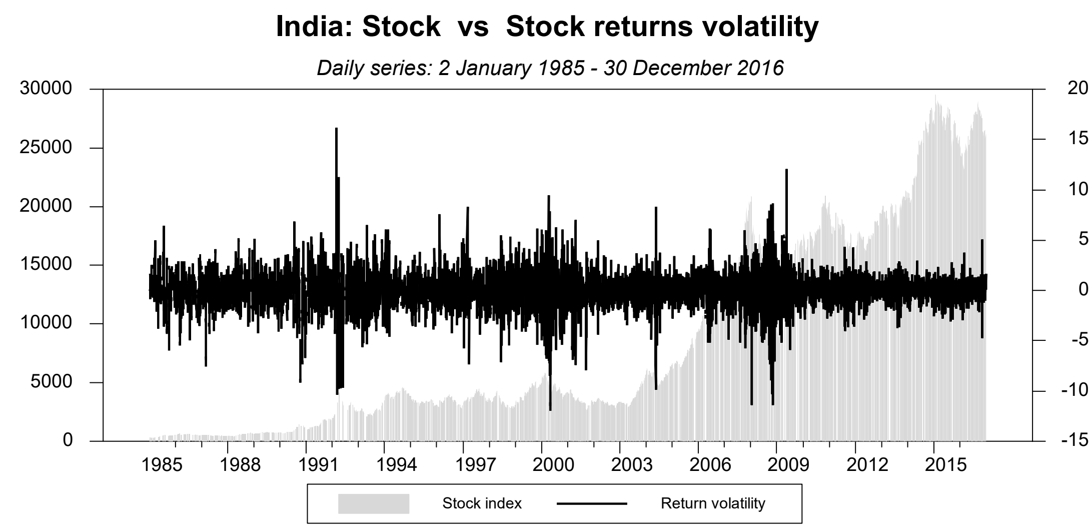

Canada: Stock vs Stock returns volatility
Daily series: 21 January 1985 - 30 December 2016
1000
750
500
250
0
10
5
0
-5
-10
-15
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
Stock index
Return volatility

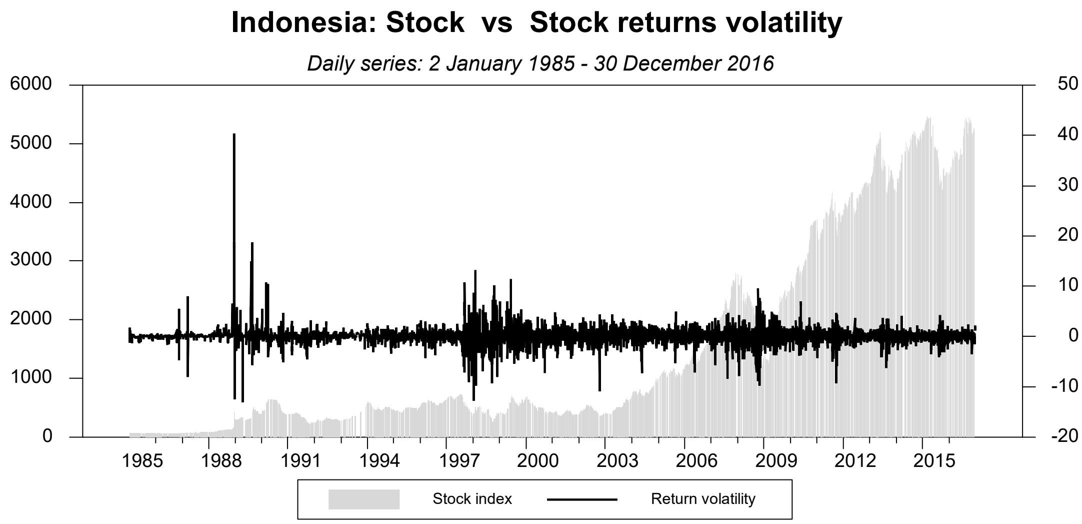

China: Stock vs Stock returns volatility
Daily series: 19 December 1990 - 30 December 2016
7000
6000
5000
4000
3000
2000
1000
0
75
50
25
0
-25
-50
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
Stock index
Return volatility

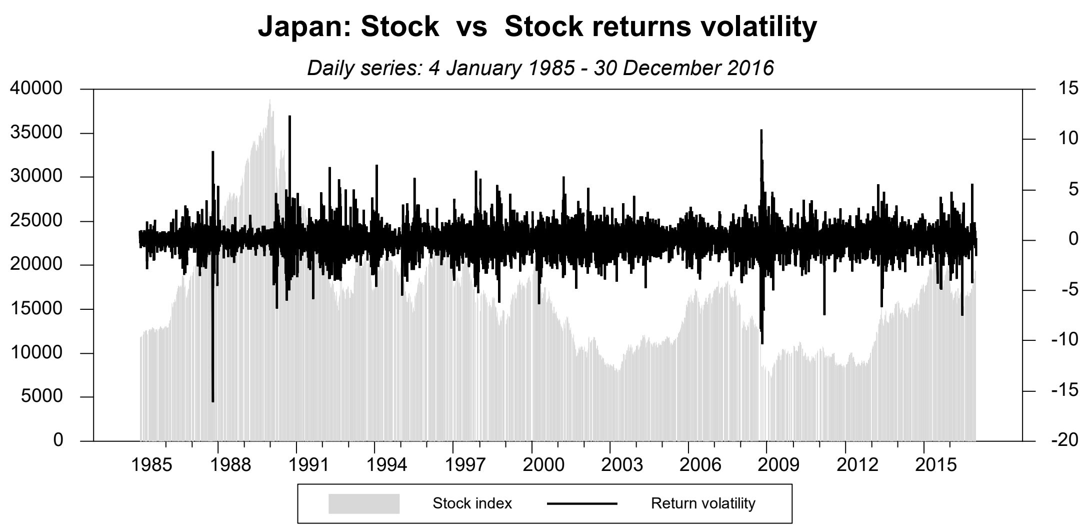

France: Stock vs Stock returns volatility
Daily series: 9 July 1987 - 30 December 2016
7000
6000
5000
4000
3000
2000
1000
0
15
10
5
0
-5
-10
-15
1987
1990
1993
1996
1999
2002
2005
2008
2011
2014
Stock index
Return volatility


Germany: Stock vs Stock returns volatility
Daily series: 21 january 1985 - 30 December 2016
12500
10000
7500
5000
2500
0
15
10
5
0
-5
-10
-15
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
Stock index
Return volatility


Hong Kong: Stock vs Stock returns volatility
Daily series: 2 January 1985 - 30 December 2016
35000
30000
25000
20000
15000
10000
5000
0
20
10
0
-10
-20
-30
-40
-50
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
Stock index
Return volatility

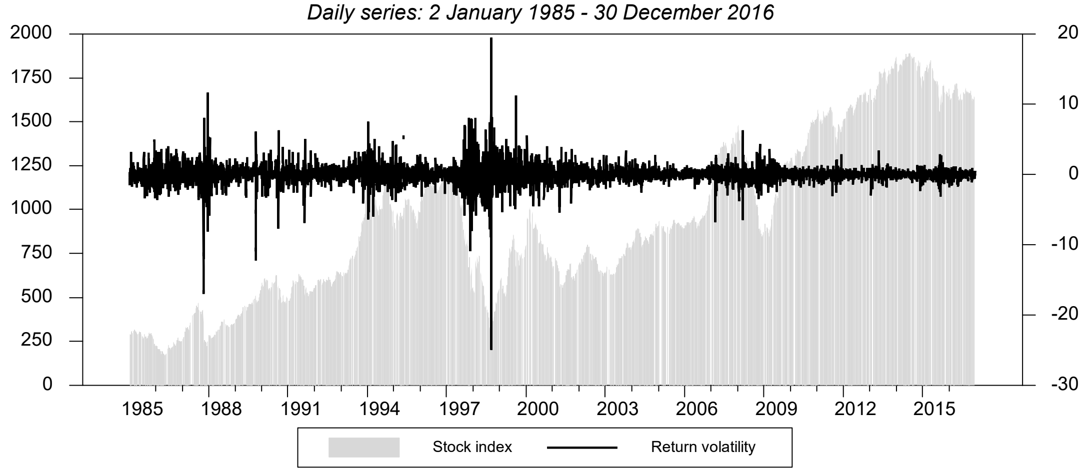

India: Stock vs Stock returns volatility
Daily series: 2 January 1985 - 30 December 2016
30000
25000
20000
15000
10000
5000
0
20
15
10
5
0
-5
-10
-15
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
Stock index
Return volatility


Indonesia: Stock vs Stock returns volatility
Daily series: 2 January 1985 - 30 December 2016
6000
5000
4000
3000
2000
1000
0
50
40
30
20
10
0
-10
-20
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
Stock index
Return volatility


Japan: Stock vs Stock returns volatility
Daily series: 4 January 1985 - 30 December 2016
40000
35000
30000
25000
20000
15000
10000
5000
0
15
10
5
0
-5
-10
-15
-20
1985
1988
1991
1994
1997
2000
2003
2006
2009
2012
2015
Stock index
Return volatility

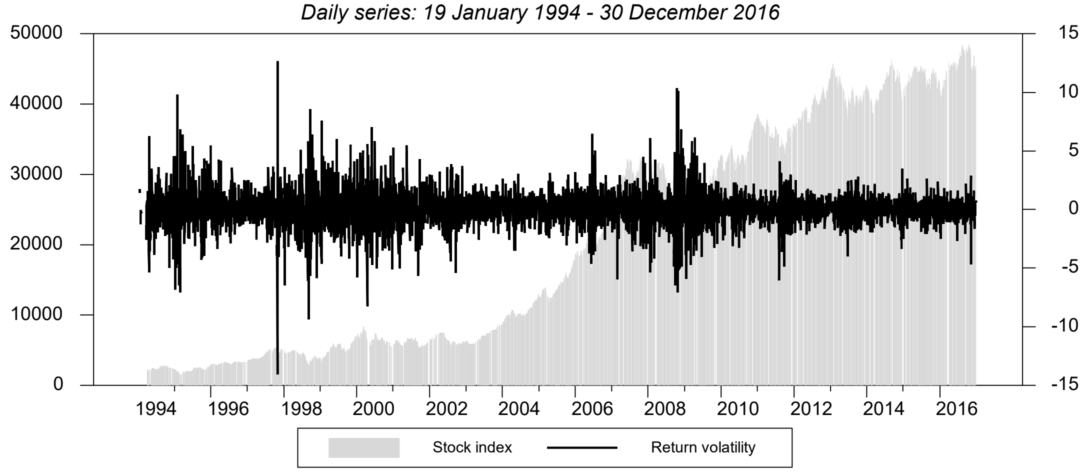
Malaysia: Stock vs Stock returns volatility

Daily series: 2 January 1985 - 30 December 2016



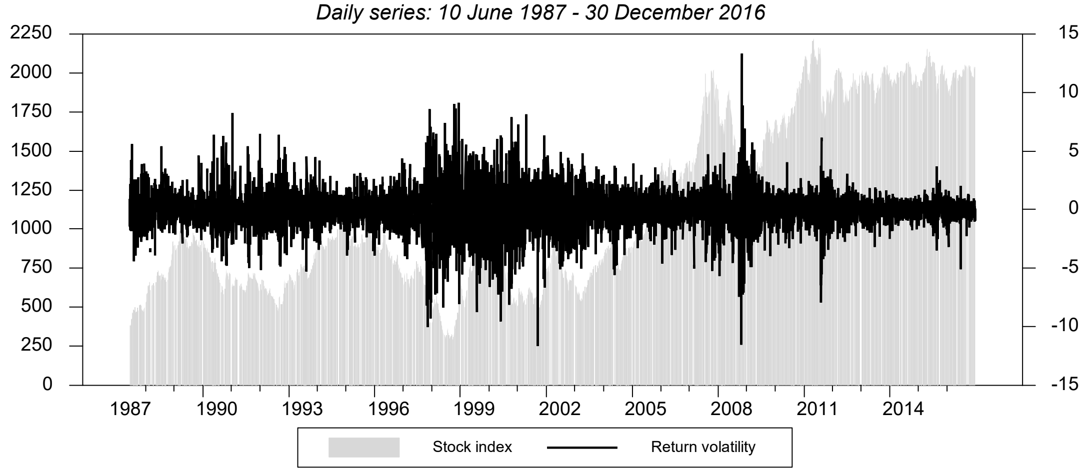
Mexico: Stock vs Stock returns volatility

Daily series: 19 January 1994 - 30 December 2016



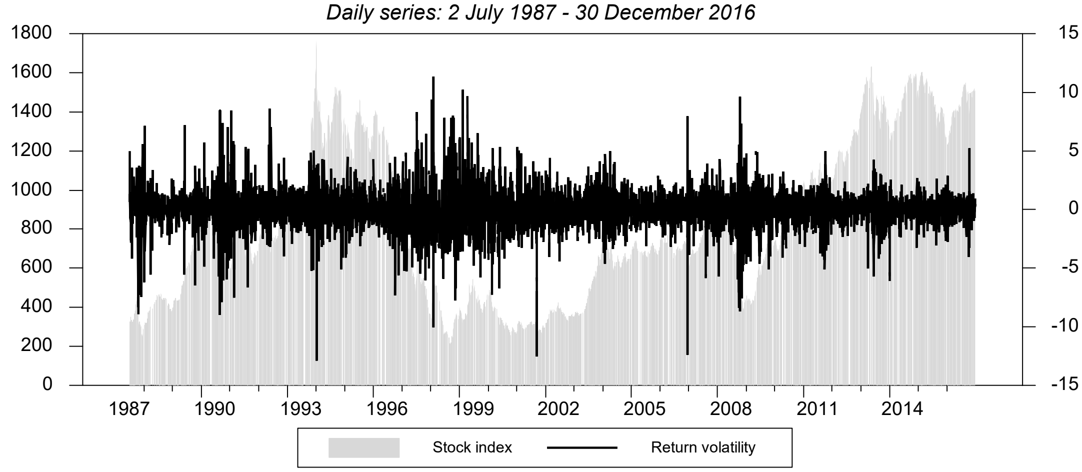
Singapore: Stock vs Stock returns volatility

