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Volatility Spillover using Multivariate GARCH Model: An Application in Futures and Spot Market Price of Black Pepper

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SUMMARY

In this study, an effort has been made to identify transmission of price signals and volatility spillover effects between the spot and futures market of black pepper, using Johansen co-integration test, VEC-BEKK and Dynamic Conditional Correlation (DCC) model. The study has been conducted on the price data ranging from 1st January, 2010 to 20th May, 2013 collected from NCDEX, India. The empirical findings revealed that futures market is the main transmitter of volatility into the spot market resulting higher persistency in volatility of black pepper spot market. Analysis of volatility spillover in this context also resulted the presence of bidirectional volatility spillover between spot and futures market of black pepper. The dynamic and time varying nature of conditional correlation between spot and futures market reflecting significant volatility spillover during the period of the year 2012. The findings also suggest of one cointegrating relationship between spot and futures price in the long run.

Keywords: BEKK model, Black pepper, DCC model, NCDEX, Volatility spillover.

1. INTRODUCTION

Volatility in agricultural commodity prices are now a days a common phenomenon. Since the seminal work by Engle (1982) and Bollerslev (1986), there are lot applications of GARCH and its family of models for modeling volatility in crop yield and agricultural commodity prices (Paul *et al*. 2009, Paul *et al*. 2014). However, besides studying volatility, price discovery and risk transfer are considered to be two important contributions of futures market towards the organization of economic activity (Garbade and Silber 1983). Price discovery refers to the use of future prices for pricing cash market transactions. It means futures price serves as markets expectations of subsequent spot price. Chopra and Bessler (2005) studied the incidence of price discovery for black pepper in the spot market and the nearby and first distant futures markets in Kerala, India. Patnaik (2013) applied dynamic conditional correlation model in the foreign exchange rates of the Indian rupee and four other prominent foreign currencies to measure volatility spillover across these exchange rates. Padhi and Lagesh (2012) studied volatility transmission between five Asia equity markets, India and USA. Malik and Ewing (2009) studied volatility transmission between oil prices and five different US equity sector indexes. Chevallier (2012) studied dynamic nature of correlation among oil, gas and CO_2 of European climate exchange, Bloomberg and Reuters dataset using Baba-Engle-Kraft-Kroner, Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) models. Lin and Li (2015) studied price and volatility spillover effect of monthly data of natural gas of US, Europe and Japan in a VEC-MGARCH model framework. Modern time series methods such as cointegration reflects the price transmission mechanism between futures and spot market. Some applications may be found in Paul and Sinha (2016).

Black pepper (*Piper nigrum*), popularly known as "Black Gold", is one of the valuable agricultural commodities of commerce and trade in the world. It

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is a perennial, climbing vine origin of Malabar Coast of India. The pungent spice comes from its berries is one of the earliest spices known and is likely the most widely used spice in the world today. Vietnam is the world's largest producer and exporter, producing about 155,000 tones (34%) of the world with a total of 409,000 tones. Other major producers of black pepper such as Indonesia (19%), India (11%) and Brazil (9%). In India Kerala is the top producer of black pepper which contributes about 47% of India's total production, followed by Karnataka (40%) and Tamil Nadu (12%). Black pepper farming is the major source of income and employment for rural households in Pepper growing state of India.

In the present investigation, spot and future market price of black pepper in India have been considered for investigating the spillover effect using multivariate GARCH model. The present study investigates price and volatility spillover effect of futures and spot market of black pepper in an error correction multivariate GARCH modeling framework. Our purpose is to investigate how price changes in one market would spillover to another market. As black pepper is one of the important commodities of country's export therefore it is necessary to understand information flow mechanism between futures and spot market for market participants. The paper has been framed as follows: section 2 describes the methodology; section 3 deals with the results and discussion followed by conclusions.

