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Abstract

Asia is presently the most important market for the production and consumption of natural rubber. World prices of rubber are not only subject to changes in demand, but also to speculation regarding future markets. Japan and Singapore are the major futures markets for rubber, while Thailand is one of the world's largest producers of rubber. As rubber prices are influenced by external markets, it is important to analyse the relationship between the relevant markets in Thailand, Japan and Singapore. The analysis is conducted using several alternative multivariate GARCH models. The empirical results indicate that the constant conditional correlations arising from the CCC model of Bollerslev (1990) lie in the low to medium range. The results from the VARMA-GARCH model of Ling and McAleer (2003) and the VARMA-AGARCH model of McAleer et al. (2009) suggest the presence of volatility spillovers and asymmetric effects of positive and negative return shocks on conditional volatility. Finally, the DCC model of Engle (2002) suggests that the conditional correlations can vary dramatically over time. In general, the dynamic conditional correlations in rubber spot and futures returns shocks can be independent or interdependent.

Keywords: Multivariate GARCH, volatility spillovers, conditional correlations, Asian rubber prices, spot returns, futures returns.

JEL Classifications: C22, C32, G17, G32, Q14

1. Introduction

Natural rubber is one of the most important agro-based industrial raw materials in the world. Rubber is produced entirely in developing countries. Asia is the largest producing region, accounting for around 96.6% of output in 2007, and Thailand is one of the world's biggest rubber producers. However, rubber prices are determined in the Singapore and Japanese markets. The factors involved in setting Thailand's rubber prices are quite interesting. According to the relevance of Thailand's rubber price to the Japanese and Singapore markets, it is important to examine the relationship between the Thai spot market and the three major global rubber futures markets, namely Tokyo Commodity Exchange (TOCOM), Singapore Commodity Exchange and Agriculture Futures Exchange (SICOM), and Osaka Mercantile Exchange (OME). In particular, volatility spillover effects will be considered across and within these markets.

Recent research has used the GARCH specification to model volatility spillovers across futures markets. The volatility transmission between futures and cash markets has received considerable attention in finance. Shocks in one market may not only affect the volatility in prices and returns in its own market, but also in related markets. Apergis and Rezitis (2003) investigated volatility spillover effects across agricultural input prices, agricultural output prices and retail food prices, using GARCH models. Feng et al. (2009) examined the inter-temporal information transmission mechanism between the palm oil futures market and the physical cash market in Malaysia.

Despite the recent developments in the multivariate GARCH framework, most of the research in agricultural futures markets has been confined to univariate GARCH specifications. It is well known that the univariate GARCH model has two important limitations: (1) it does not accommodate the asymmetric effects of positive and negative shocks of equal magnitude; and (2) it does not permit interdependencies across different assets and/or markets. Modelling volatility in a multivariate framework leads to more relevant empirical models than using separate univariate models in financial markets, wherein volatilities can move together over time and across assets and markets.

To date, few papers have paid attention to analyzing volatility spillovers across futures markets and physical cash markets in the context of multivariate GARCH models for agricultural commodity future markets. For example, Kim and Doucouliagos (2005) examined volatility spillover effects by fitting a multivariate model to realized volatility and correlations. The dynamic relationships and causality among the volatilities and correlations of three grain futures prices, namely corn, soybean and wheat, were investigated by conducting impulse response analysis based on the vector autoregressive model.

The purpose of this paper is to (1) to model the multivariate conditional volatility in the returns on rubber spot and futures price in three major rubber futures markets, namely TOCOM, OME and SICOM and two rubber spot markets, Bangkok and Singapore, using several recent models of multivariate conditional volatility, namely the CCC model of Bollerslev (1990), DCC model of Engle (2002), VARMA-GARCH model of Ling and McAleer (2003), and VARMA-AGARCH model of McAleer et al. (2009), and (2) to investigate volatility transmissions across these markets.

The remainder of the paper is organized as follows. Section 2 discusses the econometric methodology. Section 3 explains the data used in the empirical analysis, and presents some summary statistics. The empirical results are analysed in Section 4. Some concluding remarks are given in Section 5.