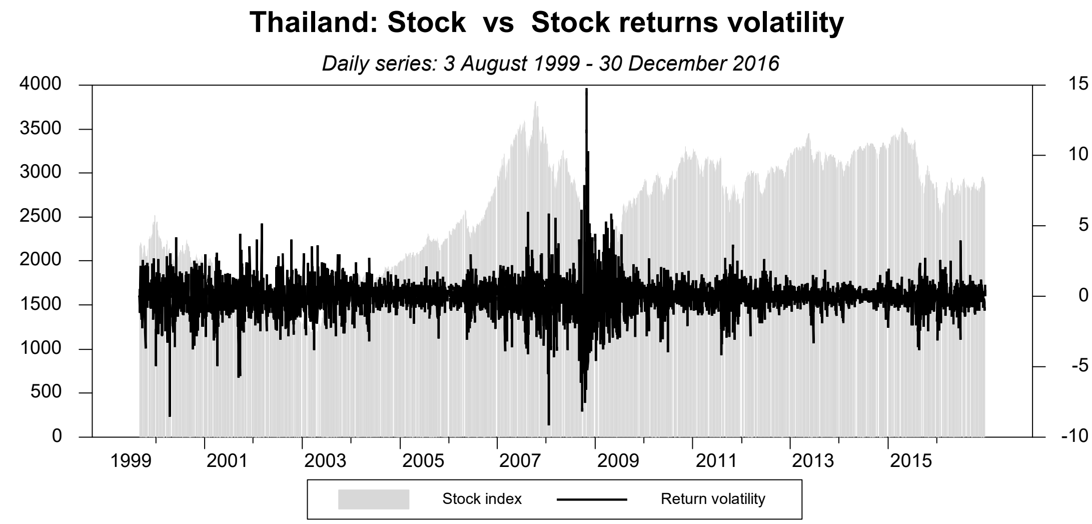
Daily series: 10 June 1987 - 30 December 2016

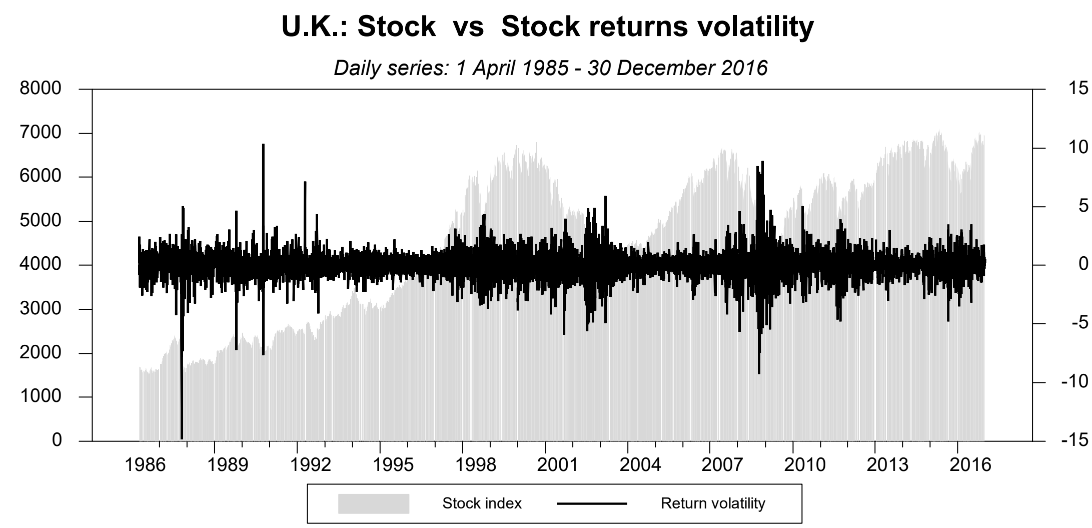


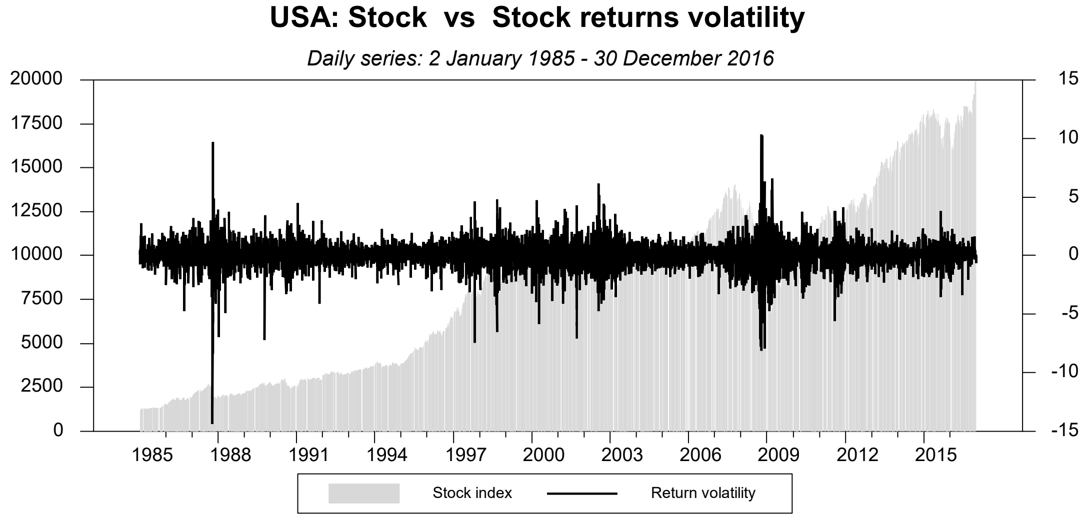
South Korea: Stock vs Stock returns volatility

Daily series: 2 July 1987 - 30 December 2016

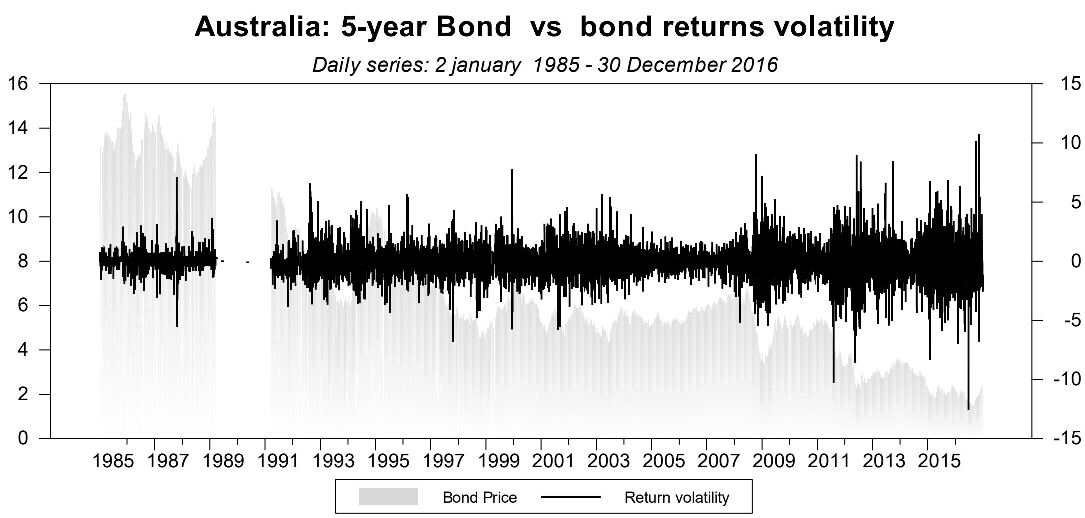


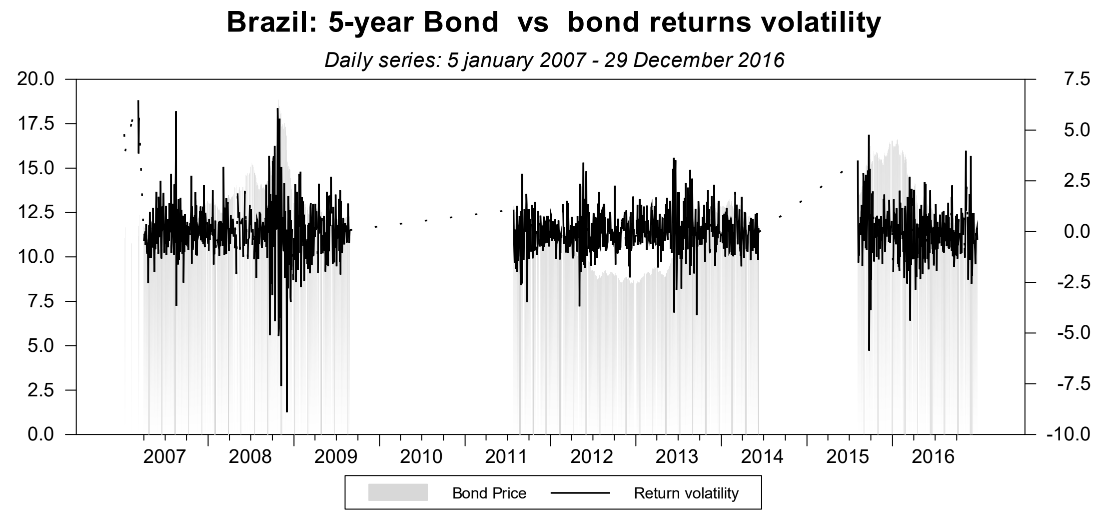

Thailand: Stock vs Stock returns volatility
Daily series: 3 August 1999 - 30 December 2016
4000
3500
3000
2500
2000
1500
1000
500
0
15
10
5
0
-5
-10
1999
2001
2003
2005
2007
2009
2011
2013
2015
Stock index
Return volatility

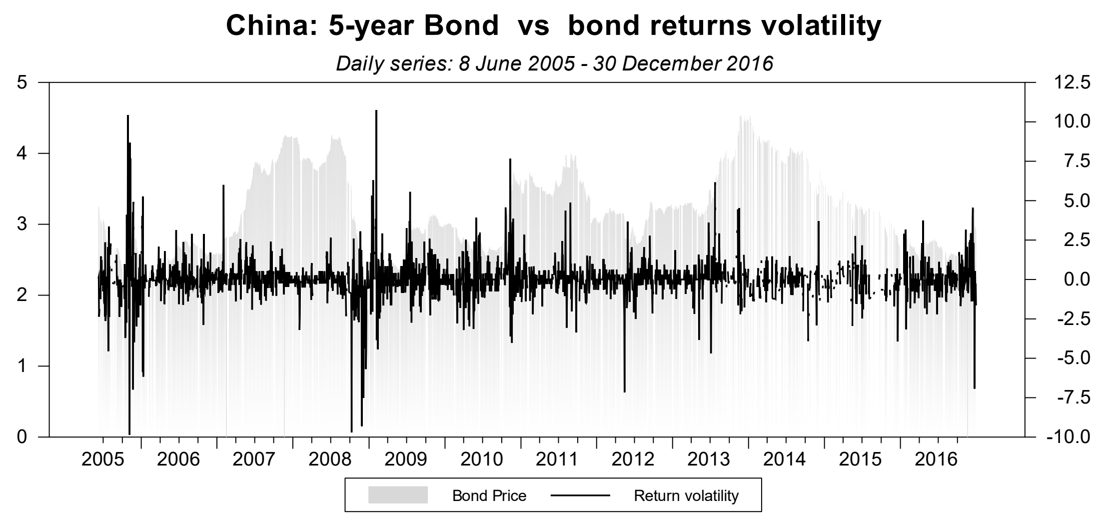

U.K.: Stock vs Stock returns volatility
Daily series: 1 April 1985 - 30 December 2016
8000
7000
6000
5000
4000
3000
2000
1000
0
15
10
5
0
-5
-10
-15
1986
1989
1992
1995
1998
2001
2004
2007
2010
2013
2016
Stock index
Return volatility



A2. Time plot of Bond of the selected countries

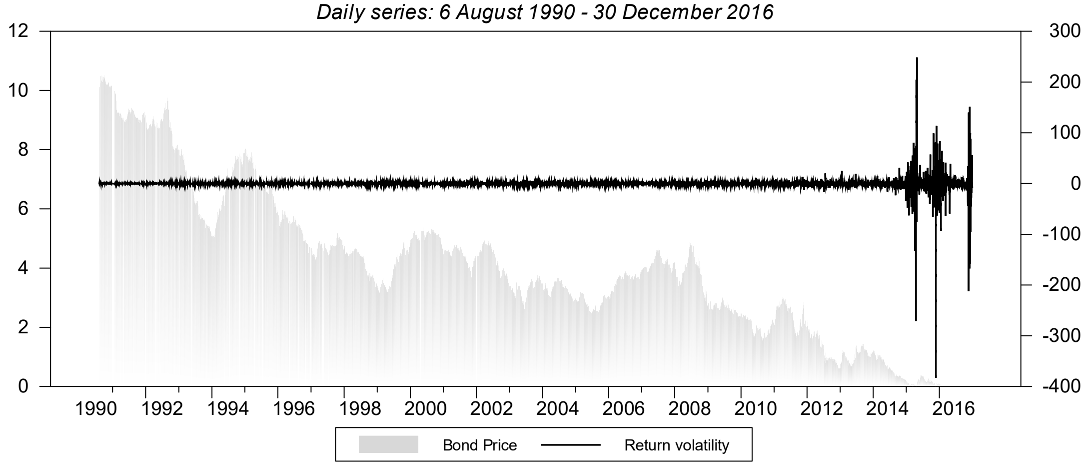



Brazil: 5-year Bond vs bond returns volatility
Daily series: 5 january 2007 - 29 December 2016
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
7.5
5.0
2.5
0.0
-2.5
-5.0
-7.5
-10.0
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Bond Price
Return volatility


China: 5-year Bond vs bond returns volatility
Daily series: 8 June 2005 - 30 December 2016
5
4
3
2
1
0
12.5
10.0
7.5
5.0
2.5
0.0
-2.5
-5.0
-7.5
-10.0
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Bond Price
Return volatility

