VaR Forecasts and Dynamic Conditional Correlations for Spot and Futures Returns on Stocks and Bonds

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Abstract

The paper investigates the interdependence and conditional correlations between futures contracts and their underlying assets, both for stock and bond markets, and the impact of the interdependence and conditional correlations on VaR forecasts. The paper finds evidence of volatility spillovers from spot (futures) to futures (spot) markets, and time-varying conditional correlations between futures and their underlying assets. It also finds evidence that the DCC model of Engle (2002) provides slightly better VaR forecasts as compared with the CCC model of Bollerslev (1990) and the BEKK model of Engle and Kroner (1995).

Keywords: Interdependence, dynamic conditional correlations, spot, futures, stocks, bonds, VaR.

JEL Classifications: G11, G15.

1. Introduction

The three standard motivations for trading futures contracts are speculation, hedging and arbitrage. A crucial measure in deciding whether to use futures to speculate or hedge is the covariance between futures contracts and their underlying assets. The covariance is determined by the variance of each market and the correlation between both markets. A key issue in modelling the variance is the nature of volatility spillovers, resulting from the comovement in financial volatilities across assets and markets. The nature of conditional correlations is useful in determining whether spot and futures returns are substitutes or complements, which can then be used to hedge against contingencies. Balasubramanyan (2004) shows that portfolios that consider time-varying correlations with volatility comovement and spillovers outperform the constant correlation model without comovement and spillovers.

Considering the importance of interdependence and the correlation between futures contracts and their underlying assets, it is surprising that the literature on this topic is relatively thin. Most papers in the literature investigate stock, currency and commodity markets. This motivates the paper to investigate bond and stock futures and their underlying assets regarding interdependence and conditional correlations.

Four government bond indices from Australia, Japan, New Zealand and USA, and seven stock indices from Australia, Indonesia, Japan, Malaysia, New Zealand, Singapore and USA, are investigated. Three multivariate GARCH models are estimated for 11 portfolios (4 bonds and 7 stocks), where each portfolio contains futures and their underlying assets. In order to accommodate the possible volatility spillovers and the time-varying conditional correlations, the BEKK model of Engle and Kroner (1995) and the DCC model of Engle (2002) are estimated. The CCC model of Bollerslev (1990) serves as a benchmark as it does not incorporate volatility spillovers or time-varying conditional correlations.

Another important aspect in constructing a portfolio is measuring risk. Value-at-Risk (VaR) represents an extension of valuation methods for derivative instruments (see Jorion (2001)). The importance of the GARCH family models in modelling and forecasting VaR has been addressed in Angelidis et al. (2004). The advantage of using multivariate GARCH models, as compared with their univariate counterparts, to calculate VaR is that it does not need to re-estimate the models if the weight vector changes. They can also capture the possibility of volatility transmission and time-varying correlations across assets in the portfolio. Varying correlations are important because markets become more closely related during periods of high volatility, namely when accurate VaR are most needed (see Longin and Solnik (1995)). The paper investigates whether such characteristics, namely volatility spillovers and time-varying conditional correlations across assets, contribute to more accurate VaR forecasts for portfolios containing futures and their underlying assets.

The remainder of the paper is organized as follows. Section 2 reviews the literature, Section 3 discusses the models to be estimated, Section 4 describes the data, Section 5 discusses the estimation results, and Section 6 gives some concluding comments.

2. Literature Review

Spot, forward and futures prices of financial assets have been investigated over an extended period, ranging from the impact of the futures trading on the volatility of the underlying assets (Antoniou and Holmes (1995), Hung et al. (2003)), alternative pricing models (Sequeira et al. (1999), Zhong et al. (2004)), and the effectiveness of hedging spot markets using the corresponding futures markets (Baillie and Myers (1991), Lien et al. (2002)).

Another important topic is the interdependence between futures contract and their underlying spot assets, which has been investigated using various GARCH models. Most papers in the literature investigate stock, currency and commodity markets. They have found evidence of volatility spillovers from futures to spot markets (Koutmos and Tucker (1996), Gannon and Choi (1998)), and from spot (futures) to futures (spot) (Gannon and Yeung (2004), Manera et al. (2006)). The results of the investigations on conditional correlations are inconclusive, namely constant (Koutmos and Tucker (1996)) and time-varying (Lien and Yang (2006), Manera et al. (2006)).

$$\varepsilon_t = \eta_t \sqrt{h_t}$$

There are several issues in forecasting VaR regarding futures markets, such as the impact of hedging on VaR and the impact of futures trading on VaR. Harris and Shen (2006) investigate the impact of minimizing the variance of hedging on Conditional VaR and VaR. They find that, although minimum-variance hedging unambiguously reduces the standard deviation of portfolio returns, it can increase both left skewness and kurtosis. As a result, the effectiveness of hedging in terms of VaR and CVaR is uncertain.

Illueca and Lafuente (2007) investigate the impact of futures trading on the underlying stock index in Spain. They find that the unexpected futures trading increases the Conditional VaR of spot returns. Lee and Locke (2006) investigate the speculative trader's strategies. Using futures floor trader's proprietary trading data, they find that floor trader VaR can be predicted somewhat, using simple market variables such as volume and volatility.

The paper investigates the interdependence and correlation across futures and their underlying assets, using the BEKK model of Engle and Kroner (1995), the CCC model of Bollerslev (1990) and the DCC model of Engle (2002). Such an analysis does not seem to have been undertaken previously, especially in relation to VaR calculations.

3. Methods

VaR at level α for returns y_t is the corresponding empirical quantile at $(1-\alpha)$. As quantiles are direct functions of the variance in parametric models, GARCH models immediately translate into conditional VaR models.

For the random variable y_t, with the conditional variance following a univariate GARCH specification,

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \eta_t \sqrt{h_t}$$

$$h_{it} = \omega_i + \sum_{l=1}^{r} \alpha_i \varepsilon_{i,t-l}^2 + \sum_{l=1}^{s} \beta_i h_{i,t-l} \,, \tag{2}$$

the VaR threshold for y_t can be calculated as:

$$VaR_t = E(y_t | F_{t-1}) - z\sqrt{h_t} \,, \tag{3}$$

where z is the critical value from the distribution of ε_t to obtain the appropriate confidence level. Alternatively, h_t can be replaced by estimates of various GARCH models to obtain an appropriate VaR.