2. Econometric methodology

This section presents models of the volatility in rubber spot and futures prices returns, namely the CCC model of Bollerslev (1990), VARMA-GARCH model of Ling and McAleer (2003), VARMA-AGARCH model of McAleer et al. (2009), and DCC model of Engle (2002). The typical specifications underlying the multivariate conditional mean and conditional variance in returns are given as follows:

$$y_t = E\left(y_t \left| F_{t-1}\right.\right) + \varepsilon_t \qquad (1)$$

$$\varepsilon_t = D_t \eta_t$$

where $y_t = \left(y_{1t},...,y_{mt}\right)'$, $\eta_t = \left(\eta_{1t},...,\eta_{mt}\right)'$ is a sequence of independently and identically distributed (iid) random vectors, F_t is the past information available to time t, $D_t = diag\left(h_1^{1/2},...,h_m^{1/2}\right)$. The constant conditional correlation (CCC) model of Bollerslev

(1990) assumes that the conditional variance for each return, h_{it}, $i=1,..,m$, follows a univariate GARCH process, that is

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j} \tag{2}$$

where α_{ij} and β_{ij} represents the ARCH effect and the GARCH effects, respectively. The conditional correlation matrix of CCC is $\Gamma = E\left(\eta_t \eta_t' \middle| F_{t-1}\right) = E\left(\eta_t \eta'\right)$, where $\Gamma = \left\{\rho_{it}\right\}$ for $i, j = 1,...,m$. From (1), $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta' D_t$, $D_t = \left(\text{diag } Q_t\right)^{1/2}$, and $E\left(\varepsilon_t \varepsilon_t' \middle| F_{t-1}\right) = Q_t = D_t \Gamma D_t$, 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 residuals in (1) and (2). Therefore, there is no multivariate estimation involved for CCC, except in the calculation of the conditional correlations.

This model assumes independence of the conditional variance across returns. In order to accommodate possible interdependencies, Ling and McAleer (2003) proposed a vector autoregressive moving average (VARMA) specification of the conditional mean in (1) and the following specification for the conditional variance:

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \tag{3}$$

where $H_t = \left(h_{1t},...,h_{mt}\right)'$, $\vec{\varepsilon} = \left(\varepsilon_{1t}^2,...\varepsilon_{mt}^2\right)'$, and W, A_i for $i=1,..,r$ and B_j for $j=1,..,s$ are $m \times m$ matrices. As in the univariate GARCH model, the VARMA-GARCH model assumes that negative and positive shocks of equal magnitude have equivalent impacts on the conditional variance. In order to separate the asymmetric impacts of the positive and negative shocks, McAleer et al. (2009) proposed the VARMA-AGARCH model for the conditional variance, namely

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-i} + \sum_{i=1}^{r} C_i I_{t-i} \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j} \tag{4}$$

where C_i are $m \times m$ matrices for $i = 1,..,r$, and $I_t = \mathrm{diag}\left(I_{1t},...,I_{mt}\right)$, where

$$I_{it} = \begin{cases} 0, & \varepsilon_{it} > 0 \\ 1, & \varepsilon_{it} \le 0 \end{cases}.$$

If $m = 1$, (3) collapses to the asymmetric GARCH, or GJR model. Moreover, the VARMA-AGARCH model reduces to VARMA-GARCH when $C_i = 0$ for all *i*. If $C_i = 0$ and A_i and B_j are diagonal matrices for all *i* and *j*, then VARMA-AGARCH reduces to the CCC model. The parameters of model (1)-(4) are obtained by maximum likelihood estimation (MLE) using a joint normal density. When η_t does not follow a joint multivariate normal distribution, the appropriate estimator is defined as the Quasi-MLE (QMLE).