2. MATERIALS AND METHODS

The methodological approach has been started by testing for stationarity using Augmented Dickey Fuller (ADF). The test for the variable (say) y_t can be expressed in a following manner:

$$\Delta y_t = \alpha + \gamma t + \rho y_{t-1} + \beta \sum_{i=1}^{p} \Delta y_{t-i} + e_t \quad (1)$$

where, y_t is a vector to be tested for cointegration, t is time or trend variable, $\Delta y_t = y_t - y_{t-1}$ and e_t is a white noise process. The null hypothesis that $\rho = 0$; signifying unit root, i.e., the time series is non-stationary and the alternative hypothesis is $\rho < 0$ signifying the time series is stationary, therefore, rejecting the null hypothesis.

Johansen's (1988) Vector Error Correction Model (VECM) is employed to investigate the causal relationship between prices after identifying the appropriate order of integration of each series. The usual step has been followed by identifying the significant lag length of VAR model on the basis of suitable information criteria. To identify the cointegration relation between the two price series, two likelihood ratio tests employed such as λ_{trace} and λ_{max} respectively.

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right)$$
$$for\ i = 0,1,\ldots,n\text{-}1 \quad (2)$$

$$\lambda_{max} = -T\, ln\left(1 - \hat{\lambda}_{r+1}\right) \quad (3)$$

where, T is the number of usable observations and $\hat{\lambda}_i$ are the estimated eigen values (also called characteristics roots). The trace test statistic (λ_{trace}) tests the null hypothesis of r cointegrating relation against the alternative hypothesis of less than or equal to r cointegrating relation while, the λ_{max} test statistic tests the null hypothesis of r cointegrating relation against $r+1$ cointegrating relations. The rank of Π can be determined by using λ_{trace} or λ_{max} test statistic. If, rank of $\Pi = 1$, then there is single cointegrating vector and Π can be factorized as $\Pi = \alpha\beta'$, where α and β' are 2×1 vectors represent error correction coefficients measuring the speed of convergence and cointegrating parameters respectively.

If price series are cointegrated we can estimate the following vector error correction model that can be seen as a VAR model including a variable representing the deviations from the long-run equilibrium. Equation 4 shows a VECM for three variables including a constant, the error correction term and a lagged term.

$$\begin{bmatrix} \Delta p_t^f \\ \Delta p_t^s \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} ECT_{-1} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \Delta p_{t-1}^f \\ \Delta p_{t-1}^s \end{bmatrix} + \begin{bmatrix} \varepsilon_t^f \\ \varepsilon_t^s \end{bmatrix} \quad (4)$$

Here the superscripts f stands for futures market, s stands for spot market. This VECM representation is particularly interesting as it allows for estimating how the variables adjust deviations towards the long-run equilibrium. The error correction coefficient (a_i) reflects the speed of adjustment.

BEKK (1,1) Model

For individual series, the volatility pattern can be assessed by simply univariate specification of GARCH model of the form:

$$h_t = c_0 + a_1\varepsilon_{t-1}^2 + \cdots + a_p\varepsilon_{t-p}^2 + b_1 h_{t-1} + \cdots + b_q h_{t-q} \quad (5)$$

where p and q are the order of the GARCH model. This can be transferred into a multivariate GARCH model of the resulting variance-covariance matrix H_t as

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \textit{ for i=1,2} \quad (6)$$

Accordingly, the BEKK (1, 1) representation of variance of error term H_t is

$$H_t = C_0'C_0 + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + B_{11}'H_{t-1}B_{11} \quad (7)$$

where, A_i and B_i are $n{\times}n$ parameter matrix and C_0 is $n{\times}n$ upper triangular matrix. The bivariate BEKK(1,1) model can be written as

$$H_t = C_0'C_0 + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \quad (8)$$

The off diagonal parameters in matrix B, b_{12} and b_{21} respectively measures the dependence of conditional price volatility in the futures market on that of spot market and vice-versa. The parameters b_{11} and b_{22} represents persistence in volatility in their own market. The parameters a_{12} or a_{21} represent the cross markets effects whereas a_{11}, a_{22} represent the own market effects. Therefore, the significant level of each parameter indicates the presence of strong ARCH or GARCH effect.