In order to investigate whether accommodating comovement among, and interactions across, assets in the conditional variance can improve the forecasts of VaR, three multivariate GARCH models will be estimated. The models are the BEKK model of Engle and Kroner (1995) and the DCC model of Engle (2002). The CCC model of Bollerslev (1990) is estimated for purposes of comparison.

Two important issues in multivariate GARCH models are the curse of dimensionality and the parametric restrictions to ensure the positive definiteness of the estimated covariance matrix. The BEKK model of Engle and Kroner (1995) resolves the positive definiteness issue of the previous models, namely the VECH model of Bollerslev et al. (1988), even though it does not resolve the problem associated with the curse of dimensionality. However, it does not incorporate the volatility transmission across assets.

The typical specification underlying the multivariate conditional mean and conditional variance in returns is given as:

$$y_t = E(y_t | F_{t-1}) + \varepsilon_t \tag{4}$$

$$\varepsilon_t = D_t \eta_t \tag{5}$$

where $y_t = (y_{1t},...,y_{mt})'$, $\eta_t = (\eta_{1t},...,\eta_{mt})'$ is a sequence of identically and independently (i.i.d) random vectors, F_t is the past information available to time t, $D_t = diag(h_{1t}^{1/2},...,h_{mt}^{1/2})$, m is the number of returns, and $t = 1,...,n$.

The conditional covariance of the BEKK model can be specified as:

$$Q_t = QQ' + A\varepsilon_{t-1}\varepsilon_{t-1}^{'}A' + BQ_{t-1}B' \tag{6}$$

where Q_t is the conditional covariance matrix. Q, A and B are $N \times N$ matrices, while Q is upper triangular.

Unlike multivariate GARCH models which focus on the dynamics of the conditional covariance matrix, models such as the CCC model of Bollerslev (1990) and the DCC model of Engle (2002) focus on the dynamics of the conditional variances and the conditional correlation matrix. The CCC model of Bollerslev (1990) assumes that the conditional variance for each return, $h_{it}, i = 1,...,m$, follows a univariate GARCH process, namely

$$h_{it} = \omega_i + \sum_{j=1}^{r}\alpha_{ij}\varepsilon_{i,t-j} + \sum_{j=1}^{s}\beta_{ij}h_{i,t-j}\ , \tag{7}$$

where α_{ij} represents the ARCH effect, or the short-run persistence of shocks to return i, and β_{ij} represents the GARCH effect, or the contribution of shocks to return i to long-run persistence, namely

$$\sum_{j=1}^{r}\alpha_{ij} + \sum_{j=1}^{s}\beta_{ij} < 1. \tag{8}$$

The conditional correlation matrix of CCC is $\Gamma = E(\eta_t\eta_t^{'}|F_{t-1}) = E(\eta_t\eta_t^{'})$, where $\Gamma = \{\rho_{ij}\}$ for $i, j = 1,...,m$. From (5), $\varepsilon_t\varepsilon_t^{'} = D_t\eta_t\eta_t^{'}D_t$, $D_t = (diagQ_t)^{1/2}$, and

$E(\varepsilon_t \varepsilon_t^{'} | F_{t-1}) = Q_t = D_t \Gamma D_t$ where Q_t is the conditional covariance matrix. The conditional correlation matrix is defined as $\Gamma = D_t^{-1} Q_t D_t^{-1}$, and each conditional correlation coefficient is estimated from the standardized residual in (4) and (7).

The DCC model is given by:

$$Z_t = (1-\theta_1-\theta_2)\overline{Z} + \theta_1 \eta_{t-1}\eta_{t-1}^{'} + \theta_2 Q_{t-1} \tag{9}$$

$$\Gamma_t^* = \{(diagZ_t)^{-1/2}\} Z_t \{(diagZ_t)^{-1/2}\}, \tag{10}$$

where θ_1 and θ_2 are scalar parameters, and Z_t is the conditional correlation matrix after it is standardized by (10). For further details regarding multivariate GARCH models, see McAleer (2005).

In order to evaluate VaR forecast accuracy, several back tests will be used, namely tests of unconditional coverage (UC), independence (IND), and conditional coverage (CC). The UC test was first proposed by Kupiec (1995). The test examines whether the failure rate of a model is statistically different from its expectation. Subsequently, Christoffersen (1998) derived likelihood ratio (LR) tests of UC, IND and CC.

In the UC test, the probability of observing x violations in a sample of size T, is given by:

$$\Pr(x) = C_x^T (f)^x (1-f)^{T-x} \tag{11}$$

where f is the desired proportion of observations. $C_x^T = \dfrac{T!}{x!(T-x)!}$ where ! denotes the factorial operator such that $T! = \prod_{i=0}^{T-1} T-i$. The null hypothesis is that the empirical failure rate, $\hat{f}$, is equal to the confidence level of the VaR, α. The LR statistic of UC is:

$$LR_{UC} = 2\log\left[\frac{(1-\alpha)^{n0}\,\alpha^{n1}}{(1-\hat{f})^{n0}\,\hat{f}^{n1}}\right], \qquad (12)$$

where $\hat{f} = x/T$, n_0 is the number of failures and n_1 is the number of success. The statistic is distributed under the null hypothesis as χ^2 with 1 degree of freedom.

A weakness of the UC test is that it tests only the equality between the VaR violations and the confidence level. However, simply testing for the correct unconditional coverage is insufficient when dynamics are present in the higher-order moments. Therefore it is also important that the VaR violations are not correlated over time. The LR statistic of Christoffersen (1998) for testing whether the series are independent is:

$$LR_{IND} = -2\log\left[\frac{(1-\hat{f})^{n_{00}+n_{10}}\,\hat{f}^{n_{01}+n_{11}})}{(1-\hat{f}_{01})^{n00}\,\hat{f}_{01}^{n01}(1-\hat{f}_{11})^{n10}\,\hat{f}_{11}^{n11}}\right], \qquad (13)$$

where n_{ij} is the number of observation with value i followed by j. The statistic is distributed under the null hypothesis as χ^2 with 1 degree of freedom.