Unless η_t is a sequence of i.i.d. random vectors, or alternatively a martingale difference process, the assumption that the conditional correlations are constant may seen unrealistic. In order to make the conditional correlation matrix time dependent, Engle (2002) proposed a dynamic conditional correlation (DCC) model. The DCC model is defined as:

$$y_t \mid \Im_{t-1} \sim (0, Q_t) \ , \quad t = 1,...,T \tag{5}$$

$$Q_t = D_t \Gamma_t D_t , \tag{6}$$

where $D_t = \mathrm{diag}\left(h_{1t},...,h_{kt}\right)$ is a diagonal matrix of conditional variance, and $\Im_t$ is the information set available to time *t*. The conditional variance, h_{it}, can be defined as a univariate GARCH model, as follows:

$$h_{it} = \omega_i + \sum_{k=1}^{p} \alpha_{ik} \varepsilon_{i,t-k} + \sum_{l=1}^{q} \beta_{il} h_{i,t-l} \tag{7}$$

If η_t is a vector of i.i.d. random variables, with zero mean and unit variance, Q_t in (9) is the conditional covariance matrix (after standardization, $\eta_{it} = y_{it} \big/ \sqrt{h_{it}}$). The η_{it} are used to estimate the dynamic conditional correlation, as follows:

$$\Gamma_t = \left\{(diag(Q_t)^{-1/2}\right\} Q_t \left\{(diag(Q_t)^{-1/2}\right\}, \tag{8}$$

where the $k \times k$ symmetric positive definite matrix Q_t is given by

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1\eta_{t-1}\eta'_{t-1} + \theta_2 Q_{t-1} \tag{9}$$

in which θ_1 and θ_2 are scalar parameters to capture the effects of previous shocks and previous dynamic conditional correlations on current dynamic conditional correlation, and α and β are non-negative scalar parameters, satisfying $\alpha + \beta < 1$. As Q_t is conditional on the vector of standardized residuals, (9) is a conditional covariance matrix. $\bar{Q}$ is the $k \times k$ unconditional variance matrix of η_t.

3. Data

The alternative multivariate GARCH models are estimated using data on daily closing prices of spot and futures returns, and are expressed in local currencies for the period 23 September 1994 to 13 March 2009, giving a total of 3,755 observations. All data are obtained from Reuters. The data set comprises 2 daily RSS3 spot prices, namely RSS3 F.O.B. spot price from Bangkok (TRSS3: Bath/kg.), RSS3 Noon spot price from Singapore (SRSS3: Singapore cent/kg.), and three daily RSS3 futures from different futures markets, namely Tokyo Commodity Exchange (TOCOM: Yen/kg.), Osaka Mercantile Exchange (OME: Yen/kg.), and Singapore Commodity Exchange and Agriculture Futures Exchange (SICOM: US cent/kg).

Returns of market *i* at time *t* are calculated as $r_{i,t} = \log\left(P_{i,t}/P_{i,t-1}\right)$, where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices of spot or futures for days *t* and *t*-1, respectively.

4. Empirical results

The empirical results of the unit root tests for all sample returns in each market are summarized in Table 1. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used to explore the existence of unit roots in the individual series. Both tests have the same null hypothesis to check for non-stationarity in each time series. The results show that all returns series are stationary. In order to see whether the conditional variances of the return series follow the ARCH process, the univariate ARMA-GARCH and ARMA-GJR models will be estimated. The ARCH and GARCH estimates are significant for the spot and futures returns, and are available from the authors upon request.

[Insert Tables 1 and 2 here]

The constant conditional correlations among the spot and futures returns from the CCC model are summarized in Table 2. Two entries for each pair are their respective estimates and the Bollerslev and Wooldridge (1992) robust *t*-ratios. For the five returns, there are 10 conditional correlations, with the highest estimated constant conditional correlation being 0.685 between the standardized shocks to the volatilities in the SICOM and TOCOM returns, and the lowest being 0.236 between the standardized shocks to the volatilities in TRSS3 and TOCOM.

The DCC estimates of the conditional correlations between the volatilities of spot and futures rubber returns based on estimating the univariate GARCH(1,1) models are given in Table 3. Based on the Bollerslev and Woodridge robust *t*-ratios, the estimates of the two DCC parameters, namely $(\hat{\theta}_1)$ and $(\hat{\theta}_2)$, are statistically significant, except for the short run persistence of shocks in the dynamic correlation $(\hat{\theta}_1)$ of trss3_ome, trss3 _tocom and trss3_sicom. The long run persistence to the conditional correlations is statistically significant and close to 0.99, which suggests that the assumption of constant conditional correlations is not supported empirically.

