Inter-sector Return Correlations between South Africa, the United States, the United Kingdom and Europe: Evidence from the DCC Multivariate GARCH Model

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Abstract

This study seeks to uncover the dynamics of inter-sector equity return correlations between South Africa, the United States (US), the United Kingdom (UK) and Europe. The paper sets out to determine whether there is scope for same sector diversification between South Africa and the developed country bourses included in the sample. The study employs the Dynamic Conditional Correlation (DCC) Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MV-GARCH) modeling technique to estimate time-varying conditional correlations. Furthermore, the study also explores how the Global Financial Crisis (GFC) affected the conditional correlations estimated. The results suggest that on aggregate same sector comovement is amplified during periods of heightened global economic uncertainty.

Keywords: Multivariate GARCH

JEL classification L250, L100

1. Introduction

Interdependencies between financial markets have risen over the last decade and as such have affected the way in which investors diversify their portfolios. In order to mitigate downside portfolio risk, many investors tend to diversify parts of their investment portfolios to financial assets offshore. However, increased comovement between asset prices specifically during periods of heightened global economic uncertainty excerbates the complexity of formulating investment strategies with foreign exposure. Generally, portfolio diversification entails holding equities across different

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sectors. A large body of literature assesses the degree of comovement across stock markets in different countries during different periods of time. However, studies which look into same sector comovement between different countries appear to be fairly limited, see for example Kalotychou, Staikouras, and Zhao (2009).

The purpose of this paper is twofold. Firstly, dynamic conditional correlations between eight[1] of South Africa's sectors and the US (SP 500), Europe (SP EURO) and the UK are studied. The parsimonious Dynamic Conditional Correlation (DCC) Multivariate (MV) GARCH modeling techniques are used to uncover how inter-sector conditional correlations changed in the period running up to, during and after the Global Financial Crisis (GFC). The results deliver insight into the degree to which investors were able to diversify their portfolios across the same sectors between South Africa and the developed countries included in the sample. Secondly, the study attempts to quantify the impact of the GFC on conditional inter-sector correlations through a dummy variable approach. The results show which sectors experienced the least and most comovement as a result of the crisis.

The paper is structured as follows: Section 2 discusses the relevant literature, section 3 describes the data used in the analysis and section 4 gives an overview of the methodology adopted in the study. Section 5 discusses the results of the models estimated which is followed by concluding remarks in section 6.

2. Literature Review

In portfolio theory, it has generally been noted that weak correlation between different stocks should increase diversification potential and reduce portfolio risk. As such, the advantages of international portfolio diversification are contingent upon the correlation structure of the studied stock markets (Zhang, Li, and Yu 2013, 725). Early studies on stock market comovement pointed

[1]The technology sector was excluded due to estimation issues.

towards an increase in cross-country stock return correlations i.e. contagion (King and Wadhwani 1990; Baig and Goldfajn 1999).

The notion that weak correlation between emerging and developed stock markets exists are diminishing (Wang and Moore 2008). For instance, studies have shown this to be the case for Central Eastern European markets (Voronkova 2004; Chelley-Steeley 2005), Asia-Pacific markets (Leong and Felmingham 2003) and markets in Latin America (Hunter 2006). In addition to this, researchers note that the GFC altered the benefits associated with international portfolio diversification (Jeong 2012; Samarakoon 2011).

To study cross-country correlations, one must consider heteroscedasticity as the effect of contagion can be artificially inflated if not accounted for (Forbes and Rigobon 2002). The DCC-GARCH model accounts for heteroscedasticity in contagion analysis and correlations are, with this method, dynamically modelled such that conditional correlations can change over time.[2]

The DCC-GARCH modelling framework, formulated by R. Engle (2002), has been employed extensively to study cross-country contagion effects. Yang (2005) investigates stock returns of Japan and the Asian Tiger economies to show the existence of spillover effects. Similarly, Chiang, Jeon, and Li (2007) examine nine Asian stock markets from 1990 to 2003 and show that correlations increased in this period, especially during and after the Asian crisis. Kalotychou, Staikouras, and Zhao (2009) study inter-sector correlations between Japan, the US and UK markets, and highlight the importance of the dynamics of return correlations for portfolio allocation. Lastly, Syllignakis and Kouretas (2011) analyse stock market correlations between Central and Eastern Europe (CEE), the US, Germany and Russia. They argue that diversification benefits are decreasing in the CEE markets due to an increase in financial openness, the increased presence of foreign investors in these markets and the integration of CEE markets with the EU.

[2] The existence of contagion must involve evidence of a dynamic increment in correlations and the heteroscedasticity problem arises from volatility increases during a crisis i.e. a correlation measurement problem (Chiang, Jeon, and Li 2007).

Most of the aforementioned literature analyses cross-country correlations at the market level, however there are promising benefits from international portfolio diversification on a sector wide level. Phylaktis and Xia (2009) study stock markets at the sector level from Europe, Asia and Latin America, their findings suggest that a divergence of integration exists across the different regions since sector level vis-a-vis market level are not so globally correlated. Additionally, Gupta and Basu (2011) highlight the potential benefits from sectoral level diversification by comparing a portfolio comprised of sector level equities against a market index. The researchers examine ten sectors from the Indian stock market by employing the Asymmetric DCC-GARCH modelling technique. Their results reveal that a portfolio comprising of sectoral level assets vis-a-vis a market index earn a higher risk-adjusted return.

It is therefore important to study contagion effects at the sector level since contagion at the market level may conceal the varying return performances of the different sectors. Also, sector level contagion can be asymmetric given that some sectors are more prone to external shocks. Sectors which are more vulnerable to shocks, like Financials, could represent a vital channel in which shocks disperse across markets during crisis episodes (Phylaktis and Xia 2009).

The Dynamic Conditional Correlation literature, which focuses on South African equity market return volatility has in general been limited (Katzke 2013). Nevertheless, Collins and Biekpe (2003) investigate the contagion effects of the 1997 Asian crisis on African equity markets, which includes South Africa, by employing adjusted Pearson's correlation coefficients. Samouilhan (2006) reports market and sector level return and volatility comovement between South Africa and the UK stock market using univariate volatility models. Chinzara, Aziakpono, and others (2009) make use of VAR modelling techniques as well as univariate GARCH models to study cross-country correlations between the South African stock market index and several other large global indices. Similarly, Chinzara (2011) report spillover effects of macroeconomic indicators onto the returns of the South African stock market index and four sectors, which include: the financial, retail, mining and industrial sectors. In addition, the spillover effects are amplified during crisis periods (like the

Asian crisis and the Financial crisis). Katzke (2013) studies the dynamics of return comovements between the largest sectors in South Africa so as to highlight the potential gains from inter-sector diversification for domestic investors. The author utilises both the DCC-GARCH and Asymmetric DCC-GARCH models. The paper shows that the ability to diversify across sectors are somewhat limited during periods of elevated market uncertainty.

The aim of this paper is to investigate inter-sector diversification benefits among different countries, from a South African perspective, by making use of the DCC GARCH model. More specifically, sectors in the South African equity market are compared with their counterparts from the UK (FTSE), the US (S&P 500) and Europe (S&P Europe 350) from 2004 to 2016. As Zhang, Li, and Yu (2013) note, investors from the US and Europe have recently shown keen interest to invest in BRICS member country equity markets.

3. Data

The continously compounded weekly returns are calculated by taking the log difference of the total return index of each listed company included in the sample as follows:

$$r_{ki,t} = ln(\frac{P_{ki,t}}{P_{ki,t-7}}) \tag{3.1}$$

where $P_{ki,t}$ denotes the total return index of company k in sector i at time t.

The return indices for Communications, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials and Materials are calculated as:

$$y_{i,t} = \sum_{k}^{n} r_{k,t}\omega_{k,t} \tag{3.2}$$

where $\omega_{k,t}$ is company k's market capitalisation divided by the indices total market capitalisation at time t. n represents the number of companies in sector i at time t.

Tables 7.1 to 7.8 show that the sector return indices for each country exhibit excess kurtosis and skewness. This behaviour is typical of financial time series and implies that the series' are not normally distributed[3]. Figures 7.1 to 7.8 display the weekly log returns of each sector for each country in the sample. The figures appear to exhibit periods of volatility clustering which can be indicative of remaining second order dependence. This points toward the presence of conditional heteroskedasticity which motivates the use of univariate GARCH models.