The joint test of unconditional coverage and independence tests is the conditional coverage test, with the following LR statistic:

$$LR_{CC} = LR_{UC} + LR_{IND}\,. \qquad (14)$$

The statistic is distributed under the null hypothesis as χ^2 with 2 degrees of freedom.

4. Data analysis

The data used in the paper are the daily closing price index of bonds and their corresponding futures from Australia, Japan, New Zealand and USA; and of stocks and their corresponding futures from Australia, Indonesia, Japan, Malaysia, New Zealand, Singapore and USA. The data are obtained from the Bloomberg and

DataStream database services. The number of observations varies from one series to the other, in order to obtain the longest observation (see Table 1). Returns of market i at time t are calculated as $R_{i,t} = 100 \times \log(P_{i,t} / P_{i,t-1})$, where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of asset i for days t and $t-1$, respectively. All returns are found to be stationary, based on both ADF and Phillips-Perron (PP) tests (see Tables 2 and 3).

In order to examine whether the conditional variances of the assets follow the ARCH process, the univariate AR(1)-GARCH(1,1) model of Bollserslev (1986) and AR(1)-GJR(1,1) model of Glosten et al. (1993) are estimated. If the properties of the univariate models are satisfied, then it would be sensible to extend the models to their multivariate counterparts.

5. Empirical Results

The estimated parameters for the AR(1)-GARCH(1,1) and AR(1)-GJR(1,1) models are given in Tables 4 and 5, respectively. The tables show that not all of the returns follow an AR(1) pattern. This can be interpreted as the behaviour of those returns is possibly also determined by other variables, such as spillovers from other markets. More importantly, those returns exhibit ARCH and/or GARCH effects. From Table 4, ARCH(1) terms are not significant only in Nzbondfut and Indstockfut, while GARCH(1) terms are significant in all returns. From Table 5, ARCH(1) is not significant for Nzbondspot, Nzbondfut, Ausstockspot, Indstockspot, Indstockfut, Nzstockspot, Nzstockfut and Usstockfut, but the corresponding GARCH(1) terms for these series are significant. Therefore, all series exhibit time-varying conditional volatilities, which can be successfully modelled using the GARCH(1,1) and GJR(1,1) models. Asymmetry is evident in more than 50% (13 of 22) series.

In order to check the structural properties of the univariate models, the second moment conditions, which are independent of the mean equations, and the log-moments, are evaluated for both AR(1)-GARCH(1,1) and AR(1)-GJR(1,1). Ling and McAleer (2003) showed that the QMLE for GARCH(r,s) is consistent if the second moment regularity condition is finite. Jeantheau (1988) showed that the log-moment regularity condition given by

$$E(\log(\alpha_1 \eta_t^2 + \beta_1)) < 0 \tag{15}$$

is sufficient for the QMLE to consistent for the GARCH(1,1) model.

The second moment condition, namely $\alpha_1 + \frac{\gamma_1}{2} + \beta_1 < 1$, is sufficient for consistency and asymptotic normality of the QMLE for GJR(1,1). Moreover, McAleer et al. (2007) established the log-moment regularity condition for the GJR(1,1) model, namely

$$E(\log((\alpha_1 + \gamma_1 I(\eta_t))\eta_t^2 + \beta_1)) < 0\,, \tag{16}$$

and showed that it is sufficient for the consistency and asymptotic normality of the QMLE for GJR(1,1). Tables 4 and 5 also provide the moment conditions for both AR(1)-GARCH(1,1) and AR(1)-GJR(1,1) models, respectively, for all returns series. Tables 4 and 5 show that all second moment and log moment conditions are satisfied, except for the second moment condition for Japbondspot and Malstockspot, both for the GARCH and GJR models, and Malstockfut for the GARCH model, which exceed one. However, the log moment conditions for the series are satisfied. Such results suggest that the empirical estimates are statistically valid for these series, which means that the AR(1)-GARCH(1,1) and AR(1)-GJR(1,1) models provide accurate measures of the volatility in each of the series.

Tables 6 and 7 show the estimates of the BEKK model, assuming normal and t distributions, respectively. Table 6 shows that volatility spillovers exist from spot (futures) to futures (spot) returns, either in the short or long run, except in the portfolio of Nzstock, where spot and futures returns are independent. Table 7 shows volatility spillovers exist from spot (futures) to futures (spot) returns, either in the short or long run, in all portfolios. From Table 8, we can see that, using the normal distribution, the coefficients of the DCC model are all significant, with Nzbond and Malstock for the long run only. Using the t distribution, all portfolios display time-varying conditional correlations. It can safely be concluded that all returns show dynamic correlations.

This section also compares the forecasting performance of the various models described in the previous section. For purposes of the empirical analysis, it is assumed that the portfolio weights are equal and constant over time, but this assumption can be relaxed. The multivariate GARCH models described in Section 3 are used to estimate the conditional variances. All the conditional volatility models are estimated under the assumption of the normal and t distributions.

The estimated models are used to forecast 1-day ahead 99% VaR thresholds. Three are 11 portfolios to be considered, namely 4 bonds and 7 stocks. Each portfolio contains futures and the underlying asset. As the length of data varies from one series to another, the sample size used for estimation also varies from one portfolio to another. Combined with achieving convergence, especially for the BEKK model, this results in different periods of forecasting. However, each portfolio is estimated, using the three multivariate models, for the same data period, and therefore provides the same period for VaR forecasts.

At the 95% confidence level, the critical value of chi-squared for LR_{UC} and LR_{IND} are 3.84, while that of LR_{CC} is 5.99. The results from the UC, IND and CC tests, assuming the normal distribution, are given in Table 9. The paper analyses the results of the CC test only, as it already considers the independence in the violation series. The CC test suggests that the DCC model fails in 3 cases, and provides better VaR forecasts than the CCC and BEKK models, which fail in 4 and 5 cases, respectively. As dynamic correlations are evident in all cases, it indicates that incorporating dynamic conditional correlations is important in forecasting VaR. However, the CCC model provides better VaR forecasts than the BEKK model, even though the BEKK model incorporates conditional correlations. As volatility spillovers are evident in almost all cases, this indicates that volatility spillovers do not contribute to improved VaR forecasts.