From the equation 8 we can have the following equations of conditional variance and conditional covariance,

$$h_{11,t} = c_1 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} \quad (9)$$

$$h_{22,t} = c_3 + a_{12}^2\varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2\varepsilon_{2,t-1}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2 h_{22,t-1} \quad (10)$$

$$h_{12,t} = c_2 + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + b_{11}b_{12}h_{11,t-1}^2 + (b_{21}b_{12} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,t-1}^2 \quad (11)$$

Dynamic Conditional Correlation (DCC) Model

According to Engle (2002), the DCC model set up can be expressed in the following manner:

$$H_t = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}} \quad (12)$$

where, H_t conditional variance co-variance matrix, R_t is the $n \times n$ conditional correlation matrix and the matrices D_t and R_t are computed as follows:

$$D_t = diag(h_{11t}^{\frac{1}{2}}, \ldots, h_{nnt}^{\frac{1}{2}}) \quad (13)$$

where h_{iit} is chosen to be a univariate GARCH (1,1) process;

$$R_t = (diagQ_t)^{-1/2}Q_t(diagQ_t)^{-1/2} \quad (14)$$

where $Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1}$ refers to a $n \times n$ symmetric positive definite matrix with $u_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$, $\bar{Q}$ is the $n \times n$ unconditional variance matrix of u_t and α and β are non negative scalar parameters satisfying $\alpha+\beta < 1$.

The conditional correlation coefficient ρ_{ij} between two markets i and j is then computed as follows:

$$\rho_{ij} = \frac{(1-\alpha-\beta)\bar{q}_{ij} + \alpha u_{i,t-1}u_{j,t-1} + \beta q_{ij,t-1}}{((1-\alpha-\beta)\bar{q}_{ii} + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1})^{1/2}((1-\alpha-\beta)\bar{q}_{jj} + \alpha u_{j,t-1}^2 + \beta q_{jj,t-1})^{1/2}} \quad (15)$$

where ρ_{ij} refers to the element located in the i^{th} row and j^{th} column of the symmetric positive definite matrix Q_t.

3. RESULTS AND DISCUSSIONS

The present study is based on the spot and futures market price of Black pepper collected from the website *www.ncdex.com*. There are a total of 989 data points in each series and data collected from 1st January 2010 to 20th May 2013. Time plot for both price series is displayed in Fig. 1.The simple descriptive statistics have been reported in Table 1 and variability has been represented by coefficient of variation (CV). The nature of stationarity for each series has been confirmed using augmented Dickey-Fuller (ADF) test. The ADF test confirms the presence of unit root in the original and transformed price series. But after first differencing of transformed series, the series were found to be stationary and therefore, were integrated of order one i.e., *I(1)*. The conformation that each level series is of *I*(1) allowed to proceed for Johansen's cointegration test. The result of the stationarity test is reported in Table 2. The corresponding correlation between price series is very high and significant (Table 3) implying higher co-movement and greater integration between price markets.

Before conducting the Johansen test of cointegration four lag for the endogenous variable are selected by three information criteria viz., Sequential modified likelihood ratio (LR) test, Final Prediction Error (FPE) and Akaike Information Criteria (AIC)as reported in Table 4. Table 5 represents the Johansen cointegration test for futures and spot market of black pepper. In this case, the trace test statistic strongly rejects the null hypothesis of no cointegration but failing to reject the alternative hypothesis of one cointegration. These results suggest that futures and spot market are well integrated in the long run. The results of vector error correction model are presented in Table 6. The results show that the coefficients of error correction term in futures market unable to fulfill the condition of negativity and significant but it is significant for spot market which indicates that when futures market deviate from equilibrium level, spot market tends to correct back towards long run equilibrium level in the next period. We have also checked the short run causality by employing Wald test. The results show that the presence of short run causality is significant in both the direction. This indicates that futures and spot market price govern each other in short run. The presence of heteroscedasticity in the residuals of fitted error correction model is also reported in the Table 7. The individual series volatility pattern has been well documented using univariate GARCH model that reflect strong condition for evolution of volatility. The sum of the coefficients of alpha and beta are less than unity fulfilling the condition of stationarity (Table 8). The results clearly indicate that past volatility has a greater influence on actual volatility than past shocks in both the cases.