4. Methodology

Consider 8 vector stochastic processes, y_t, of continuously compounded weekly sector return composites with dimensions of 4×1. Under the assumption that the returns are demeaned and follow a conditionally heteroskedastistic normal distribution the series' can be described by the notation below:

$$y_{it} = \mu_i + \varepsilon_{it} \tag{4.1}$$

$$\varepsilon_{it} = \sqrt{H_{it}}.\eta_i, \quad \varepsilon_{it} \sim N(0, H_t) \quad \& \quad \eta_i \sim N(0, I) \tag{4.2}$$

Where μ_i is the intercept and ε_{it} is the error term, H_t the 4×4 conditional covariance matrix and η_i the standardized residuals.

A range of MV GARCH modelling techniques have been proposed to model the covariance process, H_t, depicted in equation 4.2[4]. The covariance process, H_t, can either be modelled directly or through linear and non-linear combinations of univariate GARCH processes. This paper makes

[3] Each series was tested for normality using the Jarque-Bera normality test, the results can be requested from the authors.

[4] See Bauwens, Laurent, and Rombouts (2006) for a survey of MV-GARCH modeling techniques.

use of the parsimonious DCC MV GARCH modelling techniques formulated by R. Engle (2002). In order to simplify the equations showing the steps of estimation, the methodology assumes a bivariate stochastic process.

The first step entails fitting univariate volatility equations to each series in order to obtain GARCH estimates of conditional volatility. The study makes use of the E-GARCH(1,1) univariate specification in order to account for leverage effects and volatility feedback. Furthermore, due to the scope of univariate series included in the study one univariate model is used. According to Cappiello, Engle, and Sheppard (2006, 542) the choice of univariate model will not affect the sign of the standardized residual and because numerous univariate models produce relatively similar volatility patterns, it is conceivable that the correlations would be relatively insensitive to the univariate model specification within a reasonable class.

The mean, volatility and E-GARCH(1,1) equations for each univariate series take the following form:

$$y_t = \mu + \varepsilon_t \tag{4.3}$$

$$\varepsilon_t = \sqrt{h_t^2}.\eta_t \quad , \quad \eta_t \sim N(0,1) \tag{4.4}$$

$$ln(h_{ii,t}) = \omega + \alpha\frac{|\varepsilon_{ii,t-1}|}{\sqrt{h_{ii,t-1}}} + \gamma\frac{\varepsilon_{ii,t-1}}{\sqrt{h_{ii,t-1}}} + \beta_{h_{ii}} ln(h_{ii,t-1}), \quad \forall i \tag{4.5}$$

$$ln(h_{jj,t}) = \omega + \alpha\frac{|\varepsilon_{jj,t-1}|}{\sqrt{h_{jj,t-1}}} + \gamma\frac{\varepsilon_{jj,t-1}}{\sqrt{h_{jj,t-1}}} + \beta_{h_{jj}} ln(h_{jj,t-1}), \quad \forall j \tag{4.6}$$

where $\varepsilon_{ii,t-1}$ denotes the previous period's squared residual series and $h_{ii,t}$ is the univariate conditional volatility equation of series i. The conditional variances estimated in step 1 are used to standardize the residuals for each series as follows:

$$\eta_{i,t} = \varepsilon_{i,t}/\sqrt{h_{ii,t}}, \quad (\forall i, j \quad \& \quad i \neq j) \tag{4.7}$$

In the second step the standardized residuals are used to estimate time varying correlations. The DCC(1,1) model as formulated by R. Engle (2002) is defined as:

$$H_t = D_t.R_t.D_t. \tag{4.8}$$

Equation 4.8 splits the variance covariance matrix into identical diagonal matrices and an estimate of the time-varying correlation. The diagonal matrices are defined as:

$$D_t = diag(\sqrt{h_{ii,t}}, \sqrt{h_{jj,t}}) \tag{4.9}$$

The dynamic conditional correlation structure is derived as follows:

$$Q_{ij,t} = (1 - a - b)\bar{Q} + a\eta_{i,t-1}\eta'_{j,t-1} + b.Q_{ij,t-1} \tag{4.10}$$

where $Q_{ij,t}$ is the unconditional variance between series i and j, $\bar{Q}$ is the unconditional covariance between the univariate series estimated in step 1 and a and b are non-negative scalar parameters satisfying a + b < 1. In order to make sure the $R_{ij,t}$ matrix has a unique solution, the determinant will be tested for positive definiteness.

The time-varying conditional correlation matrix is derived as follows:

$$R_t = (Q^*_{ij,t})^{-1}.Q_{ij,t}.(Q^*_{ij,t})^{-1}. \tag{4.11}$$

$(Q^*_{ij,t})^{-1}$ is a diagonal matrix where the square root of the diagonal elements of $(Q_{ij,t})$ are the entries. Therefore the dynamic conditional correlation matrix entries are calculated in the following manner:

$$R_t = \rho_{ij,t} = \frac{q_{i,j,t}}{\sqrt{q_{ii,t}.q_{jj,t}}} \tag{4.12}$$

$$= \frac{(1-a-b)\bar{q}_{ij} + a\eta_{i,t-1}\eta_{j,t-1} + bq_{ij,t-1}}{\sqrt{((1-a-b)\bar{q}_{ii} + a\eta^2_{i,t-1} + bq_{ii,t-1})((1-a-b)\bar{q}_{jj} + a\eta^2_{j,t-1} + bq_{jj,t-1})}}$$

The DCC model is estimated by maximising the log-likelihood function for equation 4.10. The joint log-likelihood function takes the follow form[5]:

$$L(\gamma,\varphi) = -\frac{1}{2}\sum_{t=1}^{T}(log(2\pi) + log(|D_t R_t D_t|) + \varepsilon'_t(D_t R_t D_t)^{-1}\varepsilon_t)) \tag{4.13}$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(log(2\pi) + log(|D_t|) + log(|R_t|) + \varepsilon'_t R_t^{-1}\varepsilon_t \tag{4.14}$$

where γ and φ are the parameters in D_t and R_t respectively.

[5] According to Cappiello, Engle, and Sheppard (2006, 541) the assumption of conditional normality is not imperative, when this assumption does not hold the results should be interpreted as a standard quasi maximum likelihood estimation (QMLE).

In the second step the correlation component is maximised using the value maximised in 4.13 to solve:

$$L_c(\gamma, \varphi) = -\frac{1}{2}\sum_{t=1}^{T}(log|R_t| + \varepsilon_t'(R_t^{-1})\varepsilon_t) \tag{4.15}$$

After fitting the univariate E-GARCH models and estimating the dynamic conditional correlations for each sector, the study assesses the affect of the GFC on inter-sector conditional correlations.

5. Results

Section 5.1 of the results presents the univariate E-GARCH(1,1) models for each universe, section 5.2 discusses the results of the DCC model and section 5.3 evaluates the affect of the GFC on inter-sector conditional correlations.

5.1. Univariate E-GARCH(1,1) Models

Table 5.1 to 5.4 report the parameter values of the respective E-GARCH models. The model specifications are kept parsimonious i.e. E-GARCH(1,1) since the DCC model is relatively insensitive to the univariate model specification (Cappiello, Engle, and Sheppard 2006). Furthermore, Wang and Moore (2008) note that the E-GARCH model specification does not require parameters to be restricted in order to ensure positive variances.[6]

In general, the tables display the existence of significant leverage effects, as indicated by the parameter γ. The significance of the γ parameter implies that negative vis-a-vis positive shocks (of similar size) are succeeded by periods of more volatility. More specifically, since $\gamma > 0$ and

[6] We considered employing the GJR-GARCH(1,1) model specification. However, it performed worse with regards to information criterion tests; available upon request.

$\alpha < 0$, $\frac{\gamma}{\alpha} < 0$. Additionally, the tables display weak levels of persistence, given that $\beta + \alpha < 1$. This implies that the weekly return series are stationary and absent of volatility clustering or market momentum. Lastly, the statistical significance of all the coefficients indicate the presence of conditional heteroskedasticity in the weekly return series.