The VaR forecasts calculated using a t distribution in Table 10 show that, for the CC test, the BEKK, CCC and DCC models fail in 6, 7 and 5 cases, respectively. This provides additional evidence to support the superiority of the DCC model in providing VaR forecasts.

6. Concluding Remarks and Further Research

The paper estimated two univariate GARCH models, namely the GARCH and GJR models, and found that futures of bond and stock showed conditional volatility patterns. It also estimated three multivariate GARCH models, namely the CCC, BEKK and DCC models, and found that volatility spillovers are evident from spot (futures) to futures (spot) returns. Evidence of time-varying conditional correlations was found in all series.

Based on the backtest on VaR forecasts from the multivariate models, assuming both the normal and t distributions, the DCC model performed the best. This might be due to the importance of incorporating time-varying conditional correlations and the simplicity of the model, as compared with the CCC model, which assumes constant conditional correlations, and with the BEKK model, which lacks parsimony.

As more than 50% of the returns show asymmetric effects of negative and positive shocks on conditional variance, it might be useful to estimate multivariate GARCH models that incorporate such asymmetric effect to achieve improved VaR forecasts. In this group is the VARMA-AGARCH model of McAleer et al. (2009). It is also worthwhile checking the consistency of models incorporating time-varying conditional correlations in providing superior VaR forecasts by estimating alternative models, such as the Generalized Autoregressive Conditional Correlation (GARCC) model of McAleer et al. (2008).

Future research might also consider the use of skewed t distribution in calculating VaR forecasts as most asset returns exhibit fatter tails and volatility clustering (see Wu and Shieh (2007) and Bauwens and Laurent (2005), among others).

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Table 1. Price Index of Bonds and Stocks

Asset	Index	Data Range	Observations
Ausbond	Australian Government Bond	18/8/1998-13/2/2008	2477
Japbond	Japanese Govt. Bond 10 Year series	27/5/1998-13/2/2008	2536
Nzbond	New Zealand Government Bond	2/9/2005-13/2/2008	639
Usbond	US Benchmark 10 Year	9/5/2003-13/2/2008	1244
Ausstock	S&P/ASX 200	3/5/2000-13/2/2008	2031
Indstock	LQ45 Stock Index	16/5/2005-13/2/2008	678
Japstock	Nikkei 225	2/1/1990-13/2/2008	4727
Malstock	KLCI stock Index	18/12/1995-13/2/2008	3173
Nzstock	NZX15 Gross Index	21/3/2005-13/2/2008	759
Sgstock	MSCI Sing Cash IX Index	8/9/1998-13/2/2008	2462
Usstock	S&P 500 Index	2/1/1990-13/2/2008	4727

Table 2. ADF Unit Root Test

Series	δ	t-statistic	Critical Value (1%)	Probability
Ausbondspot	-1.092	-37.807	-3.962	0
Ausbondfut	0.029	-37.444	-3.962	0
Japbondspot	-0.993	-35.774	-3.962	0
Japbondfut	-1.045	-36.848	-3.962	0
Nzbondspot	-0.959	-18.056	-3.973	0
Nzbondfut	-0.918	-17.321	-3.973	0
Usbondspot	-1.021	-31.470	-3.963	0
Usbondfut	-1.042	-31.671	-3.963	0
Ausstockspot	-1.075	-33.880	-3.963	0
Ausstockfut	-1.075	-33.759	-3.963	0
Indstockspot	-1.004	-19.094	-3.972	0
Indstockfut	-0.834	-17.157	-3.972	0
Japstockspot	-1.072	-51.619	-3.960	0
Japstockfut	-1.059	-50.563	-3.960	0
Malstockspot	-0.914	-37.216	-3.961	0
Malstockfut	-1.083	-40.978	-3.961	0
Nzstockspot	-0.891	-18.336	-3.970	0
Nzstockfut	-0.889	-18.767	-3.970	0
Sgstockspot	-0.989	-35.699	-3.962	0
Sgstockfut	-1.045	-36.365	-3.962	0
Usstockspot	-1.056	-37.715	-3.433	0
Usstockfut	-1.055	-37.833	-3.433	0

Note: spot and fut refer to spot and futures assets, respectively.

Table 3. PP Unit Root Test

Series	δ	t -statistic	Critical Value (1%)	Probability
Ausbondspot	-1.034	-51.568	-3.962	0
Ausbondfut	-1.023	-51.041	-3.962	0
Japbondspot	-0.976	-49.134	-3.962	0
Japbondfut	-1.019	-51.313	-3.962	0
Nzbondspot	-0.900	-22.884	-3.440	0
Nzbondfut	-0.897	-22.793	-3.973	0
Usbondspot	-0.983	-42.442	-3.963	0
Usbondfut	-1.013	-43.719	-3.963	0
Ausstockspot	-1.024	-46.144	-3.963	0
Ausstockfut	-1.030	-46.536	-3.963	0
Indstockspot	-0.934	-24.253	-3.972	0
Indstockfut	-0.794	-21.066	-3.972	0
Japstockspot	-1.020	-70.166	-3.960	0
Japstockfut	-1.036	-71.277	-3.960	0
Malstockspot	-0.958	-53.963	-3.961	0
Malstockfut	-1.106	-62.810	-3.961	0
Nzstockspot	-0.888	-24.501	-3.970	0
Nzstockfut	-0.873	-24.900	-3.970	0
Sgstockspot	-0.944	-46.893	-3.962	0
Sgstockfut	-1.014	-50.299	-3.962	0
Usstockspot	-1.032	-53.455	-3.433	0
Usstockfut	-1.025	-53.103	-3.433	0

Note: spot and fut refer to spot and futures assets, respectively.