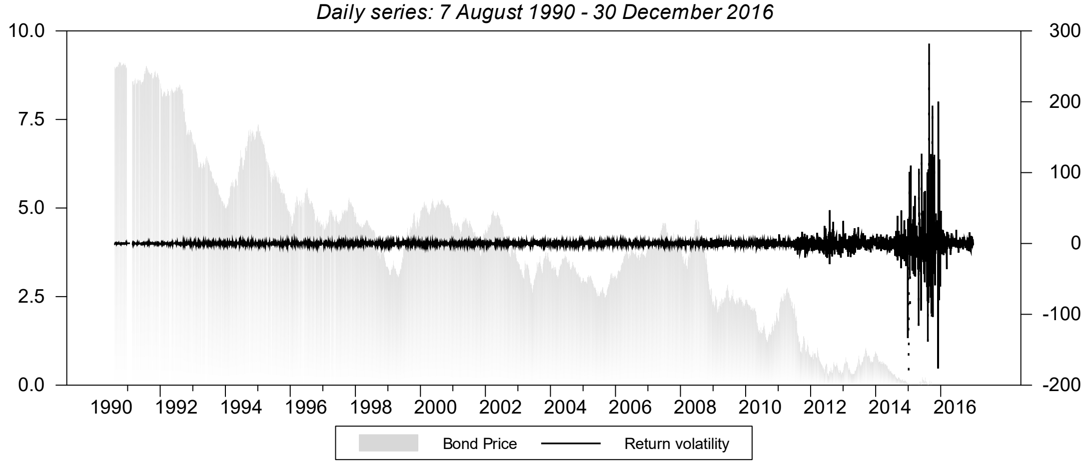
France: 5-year Bond vs bond returns volatility

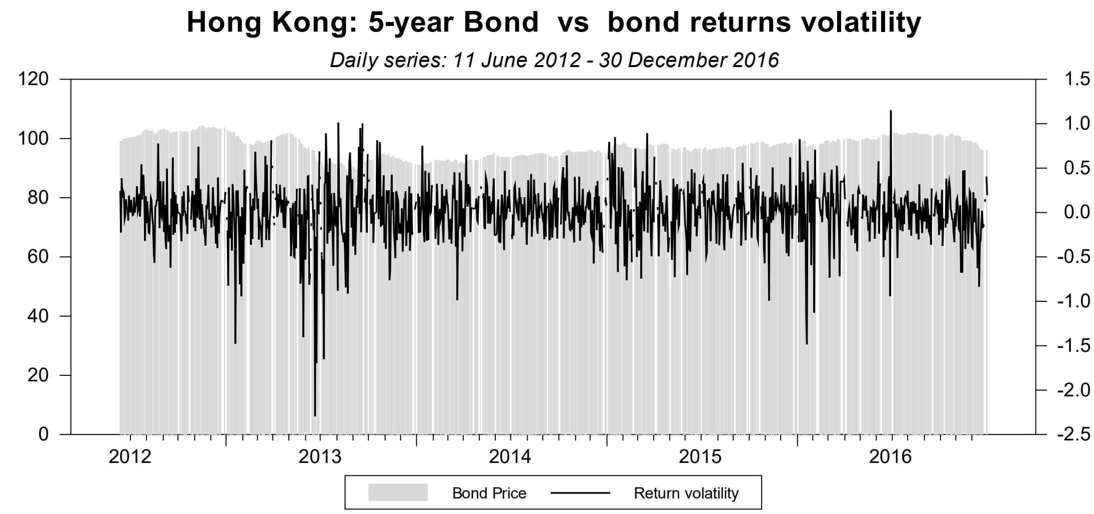
Daily series: 6 August 1990 - 30 December 2016

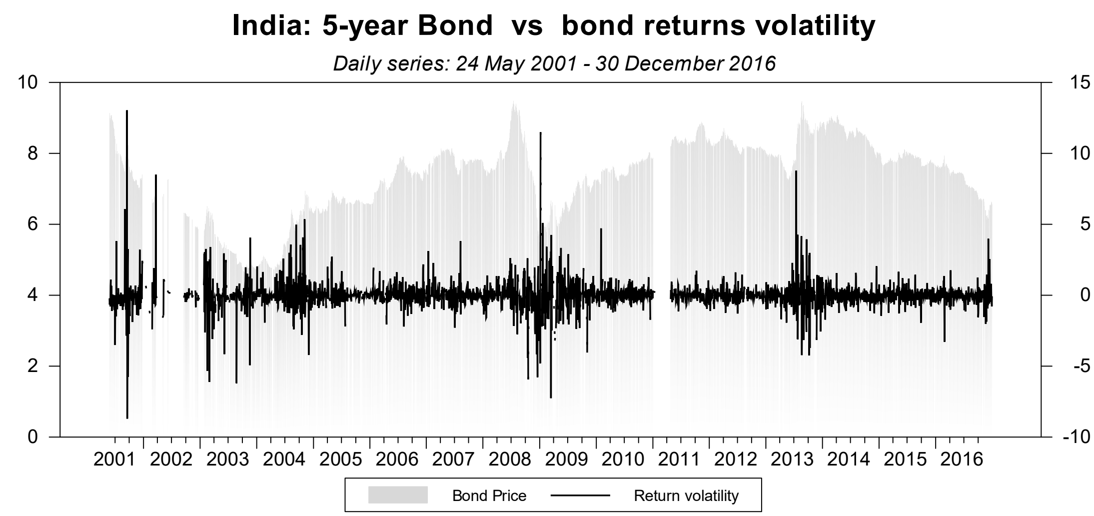


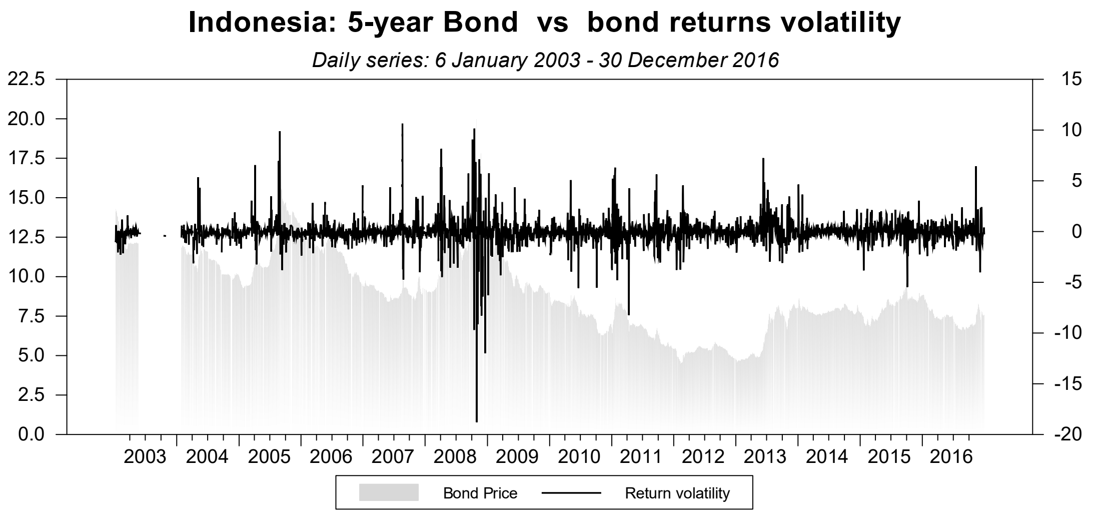
Germany: 5-year Bond vs bond returns volatility

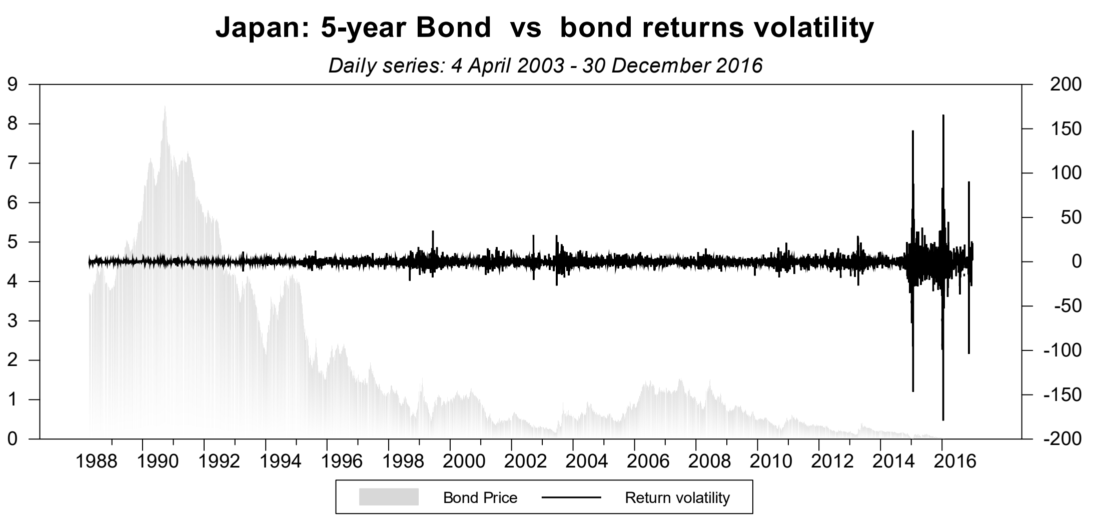
Daily series: 7 August 1990 - 30 December 2016

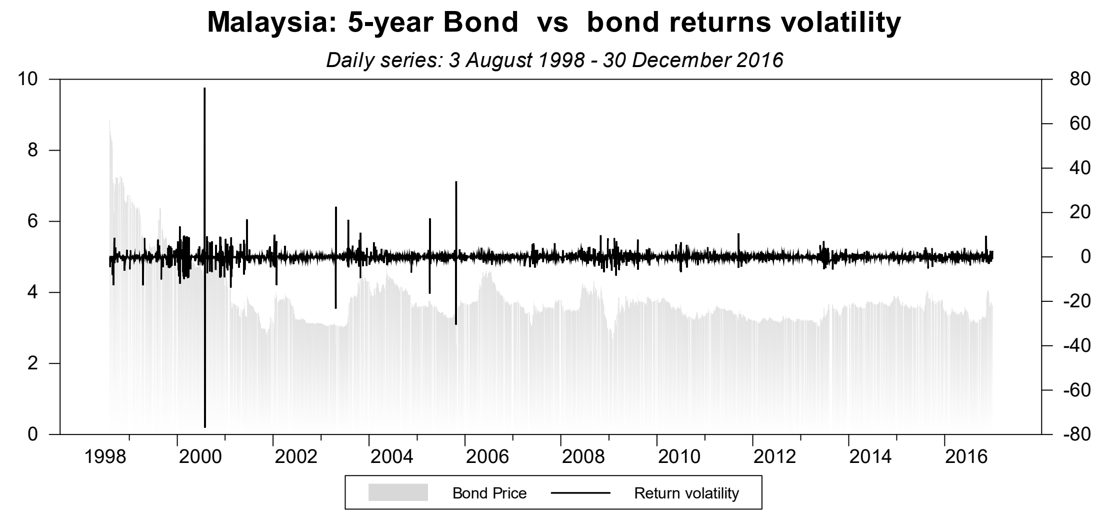


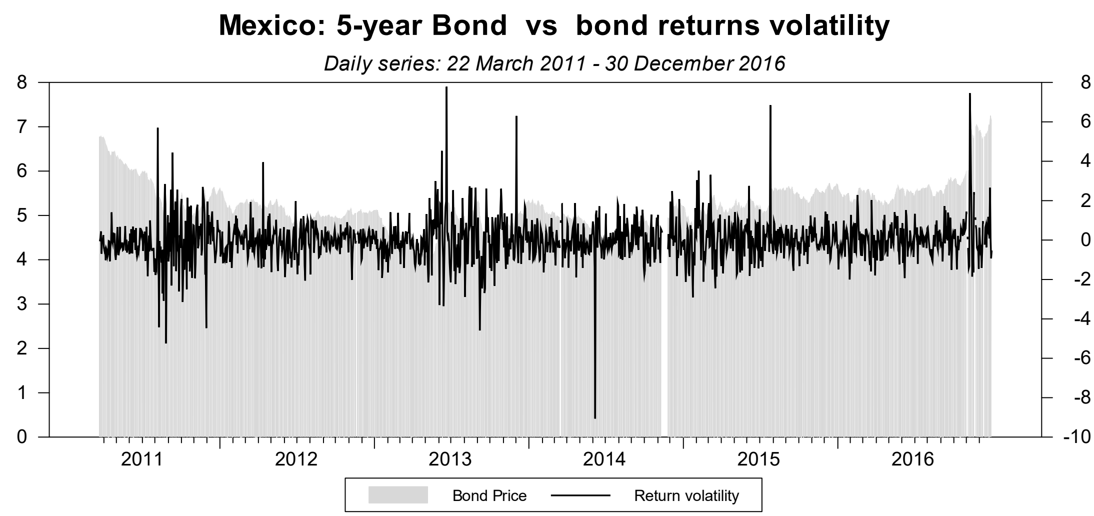

Hong Kong: 5-year Bond vs bond returns volatility
Daily series: 11 June 2012 - 30 December 2016
120
100
80
60
40
20
0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
-2.5
2012
2013
2014
2015
2016
Bond Price
Return volatility

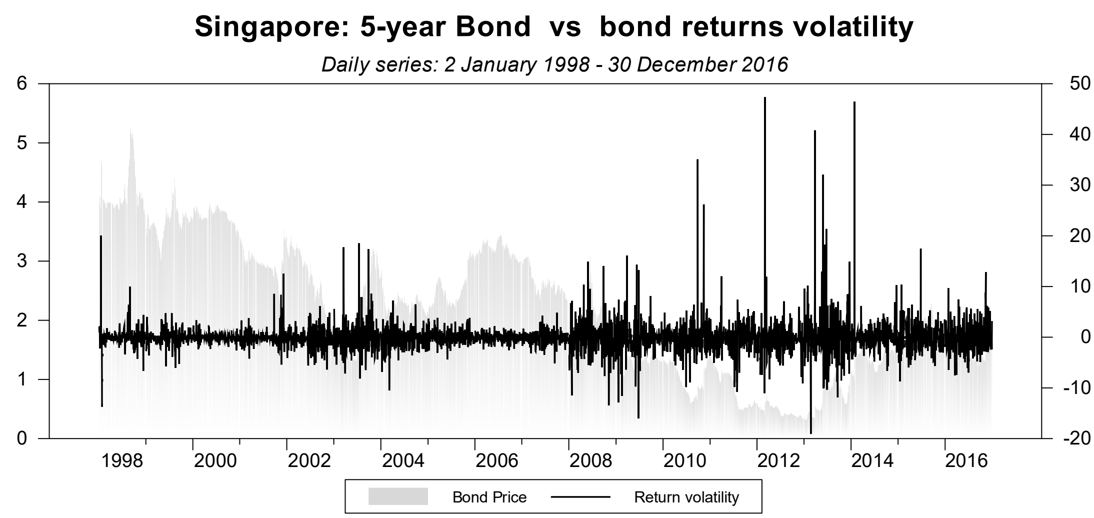

India: 5-year Bond vs bond returns volatility
Daily series: 24 May 2001 - 30 December 2016
10
8
6
4
2
0
15
10
5
0
-5
-10
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Bond Price
Return volatility