The short-run persistence of shocks in the dynamic conditional correlations is greatest between the returns in ome_tocom, at 0.108, whereas the largest long run persistence of shocks to the conditional correlations is between the returns of srss3_sicom, at 0.998 = 0.996+0.002. The time-varying conditional correlations between pairs of returns are given in Figure 1, where it is clear there is significant variation in the conditional correlations over time.

[Insert Table 3 and Figure 1 here]

Finally, the volatility spillover estimates between the volatilities of spot and futures rubber returns, based on estimating the VARMA-GARCH and VARMA-AGARCH models, are given in Tables 4 and 5, respectively. Panels 4a-4j show that volatility spillovers from the VARMA-GARCH model are evident in 7 of 10 cases, whereas interdependences are evident in the remaining 3 cases. Panels 5a-5j present evidence of volatility spillovers of the VARMA-AGARCH model in 8 of 10 cases, while significant interdependences are evidence in the remaining 2 cases. In addition, the estimates of the conditional variance show significant asymmetric effects of positive and negative returns shocks of equal magnitude on conditional volatility in all cases, thereby suggesting that the VARMA-AGARCH model is preferable to its VARMA-GARCH counterpart.

[Insert Tables 4 and 5 here]

5. Conclusion

In this paper, we estimated four multivariate conditional volatility models in rubber spot and futures returns from Asian rubber markets, namely Thailand, Singapore and Japan, for the period 23 September 1994 to 13 March 2009. All rubber return series were found to be stationary. The constant conditional correlations between spot and futures rubber returns from the CCC model were found to lie in the low to medium range. The VARMA-GARCH results showed that there were spillover effects between most pairs of spot and futures rubber returns, while some pairs of returns showed evidence of interdependence, as did the results arising from the VARMA-AGARCH model.

In addition, the statistically significant asymmetric effects of negative and positive shocks of equal magnitude on the conditional variance suggested that VARMA-AGARCH was preferable to its VARMA-GARCH counterpart. The DCC estimates of the conditional correlations between the volatilities of spot and futures returns were statically significant, thereby suggesting that the conditional correlations were dynamic.

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Table 1

Unit root tests

Returns	ADF test (t-statistic)			Phillips-Perron test		
	None	**C**	**C&T**	**None**	**C**	**C&T**
OME	**-57.7**	**-57.7**	**-57.7**	**-57.7**	**-57.7**	**-57.7**
SICOM	**-35.8**	**-35.8**	**-35.8**	**-51.8**	**-51.8**	**-51.7**
SRSS3	**-27.1**	**-27.1**	**-27.1**	**-46.7**	**-46.7**	**-46.7**
TOCOM	**-58.5**	**-58.5**	**-58.5**	**-58.5**	**-58.5**	**-58.5**
TRSS3	**-22.0**	**-22.1**	**-22.1**	**-48.7**	**-48.7**	**-48.6**

Note: None denotes no intercept and trend, C is intercept and T is trend. Entries in bold are significant at the 5% level.

Table 2

Constant Conditional Correlations

Returns	OME	SICOM	t-ratios	SRSS3	t-ratios	TOCOM	t-ratios	TRSS3	t-ratios
OME	1	**0.483**	**(46.62)**	**0.393**	**(30.47)**	**0.685**	**(132.0)**	**0.262**	**(19.05)**
SICOM		1		**0.526**	**(47.98)**	**0.524**	**(50.7)**	**0.275**	**(19.05)**
SRSS3				1		**0.401**	**(32.27)**	**0.491**	**(44.35)**
TOCOM						1		**0.236**	**(16.12)**
TRSS3								1	

Note: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*-ratios. Entries in bold are significant at the 5% level.