Table 4: Univariate AR(1)-GARCH(1,1) and Moment Conditions for All Series

Series	Constant	AR(1)	ω	α	β	Second Moment	log Moment
Ausbondspot	**-0.011**	0.003	0.000	**0.013**	**0.985**	0.998	-0.002
	-6.022	0.165	-1.268	**2.830**	**231.909**		
Ausbondfut	0.000	-0.017	0.000	**0.015**	**0.984**	0.998	-0.002
	-0.230	-0.880	1.235	**3.601**	**211.513**		
Japbondspot	**-0.003**	**0.052**	**0.000**	**0.093**	**0.919**	1.011	-0.003
	-8.502	**2.196**	**-228.3**	**5.143**	**72.307**		
Japbondfut	0.006	-0.032	0.001	**0.076**	**0.915**	0.991	-0.020
	1.262	-1.358	1.798	**3.507**	**38.003**		
Nzbondspot	**-0.009**	**0.171**	**0.000**	**0.123**	**0.826**	0.950	-0.075
	-2.497	**4.082**	**2.264**	**2.862**	**17.073**		
Nzbondfut	-0.002	**0.106**	0.000	0.031	**0.955**	0.987	-0.015
	-0.917	**2.911**	0.895	1.402	**27.261**		
Usbondspot	0.000	0.012	**0.001**	**0.036**	**0.958**	0.994	-0.008
	-0.040	0.530	**2.046**	**5.041**	**123.003**		
Usbondfut	-0.001	-0.014	0.000	**0.032**	**0.965**	0.997	-0.005
	-0.151	-0.614	1.661	**5.577**	**158.966**		
Ausstockspot	**0.057**	-0.026	**0.011**	**0.093**	**0.891**	0.984	-0.027
	4.289	-1.057	**2.975**	**4.351**	**44.762**		
Ausstockfut	**0.051**	**-0.052**	**0.017**	**0.081**	**0.895**	0.977	-0.033
	3.415	**-2.151**	**3.162**	**4.055**	**42.286**		
Indstockspot	**0.208**	**0.122**	**0.273**	**0.239**	**0.648**	0.887	-0.189
	4.147	**2.519**	**2.663**	**3.515**	**7.798**		
Indstockfut	**0.158**	**0.198**	0.044	0.049	**0.928**	0.889	-0.132
	2.647	**4.721**	1.129	1.564	**18.848**		
Japstockspot	0.018	-0.012	**0.043**	**0.085**	**0.896**	0.981	-0.029
	1.065	-0.744	**3.540**	**7.270**	**65.268**		
Japstockfut	0.013	**-0.033**	**0.040**	**0.076**	**0.907**	0.983	-0.025
	0.776	**-2.160**	**3.422**	**7.634**	**72.638**		
Malstockspot	**0.045**	**0.154**	**0.008**	**0.102**	**0.900**	1.002	-0.014
	2.817	**7.338**	**2.609**	**7.306**	**67.891**		
Malstockfut	**0.042**	-0.005	**0.013**	**0.093**	**0.906**	1.000	-0.013
	2.535	-0.234	**2.997**	**6.428**	**65.876**		
Nzstockspot	0.035	**0.119**	0.056	**0.061**	**0.829**	0.890	-0.121
	1.236	**3.068**	1.739	**2.479**	**10.615**		
Nzstockfut	0.030	**0.128**	**0.105**	**0.095**	**0.707**	0.802	-0.235
	1.038	**3.485**	**2.008**	**2.440**	**5.721**		
Sgstockspot	**0.060**	0.032	**0.013**	**0.098**	**0.900**	0.998	-0.013
	2.991	1.403	**2.836**	**6.241**	**63.205**		
Sgstockfut	**0.057**	-0.018	**0.018**	**0.098**	**0.899**	0.997	-0.015
	2.708	-0.819	**2.828**	**6.433**	**63.131**		
Usstockspot	**0.037**	-0.035	0.009	**0.062**	**0.932**	0.993	-0.012
	2.243	-1.795	1.904	**5.562**	**83.979**		
Usstockfut	**0.037**	-0.018	0.011	**0.066**	**0.926**	0.992	-0.014
	2.295	-0.929	1.842	**5.864**	**86.630**		

Note: spot and fut refer to spot and futures assets, respectively. The 2 entries for each parameter are the parameter estimate and Bollerslev and Wooldridge t ratios. Entries in **bold** are significant at the 95% level.