	μ	ω	α	β	γ
Communications	0.003502	-0.43683	-0.112483	0.936348	0.206042
	(0.00221)	(0.086789)	(0.011164)	(0)	(0.00163)
Consumer Discretionary	0.003647	-0.448381	-0.122628	0.93829	0.140246
	(0.000221)	(0)	(0)	(0)	(0)
Consumer Staples	0.003727	-2.079474	-0.164076	0.731555	0.251985
	(0)	(0.025679)	(0.004477)	(0)	(0.002145)
Energy	0.002151	-0.152745	-0.069584	0.975102	0.165886
	(0.134625)	(0.014811	(0.037301)	(0)	(0.000029)
Financials	0.00291	-0.522555	-0.153743	0.929305	0.164943
	(0.001166)	(0)	(0)	(0)	(0)
Health Care	0.003952	-0.578853	-0.092615	0.921751	0.165517
	(0.001219)	(0.066354)	(0.010569)	(0)	(0.001219)
Industrials	0.001937	-0.294376	-0.016708	0.95197	0.186474
	(0.218001)	(0.23027)	(0.709721)	(0)	(0.133537)
Materials	0.000924	-0.233811	-0.090774	0.963599	0.11953
	(0.521471)	(0)	(0.000139)	(0)	(0)

Note: P-values in brackets.

Table 5.1: JALSH Univariate E-GARCH Models

	μ	ω	α	β	γ
Communications	0.001712	-0.641717	-0.209038	0.916533	0.15032
	(0.017669)	(0)	(0)	(0)	(0)
Consumer Discretionary	0.000804	-0.577051	-0.181995	0.921253	0.222724
	(0.351051)	(0.028262)	(0.000245)	(0)	(0.000809)
Consumer Staples	0.001295	-0.993627	-0.238108	0.880158	0.16308
	(0.001332)	(0)	(0.00044)	(0)	(0.019923)
Energy	0.001289	-0.447909	-0.117311	0.934988	0.277201
	(0.21809)	(0.005527)	(0.003396)	(0)	(0.000134)
Financials	0.001048	-0.195558	-0.174231	0.973334	0.114314
	(0.104989)	(0)	(0)	(0)	(0)
Health Care	0.001244	-1.406158	-0.312919	0.82235	0.200408
	(0.02605)	(0)	(0)	(0)	(0.000648)
Industrials	0.00138	-0.279382	-0.142762	0.962423	0.125942
	(0.102283)	(0)	(0)	(0)	(0)
Materials	0.00107	-0.604559	-0.188169	0.915631	0.218621
	(0.259609)	(0.027132)	(0.000668)	(0)	(0.000009)

Note: P-values in brackets.

Table 5.2: SP 500 Univariate E-GARCH Models

	μ	ω	α	β	γ
Communications	0.000463	-0.372559	-0.109039	0.948684	0.129086
	(0.609039)	(0)	(0.000165)	(0)	(0)
Consumer Discretionary	0.001096	-0.527339	-0.170981	0.92367	0.237471
	(0.8492)	(0.942809)	(0.889616)	(0.37989)	(0.571406)
Consumer Staples	0.001331	-0.236826	-0.120282	0.968451	0.148096
	(0.08908)	(0)	(0.00637)	(0)	(0)
Energy	0.000257	-0.465367	-0.186455	0.933693	0.126806
	(0.794012)	(0)	(0)	(0)	(0.00328)
Financials	0.000344	-0.237621	-0.177526	0.965144	0.110598
	(0.702904)	(0)	(0)	(0)	(0)
Health Care	0.001358	-0.257977	-0.092712	0.964543	0.143312
	(0.117163)	(0.000167)	(0.042919)	(0)	(0)
Industrials	0.001661	-0.601414	-0.213359	0.917291	0.155704
	(0)	(0)	(0)	(0)	(0.000017)
Materials	0.002145	-0.499384	-0.183967	0.92895	0.160896
	(0.001054)	(0.00792)	(0)	(0)	(0.077278)

Note: P-values in brackets.

Table 5.3: SP EURO Univariate E-GARCH Models

	μ	ω	α	β	γ
Communications	0.001322	-0.436246	-0.117965	0.94136	0.1607
	(0.156351)	(0.040704)	(0.034733)	(0)	(0.000003)
Consumer Discretionary	0.00086	-0.348316	-0.102156	0.951731	0.170108
	(0.3404)	(0.118779)	(0.086266)	(0)	(0.000007)
Consumer Staples	0.00196	-0.198724	-0.136833	0.973924	0.104385
	(0.000009)	(0)	(0.000624)	(0)	(0.000009)
Energy	0.000671	-0.370364	-0.100042	0.946599	0.188207
	(0.539963)	(0.00225)	(0.031868)	(0)	(0.001919)
Financials	0.000083	-0.161496	-0.143779	0.976576	0.148345
	(0.559373)	(0.000008)	(0.000012)	(0)	(0.001166)
Health Care	0.00112	-0.091123	-0.032134	0.986798	0.115754
	(0.293401)	(0.000676)	(0.440956)	(0)	(0.000272)
Industrials	0.002129	-0.508407	-0.17973	0.9303	0.089264
	(0.012452)	(0)	(0)	(0)	(0.000004)
Materials	0.001362	-0.158912	-0.076015	0.974182	0.159745
	(0.432958)	(0.106321)	(0.022478)	(0)	(0.003914)

Note: P-values in brackets.

Table 5.4: UK Univariate E-GARCH Models

5.2. *Inter-sector Comovements*

The second stage of the estimation makes use of the standardized residuals obtained from the abovementioned estimated E-GARCH(1,1) univariate models in order to estimate the time-varying DCC correlations.

Figure 7.9 to 7.16 in the Appendix report the time-varying dynamic conditional correlations of the respective sectors, between the South African equity market (JSE), the S&P EURO, the UK and the S&P 500. The figures point towards heterogeneity in the correlations between the sector pairs over time and reveals that static estimates of comovement (in modeling terms, the Constant Conditional Correlations or CCC) might be misleading. For instance, the sector pairs for materials as compared to financials, industrials or energy seems to be relatively stable over the whole period. Nevertheless, in most cases, the correlations tend to moderate or return to the levels as displayed before the GFC.

Table 5.5 indicates that the time-varying correlations are mean reverting since $a + b < 1$, for all eight sectors. The coefficient a measures the effect of past standardised innovations on dynamic conditional correlations, while b report the impact of lagged dynamic conditional correlations on the current dynamic conditional correlations (Katzke 2013). In addition to this, the parameters in table 5.5 are mostly significant, indicating significant variation over the specified period. More specifically, the statistical significance of a and b indicates that a DCC model vis-a-vis CCC model is more suitable.

The next step is to check for the presence of conditional heteroscedasicity in the estimated DCC models. This is done by testing for serial correlation, as revealed in table 7.9 in the Appendix. The parameters $Q(m)$ and $Q^k(m)$ struggle to detect conditional heteroscedasticity when innovations are heavy-tailed; therefore the robust parameter $Q_r^k(m)$ is preferable (Tsay 2013). Also, the rank-based test does well when the distribution is assumed to be normal. So when considering the rank-based test and the robust parameter $Q_r^k(m)$, the fitted DCC models are mostly, except for financials, absent of serial correlation or conditional heteroscedasticity.

	a	b
Communications	0.007223	0.971085
	(0.03427)	(0)
Consumer Discretionary	0.010797	0.954017
	(0.017561)	(0)
Consumer Staples	0.015374	0.958688
	(0.190941)	(0)
Energy	0.018204	0.947486
	(0.07113)	(0)
Financials	0.01919	0.951009
	(0.003881)	(0)
Health Care	0.012484	0.9055
	(0.120582)	(0)
Industrials	0.025625	0.907533
	(0.007717)	(0)
Materials	0.026159	0.899398
	(0.309274)	(0)
Note: P-values in brackets.		

Table 5.5: DCC Model

5.3. *The long-run impact of the GFC*

The following regression is estimated to gauge the effect of the GFC on inter-sector conditional correlations:

$$\rho_t = c + d_{GFC} + \varepsilon_t \tag{5.1}$$

The conditional correlations are regressed on a constant and a dummy variable. The dummy variable is equal to 1 from 15 September 2008 until the end of the sample and takes a value of zero otherwise. The fall of the Lehman Brothers is chosen as the proxy date for the commencement of the GFC. Table 5.6 shows the results of the regression. The majority of the d coefficients are positive and statistically significant at a 1% level, indicating that inter-sector conditional correlations were higher during and after the crisis period.

The d coefficients for South Africa and the UK are generally higher relative to the other pairs suggesting that aggregate inter-sector comovement between these two countries was higher during and after the crisis period compared to the other pairs in the sample. Furthermore, there appear to notable increases in the conditional correlations between the consumer staples and energy sectors for the abovementioned pair. However, the regressions also reveal the potential benefits associated with inter-sector diversification. For instance, lower conditional correlations are reported for the sector pair JALSH-SPEURO in financials and similarly for the sector pair JALSH-SP500 in consumer staples. Moreover, in comparison to Gjika and Horvath (2013), which use the same dummy variable approach to study cross-country market-level diversification, the effect of the crisis period is significantly smaller. The crisis period in their paper contributed, on average, 10.93% to the conditional correlations, whereas this paper found the effect to be 1.69%. Lastly, in studying sector-level diversification for the South African equity market using a similar approach Katzke (2013) reports no decrease in conditional correlations for any sector pair during times of uncertainty.