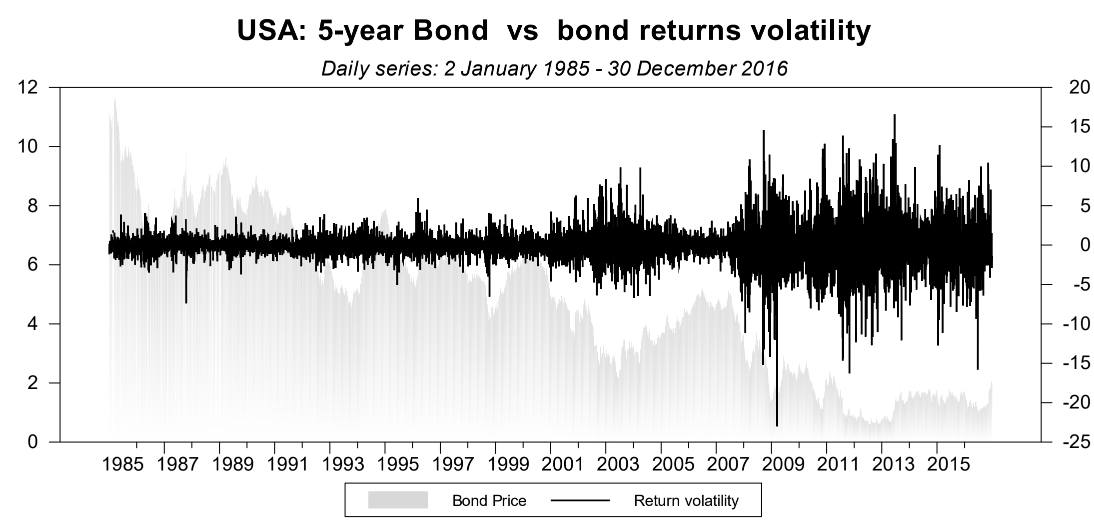

Indonesia: 5-year Bond vs bond returns volatility
Daily series: 6 January 2003 - 30 December 2016
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
15
10
5
0
-5
-10
-15
-20
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Bond Price
Return volatility


Japan: 5-year Bond vs bond returns volatility
Daily series: 4 April 2003 - 30 December 2016
9
8
7
6
5
4
3
2
1
0
200
150
100
50
0
-50
-100
-150
-200
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
Bond Price
Return volatility

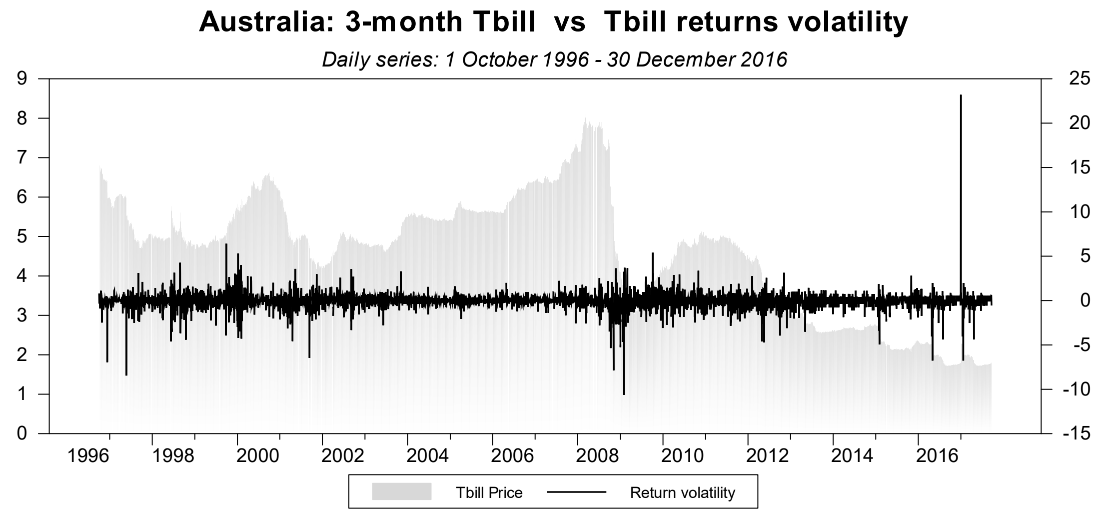

Malaysia: 5-year Bond vs bond returns volatility
Daily series: 3 August 1998 - 30 December 2016
10
8
6
4
2
0
80
60
40
20
0
-20
-40
-60
-80
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
Bond Price
Return volatility

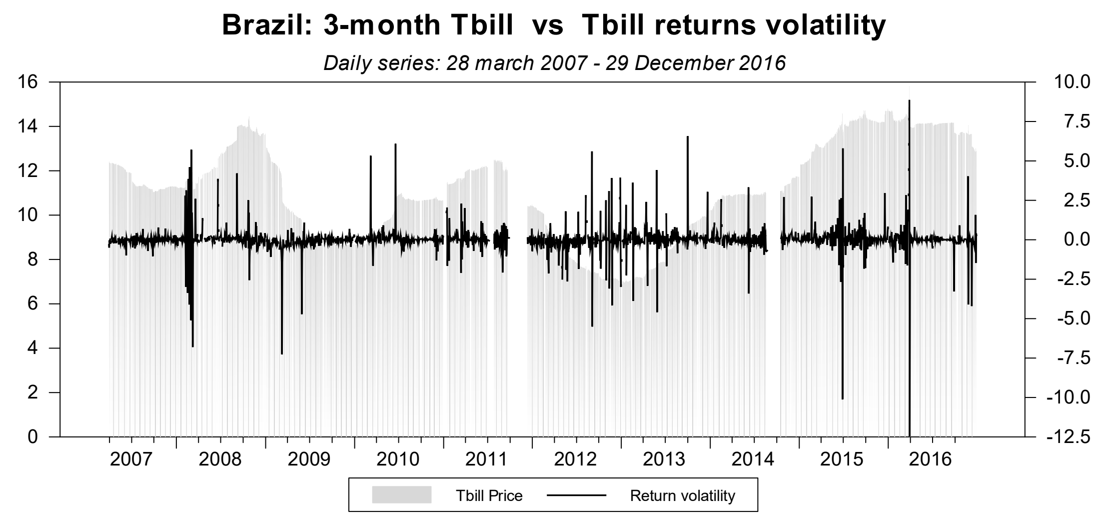

Mexico: 5-year Bond vs bond returns volatility
Daily series: 22 March 2011 - 30 December 2016
8
7
6
5
4
3
2
1
0
8
6
4
2
0
-2
-4
-6
-8
-10
2011
2012
2013
2014
2015
2016
Bond Price
Return volatility

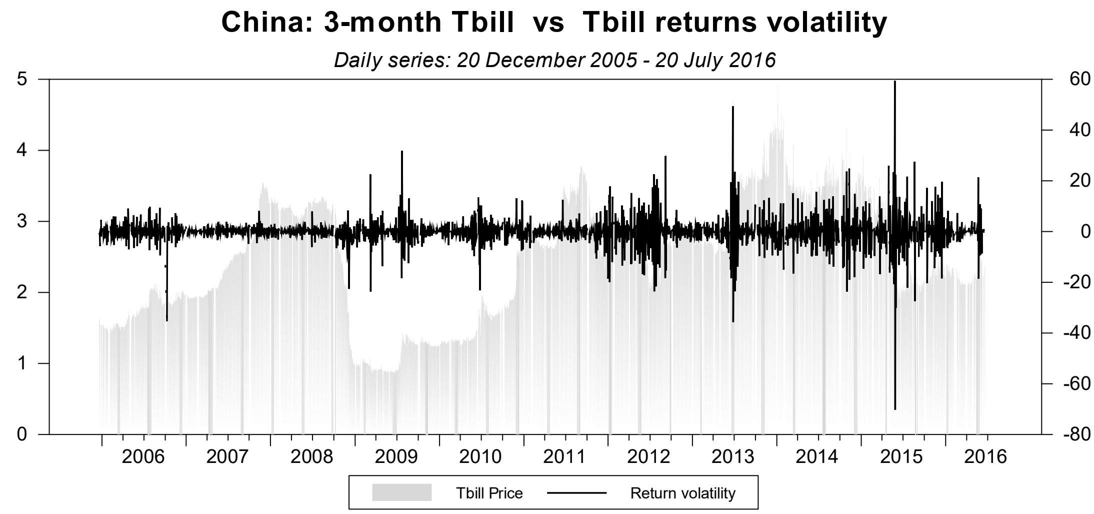

Singapore: 5-year Bond vs bond returns volatility
Daily series: 2 January 1998 - 30 December 2016
6
5
4
3
2
1
0
50
40
30
20
10
0
-10
-20
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
Bond Price
Return volatility

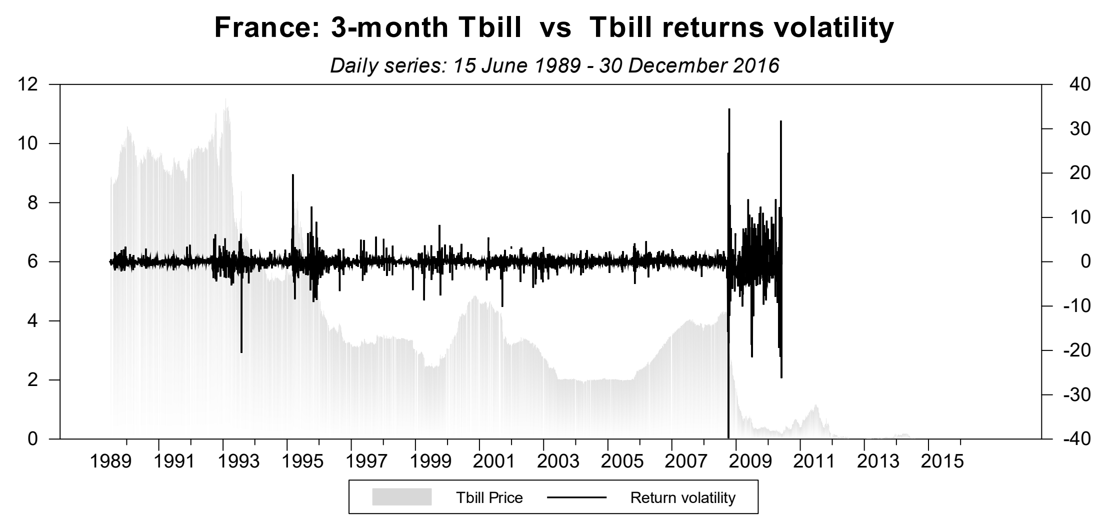

USA: 5-year Bond vs bond returns volatility
Daily series: 2 January 1985 - 30 December 2016
12
10
8
6
4
2
0
20
15
10
5
0
-5
-10
-15
-20
-25
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011
2013
2015
Bond Price
Return volatility

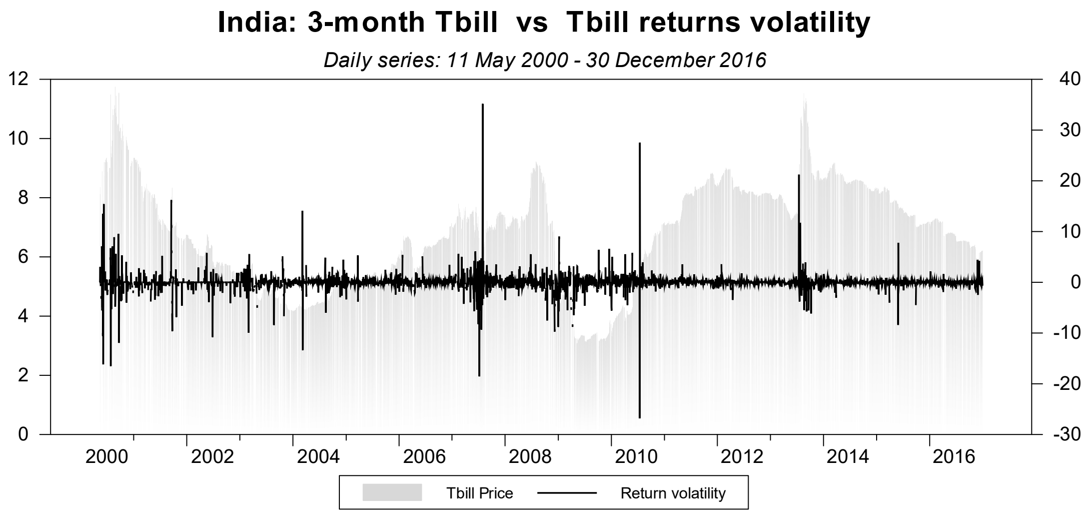
A3. Time plot of Tbill of the selected countries

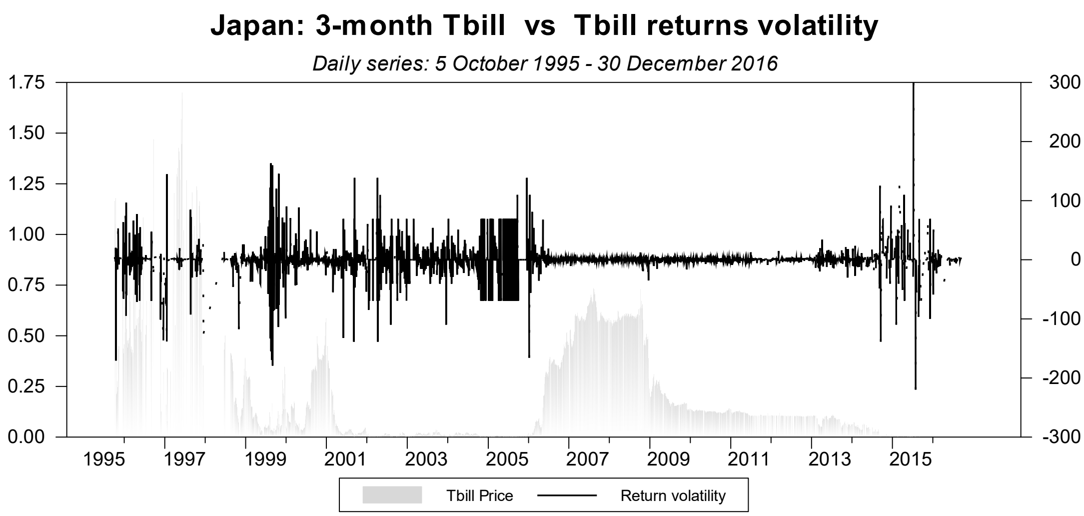





China: 3-month Tbill vs Tbill returns volatility
Daily series: 20 December 2005 - 20 July 2016
0 1 2 3 4 5
-80 -60 -40 -20 0 20 40 60
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
Tbill Price
Return volatility