Table 9 represents the result on fitted BEKK model. Almost all the coefficients are significant. For the price series, the estimated GARCH parameters are considerably larger than the corresponding ARCH coefficients (ranging from -0.154 to 0.991 as compared with the lagged innovation parameter estimates of 0.028 to 0.218). This indicates that the variances of these prices are more influenced by their own lagged values, rather than by "fresh news" which are reflected by the lagged innovations. All the estimated parameters in the cross market effects are positive suggesting shocks in both the markets will affect the covariance in a positive manner. The transmission of volatility from futures to spot market is 0.451 which imply 1% increase in the price of futures market transmit 45.10% volatility to spot market. Whereas the transmission of volatility from spot to futures market is little low and has a negative influence. The impact of information shock is also much higher from futures to spot market as compared to spot to futures market. Fig. 2 and 3 describes that conditional variance of futures and spot markets are not constant and vary over time. The plot shows that both price series are highly volatile during the period of 2012 with higher levels of conditional volatility in the past that are associated with higher conditional volatility in the current period.

The results of DCC model as reported in Table 10, reflects the changing pattern of the dependence or influence of volatility of one price on the other. GARCH (1,1) parameters are highly significant suggesting time varying variance covariance process also establish valid reason to use bivariate GARCH modeling for futures and spot market. The persistence of volatility is achieved by $(\alpha + \beta)$ which is less than one therefore the unconditional variance is finite. The estimated ARCH parameter DCC α in the conditional correlation is small, positive and also significant. The GARCH parameters DCC β is comparatively large which point out that time varying correlation displays a high degree of persistence. The DCC results suggest the existence of dynamic and time varying correlation between the two markets. We also observe the positive association between the two markets during the entire period within a range of 0.4 to 0.8 exhibiting a direct relationship among the price volatilities (i.e., increase in volatility, one price leads to increase in volatility of the other price) and high degree of correlation during the period of 2012. These findings are in line with the results obtained by BEKK model. The validity of the MV GARCH model is tested by using LM test for serial correlation of the probability integral transforms, and is found significant.

4. CONCLUSION

In this study we try to explore the existence of volatility spillover in a VEC-BEKK and DCC model framework. High persistence of volatility has been observed in each market price. The interdependence and volatility spillover between futures and spot

Table 1. Descriptive statistics of futures and spot price of Black pepper

Statistics	Futures price	Spot price
Mean (Rs/Quintal)	30073.25	29466.62
Standard Deviation (Rs/Quintal)	8889.07	9410.97
Minimum (Rs/Quintal)	13860.00	12982.55
Maximum (Rs/Quintal)	46290.00	43031.13
Skewness	-.22	-0.24
Kurtosis	-1.11	-1.34
Coefficient of Variation (%)	0.29	0.32

Table 2. Augmented Dickey Fuller stationarity test for different series

Market price series	Level series		Logarithmic transformed series		First difference of transformed series	
	t statistic	p-value	t statistic	p-value	t statistic	p-value
Futures price	-1.578	0.493	-1.846	0.358	-28.903	<0.001
Spot price	-1.529	0.518	-1.936	0.316	-24.654	<0.001

Table 3. Correlation between price series

Price series	Spot price	Futures price
Spot price	1	0.97^{***}
Futures price	0.97^{***}	1

Note: *** indicates correlations significant at 1% level of significance

Table 4. VAR lag order selection criteria

Lag	LR	FPE	AIC
0	-	1.53e-05	-5.410
1	10313.160	4.24e-10	-15.904
2	216.845	3.43e-10	-16.117
3	20.833	3.38e-10	-16.131
4	15.244^{*}	3.36e-10*	-16.138^{*}

Note: * indicates lag order selected by the criteria

Table 5. Test for Cointegration

Maximum rank	10% Critical value	5% Critical value	1% Critical value	Futures price-spot price
Trace statistics				
0	15.66	17.95	23.50	23.52
1	6.50	8.18	11.65	3.30
Number of cointegrating relation			1	
Max statistics				
0	12.91	14.90	19.19	20.22
1	6.50	8.18	11.65	3.30
Number of cointegrating relation			1	

market price of black pepper has been established. More precisely, bidirectional volatility spillover has been found because of the strong inter-relation in terms of investment and international trade of black pepper commodity markets. The evidence of decrease of dynamic conditional correlation has also been established after the period of 2012 but for not prolonged duration. Finally the results suggest that volatility pattern of this type of markets may be highly useful for hedging and information sharing by investors.