	JALSH-SPEURO		JALSH-UK		JALSH-SP500	
	c	d	c	d	c	d
Communications	0.295006	0.022891	0.301184	0.026766	0.363201	0.017406
	(0)	(0)	(0)	(0)	(0)	(0)
Consumer Discretionary	0.557741	0.009491	0.522122	0.003966	0.485935	0.019371
	(0)	(0.00099)	(0)	(0.0818)	(0)	(0)
Consumer Staples	0.485278	0.0042	0.485054	0.059262	0.315855	-0.0127
	(0)	(0.214)	(0)	(0)	(0)	(0.000961)
Energy	0.531925	0.023695	0.48899	0.040268	0.545225	0.034706
	(0)	(0)	(0)	(0)	(0)	(0)
Financials	0.558235	-0.01585	0.584756	0.022608	0.495627	0.004336
	(0)	(0.000691)	(0)	(0)	(0)	(0.245)
Health Care	0.345418	0.015454	0.263601	0.025643	0.305414	0.007585
	(0)	(0)	(0)	(0)	(0)	(0.00204)
Industrials	0.370548	0.004882	0.310728	0.029019	0.340907	0.018601
	(0)	(0.342)	(0)	(0)	(0)	(0)
Materials	0.622208	0.015839	0.841076	0.005246	0.615442	0.023356
	(0)	(0)	(0)	(0.000212)	(0)	(0)

Note: P-values in brackets.

Table 5.6: Dummy Variable OLS Regression

6. Conclusion

This paper explores inter-sector comovement between three major developed markets and the South African equity market by employing dynamic conditional correlation modeling techniques.

The DCC E-GARCH model allows for the extraction of time-varying conditional correlations from the variance component, highlighting the dynamics of cross-country sector comovement. The E-GARCH model controls for leverage effects in the conditional variance and in the conditional correlation. As such, it is well suited to investigate equity market developments during crisis episodes. Additionally, OLS regressions are estimated in order to evaluate the degree of correlation during the recent financial crisis.

The results indicate that, in terms of GARCH modeling, asymmetric effects do exist and that negative shocks are usually succeeded by more volatility. The time-varying conditional correlations do exhibit heterogeneity with regards to the different sector pairs for the respective countries. In general, higher comovement exists between the South African equity market and the UK equity market. Sectors that display high levels of conditional correlations, typically between 0.5 - 0.8, include: consumer discretionary, energy, financials and materials; while sectors with low levels of conditional correlations, typically below 0.4, include: communications, health care and industrials.

In comparison to Gjika and Horvath (2013), who follow the same dummy variable approach, our results show the potential benefits of diversifying at the sector-level vis-a-vis market level. The global financial crisis dummy resulted in an increase of 10.93% in the conditional correlations in Gjika and Horvath (2013), whereas this paper found the effect to be 1.69%. However, we are cognisant of the fact that the financial crisis dummy might not adequately proxy for changes in market uncertainty or market sentiment given its static nature. In spite of this, the results still reveal that cross-country inter-sector diversification should be considered as an investment strategy to hedge against crisis periods.

7. Appendix

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1621	-0.2118	-0.2364	-0.1813
Quartile 1	-0.0147	-0.0116	-0.0143	-0.0127
Median	0.0045	0.0024	0.0024	0.0028
Arithmetic Mean	0.0040	0.0017	0.0005	0.0015
Geometric Mean	0.0034	0.0014	0.0002	0.0011
Quartile 3	0.0235	0.0154	0.0170	0.0174
Maximum	0.2773	0.1467	0.1479	0.1205
SE Mean	0.0013	0.0010	0.0010	0.0010
LCL Mean (0.95)	0.0014	-0.0002	-0.0015	-0.0005
UCL Mean (0.95)	0.0065	0.0036	0.0026	0.0034
Variance	0.0012	0.0006	0.0007	0.0007
Stdev	0.0341	0.0254	0.0270	0.0262
Skewness	0.4548	-0.7307	-0.9023	-0.5848
Kurtosis	6.9016	9.7193	9.5605	4.5434

Table 7.1: Descriptive Statistics Communications

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1167	-0.1849	-0.2535	-0.2054
Quartile 1	-0.0121	-0.0117	-0.0151	-0.0129
Median	0.0049	0.0032	0.0036	0.0027
Arithmetic Mean	0.0038	0.0016	0.0018	0.0014
Geometric Mean	0.0034	0.0012	0.0012	0.0010
Quartile 3	0.0208	0.0175	0.0198	0.0178
Maximum	0.1506	0.1484	0.4392	0.1719
SE Mean	0.0011	0.0011	0.0014	0.0011
LCL Mean (0.95)	0.0016	-0.0006	-0.0010	-0.0007
UCL Mean (0.95)	0.0059	0.0038	0.0046	0.0035
Variance	0.0008	0.0008	0.0014	0.0008
Stdev	0.0280	0.0289	0.0371	0.0283
Skewness	-0.1438	-0.3804	1.6567	-0.4771
Kurtosis	2.0777	5.0698	31.4848	7.2754

Table 7.2: Descriptive Statistics Consumer Discretionary

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.0707	-0.1721	-0.1970	-0.2144
Quartile 1	-0.0085	-0.0084	-0.0106	-0.0089
Median	0.0048	0.0030	0.0026	0.0030
Arithmetic Mean	0.0037	0.0016	0.0017	0.0023
Geometric Mean	0.0035	0.0015	0.0014	0.0020
Quartile 3	0.0164	0.0117	0.0158	0.0141
Maximum	0.1273	0.0827	0.0811	0.0858
SE Mean	0.0008	0.0007	0.0009	0.0008
LCL Mean (0.95)	0.0021	0.0003	-0.0001	0.0006
UCL Mean (0.95)	0.0054	0.0030	0.0035	0.0039
Variance	0.0005	0.0003	0.0006	0.0005
Stdev	0.0216	0.0172	0.0236	0.0214
Skewness	0.0997	-1.5163	-1.1000	-1.5482
Kurtosis	2.2816	15.5102	7.8595	15.9224

Table 7.3: Descriptive Statistics Consumer Staples

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1746	-0.2949	-0.2677	-0.2165
Quartile 1	-0.0195	-0.0154	-0.0164	-0.0148
Median	0.0031	0.0039	0.0027	0.0022
Arithmetic Mean	0.0029	0.0016	0.0009	0.0013
Geometric Mean	0.0018	0.0010	0.0003	0.0008
Quartile 3	0.0247	0.0213	0.0201	0.0191
Maximum	0.2541	0.1240	0.1638	0.1606
SE Mean	0.0017	0.0013	0.0013	0.0012
LCL Mean (0.95)	-0.0006	-0.0010	-0.0016	-0.0011
UCL Mean (0.95)	0.0063	0.0041	0.0034	0.0038
Variance	0.0020	0.0012	0.0011	0.0010
Stdev	0.0453	0.0342	0.0332	0.0323
Skewness	0.1664	-1.2434	-0.9593	-0.3116
Kurtosis	3.0346	9.1324	8.0178	5.4251

Table 7.4: Descriptive Statistics Energy

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1310	-0.2749	-0.2757	-0.3251
Quartile 1	-0.0116	-0.0142	-0.0212	-0.0179
Median	0.0045	0.0024	0.0018	0.0021
Arithmetic Mean	0.0029	0.0002	-0.0011	-0.0001
Geometric Mean	0.0025	-0.0006	-0.0020	-0.0009
Quartile 3	0.0182	0.0171	0.0222	0.0188
Maximum	0.1159	0.2727	0.1714	0.1870
SE Mean	0.0010	0.0015	0.0016	0.0015
LCL Mean (0.95)	0.0009	-0.0027	-0.0043	-0.0031
UCL Mean (0.95)	0.0049	0.0031	0.0021	0.0029
Variance	0.0007	0.0015	0.0018	0.0016
Stdev	0.0268	0.0387	0.0425	0.0397
Skewness	-0.4934	-0.4150	-0.9857	-1.4155
Kurtosis	3.4660	14.4975	5.9184	12.5762