Table 5: Univariate AR(1)-GJR(1,1) and Moment Conditions for All Series

Series	Constant	AR(1)	ω	α	γ	β	Second Moment	log Moment
Ausbondspot	**-0.011**	0.004	0.000	**0.015**	-0.005	**0.986**	0.998	-0.002
	-5.879	0.182	-1.424	**2.683**	-0.868	**234.117**		
Ausbondfut	0.000	-0.017	0.000	**0.018**	-0.006	**0.984**	0.998	-0.002
	-0.141	-0.874	1.165	**3.081**	-0.866	**216.648**		
Japbondspot	**-0.003**	**0.055**	**0.000**	**0.061**	0.043	**0.926**	1.009	-0.003
	-8.202	**2.238**	**-212.2**	**2.293**	1.067	**81.070**		
Japbondfut	0.004	-0.029	**0.001**	**0.050**	**0.055**	**0.908**	0.985	-0.026
	0.914	-1.223	**2.181**	**1.994**	**2.332**	**37.251**		
Nzbondspot	**-0.009**	**0.172**	**0.000**	0.119	0.015	**0.823**	0.950	-0.075
	-2.575	**4.101**	**2.227**	1.782	0.210	**15.945**		
Nzbondfut	-0.002	**0.100**	0.000	0.024	0.014	**0.959**	0.990	-0.012
	-1.127	**2.720**	0.793	0.868	0.462	**29.601**		
Usbondspot	0.002	0.009	0.001	**0.045**	-0.019	**0.959**	0.995	-0.007
	0.243	0.408	1.869	**4.094**	-1.306	**123.136**		
Usbondfut	0.000	-0.014	0.000	**0.040**	-0.012	**0.964**	0.998	-0.005
	0.032	-0.644	1.549	**3.361**	-0.759	**154.762**		
Ausstockspot	**0.030**	-0.016	**0.014**	-0.016	**0.157**	**0.911**	0.973	-0.035
	2.222	-0.647	**4.509**	-0.963	**6.161**	**56.499**		
Ausstockfut	0.024	-0.038	**0.016**	**-0.023**	**0.139**	**0.928**	0.974	-0.033
	1.608	-1.512	**4.153**	**-1.927**	**6.750**	**64.282**		
Indstockspot	**0.132**	**0.134**	**0.318**	-0.005	**0.376**	**0.669**	0.853	-0.236
	2.445	**2.968**	**3.557**	-0.148	**3.055**	**8.545**		
Indstockfut	**0.124**	**0.207**	0.182	-0.024	0.142	**0.842**	0.977	-0.029
	2.033	**4.988**	0.951	-1.105	1.914	**5.532**		
Japstockspot	-0.018	-0.005	**0.041**	**0.022**	**0.113**	**0.903**	0.982	-0.029
	-1.081	-0.327	**4.416**	**2.106**	**6.352**	**81.148**		
Japstockfut	-0.020	-0.028	**0.040**	**0.017**	**0.105**	**0.912**	0.982	-0.026
	-1.148	-1.888	**4.495**	**1.965**	**6.856**	**90.107**		
Malstockspot	0.023	**0.162**	**0.009**	**0.059**	**0.074**	**0.904**	1.000	-0.015
	1.441	**7.937**	**2.654**	**4.250**	**2.977**	**70.731**		
Malstockfut	0.020	-0.002	**0.015**	**0.055**	**0.071**	**0.908**	0.999	-0.014
	1.213	-0.105	**3.378**	**3.089**	**3.118**	**66.779**		
Nzstockspot	0.020	**0.103**	**0.043**	-0.028	**0.123**	**0.880**	0.914	-0.097
	0.728	**2.742**	**2.540**	-1.374	**3.343**	**20.643**		
Nzstockfut	0.015	**0.129**	**0.032**	-0.017	**0.101**	**0.906**	0.940	-0.068
	0.515	**3.657**	**2.196**	-1.255	**3.107**	**24.925**		
Sgstockspot	**0.042**	0.033	**0.014**	**0.067**	**0.058**	**0.901**	0.997	-0.014
	2.046	1.438	**2.978**	**3.293**	**2.188**	**62.133**		
Sgstockfut	**0.041**	-0.017	**0.018**	**0.072**	0.048	**0.901**	0.996	-0.015
	1.935	-0.727	**2.879**	**3.334**	1.707	**62.273**		
Usstockspot	0.000	-0.023	**0.010**	**-0.022**	**0.129**	**0.950**	0.992	-0.013
	-0.006	-1.201	**3.176**	**-2.262**	**7.919**	**120.350**		
Usstockfut	0.001	-0.005	**0.011**	-0.016	**0.131**	**0.941**	0.990	-0.015
	0.038	-0.261	**2.896**	-1.433	**7.428**	**110.709**		

Note: spot and fut refer to spot and futures assets, respectively. The 2 entries for each parameter are the parameter estimate and Bollerslev and Wooldridge t ratios. Entries in **bold** are significant at the 95% level.

Table 6. BEKK Normal Distribution Estimates

Portfolio	q_{ss}	q_{fs}	q_{ff}	a_{ss}	a_{sf}	a_{fs}	a_{ff}	b_{ss}	b_{sf}	b_{fs}	b_{ff}
Ausbond_s_f	-0.002	0.001	0.000	**0.194**	0.003	-0.058	**0.155**	**0.981**	0.000	0.008	**0.986**
	-0.465	0.547	0.022	**5.040**	0.447	-0.897	**5.151**	**133.793**	-0.127	0.723	**217.649**
Japbond_s_f	**0.007**	0.037	**0.020**	**0.349**	**-0.442**	**0.068**	**0.831**	**-0.960**	**-0.174**	**0.027**	**-0.767**
	2.128	1.799	**3.453**	**6.609**	**-2.757**	**2.192**	**4.820**	**-70.298**	**-4.121**	**2.851**	**-15.785**
Nzbond_s_f	**0.023**	**0.027**	0.000	**0.193**	-0.034	-0.224	-0.159	**1.158**	**0.312**	**-1.062**	**-0.796**
	3.174	**6.183**	0.008	**2.920**	-0.520	-1.015	-0.997	**29.072**	**4.682**	**-3.488**	**-4.639**
Usbond_s_f	0.044	-0.043	-0.011	-0.074	**-1.386**	0.299	**1.757**	**1.185**	**0.897**	-0.248	-0.065
	0.894	-0.841	-0.150	-0.169	**-2.883**	0.625	**3.163**	**3.875**	**2.369**	-0.697	-0.138
Ausstock_s_f	0.052	**0.295**	0.000	0.222	**0.474**	-0.006	-0.091	**0.737**	**0.594**	0.225	0.323
	0.731	**4.183**	-0.003	1.249	**2.678**	-0.043	-0.630	**2.869**	**2.769**	0.872	1.289
Indstock_s_f	**0.694**	**0.507**	0.000	-0.092	**0.364**	**-0.433**	**-0.518**	**0.881**	**0.268**	**-0.256**	**0.585**
	7.222	**5.030**	-0.002	-0.855	**3.909**	**-3.383**	**-4.785**	**7.139**	**3.951**	**-2.111**	**8.212**
Japstock_s_f	**0.244**	**0.195**	0.000	**0.137**	**-0.178**	**0.142**	**0.406**	**1.019**	**0.091**	**-0.075**	**0.876**
	8.107	**7.830**	0.008	**2.458**	**-3.612**	**2.278**	**9.082**	**46.858**	**11.588**	**-3.057**	**82.291**
Malstock_s_f	**0.103**	**0.067**	**0.052**	**0.413**	**0.440**	**-0.128**	**-0.244**	**-1.410**	**-2.364**	**0.462**	**1.435**
	2.604	**4.232**	**2.697**	**7.209**	**7.437**	**-50.350**	**-60.680**	**-82.608**	**-237.7**	**6811.798**	**262.173**
Nzstock_s_f	**0.630**	**0.629**	**0.064**	-0.180	-2.302	0.427	2.529	-0.008	-0.005	-0.267	-0.272
	20.621	**23.277**	**2.513**	-0.152	-1.156	0.370	1.333	-0.017	-0.012	-0.906	-0.909
Sgstock_s_f	0.073	0.074	-0.012	**0.210**	**0.382**	0.038	-0.117	**0.568**	**-0.477**	**-1.348**	**-0.550**
	1.817	1.597	-0.630	**2.919**	**5.396**	0.557	-1.250	**120.942**	**-59.952**	**-95.826**	**-24.579**
Usstock_s_f	**0.150**	**0.150**	0.000	**-0.141**	-0.039	**0.410**	**0.317**	**-0.919**	**0.077**	-0.033	**-1.027**
	10.200	**9.672**	0.003	**-2.017**	-0.479	**5.245**	**3.297**	**-50.141**	**4.608**	-1.524	**-48.570**