Table 3

Dynamic Conditional Correlations

Returns	$\hat{\theta}_1$	**t-ratios**	$\hat{\theta}_2$	**t-ratios**
trss3_srss3	**0.014**	**(5.394)**	**0.981**	**(267.432)**
trss3_ome	0.003	(0.866)	**0.987**	**(49.265)**
trss3_tocom	0.003	(1.370)	**0.991**	**(125.691)**
trss3_sicom	0.002	(1.465)	**0.994**	**(245.050)**
srss3_ome	**0.021**	**(4.034)**	**0.958**	**(87.349)**
srss3_tocom	**0.020**	**(3.776)**	**0.959**	**(85.918)**
srss3_sicom	**0.002**	**(2.423)**	**0.996**	**(497.70)**
ome_tocom	**0.108**	**(30.558)**	**0.878**	**(211.640)**
ome_sicom	**0.017**	**(7.132)**	**0.978**	**(328.651)**
tocom_sicom	**0.053**	**(12.488)**	**0.936**	**(181.221)**

Note: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*-ratios. Entries in bold are significant at the 5% level.

Table 4

VARMA(1-1)-GARCH(1,1) Estimates

Panel 4a. VARMA-GARCH: TRSS3_SRSS3

	ϖ	α_{TRSS3}	α_{SRSS3}	β_{TRSS3}	β_{SRSS3}
TRSS3	**0.013**	**0.088**	**0.802**	**0.117**	-0.025
	(3.224)	**(5.298)**	**(27.089)**	**(5.379)**	(-1.554)
SRSS3	**0.015**	**0.078**	**0.868**	0.004	0.046
	(3.860)	**(6.106)**	**(37.473)**	(0.200)	(4.737)

Panel 4b. VARMA-GARCH: OME_TRSS3

	ϖ	α_{OME}	α_{TRSS3}	β_{OME}	β_{TRSS3}
OME	0.109	**0.058**	**0.914**	**0.089**	-0.048
	(1.807)	**(3.533)**	**(31.831)**	**(1.984)**	(-0.843)
TRSS3	**0.019**	**0.090**	**0.882**	**-0.006**	**0.009**
	(2.693)	**(6.716)**	**(63.377)**	**(3.317)**	**(-2.154)**

Panel 4c. VARMA-GARCH: TRSS3_TOCOM

	ϖ	α_{TRSS3}	α_{TOCOM}	β_{TRSS3}	β_{TOCOM}
TRSS3	**0.013**	**0.107**	**0.006**	**0.856**	**0.040**
	(9.172)	**(17.719)**	**(2.877)**	**(98.607)**	**(3.449)**
TOCOM	**0.774**	**-0.314**	**0.265**	**1.650**	**0.514**
	(15.620)	**(-10.097)**	**(25.674)**	**(8.166)**	**(33.838)**

Panel 4d. VARMA-GARCH: SICOM_TRSS3

	ϖ	α_{SICOM}	α_{TRSS3}	β_{SICOM}	β_{TRSS3}
SICOM	**0.032**	**0.081**	**0.880**	**0.060**	-0.021
	(4.600)	**(6.111)**	**(44.355)**	**(3.660)**	(-0.949)
TRSS3	**0.044**	**0.116**	**0.674**	**-0.030**	**0.114**
	(4.297)	**(5.233)**	**(14.038)**	**(-2.487)**	**(5.694)**

Panel 4e. VARMA-GARCH: OME_SRSS3

	ϖ	α_{OME}	α_{SRSS3}	β_{OME}	β_{SRSS3}
OME	**0.623**	**0.121**	**0.667**	0.276	0.065
	(3.744)	**(4.110)**	**(8.962)**	(1.625)	(0.486)
SRSS3	**0.021**	**0.097**	**0.886**	**-0.004**	**0.004**
	(4.700)	**(8.128)**	**(69.017)**	**(-2.923)**	**(3.782)**