Table 7.5: Descriptive Statistics Financials

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1038	-0.2031	-0.2119	-0.2054
Quartile 1	-0.0110	-0.0096	-0.0123	-0.0131
Median	0.0041	0.0026	0.0030	0.0015
Arithmetic Mean	0.0037	0.0014	0.0017	0.0014
Geometric Mean	0.0034	0.0012	0.0013	0.0011
Quartile 3	0.0184	0.0134	0.0175	0.0173
Maximum	0.1038	0.0887	0.0868	0.1271
SE Mean	0.0010	0.0008	0.0010	0.0010
LCL Mean (0.95)	0.0018	-0.0002	-0.0003	-0.0006
UCL Mean (0.95)	0.0056	0.0031	0.0036	0.0034
Variance	0.0006	0.0005	0.0007	0.0007
Stdev	0.0253	0.0217	0.0259	0.0266
Skewness	-0.1670	-1.4960	-1.3534	-0.9269
Kurtosis	1.3874	13.3398	8.7316	8.8473

Table 7.6: Descriptive Statistics Health Care

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1669	-0.1344	-0.2093	-0.2008
Quartile 1	-0.0158	-0.0113	-0.0148	-0.0132
Median	0.0019	0.0031	0.0037	0.0035
Arithmetic Mean	0.0028	0.0016	0.0015	0.0021
Geometric Mean	0.0021	0.0012	0.0010	0.0017
Quartile 3	0.0220	0.0163	0.0194	0.0182
Maximum	0.4289	0.1217	0.1587	0.1422
SE Mean	0.0015	0.0011	0.0012	0.0011
LCL Mean (0.95)	-0.0002	-0.0006	-0.0008	-0.0001
UCL Mean (0.95)	0.0059	0.0037	0.0039	0.0043
Variance	0.0016	0.0008	0.0009	0.0008
Stdev	0.0399	0.0281	0.0308	0.0288
Skewness	1.2810	-0.4118	-0.6339	-0.7304
Kurtosis	20.9124	3.5302	4.8899	6.3751

Table 7.7: Descriptive Statistics Industrials

	JALSHAll	SP500	SPEURO	UK
Observations	673.0000	673.0000	673.0000	673.0000
NAs	0.0000	0.0000	0.0000	0.0000
Minimum	-0.1717	-0.1958	-0.2496	-0.2550
Quartile 1	-0.0242	-0.0138	-0.0156	-0.0233
Median	0.0010	0.0041	0.0057	0.0032
Arithmetic Mean	0.0016	0.0013	0.0014	0.0016
Geometric Mean	0.0008	0.0008	0.0008	0.0004
Quartile 3	0.0254	0.0179	0.0199	0.0285
Maximum	0.2896	0.1399	0.1786	0.2358
SE Mean	0.0016	0.0012	0.0014	0.0019
LCL Mean (0.95)	-0.0015	-0.0011	-0.0013	-0.0020
UCL Mean (0.95)	0.0048	0.0037	0.0041	0.0053
Variance	0.0017	0.0010	0.0013	0.0024
Stdev	0.0418	0.0318	0.0355	0.0487
Skewness	0.4515	-0.7968	-0.9241	-0.1285
Kurtosis	4.7800	5.0278	6.8532	4.0804