Note: spot and fut refer to spot and futures assets, respectively. The 2 entries for each parameter are the parameter estimate and Bollerslev and Wooldridge t ratios. Entries in **bold** are significant at the 95% level.

Table 7. BEKK t Distribution Estimates

Portfolio	q_{ss}	q_{fs}	q_{ff}	a_{ss}	a_{sf}	a_{fs}	a_{ff}	b_{ss}	b_{sf}	b_{fs}	b_{ff}
Ausbond_s_f	-0.008	-0.001	-0.001	**6.533**	0.072	-0.251	**6.120**	**0.984**	0.001	-0.009	**0.980**
	-0.251	-0.208	-0.361	**25.275**	0.316	-0.075	**3.196**	**135.996**	0.416	-0.420	**177.739**
Japbond_s_f	**0.037**	0.000	**0.062**	**5.461**	**1.472**	**-0.158**	**3.786**	**-0.935**	**0.013**	**-0.002**	**-0.953**
	4.319	0.019	**5.104**	**89.149**	**31.067**	**-3.407**	**102.640**	**-115.566**	**4.148**	**-4.023**	**-121.233**
Nzbond_s_f	0.000	-0.005	-0.008	**0.275**	-0.006	-0.199	**0.211**	**0.958**	0.012	0.063	**0.939**
	0.046	-0.838	-1.257	**4.469**	-0.132	-1.747	**2.552**	**60.976**	0.894	1.848	**34.314**
Usbond_s_f	**0.220**	**0.122**	0.000	**0.635**	**0.304**	**-0.292**	**-0.039**	**0.020**	**-0.485**	**1.029**	**1.501**
	12.401	**11.354**	0.016	**30.121**	**30.441**	**-10.713**	**-3.096**	**10.030**	**-1505.264**	**518.719**	**1321.046**
Ausstock_s_f	**0.096**	**0.130**	0.005	**-0.144**	**-0.264**	-0.041	0.017	**1.074**	**0.095**	**-1.698**	**-1.035**
	5.921	**6.852**	0.539	**-7.885**	**-12.034**	-1.250	0.497	**557.712**	**61.666**	**-92.966**	**-115.745**
Indstock_s_f	**0.225**	**0.222**	-0.001	**-0.266**	0.000	0.079	**-0.202**	-0.138	**0.812**	**1.132**	0.143
	2.165	**2.809**	-0.026	**-3.362**	-0.007	0.729	**-2.857**	-0.465	**3.043**	**4.156**	0.469
Japstock_s_f	**0.156**	**0.103**	**0.111**	**-0.226**	**0.206**	0.002	**-0.404**	**-0.921**	-0.062	-0.051	**-0.914**
	6.012	**3.352**	**4.092**	**-3.228**	**2.777**	0.026	**-6.044**	**-30.916**	-1.836	-1.759	**-28.584**
Malstock_s_f	**1.498**	**0.625**	**0.525**	**2.953**	**4.094**	-0.117	**-2.085**	**-1.410**	**-2.332**	**0.467**	**1.428**
	9.346	**2.944**	**7.327**	**16.027**	**12.121**	-1.444	**-15.491**	**-65.904**	**-37.647**	**2008.662**	**118.235**
Nzstock_s_f	**0.330**	**0.318**	0.000	**-1.456**	**-1.517**	**1.942**	**2.004**	**0.316**	**-0.315**	**0.647**	**1.281**
	25.496	**24.354**	-0.078	**-3.009**	**-3.114**	**3.614**	**3.713**	**149.335**	**-205.894**	**210.805**	**216.426**
Sgstock_s_f	**0.050**	**0.080**	-0.003	**0.124**	**0.313**	**0.055**	**-0.138**	**-1.415**	**-0.531**	**0.445**	**-0.513**
	3.665	**8.260**	-0.095	**3.778**	**5.260**	**19.069**	**-4.692**	**-59.726**	**-20.404**	**18.957**	**-19.971**
Usstock_s_f	**0.093**	**0.099**	**-0.032**	-0.178	0.104	-0.008	-0.302	**-0.956**	-0.006	-0.025	**-0.971**
	4.139	**2.652**	**-2.094**	-1.080	0.521	-0.051	-1.550	**-16.480**	-0.088	-0.423	**-15.261**

Note: spot and fut refer to spot and futures assets, respectively. The 2 entries for each parameter are the parameter estimate and Bollerslev and Wooldridge t ratios. Entries in **bold** are significant at the 95% level.