Panel 4f. VARMA-GARCH: SRSS3_TOCOM

	ϖ	α_{SRSS3}	α_{TOCOM}	β_{SRSS3}	β_{TOCOM}
SRSS3	**0.033**	**0.093**	**0.890**	**0.008**	**-0.009**
	(7.347)	**(8.312)**	**(78.160)**	**(5.703)**	**(-6.221)**
TOCOM	**0.792**	**0.244**	**0.561**	**0.509**	**0.018**
	(3.246)	**(3.004)**	**(5.383)**	**(2.418)**	**(0.179)**
Panel 4g. VARMA-GARCH: SRSS3_SICOM					
	ϖ	α_{SRSS3}	α_{SICOM}	β_{SRSS3}	β_{SICOM}
SRSS3	0.041	0.022	-0.002	**0.343**	**0.242**
	(1.329)	(0.876)	(-0.025)	**(4.846)**	**(10.442)**
SICOM	**0.030**	**0.086**	**0.879**	-0.018	0.049
	(4.370)	**(5.600)**	**(32.613)**	(2.664)	(-0.635)
Panel 4h. VARMA-GARCH: OME_TOCOM					
	ϖ	α_{OME}	α_{TOCOM}	β_{OME}	β_{TOCOM}
OME	**0.284**	**0.047**	**0.915**	**0.075**	**-0.083**
	(4.545)	**(2.286)**	**(27.924)**	**(2.664)**	**(-2.132)**
TOCOM	0.526	**0.188**	**0.246**	**0.492**	**0.134**
	(1.713)	**(2.997)**	**(2.235)**	**(2.994)**	**(2.022)**
Panel 4i. VARMA-GARCH: OME_SICOM					
	ϖ	α_{OME}	α_{SICOM}	β_{OME}	β_{SICOM}
OME	**0.489**	**0.108**	**0.698**	0.170	0.088
	(3.518)	**(3.416)**	**(9.896)**	(1.421)	(0.814)
SICOM	**0.036**	**0.099**	**0.879**	-0.004	**0.006**
	(4.606)	**(7.038)**	**(55.106)**	(-1.337)	**(2.096)**
Panel 4j. VARMA-GARCH: SICOM_TOCOM					
	ϖ	α_{SICOM}	α_{ENI}	β_{SICOM}	β_{ENI}
SICOM	**0.036**	**0.108**	**0.875**	0.001	-0.002
	(4.518)	**(7.248)**	**(55.777)**	(1.105)	(-1.113)
TOCOM	**0.817**	**0.241**	**0.546**	0.219	0.181
	(3.083)	**(2.654)**	**(4.544)**	(1.270)	(2.005)

Note: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Table 5

VARMA(1-1)-AGARCH(1,1) estimates

Panel 5a. VARMA-AGARCH: SRSS3_TRSS3

	ϖ	α_{TRSS3}	α_{SRSS3}	γ	β_{TRSS3}	β_{SRSS3}
SRSS3	**0.015**	**0.087**	-0.019	**0.871**	**0.048**	0.002
	(3.942)	**(5.225)**	(-0.979)	**(38.500)**	**(4.827)**	(0.080)
TRSS3	**0.013**	**0.094**	-0.012	**0.802**	**-0.026**	0.118
	(3.220)	**(4.542)**	(-0.376)	**(26.605)**	**(-1.541)**	(5.458)

Panel 5b. VARMA-AGARCH: OME_TRSS3

	ϖ	α_{OME}	α_{TRSS3}	γ	β_{OME}	β_{TRSS3}
OME	0.112	**0.054**	0.008	**0.912**	**0.090**	-0.047
	(1.871)	**(2.099)**	(0.262)	**(30.861)**	**(1.972)**	(-0.775)
TRSS3	**0.019**	**0.100**	-0.024	**0.887**	**-0.006**	**0.008**
	(2.695)	**(4.667)**	(-0.809)	**(66.205)**	**(-2.264)**	**(3.405)**

Panel 5c. VARMA-AGARCH: TOCOM_TRSS3

	ϖ	α_{TRSS3}	α_{TOCOM}	γ	β_{TRSS3}	β_{TOCOM}
TOCOM	**0.823**	**0.274**	-0.056	**0.584**	0.056	**0.357**
	(3.360)	**(2.180)**	(-0.494)	**(5.934)**	(0.767)	**(2.001)**
TRSS3	**0.050**	**0.100**	-0.024	**0.867**	**-0.016**	**0.017**
	(5.726)	**(4.831)**	(-0.787)	**(61.334)**	**(-4.574)**	**(4.809)**