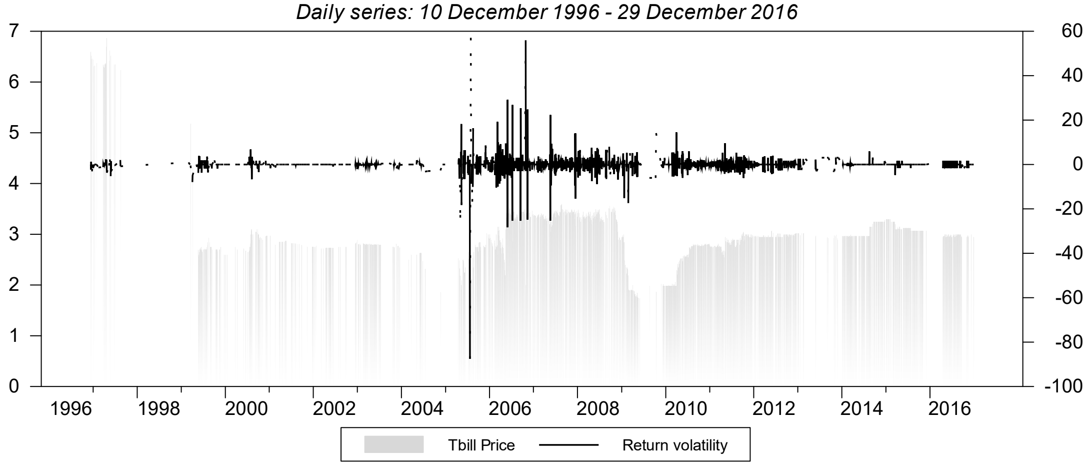

France: 3-month Tbill vs Tbill returns volatility
Daily series: 15 June 1989 - 30 December 2016
0 2 4 6 8 10 12
-40 -30 -20 -10 0 10 20 30 40
1989 1991 1993 1995 1997 1999 2001 2003 2005 2007 2009 2011 2013 2015
Tbill Price
Return volatility


India: 3-month Tbill vs Tbill returns volatility
Daily series: 11 May 2000 - 30 December 2016
12
10
8
6
4
2
0
40
30
20
10
0
-10
-20
-30
2000
2002
2004
2006
2008
2010
2012
2014
2016
Tbill Price
Return volatility


Japan: 3-month Tbill vs Tbill returns volatility
Daily series: 5 October 1995 - 30 December 2016
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
300
200
100
0
-100
-200
-300
1995
1997
1999
2001
2003
2005
2007
2009
2011
2013
2015
Tbill Price
Return volatility

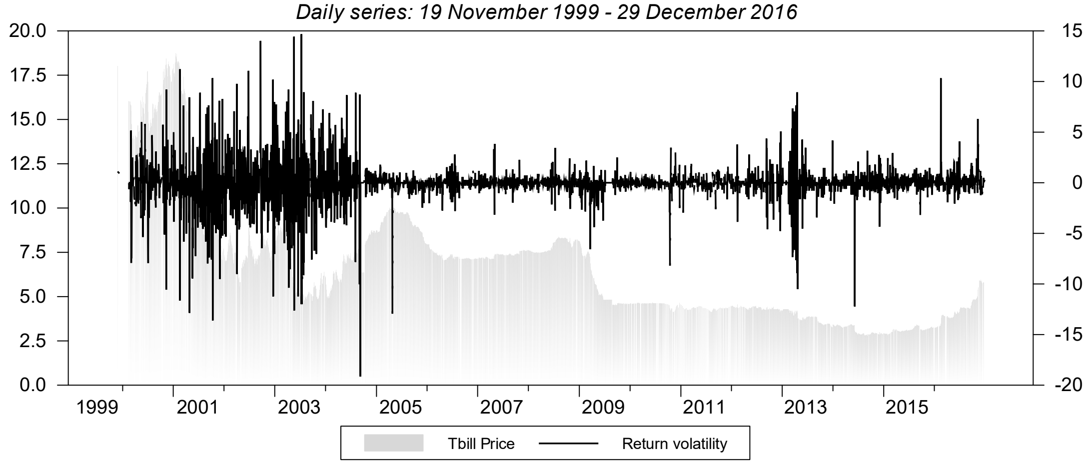
Malaysia: 3-month Tbill vs Tbill returns volatility

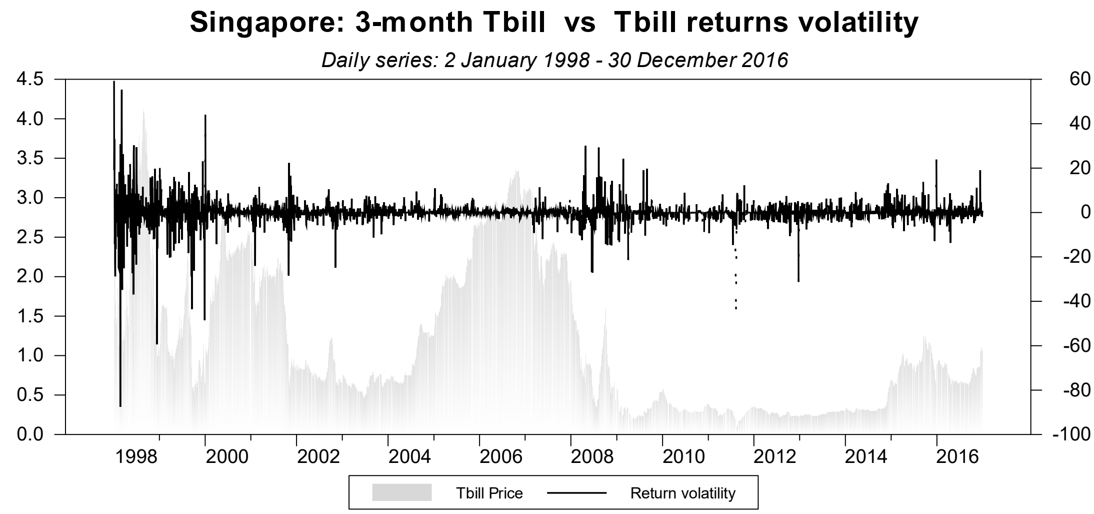
Daily series: 10 December 1996 - 29 December 2016

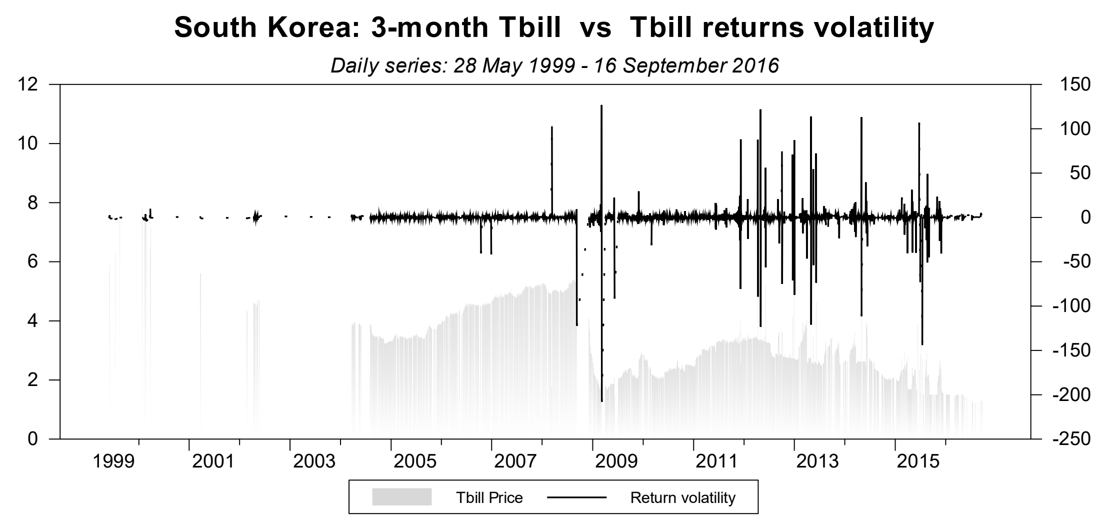


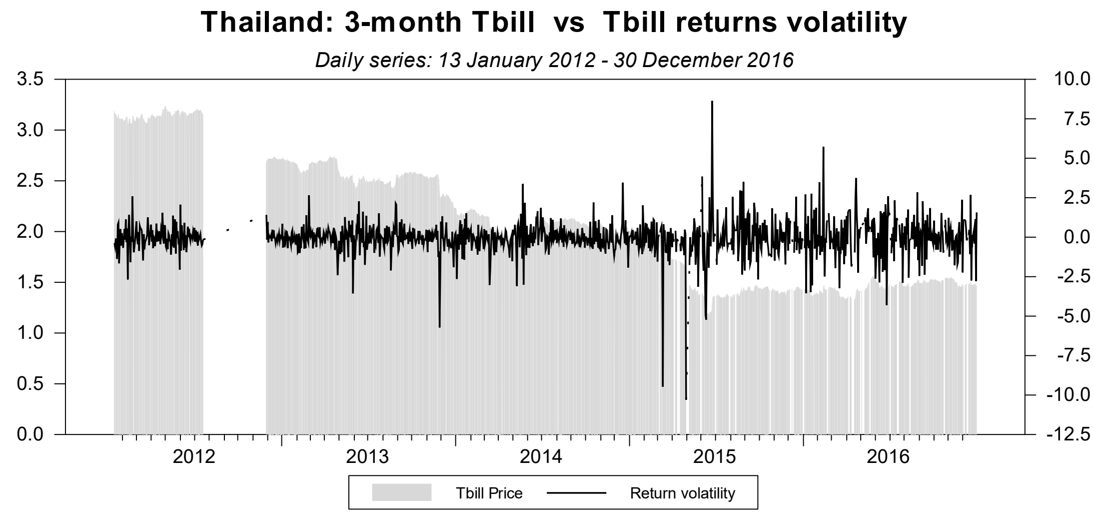
Mexico: 3-month Tbill vs Tbill returns volatility

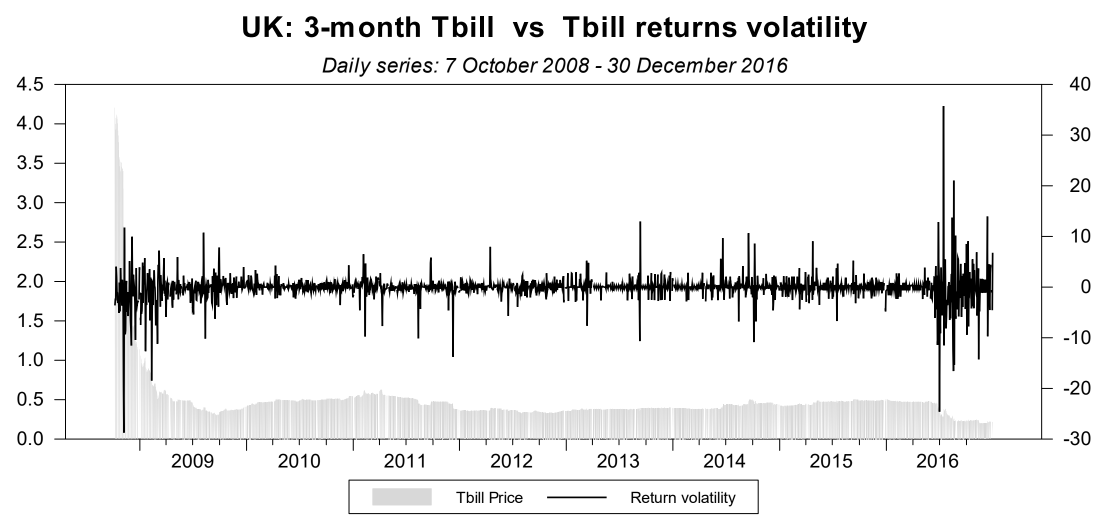
Daily series: 19 November 1999 - 29 December 2016

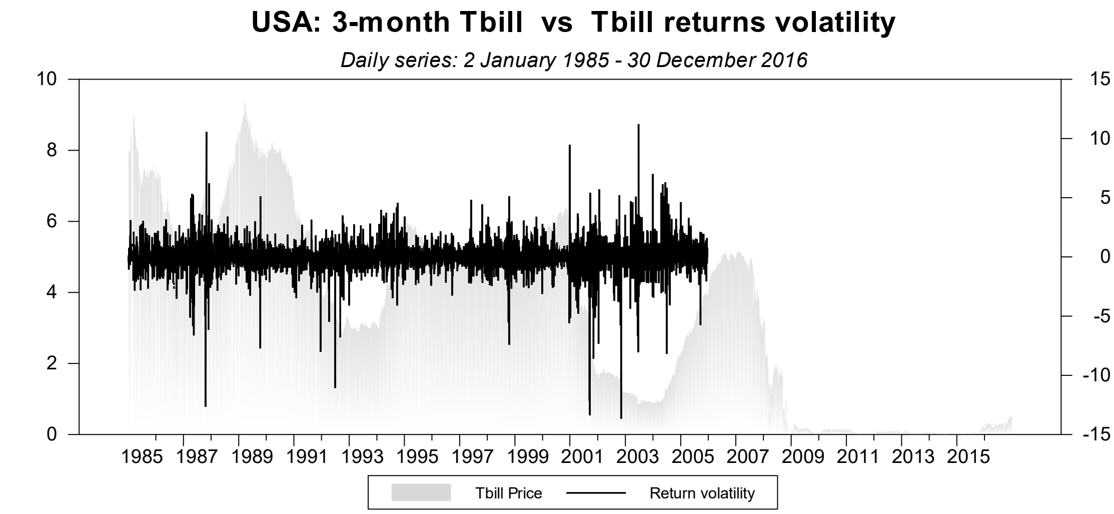



Singapore: 3-month Tbill vs Tbill returns volatility
Daily series: 2 January 1998 - 30 December 2016
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
60
40
20
0
-20
-40
-60
-80
-100
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
Tbill Price
Return volatility