Table 7.8: Descriptive Statistics Materials

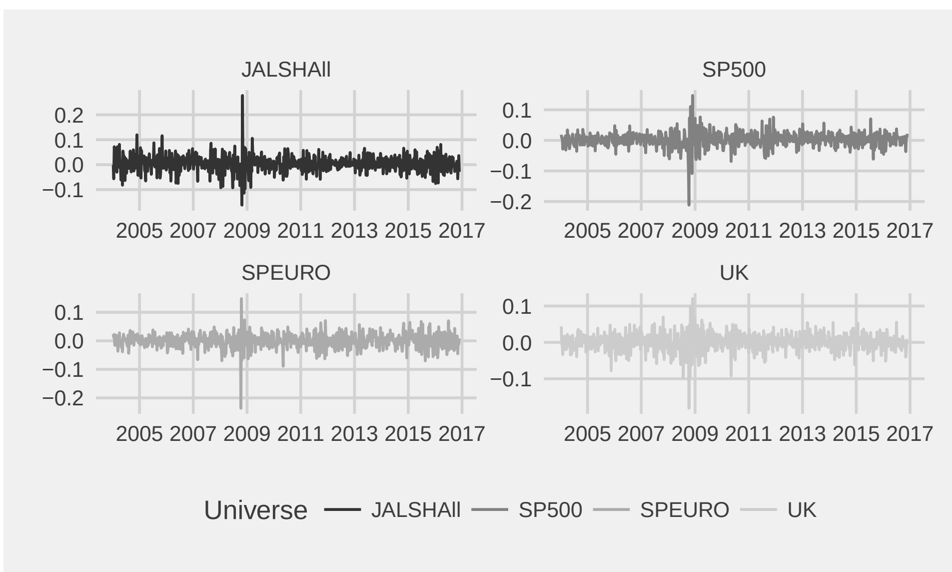

Figure 7.1: Communications Weekly Log Returns

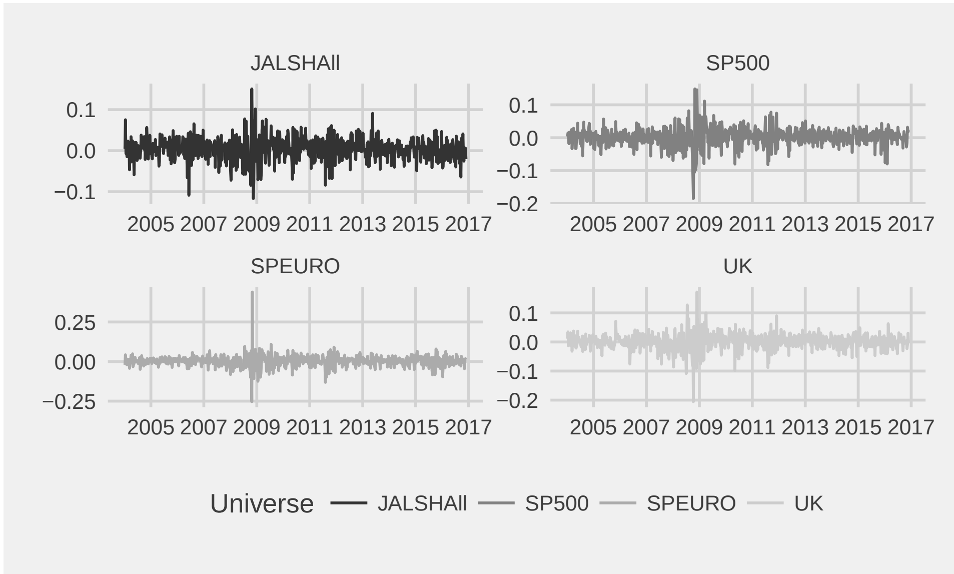

Figure 7.2: Consumer Discretionary Weekly Log Returns

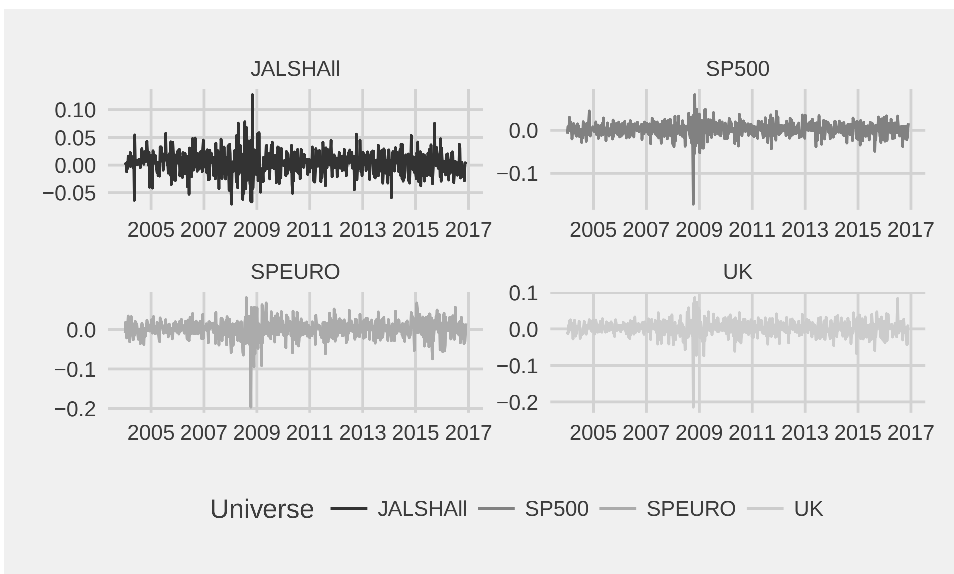

Figure 7.3: Consumer Staples Weekly Log Returns

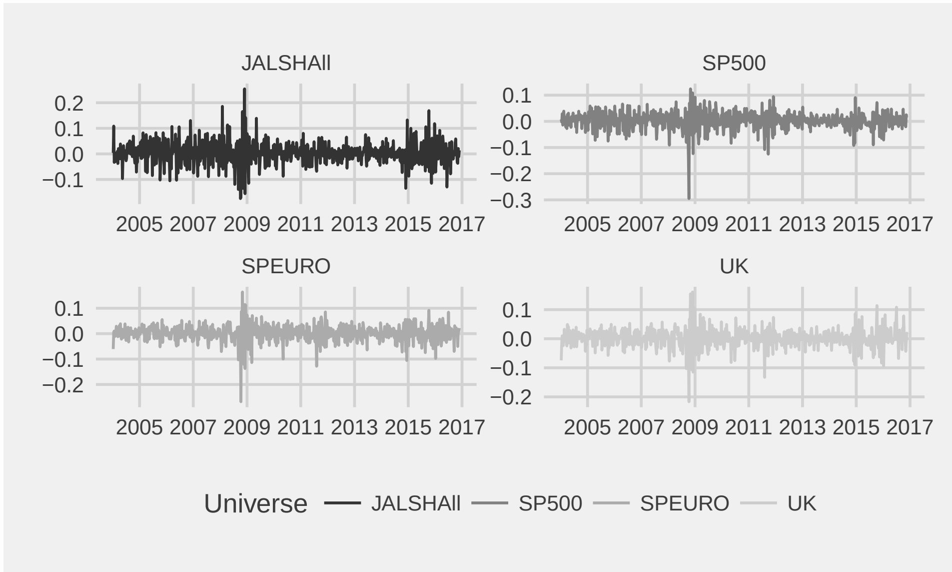

Figure 7.4: Energy Weekly Log Returns

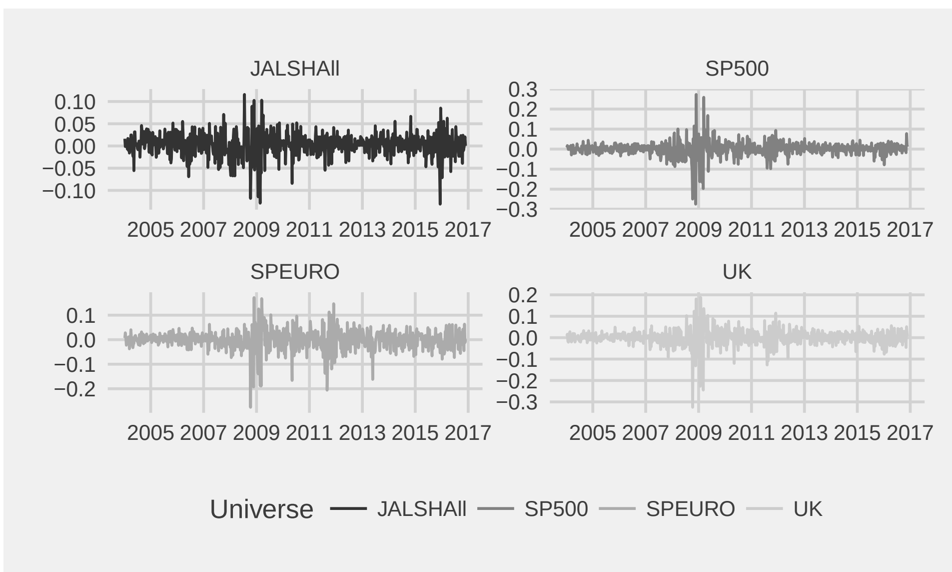

Figure 7.5: Financials Weekly Log Returns

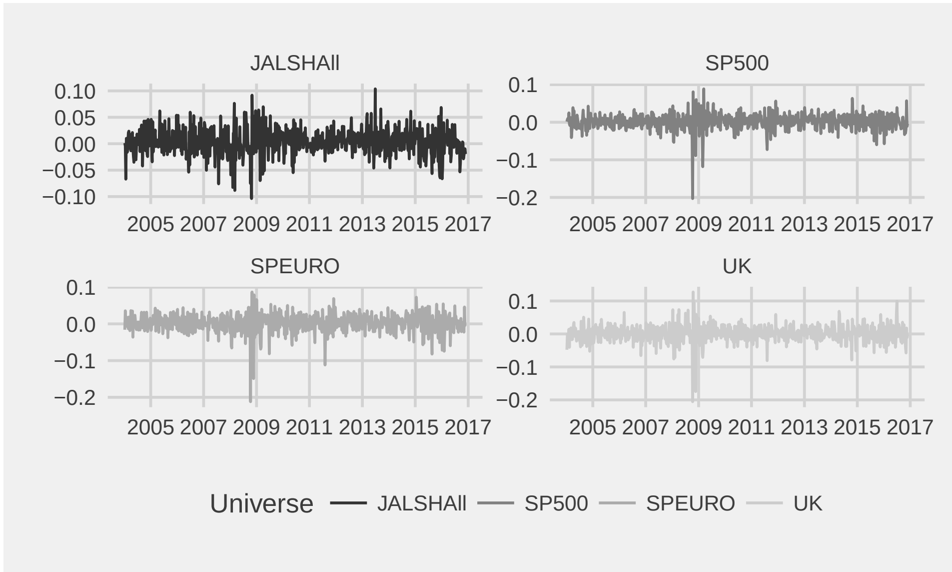

Figure 7.6: Health Care Weekly Log Returns

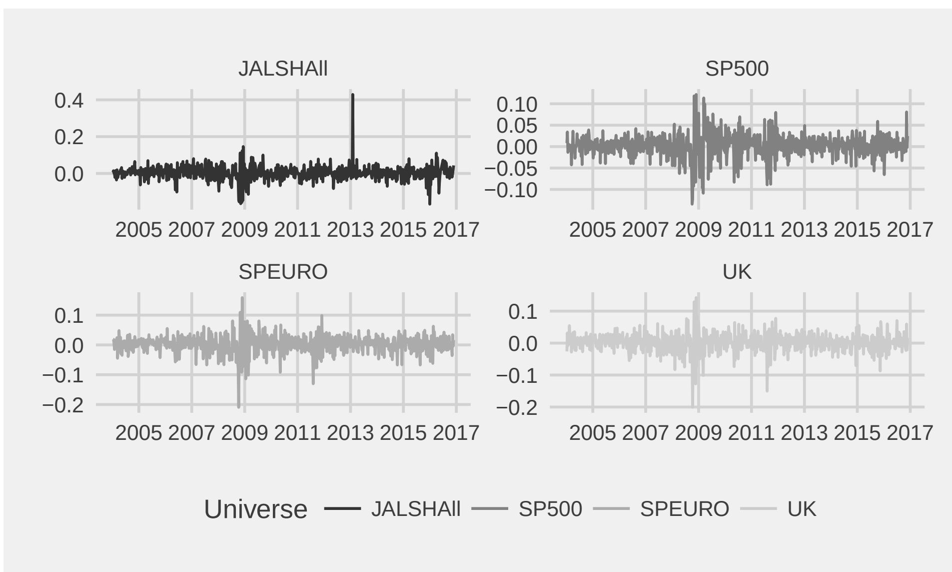

Figure 7.7: Industrials Weekly Log Returns

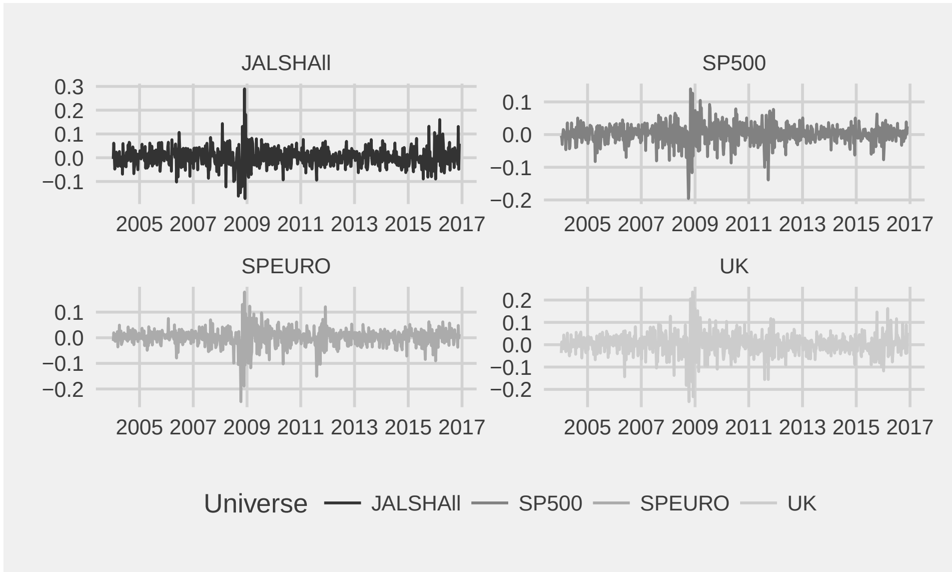

Figure 7.8: Materials Weekly Log Returns