Panel 5d. VARMA-AGARCH: SICOM_TRSS3

	ϖ	α_{SICOM}	α_{TRSS3}	γ	β_{SICOM}	β_{TRSS3}
SICOM	**0.032**	**0.084**	-0.008	**0.883**	**0.062**	-0.022
	(4.636)	**(5.053)**	(-0.382)	**(44.908)**	**(3.767)**	(-1.009)
TRSS3	**0.045**	**0.101**	0.032	**0.675**	**-0.030**	**0.114**
	(4.291)	**(3.978)**	(0.792)	**(14.244)**	**(-2.498)**	**(5.737)**

Panel 5e. VARMA-AGARCH: OME_SRSS3

	ϖ	α_{OME}	α_{SRSS3}	γ	β_{OME}	β_{SRSS3}
OME	**0.629**	**0.108**	0.030	**0.664**	0.279	0.068
	(3.833)	**(2.603)**	(0.596)	**(9.018)**	(1.650)	(0.497)
SRSS3	**0.021**	**0.105**	-0.016	**0.887**	**-0.005**	**0.005**
	(4.701)	**(6.566)**	(-0.708)	**(70.423)**	**(-2.967)**	**(3.731)**

Panel 5f. VARMA-AGARCH: SRSS3_TOCOM

	ϖ	α_{SRSS3}	α_{TOCOM}	γ	β_{SRSS3}	β_{TOCOM}

SRSS3	**0.032**	**0.105**	-0.011	**0.882**	**0.007**	**-0.008**
	(5.614)	**(6.414)**	(-0.461)	**(71.498)**	**(4.710)**	**(-4.549)**
TOCOM	**0.793**	**0.276**	-0.068	**0.559**	**0.526**	0.022
	(3.242)	**(2.128)**	(-0.591)	**(5.316)**	**(2.434)**	(0.223)
Panel 5g. VARMA-AGARCH: SICOM_SRSS3						
	ϖ	α_{SRSS3}	α_{SICOM}	γ	β_{SRSS3}	β_{SICOM}
SICOM	**0.031**	**0.084**	0.005	**0.879**	**0.050**	-0.018
	(4.362)	**(4.932)**	(0.202)	**(32.493)**	**(2.630)**	(-0.621)
SRSS3	0.042	0.031	-0.022	0.004	**0.338**	**0.242**
	(1.386)	(0.875)	(-0.602)	(0.059)	**(4.811)**	**(10.449)**
Panel 5h. VARMA-AGARCH: OME_TOCOM						
	ϖ	α_{OME}	α_{TOCOM}	γ	β_{OME}	β_{TOCOM}
OME	**0.292**	**0.041**	0.012	**0.914**	**0.076**	**-0.085**
	(4.826)	**(2.089)**	(0.455)	**(29.174)**	**(2.769)**	**(-2.277)**
TOCOM	0.513	**0.233**	-0.090	**0.223**	**0.524**	**0. 137**
	(1.686)	**(2.454)**	(-0.924)	**(2.047)**	**(3.208)**	**(2.100)**
Panel 5i. VARMA-GARCH: OME_SICOM						
	ϖ	α_{OME}	α_{SICOM}	γ	β_{OME}	β_{SICOM}
OME	**0.483**	**0.092**	0.032	**0.698**	0.168	0.093
	(3.610)	**(2.101)**	(0.660)	**(10.276)**	(1.414)	(0.843)
SICOM	**0.036**	**0.100**	-0.002	**0.879**	-0.005	**0.006**
	(4.603)	**(6.062)**	(-0.082)	**(55.146)**	(-1.341)	**(2.101)**
Panel 5j. VARMA-AGARCH: SICOM_TOCOM						
	ϖ	α_{SICOM}	α_{ENI}	γ	β_{SICOM}	β_{ENI}
SICOM	**0.037**	**0.107**	0.003	**0.874**	0.001	-0.002
	(4.514)	**(6.157)**	(0.125)	**(55.548)**	(1.084)	(-1.106)
TOCOM	**0.826**	0.280	-0.083	**0.541**	0.234	**0.189**
	(3.098)	(1.918)	(-0.652)	**(4.374)**	(1.247)	**(2.047)**

Note: The two entries for each parameter are their respective parameter estimates and Bollerslev and Wooldridge (1992) robust *t*- ratios. Entries in bold are significant at the 5% level.

Figure 1

Dynamic Conditional Correlations Between Pairs of Rubber Spot and Futures