Table 6. Results of error correction model

Pepper price series	Cointegration rank	ECT	Wald test of equality of coefficients
Futures price	1	0.007 (0.370)	20.720 (0.0004)
Spot price	1	0.014 (0.002)	137.995 (< 0.001)

Note: in parenthesis p-value is attached

Table 7. VECM residuals heteroscedasticity test

Series	Test Statistic value	P-Value
Residuals of futures market	251.580	< 0.001
Residuals of spot market	282.325	< 0.001
Cross product of residuals	315.467	< 0.001

Table 8. Estimation results of univariate GARCH model

Market price series	Constant	AR(1)	MA(1)	MA(2)	ARCH(1)	GARCH(1)
Futures price	0.00025 (0.0002)	---	0.078* (0.0364)	---	0.0482*** (0.0141)	0.939*** (0.0218)
Spot price	0.0008 (0.0004)	0.892*** (0.0455)	-0.678*** (0.0578)	-0.973* (0.0405)	0.0734*** (0.0185)	0.9177*** (0.0206)

Table 9. Estimation results of BEKK model

Coefficients	Value
C_{11}	0.004*** (0.0007)
C_{21}	0.002** (0.0005)
C_{22}	0.001* (0.0005)
a_{11}	0.028 (0.046)
a_{21}	0.186*** (0.0313)
a_{12}	0.218* (0.093)
a_{22}	0.158*** (0.041)
b_{11}	0.760*** (0.026)
b_{21}	-0.154*** (0.016)
b_{12}	0.451*** (0.058)
b_{22}	0.991*** (0.0367)

Note: in parenthesis SE is given.

* significant at 10%

** significant at 5%

*** significant at 1%

Table 10. Estimation results of DCC model

Coefficient	Estimates	Standard error	P. value
ω_1	0.0003	0.0005	0.5424
α_1	0.048	0.0160	0.0685
β_1	0.938	0.046	0.0001
ω_2	0.002	0.0001	0.2571
α_2	0.108	0.041	0.0074
β_2	0.878	0.046	0.0001
DCC α	0.015	0.012	0.0152
DCC β	0.941	0.041	0.0001