South Korea: 3-month Tbill vs Tbill returns volatility
Daily series: 28 May 1999 - 16 September 2016
12
10
8
6
4
2
0
150
100
50
0
-50
-100
-150
-200
-250
1999
2001
2003
2005
2007
2009
2011
2013
2015
Tbill Price
Return volatility


Thailand: 3-month Tbill vs Tbill returns volatility
Daily series: 13 January 2012 - 30 December 2016
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
10.0
7.5
5.0
2.5
0.0
-2.5
-5.0
-7.5
-10.0
-12.5
2012
2013
2014
2015
2016
Tbill Price
Return volatility


UK: 3-month Tbill vs Tbill returns volatility
Daily series: 7 October 2008 - 30 December 2016
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
40
30
20
10
0
-10
-20
-30
2009
2010
2011
2012
2013
2014
2015
2016
Tbill Price
Return volatility


USA: 3-month Tbill vs Tbill returns volatility
Daily series: 2 January 1985 - 30 December 2016
10
8
6
4
2
0
15
10
5
0
-5
-10
-15
1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007 2009 2011 2013 2015
Tbill Price
Return volatility

Appendix B

Univariate Stock return and volatility of return model for 17 selected countries

$$r_{it} \mid \Im_{t-1} = \phi_{i0} + \phi_{i1} r_{it-1} + \theta_{i1}\varepsilon_{it-1} + \varepsilon_{it}, i = 1,2,3,......17$$

$$h_{it} \mid \Im_{t-1} = w_{i0} + \alpha_{i1}\varepsilon_{it-1}^{2} + \beta_{i1} h_{it-1}, \quad i = 1,2,3,..........,17$$

suffix i is the country index

	Country	ϕ_{i0}	ϕ_{i1}	θ_{i1}	w_{i0}	α_{i1}	β_{i1}	$Q(10)$	$Q(20)$	$Q^2(10)$	$Q^2(20)$	JB	ARCH-Test	LL	AIC
1	Australia	0.079*** (0.015)	-0.271* (0.158)	0.373** (0.152)	0.031*** (0.004)	0.155*** (0.010)	0.816*** (0.013)	20.847** [0.022]	34.196** [0.025]	9.899 [0.449]	11.693 [0.926]	16605.65*** (0.000)	10.168 [0.601]	-9734.68	2.405
2	Brazil	0.140** (0.047)	-0.093 (0.319)	0.123 (0.318)	0.053*** (0.009)	0.099*** (0.008)	0.894*** (0.008)	31.621*** [0.0004]	68.368*** [0.000]	15.739 [0.107]	35.510** [0.017]	627.46*** (0.000)	18.108 [0.112]	-13366.96	4.264
3	Canada	0.053*** (0.011)	-0.018 (0.138)	0.103 (0.138)	0.012*** (0.002)	0.091*** (0.006)	0.898 (0.007)	10.821 [0.371]	16.687 [0.673]	11.604 [0.312]	21.223 [0.384]	5272.79*** (0.000)	12.902 [0.376]	-10065.94	2.502
4	China	0.008* (0.004)	0.721*** (0.035)	- 0.761*** (0.032)	0.055*** 0.008	0.221*** (0.014)	0.824*** (0.009)	142.268*** [0.000]	177.767*** [0.000]	1.025 [0.999]	2.066 [0.999]	622023.1*** [0.000]	1.342 [0.999]	-13164.54	4.137
5	France	0.052** (0.018)	0.115 (0.256)	-0.169 (0.254)	0.045*** (0.005)	0.106*** (0.007)	0.873*** (0.009)	7.620 [0.665]	13.838 [0.838]	9.840 [0.454]	17.541 [0.617]	1411.863*** (0.000)	12.756 [0.386]	-12341.95	3.308
6	Germany	0.086** (0.029)	-0.048 (0.329)	0.073 (0.329)	0.026*** (0.003)	0.090*** (0.006)	0.896*** (0.007)	16.962* [0.075]	29.594* [0.077]	9.364 [0.498]	14.188 [0.821]	3622.954*** [0.000]	10.784 [0.547]	-12842.18	3.181
7	Hong Kong	0.078*** (0.018)	0.104 (0.150)	-0.020 (0.151)	0.052*** (0.006)	0.109*** (0.007)	0.871*** (0.008)	21.557** [0.017]	35.037** [0.020]	152.182*** [0.000]	158.348*** [0.000]	6371.96*** [0.000]	157.127*** [0.000]	-13567.35	3.434
8	India	0.110*** (0.032)	-0.226 (0.290)	0.261 (0.288)	0.044*** (0.007)	0.116*** (0.008)	0.874*** (0.008)	24.251*** [0.007]	39.513*** [0.006]	24.837*** [0.005]	30.656* [0.060]	421.440** [0.000]	25.361 [0.013]	-13918.76	3.697
9	Indonesia	0.010	0.208**	-0.043	0.017***	0.139***	0.877***	54.688***	119.218***	9.235	208.281***	251127.2***	9.522	-12085.4	3.116

		(0.009)	(0.080)	(0.082)	(0.002)	(0.007)	(0.005)	[0.000]	[0.000]	[0.510]	[0.000]	[0.000]	[0.658]		
10	Japan	0.079*** (0.020)	-0.140 (0.211)	0.194 (0.210)	0.033*** (0.005)	0.124*** (0.008)	0.866*** (0.009)	14.107 [0.168]	20.409 [0.432]	12.182 [0.273]	17.885 [0.595]	8106.74*** (0.000)	14.003 [0.300]	-12701.4	3.229
11	Malaysia	0.025** (0.008)	0.269*** (0.069)	-0.113 (0.071)	0.015*** (0.002)	0.135*** (0.010)	0.868*** (0.009)	17.759* [0.059]	29.587* [0.077]	7.467 [0.680]	11.175 [0.941]	80128.43*** [0.000]	8.140 [0.774]	-10912.16	2.772
12	Mexico	0.092*** (0.019)	-0.094 (0.116)	0.198* (0.114)	0.019*** (0.004)	0.096*** (0.008)	0.898*** (0.008)	13.667 [0.188]	18.774 [0.536]	19.571** [0.033]	32.310** [0.040]	789.696*** [.000]	23.806** [0.021]	-9414.499	3.286
13	Singapore	3.286* (0.025)	-0.106 (0.438)	0.123 (0.438)	0.014*** (0.003)	0.071*** (0.006)	0.925*** (0.006)	17.289* [0.068]	27.042 [0.134]	19.346** [0.0361]	26.741 [0.142]	1090.134*** [0.000]	20.869* [0.052]	-12929.5	3.559
14	South Korea	0.048*** (0.012)	0.500*** (0.095)	- 0.417*** (0.101)	0.060*** (0.008)	0.160*** (0.010)	0.829*** (0.010)	25.226*** [0.005]	41.004*** [0.003]	14.524 [0.150]	22.197 [0.330]	5449.359*** [0.000]	15.417 [0.219]	-12717.78	3.522
15	Thailand	0.011 (0.007)	0.656*** (0.182)	- 0.631*** (0.186)	0.007*** (0.002)	0.096*** (0.008)	0.903*** (0.007)	12.489 [0.253]	17.423 [0.625]	20.296** [0.026]	30.093* [0.068]	498.852*** [0.000]	23.782** [0.022]	-6147.694	2.827
16	U.K.	0.003** (0.001)	0.934*** (0.020)	- 0.953*** (0.017)	0.020*** (0.003)	0.100*** (0.007)	0.886*** (0.008)	14.825 [0.138]	22.406 [0.319]	10.484 [0.399]	23.697 [0.256]	2340.466*** [0.000]	15.934 [0.194]	-10861.9	2.796
17	U.S.A.	0.013* (0.006)	0.787*** (0.100)	- 0.808*** (0.099)	0.016*** (0.002)	0.082*** (0.006)	0.903*** (0.007)	14.473 [0.152]	31.346* [0.051]	11.574 [0.314]	19.748 [0.473]	5296.673*** [0.000]	12.639 [0.395]	-10664.55	2.645

Appendix C

C1. Decomposition of forecast error variance

Decomposition of forecast error variance for Australia stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.04389912	100	0	0	0	0	0	0	0	0	0
2	1.13880164	84.476	9.905	5.169	0.11	0.109	0	0.102	0.005	0.087	0.036
3	1.14060752	84.209	10.057	5.182	0.119	0.121	0.001	0.112	0.074	0.086	0.04
4	1.14142566	84.113	10.122	5.176	0.138	0.131	0.002	0.113	0.075	0.087	0.043
5	1.14145147	84.112	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
6	1.14145609	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
7	1.14145658	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
8	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
9	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
10	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
11	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
12	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
13	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
14	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
15	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
16	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
17	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
18	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
19	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043
20	1.14145661	84.111	10.122	5.177	0.138	0.131	0.002	0.113	0.076	0.087	0.043

Decomposition of forecast error variance for Canada stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.24152262	11.714	88.286	0	0	0	0	0	0	0	0
2	1.24901949	11.999	87.234	0.453	0.047	0.002	0.015	0.015	0.085	0.122	0.029
3	1.25198878	11.959	87.044	0.48	0.115	0.052	0.024	0.016	0.115	0.156	0.04
4	1.25208518	11.957	87.034	0.48	0.122	0.052	0.024	0.017	0.117	0.157	0.04
5	1.25211092	11.957	87.032	0.48	0.122	0.052	0.024	0.018	0.117	0.157	0.04
6	1.25211183	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
7	1.25211205	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
8	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
9	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
10	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
11	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
12	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
13	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
14	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
15	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
16	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
17	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
18	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
19	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04
20	1.25211207	11.957	87.031	0.48	0.122	0.052	0.024	0.018	0.118	0.157	0.04

Decomposition of forecast error variance for Germany stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.62484531	9.635	16.845	73.52	0	0	0	0	0	0	0
2	1.6357311	9.633	17.539	72.624	0.014	0.005	0	0.088	0.003	0.052	0.044
3	1.63946412	9.848	17.495	72.319	0.017	0.046	0.014	0.105	0.023	0.059	0.074
4	1.63972898	9.846	17.492	72.318	0.018	0.046	0.014	0.105	0.028	0.059	0.074
5	1.63977618	9.847	17.492	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
6	1.6397838	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
7	1.63978414	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
8	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
9	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
10	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
11	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
12	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
13	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
14	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
15	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
16	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
17	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
18	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
19	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074
20	1.63978419	9.847	17.493	72.314	0.019	0.046	0.014	0.105	0.029	0.059	0.074

Decomposition of forecast error variance for Hong Kong stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.89464978	10.702	11.035	3.964	74.3	0	0	0	0	0	0
2	1.95313249	11.824	11.509	3.971	71.063	0.141	0.019	0.573	0.418	0.013	0.469
3	1.95557336	11.814	11.482	3.961	70.887	0.141	0.041	0.576	0.563	0.017	0.517
4	1.95570846	11.819	11.481	3.961	70.877	0.143	0.042	0.576	0.566	0.017	0.518
5	1.95572791	11.82	11.48	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
6	1.9557294	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
7	1.95572952	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
8	1.95572952	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
9	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
10	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
11	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
12	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
13	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
14	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
15	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
16	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
17	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
18	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
19	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518
20	1.95572953	11.82	11.481	3.961	70.876	0.143	0.042	0.576	0.566	0.017	0.518

Decomposition of forecast error variance for India stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	2.02205634	2.373	3.252	1.978	2.435	89.962	0	0	0	0	0
2	2.03142564	2.385	3.72	1.961	2.462	89.236	0.001	0.007	0.007	0.054	0.167
3	2.03550824	2.419	3.708	2.074	2.452	88.879	0.002	0.051	0.017	0.058	0.341
4	2.03568751	2.419	3.711	2.073	2.453	88.863	0.002	0.052	0.019	0.06	0.347
5	2.03570327	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
6	2.03570483	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
7	2.03570512	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
8	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
9	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
10	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
11	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
12	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
13	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
14	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
15	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
16	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
17	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
18	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
19	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347
20	2.03570515	2.419	3.711	2.074	2.453	88.862	0.002	0.052	0.019	0.06	0.347

Decomposition of forecast error variance for Indonesia stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.91556328	1.957	1.172	0.605	4.443	0.946	90.877	0	0	0	0
2	1.96892835	2.058	3.838	1.262	4.598	0.92	87.12	0.044	0.001	0.084	0.074
3	1.98076827	2.115	3.804	1.26	4.552	0.919	87.111	0.057	0.026	0.083	0.073
4	1.9816224	2.119	3.814	1.275	4.55	0.918	87.083	0.057	0.026	0.085	0.074
5	1.98183396	2.118	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
6	1.98184999	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
7	1.98185333	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
8	1.9818537	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
9	1.98185376	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
10	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
11	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
12	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
13	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
14	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
15	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
16	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
17	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
18	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
19	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074
20	1.98185377	2.119	3.816	1.275	4.549	0.918	87.081	0.057	0.026	0.085	0.074

Decomposition of forecast error variance for Japan stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.53711693	10.859	3.27	3.371	3.358	0.086	0.087	78.967	0	0	0
2	1.60404552	10.45	7.459	5.231	3.092	0.108	0.085	73.178	0.04	0.259	0.099
3	1.60803213	10.398	7.528	5.354	3.133	0.124	0.132	72.839	0.045	0.341	0.106
4	1.60913083	10.403	7.597	5.347	3.131	0.126	0.132	72.745	0.048	0.357	0.114
5	1.60918686	10.403	7.599	5.348	3.131	0.126	0.132	72.74	0.049	0.358	0.114
6	1.60919404	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
7	1.60919559	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
8	1.60919569	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
9	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
10	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
11	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
12	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
13	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
14	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
15	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
16	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
17	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
18	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
19	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114
20	1.6091957	10.403	7.599	5.348	3.131	0.126	0.132	72.739	0.049	0.358	0.114