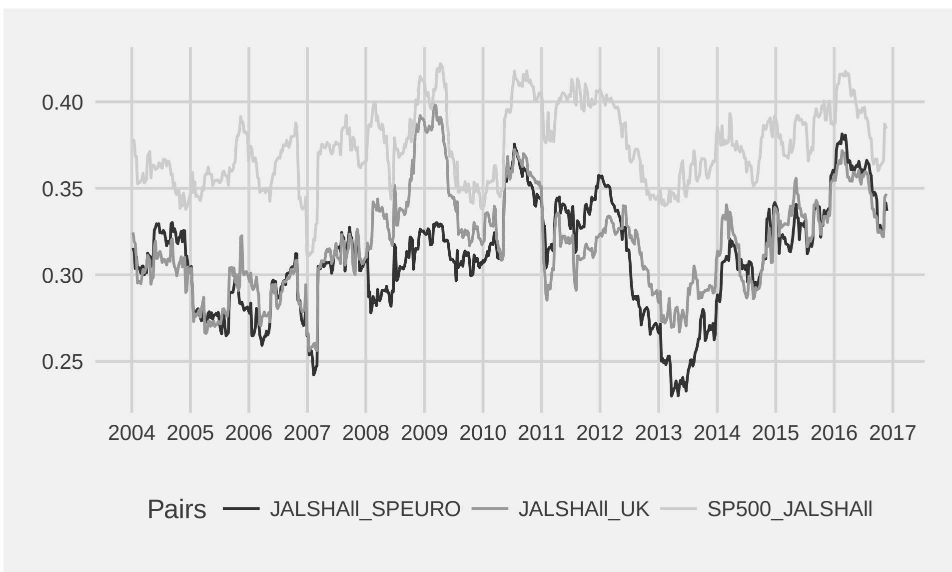

Figure 7.9: DCC Communications

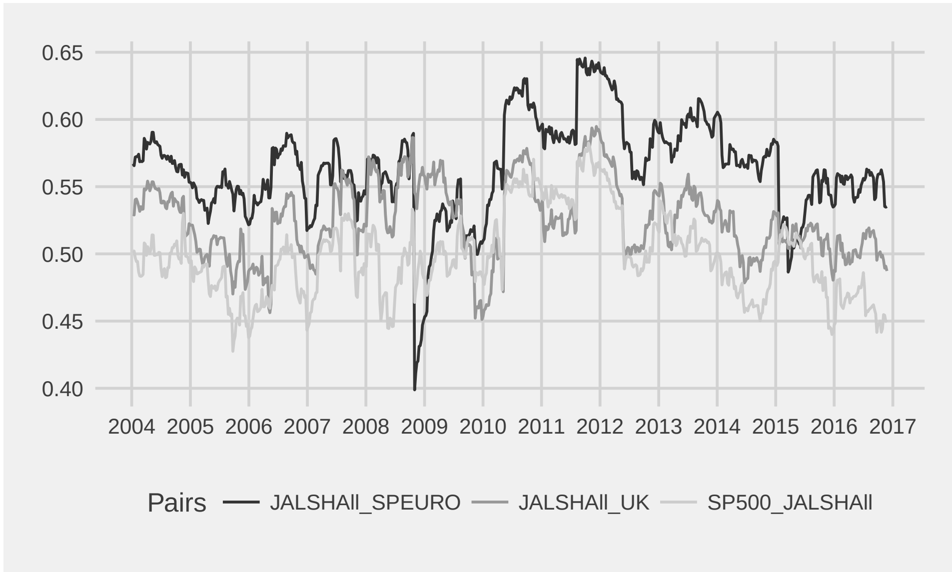

Figure 7.10: DCC Consumer Discretionary

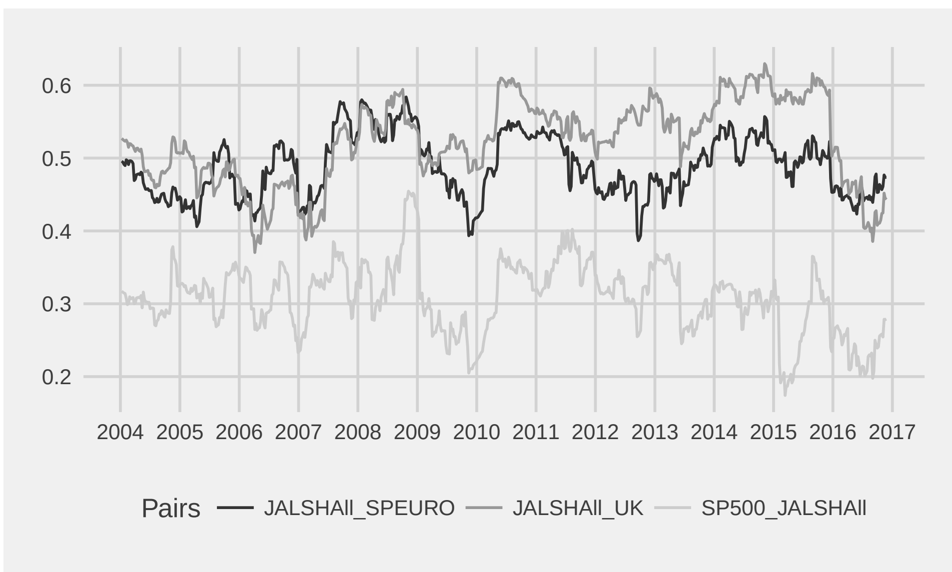

Figure 7.11: DCC Consumer Staples

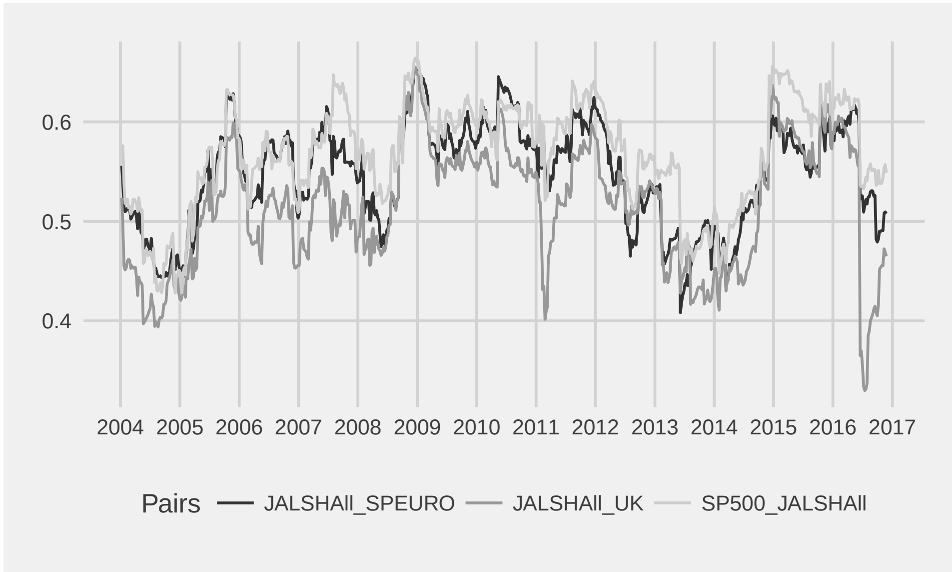

Figure 7.12: DCC Energy

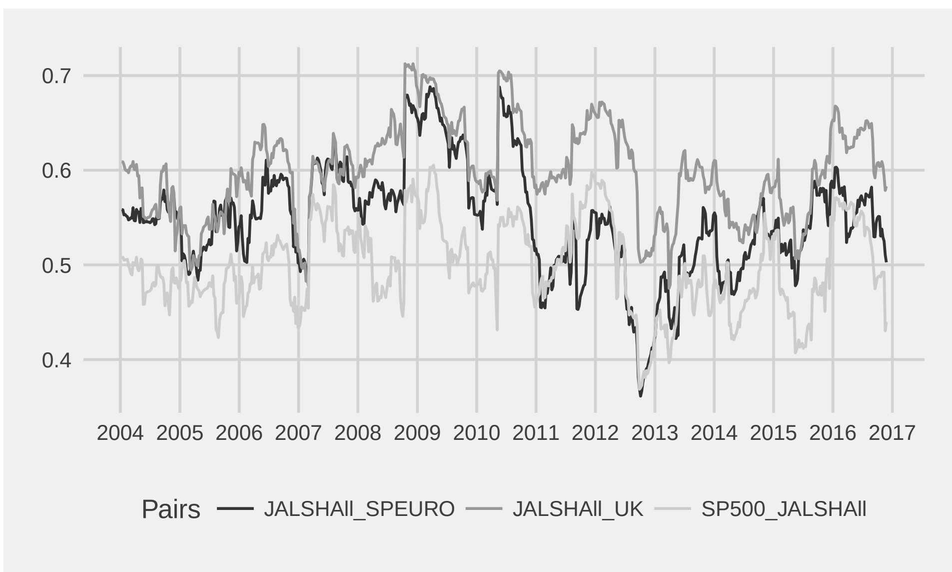

Figure 7.13: DCC Financials

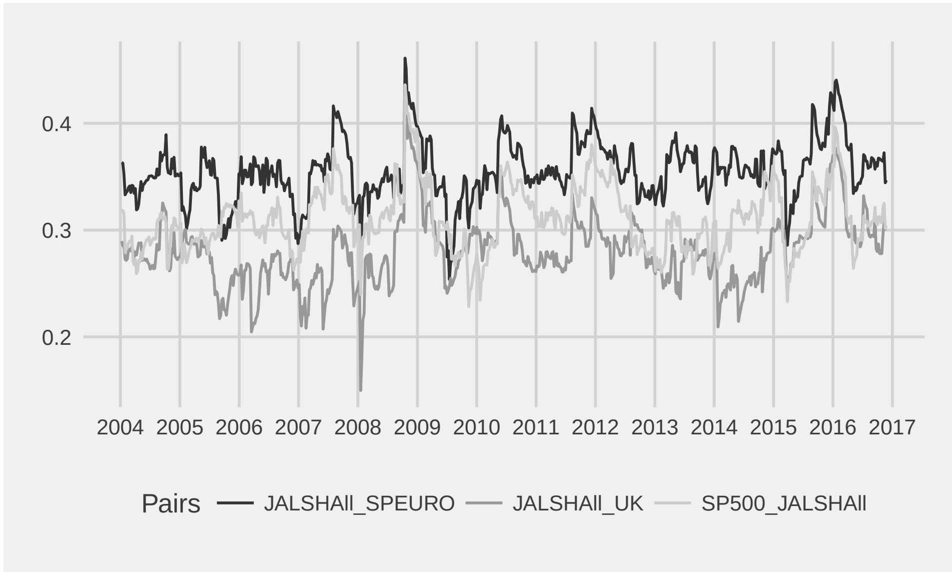

Figure 7.14: DCC Health Care

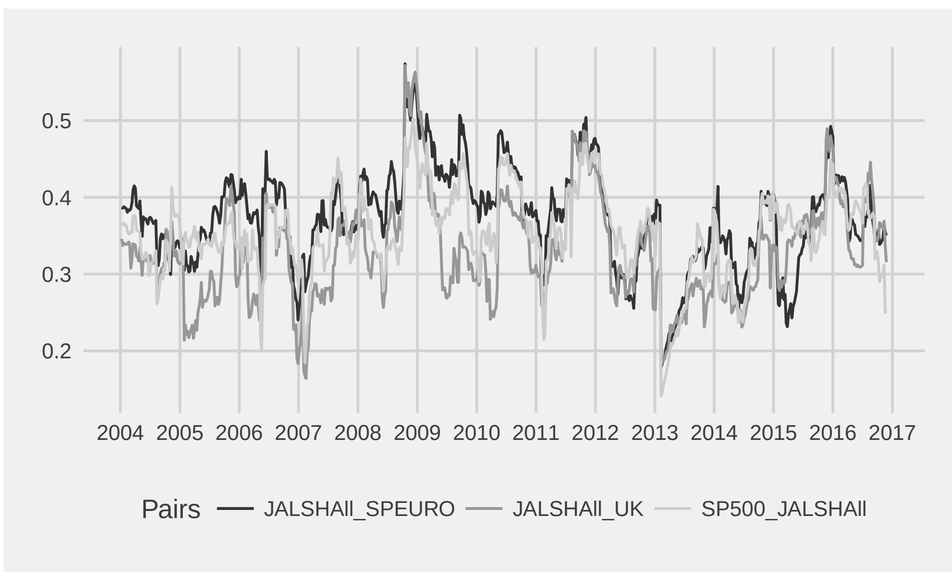

Figure 7.15: DCC Industrials

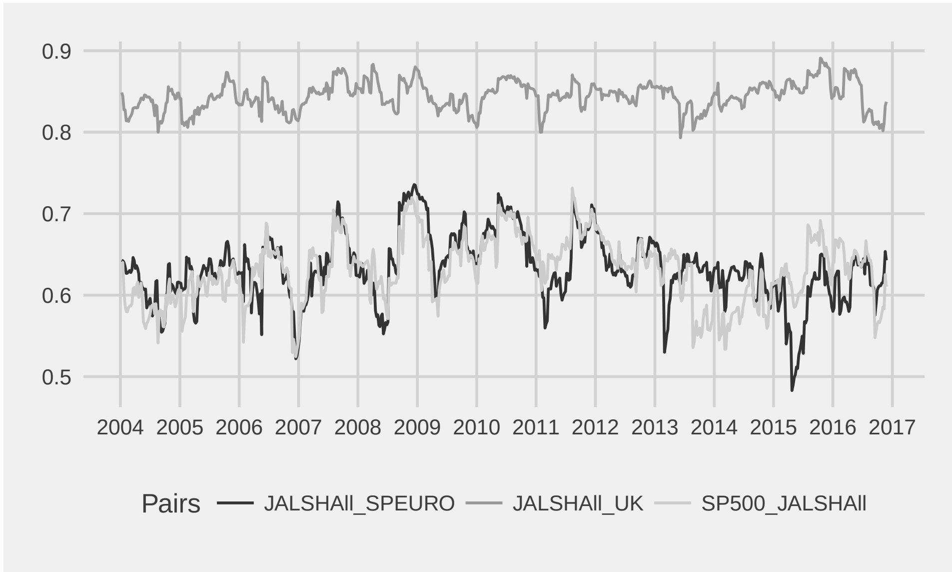

Figure 7.16: DCC Materials

	$Q(m)$	Rank-based test	$Q^k(m)$	$Q_r^k(m)$
Communications	23.82289	13.36319	280.7557	165.7635
	(0.008084642)	(0.2040681)	(0)	(0.361082)
Consumer Discretionary	46.38282	25.58971	369.819	175.4794
	(0)	(0.004333015)	(0)	(0.1905465)
Consumer Staples	8.396633	10.80702	177.8301	140.7444
	(0.5901544)	(0.3727492)	(0.1589239)	(0.8610932)
Energy	29.41584	12.54156	178.3562	149.0881
	(0.001066761)	(0.2504443)	(0.1523825)	(0.7213806)
Financials	12.33973	27.08367	209.4543	207.2083
	(0.2629628)	(0.002526117)	(0.005255538)	(0.007081871)
Health Care	18.67727	10.16494	229.4066	175.4396
	(0.04455863)	(0.4261441)	(0.0002654627)	(0.1911168)
Industrials	1.371009	4.776103	151.5575	134.4677
	(0.9992841)	(0.9056238)	(0.6711427)	(0.9296754)
Materials	13.74776	14.30728	225.2005	192.7874
	(0.1848111)	(0.1594315)	(0.0005226868)	(0.0394186)

Note: P-values in brackets. 10 lags included.

Table 7.9: Model Diagnostic Table

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