Table 8. DCC Estimates

Portfolio	Normal distribution		*t* disribution	
	θ_1	θ_2	θ_1	θ_2
Ausbond_s_f	**0.025**	**0.972**	**0.047**	**0.952**
	14.74	**494.7**	**10.626**	**209.913**
Japbond_s_f	**0.243**	**0.709**	**0.155**	**0.844**
	4.497	**6.987**	**15.310**	**82.699**
Nzbond_s_f	0.018	**0.962**	**0.032**	**0.958**
	1.33	**37.049**	**2.372**	**60.885**
Ussbond_s_f	**0.414**	**0.227**	**0.370**	**0.551**
	4.827	**2.53**	**10.778**	**13.433**
Ausstock_s_f	**0.029**	**0.923**	**0.016**	**0.968**
	3.334	**31.191**	**2.430**	**59.832**
Indstock_s_f	**0.063**	**0.932**	**0.053**	**0.947**
	6.897	**125.932**	**561491**	**123514**
Japstock_s_f	**0.054**	**0.937**	**0.059**	**0.935**
	20.41	**265.3**	**11.744**	**163.034**
Malstock_s_f	0	**0.198**	**0.032**	**0.953**
	0	**100.446**	**4.579**	**82.304**
Nzstock_s_f	**0.583**	0.119	**0.770**	**0.227**
	3.823	1.341	**574.360**	**182.579**
Sgstock_s_f	**0.071**	**0.884**	**0.045**	**0.927**
	11.008	**72.127**	**2.069**	**20.355**
Usstock_s_f	**0.017**	**0.982**	**0.020**	**0.977**
	10.41	**566.3**	**5.604**	**234.068**

Note: spot and fut refer to spot and futures assets, respectively. The 2 entries for each parameter are the parameter estimate and Bollerslev and Wooldridge *t* ratios. Entries in **bold** are significant at the 95% level.

Table 9. Test of VaR Forecasts, Normal Distribution

Portfolio	Models	Total Forecast	Number of Violations	LR_{UC}	LR_{IND}	LR_{CC}
Ausbond_s_f	BEKK	477	11	**6.00**	0.47	**6.48**
	CCC	477	1	**4.45**	0.00	4.45
	DCC	477	1	**4.45**	0.00	4.45
Japbond_s_f	BEKK	500	10	**3.91**	0.37	4.28
	CCC	500	8	1.54	0.23	1.77
	DCC	500	10	**3.91**	0.37	4.28
Nzbond_s_f	BEKK	139	2	0.24	0.06	0.30
	CCC	139	2	0.24	0.06	0.30
	DCC	139	2	0.24	0.06	0.30
Usbond_s_f	BEKK	600	5	0.18	0.07	0.25
	CCC	600	4	0.76	0.04	0.80
	DCC	600	3	1.86	0.02	1.88
Ausstock_s_f	BEKK	500	17	**17.90**	**5.88**	**23.78**
	CCC	500	23	**34.86**	**6.18**	**41.04**
	DCC	500	23	**34.86**	**6.18**	**41.04**
Indstock_s_f	BEKK	177	5	**3.98**	**5.74**	**9.73**
	CCC	177	4	2.09	**6.23**	**8.32**
	DCC	177	2	0.03	0.05	0.07
Japstock_s_f	BEKK	500	12	**7.11**	**6.12**	**13.24**
	CCC	500	13	**8.97**	0.69	**9.67**
	DCC	500	13	**8.97**	0.69	**9.67**
Malstock_s_f	BEKK	673	15	**7.61**	**12.28**	**19.89**
	CCC	673	11	2.30	0.37	2.66
	DCC	673	10	1.40	0.30	1.70
Nzstock_s_f	BEKK	308	8	**5.51**	0.37	5.88
	CCC	308	7	3.70	0.28	3.98
	DCC	308	4	0.25	0.08	0.33
Sgstock_s_f	BEKK	562	11	**4.07**	0.44	4.51
	CCC	562	14	**8.92**	**6.15**	**15.07**
	DCC	562	12	**5.52**	0.52	**6.04**
Usstock_s_f	BEKK	739	10	0.84	0.27	1.11
	CCC	739	13	3.51	0.47	3.97
	DCC	739	13	3.51	0.47	3.97

Note: spot and fut refer to spot and futures assets, respectively. Entries in **bold** are significant at the 95% level.

Table 10. Test of VaR Forecasts, t Distribution

Portfolio	Models	Total Forecast	Number of Violations	LR_{UC}	LR_{IND}	LR_{CC}
Ausbond_s_f	BEKK	477	1	**4.45**	0.00	4.45
	CCC	477	1	**4.45**	0.00	4.45
	DCC	477	1	**4.45**	0.00	4.45
Japbond_s_f	BEKK	500	1	**4.81**	0.00	4.81
	CCC	500	1	**4.81**	0.00	4.81
	DCC	500	1	**4.81**	0.00	4.81
Nzbond_s_f	BEKK	139	0	2.79	0.00	2.79
	CCC	139	0	2.79	0.00	2.79
	DCC	139	0	2.79	0.00	2.79
Usbond_s_f	BEKK	600	1	**6.46**	0.00	**6.46**
	CCC	600	1	**6.46**	0.00	**6.46**
	DCC	600	1	**6.46**	0.00	**6.46**
Ausstock_s_f	BEKK	500	7	0.72	0.17	0.89
	CCC	500	10	**3.91**	**6.33**	**10.25**
	DCC	500	8	1.54	0.23	1.77
Indstock_s_f	BEKK	177	0	3.56	0.00	3.56
	CCC	177	0	3.56	0.00	3.56
	DCC	177	1	0.40	0.01	0.41
Japstock_s_f	BEKK	500	0	**10.05**	0.00	**10.05**
	CCC	500	0	**10.05**	0.00	**10.05**
	DCC	500	0	**10.05**	0.00	**10.05**
Malstock_s_f	BEKK	673	0	**13.53**	0.00	**13.53**
	CCC	673	0	**13.53**	0.00	**13.53**
	DCC	673	0	**13.53**	0.00	**13.53**
Nzstock_s_f	BEKK	308	1	**13.38**	0.00	**13.38**
	CCC	308	1	**13.38**	0.00	**13.38**
	DCC	308	1	**13.38**	0.00	**13.38**
Sgstock_s_f	BEKK	562	3	**32.88**	0.00	**32.88**
	CCC	562	3	**32.88**	0.00	**32.88**
	DCC	562	2	**25.68**	0.00	**25.68**
Usstock_s_f	BEKK	739	1	**8.84**	0.00	**8.84**
	CCC	739	1	**8.84**	0.00	**8.84**
	DCC	739	1	**8.84**	0.00	**8.84**

Note: spot and fut refer to spot and futures assets, respectively. Entries in **bold** are significant at the 95% level.