Decomposition of forecast error variance for Malaysia stock returns

Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.63616353	10.208	1.517	1.206	4.959	0.019	1.605	0	80.485	0	0
2	1.65724371	10.09	3.206	1.375	4.996	0.02	1.722	0.07	78.472	0.021	0.028
3	1.66670888	10.616	3.254	1.385	4.945	0.033	1.734	0.082	77.868	0.055	0.028
4	1.66720417	10.611	3.281	1.401	4.944	0.033	1.74	0.082	77.822	0.055	0.032
5	1.66726366	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
6	1.66726652	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
7	1.667267	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
8	1.66726704	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
9	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
10	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
11	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
12	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
13	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
14	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
15	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
16	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
17	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
18	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
19	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032
20	1.66726705	10.613	3.282	1.401	4.944	0.033	1.741	0.082	77.817	0.055	0.032

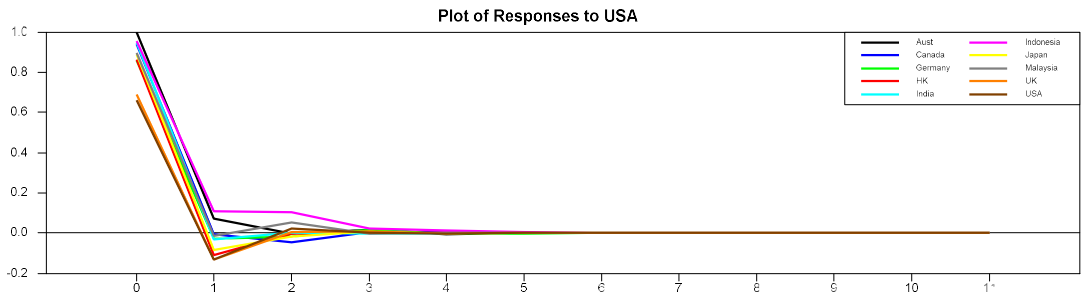
Decomposition of forecast error variance for UK stock returns

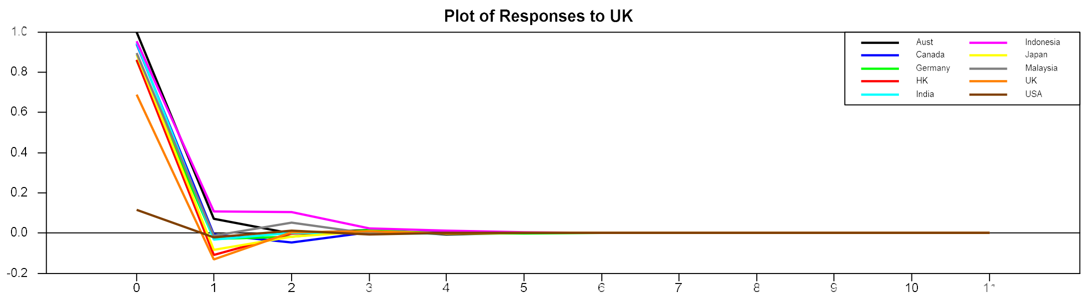
Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.27193188	21.865	8.316	20.067	1.11	0.085	0.003	0.809	0.403	47.342	0
2	1.32695325	20.204	13.291	18.524	1.181	0.089	0.003	0.966	0.501	45.067	0.174
3	1.33032003	20.278	13.274	18.533	1.211	0.15	0.028	0.964	0.545	44.842	0.174
4	1.3309884	20.258	13.317	18.528	1.223	0.15	0.028	0.966	0.554	44.802	0.175
5	1.33109826	20.26	13.319	18.526	1.225	0.151	0.028	0.965	0.556	44.795	0.175
6	1.33110415	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
7	1.33110494	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
8	1.33110501	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
9	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
10	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
11	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
12	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
13	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
14	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
15	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
16	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
17	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
18	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
19	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175
20	1.33110502	20.261	13.319	18.525	1.225	0.151	0.028	0.965	0.556	44.795	0.175

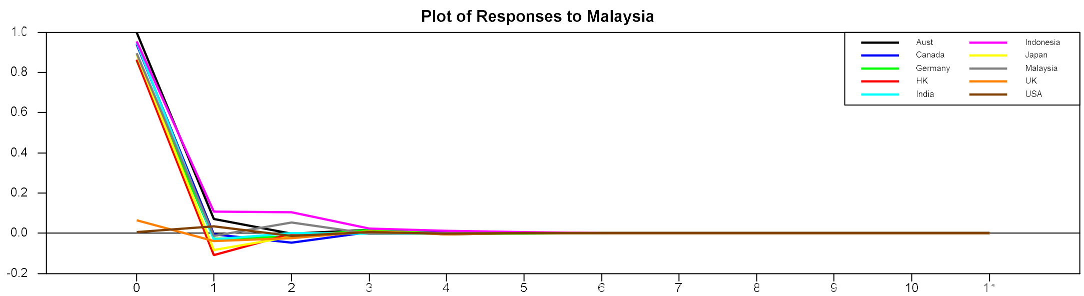
Decomposition of forecast error variance for USA stock returns

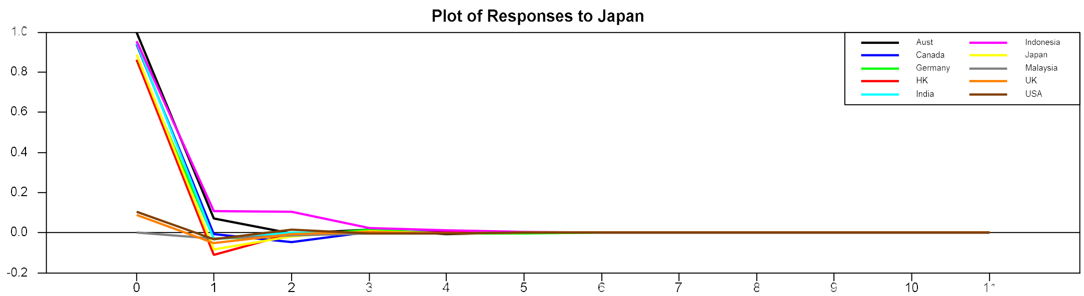
Step	Std Error	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.23712215	16.415	24.477	11.314	1.775	0.051	0.007	1.058	0.004	1.351	43.547
2	1.25847898	15.952	24.451	11.229	1.969	0.066	0.017	1.126	0.115	1.351	43.724
3	1.26183938	15.87	24.662	11.191	1.972	0.096	0.026	1.148	0.133	1.363	43.539
4	1.26195984	15.87	24.668	11.19	1.973	0.096	0.026	1.148	0.134	1.365	43.531
5	1.26197974	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.531
6	1.26198317	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
7	1.26198326	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
8	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
9	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
10	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
11	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
12	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
13	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
14	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
15	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
16	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
17	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
18	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
19	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53
20	1.26198327	15.869	24.668	11.189	1.973	0.096	0.027	1.148	0.134	1.365	43.53

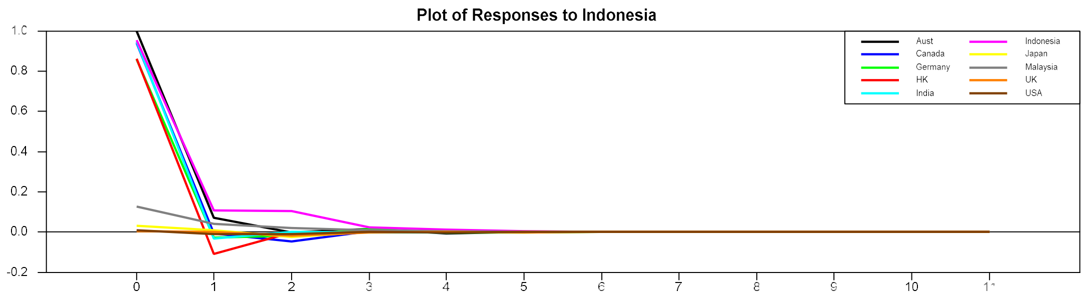
C2. Impulse Response Function










Plot of Responses to Indonesia
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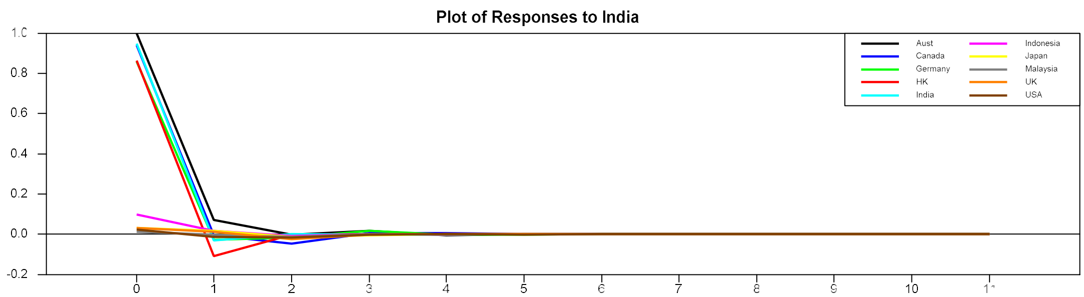
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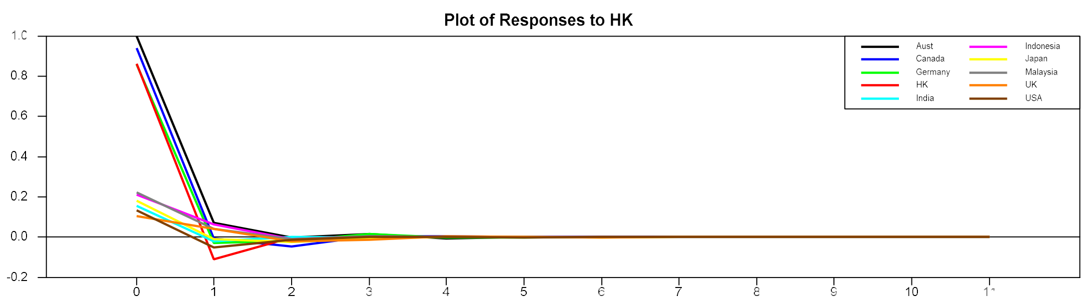
Plot of Responses to HK
Aust
Canada
Germany
HK
India
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Japan
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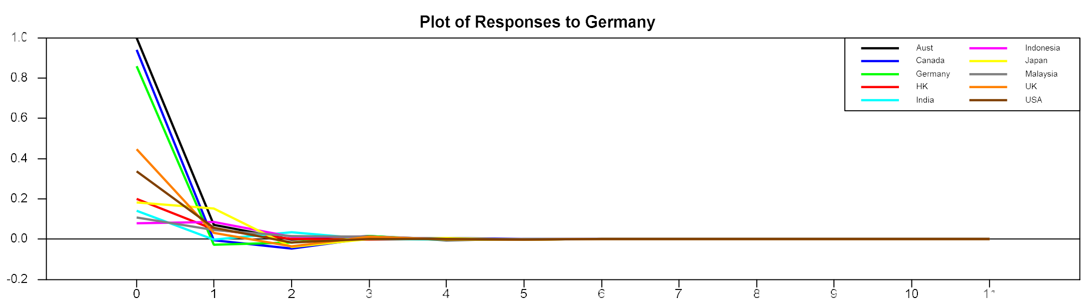
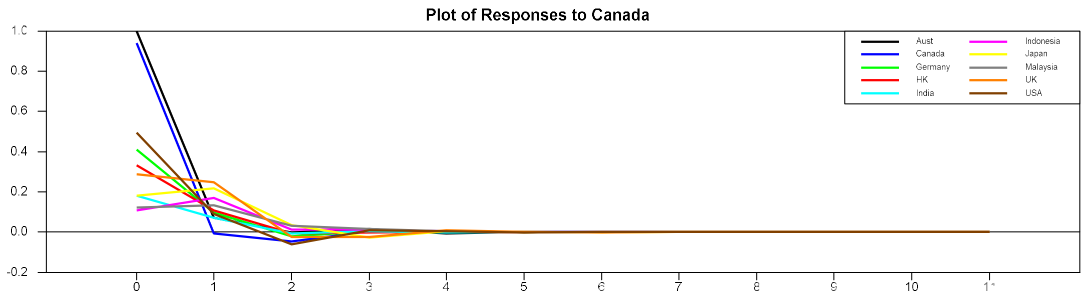
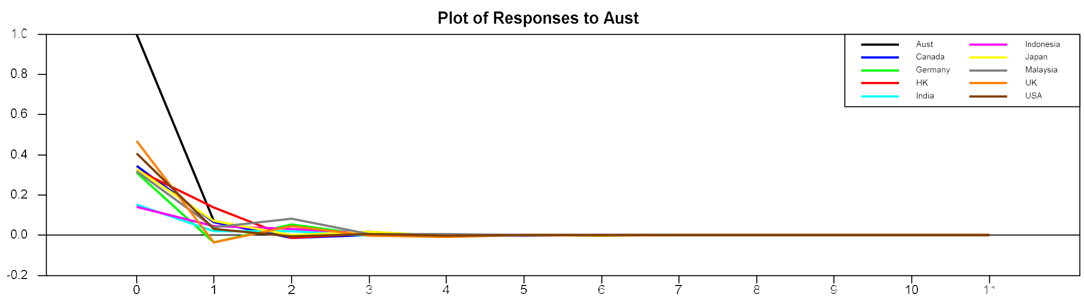
UK
USA


Plot of Responses to Germany
Aust
Canada
Germany
HK
India
Indonesia
Japan
Malaysia
UK
USA


Plot of Responses to Canada
Aust
Canada
Germany
HK
India
Indonesia
Japan
Malaysia
UK
USA


Plot of Responses to Aust
Aust
Canada
Germany
HK
India
Indonesia
Japan
Malaysia
UK
USA