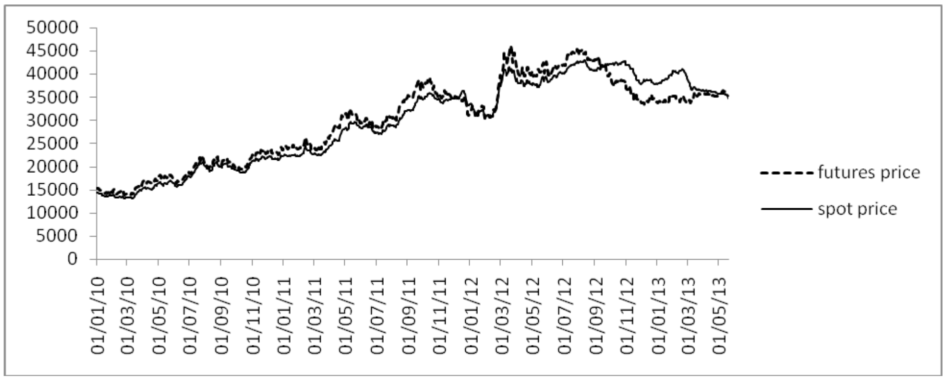

Fig. 1: Futures and Spot price of black pepper

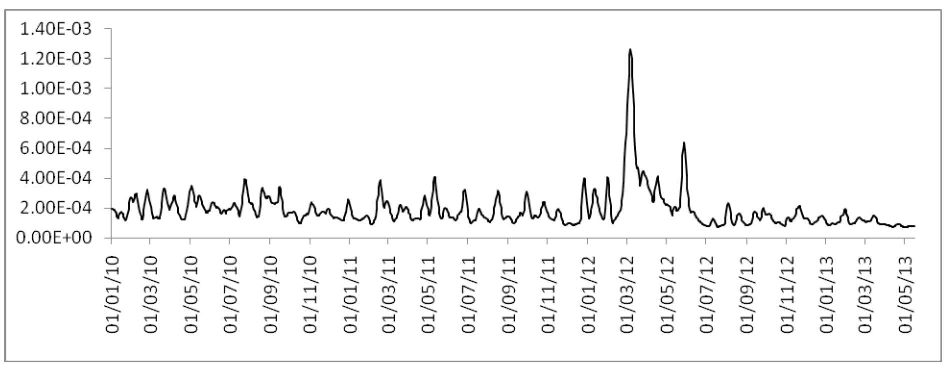

Fig. 2: Conditional variance of futures price

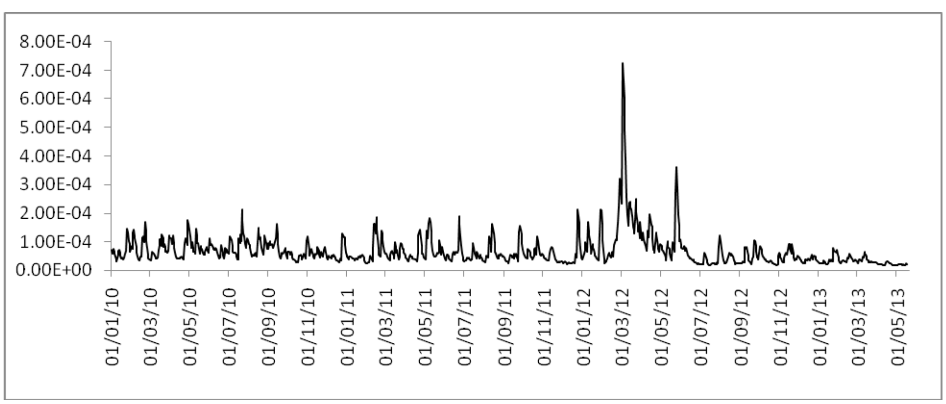

Fig. 3: Conditional variance of spot price

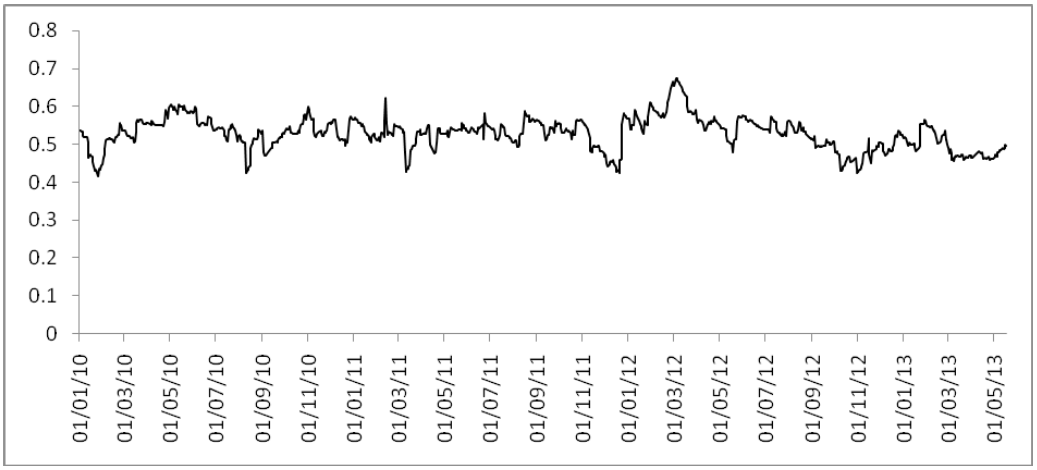

Fig. 4: Dynamic conditional correlation between futures and spot prices

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