C3. Granger Causality

Responses to Shock in Australia

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	1.04390	0.42491	0.50435	0.61980	0.31148	0.26796	0.50653	0.52275	0.59476	0.50123
2	0.07628	0.08149	-0.05801	0.25865	0.03735	0.08937	0.11089	0.06206	-0.04488	0.03751
3	-0.00045	-0.01611	0.08346	-0.02719	0.04272	0.05655	0.00144	0.13333	0.05584	-0.00701
4	0.01808	0.00280	0.00416	0.01645	-0.00343	0.01430	0.02223	0.00563	-0.00106	0.00637
5	-0.00574	0.00245	-0.00716	-0.00557	-0.00015	0.00375	-0.00538	0.00953	-0.01022	-0.00127
6	-0.00029	-0.00049	0.00300	-0.00014	0.00146	0.00274	0.00059	0.00149	0.00314	0.00037
7	0.00043	0.00051	-0.00077	-0.00025	-0.00069	0.00045	0.00125	0.00015	-0.00051	-0.00023
8	-0.00020	-0.00012	-0.00009	-0.00007	0.00018	0.00024	-0.00044	0.00015	-0.00023	0.00002
9	0.00000	0.00001	0.00007	-0.00003	-0.00005	0.00012	0.00010	0.00004	0.00009	-0.00001
10	0.00001	0.00001	-0.00003	0.00000	0.00000	0.00002	0.00001	-0.00001	-0.00002	0.00000
11	-0.00001	0.00000	0.00000	0.00000	0.00000	0.00002	-0.00001	0.00001	0.00000	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in Canada

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	1.16654	0.66688	0.62937	0.36462	0.20737	0.27797	0.20154	0.36679	0.61205
2	0.35841	-0.00795	0.15662	0.20718	0.14337	0.32525	0.33862	0.21780	0.31543	0.11240
3	0.04873	-0.05926	-0.03110	-0.00849	-0.01101	0.02153	0.05221	0.04831	-0.02965	-0.07376
4	-0.03230	0.00623	0.00880	-0.00283	0.01287	0.02223	-0.04522	0.02825	-0.03159	0.01261
5	0.00152	0.00507	0.00605	0.00067	-0.00219	0.01167	0.00821	0.00681	0.00891	0.00488
6	0.00232	0.00022	-0.00310	-0.00159	-0.00010	0.00211	0.00331	0.00026	-0.00025	-0.00242
7	-0.00079	-0.00033	-0.00005	-0.00019	0.00048	0.00100	-0.00119	0.00070	-0.00101	0.00004
8	-0.00007	0.00008	0.00021	-0.00003	-0.00023	0.00049	0.00017	0.00020	0.00019	0.00010
9	0.00004	0.00004	-0.00009	-0.00004	0.00000	0.00012	0.00005	0.00000	-0.00003	-0.00004
10	-0.00001	-0.00001	0.00000	-0.00001	0.00002	0.00006	-0.00003	0.00002	-0.00002	0.00000
11	0.00000	0.00000	0.00000	0.00000	-0.00001	0.00002	0.00001	0.00001	0.00001	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in Germany

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	1.39320	0.37722	0.28439	0.14901	0.28224	0.17972	0.56977	0.41612
2	0.25891	0.08408	-0.04596	0.09581	-0.00760	0.16346	0.23437	0.07394	0.03917	0.06846
3	-0.01944	-0.02114	-0.02640	0.00176	0.07059	0.02264	-0.06208	0.02680	-0.04263	-0.01872
4	-0.00443	0.00239	0.02428	-0.00471	0.00222	0.02498	0.00422	0.02138	0.01545	0.00244
5	0.00399	0.00247	-0.00409	0.00246	-0.00246	0.00358	0.00574	0.00016	-0.00226	0.00091
6	-0.00122	-0.00047	-0.00116	-0.00163	0.00056	0.00231	-0.00190	0.00181	-0.00154	-0.00080
7	-0.00006	-0.00003	0.00062	0.00002	0.00002	0.00074	0.00033	0.00021	0.00055	0.00007
8	0.00005	0.00013	-0.00022	-0.00006	-0.00013	0.00026	0.00011	0.00005	-0.00018	-0.00001
9	-0.00003	-0.00003	0.00000	-0.00002	0.00004	0.00010	-0.00007	0.00004	-0.00001	0.00000
10	0.00000	0.00001	0.00001	-0.00001	-0.00001	0.00004	0.00002	0.00001	0.00001	-0.00001
11	0.00000	0.00000	-0.00001	0.00000	0.00000	0.00001	0.00000	0.00000	-0.00001	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in Hong Kong

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	0.00000	1.63314	0.31555	0.40377	0.28169	0.36437	0.13398	0.16481
2	0.03780	-0.02705	0.01913	-0.20908	-0.04500	0.12343	-0.01434	0.06672	0.05339	-0.06347
3	0.01118	-0.03280	-0.00885	-0.00762	0.00081	-0.01829	-0.03826	-0.01270	-0.02512	-0.01477
4	-0.01568	0.01036	-0.00704	0.00066	-0.00673	0.00896	-0.00775	0.00689	-0.01514	0.00353
5	0.00083	0.00069	0.00372	0.00016	0.00152	0.00200	0.00237	0.00091	0.00687	0.00140
6	0.00152	-0.00008	-0.00117	-0.00044	-0.00075	0.00071	0.00188	-0.00044	-0.00030	-0.00099
7	-0.00048	-0.00020	-0.00015	0.00003	0.00022	0.00002	-0.00087	0.00018	-0.00064	0.00008
8	-0.00003	0.00005	0.00017	-0.00002	-0.00007	0.00020	0.00008	0.00007	0.00018	0.00004
9	0.00004	0.00002	-0.00005	0.00000	0.00000	0.00001	0.00005	-0.00002	-0.00001	-0.00001
10	-0.00001	-0.00001	-0.00001	0.00000	0.00001	0.00002	-0.00002	0.00001	-0.00001	0.00000
11	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in India

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	0.00000	0.00000	1.91789	0.18634	0.04511	0.02261	0.03709	0.02803
2	0.03760	0.00528	0.01126	-0.07345	-0.06486	0.03045	0.02734	-0.00653	0.01360	-0.01631
3	-0.01267	-0.02810	-0.03338	-0.00287	-0.00054	-0.02017	-0.02048	-0.01880	-0.03314	-0.02187
4	-0.01167	0.00097	0.00177	-0.00780	-0.00267	-0.00019	-0.00782	-0.00020	-0.00246	-0.00050
5	0.00097	0.00104	0.00026	0.00101	-0.00083	-0.00142	0.00147	-0.00328	0.00180	0.00137
6	0.00030	-0.00018	-0.00096	-0.00043	-0.00021	-0.00031	0.00006	-0.00052	-0.00037	-0.00056
7	-0.00012	-0.00018	0.00019	0.00011	0.00015	-0.00020	-0.00027	-0.00015	0.00006	0.00002
8	0.00001	0.00005	0.00001	0.00002	-0.00007	-0.00002	0.00004	-0.00003	0.00001	0.00003
9	0.00001	-0.00001	-0.00001	0.00001	0.00002	-0.00002	-0.00001	-0.00002	0.00000	0.00000
10	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
11	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in Indonesia

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	0.00000	0.00000	0.00000	1.82609	0.04540	0.20727	0.00668	0.01056
2	0.00131	-0.01515	-0.00114	-0.02662	0.00715	0.20673	0.01091	0.06580	0.00021	-0.01249
3	0.00352	0.01181	-0.01928	-0.02955	-0.00523	0.20094	-0.03519	0.02984	-0.02130	-0.01218
4	-0.00324	0.00091	0.00011	0.00251	0.00323	0.04340	0.00063	0.01335	-0.00087	0.00155
5	0.00116	0.00176	-0.00163	-0.00396	-0.00302	0.02514	0.00078	0.00596	0.00006	-0.00219
6	-0.00015	-0.00003	-0.00056	-0.00009	0.00044	0.00667	-0.00043	0.00169	-0.00090	-0.00006
7	-0.00011	0.00020	-0.00015	-0.00051	-0.00034	0.00331	-0.00010	0.00097	-0.00017	-0.00017
8	0.00001	0.00004	-0.00004	-0.00005	0.00002	0.00101	0.00002	0.00024	-0.00002	-0.00002
9	0.00000	0.00003	-0.00004	-0.00006	-0.00003	0.00044	0.00000	0.00012	-0.00004	-0.00003
10	0.00000	0.00000	0.00000	-0.00001	0.00000	0.00015	0.00000	0.00004	-0.00001	0.00000
11	0.00000	0.00000	0.00000	-0.00001	0.00000	0.00006	0.00000	0.00002	0.00000	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00002	0.00000	0.00001	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00001	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in Japan

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.36594	0.00242	0.11442	0.12728
2	-0.03642	-0.01505	-0.04850	-0.14788	-0.01665	-0.04148	-0.13056	-0.04362	-0.06266	-0.04036
3	-0.01132	-0.00517	0.02167	0.01229	0.04275	0.02232	-0.02476	-0.01925	-0.00643	0.02105
4	0.00433	0.00449	-0.00332	-0.00256	-0.00748	0.00288	0.01158	-0.00123	0.00673	-0.00273
5	0.00046	-0.00122	-0.00117	0.00063	0.00289	0.00126	-0.00242	-0.00210	-0.00091	-0.00082
6	-0.00032	-0.00015	0.00041	-0.00010	-0.00043	0.00071	-0.00027	0.00048	-0.00014	0.00014
7	0.00008	0.00002	-0.00002	0.00008	-0.00007	0.00018	0.00002	-0.00012	0.00010	0.00000
8	-0.00001	0.00002	-0.00004	-0.00003	0.00002	0.00008	-0.00003	0.00002	-0.00004	-0.00002
9	0.00000	-0.00001	0.00002	0.00001	0.00000	0.00003	-0.00001	0.00001	0.00001	0.00001
10	0.00000	0.00000	0.00000	0.00000	-0.00001	0.00001	0.00001	0.00000	0.00000	0.00000
11	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in Malaysia

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.46786	0.08075	0.00806
2	0.00820	0.03640	0.00876	0.12622	-0.01732	-0.00593	0.03201	-0.02447	-0.04795	0.04194
3	-0.02985	0.02177	-0.02344	-0.07484	-0.02040	-0.03107	0.01168	0.08887	-0.02865	-0.01698
4	0.00471	-0.00573	0.01090	0.01079	0.00788	-0.00380	0.00854	-0.00525	0.01291	0.00418
5	-0.00190	0.00321	-0.00546	-0.00441	-0.00486	-0.00467	0.00473	0.00281	-0.00626	-0.00164
6	-0.00065	-0.00097	0.00112	0.00025	0.00167	-0.00081	-0.00196	-0.00028	0.00077	0.00065
7	0.00017	0.00024	-0.00007	-0.00019	-0.00049	-0.00038	0.00096	-0.00012	0.00011	-0.00017
8	-0.00004	-0.00003	-0.00009	0.00003	0.00012	-0.00021	-0.00020	-0.00009	-0.00012	0.00003
9	-0.00001	-0.00001	0.00004	-0.00001	-0.00001	-0.00003	0.00002	0.00000	0.00003	0.00000
10	0.00001	0.00000	0.00000	0.00000	0.00000	-0.00003	0.00001	-0.00001	0.00000	0.00000
11	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00001	0.00000	0.00000	0.00000	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in UK

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.87516	0.14380
2	0.03350	0.04363	-0.03714	0.02250	-0.04729	-0.05713	-0.08164	-0.02398	-0.16622	-0.02677
3	-0.00129	-0.02313	0.01428	0.01251	0.01269	-0.00217	-0.04638	0.03076	0.00756	0.01727
4	0.00232	0.00476	0.00127	0.00176	-0.00936	-0.00732	0.02088	-0.00322	0.00935	-0.00657
5	-0.00085	0.00131	-0.00140	-0.00025	0.00246	-0.00297	-0.00357	0.00126	-0.00355	0.00154
6	0.00023	-0.00066	0.00093	0.00040	-0.00024	-0.00017	0.00044	0.00028	0.00092	0.00028
7	0.00006	0.00009	-0.00022	-0.00015	-0.00016	-0.00055	0.00035	-0.00014	-0.00005	-0.00025
8	-0.00008	0.00001	0.00001	0.00003	0.00011	-0.00009	-0.00018	0.00000	-0.00009	0.00008
9	0.00001	-0.00001	0.00003	0.00000	-0.00002	-0.00003	0.00005	0.00000	0.00005	0.00000
10	0.00000	0.00000	-0.00001	0.00000	0.00000	-0.00002	0.00000	-0.00001	-0.00001	-0.00001
11	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00001	-0.00001	0.00000	0.00000	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Responses to Shock in US

Entry	Australia	Canada	Germany	HK	India	Indonesia	Japan	Malaysia	UK	US
1	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.81638
2	0.02171	0.02129	-0.03439	-0.13379	-0.08290	-0.05363	-0.05038	-0.02777	0.05529	-0.16129
3	0.00669	0.01293	0.02846	0.04333	0.08510	0.00120	-0.01419	-0.00357	0.00550	0.02747
4	0.00620	0.00208	-0.00004	0.00582	-0.01670	0.00467	0.01461	0.00994	0.00230	0.00389
5	0.00046	-0.00292	-0.00075	-0.00139	0.00179	-0.00224	-0.00125	-0.00037	0.00061	-0.00310
6	-0.00078	0.00057	0.00035	-0.00015	0.00017	0.00003	-0.00062	0.00049	-0.00096	0.00048
7	0.00005	0.00008	0.00007	0.00016	-0.00008	-0.00005	0.00011	0.00006	0.00019	0.00021
8	0.00006	-0.00002	-0.00006	-0.00007	0.00000	-0.00002	0.00011	-0.00002	0.00004	-0.00010
9	-0.00002	-0.00001	0.00000	0.00001	0.00002	-0.00002	-0.00003	0.00000	-0.00003	0.00001
10	0.00000	0.00000	0.00000	0.00000	-0.00001	0.00000	0.00000	0.00000	0.00000	0.00000
11	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
12	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
13	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
14	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
15	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
16	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
17	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
18	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
19	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
20	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Appendix D

D1. Spearsman rank correlation test

	Australia	Hong Kong	Japan	UK	USA
Australia	1				
Hong Kong	0.282*	1			
Japan	0.323*	0.392**	1		
UK	0.363*	0.401**	0.375**	1	
USA	0.274	0.445**	0.391**	0.482***	1

Note. *** significant at the 1% level

D2. Pearson correlation test

	Australia	Hong Kong	Japan	UK	USA
Australia	1				
Hong Kong	0.338***	1			
Japan	0.394***	0.381***	1		
UK	0.508***	0.404***	0.419***	1	
USA	0.408***	0.491***	0.413***	0.574***	1

Note. *** significant at the 1% level