ISSN 1440-771X

MONASH University

Australia

Department of Econometrics
and Business Statistics

http://www.buseco.monash.edu.au/depts/ebs/pubs/wpapers/

# Realized Volatility and Correlation in Grain Futures Markets: Testing for Spill-Over Effects

Jae H. Kim and Hristos Doucouliagos

September 2005

Working Paper 22/05

# Realized Volatility and Correlation in Grain Futures Markets: Testing for Spill-Over Effects

Jae H. Kim[a1] and Hristos Doucouliagos[b]

[a]Department of Econometrics and Business Statistics, Monash University, Caulfield East, VIC 3145, Australia
Tel. (61 3) 99031596, Fax. (61 3) 99032007
Email. Jae.Kim@buseco.monash.edu.au

[b]School of Accounting, Economics and Finance, Deakin University, Burwood, 3125, Victoria, Australia
Email: Douc@Deakin.edu.au

**Abstract**

Fluctuations in commodity prices are a major concern to many market participants. This paper uses realized volatility methods to calculate daily volatility and correlation estimates for three grain futures prices (corn, soybean and wheat). The realized volatility estimates exhibit the properties consistent with the stylized facts observed in earlier studies. According to the realized correlations and regression coefficients, the spot returns from the three grain futures are positively related. The realized estimates are then used to evaluate the degree of volatility transmissions across grain future prices. The impulse response analysis is conducted by fitting the vector autoregressive model to realized volatility and correlation estimates, using the bootstrap method for statistical inference. The results indicate that there exist rich dynamic interactions among the volatilities and correlations across the grain futures markets.

Keywords: Volatility Transmission, Vector Autoregressive Model, Impulse Response Analysis, Bootstrap

JEL Classifications: G13, C32

[1] Corresponding author
We would like to thank Robert Brooks, Jonathan Dark, and Brett Inder for helpful comments.

## 1. Introduction

Understanding the behaviour of asset return volatility has been a subject of much attention. Volatility modelling and forecasting have strong implications to those involved in financial and speculative asset markets, especially for forecasting, risk management, hedging, and optimal asset allocation. In addition, with an increasing degree of financial market integration, the transmission of volatility across different financial markets has become a topic of practical interest to many market participants. Extensive empirical research has been conducted in this area; notable examples include King and Wadhwani (1990), Karolyi (1995), Kim and Rogers (1995), Darbar and Deb (1997), Kearney and Patton (2000) and Ewing *et al.* (2002).

The above-mentioned studies use the GARCH model of Bollerslev (1986) (or its generalizations) or multivariate GARCH models (for a review of the latter, see Franses and van Dijk, 2000). The latter are multivariate extensions of the former, and they describe how volatilities and covariation of different asset returns are related over time. Although widely used, these models are parametric in nature, depending heavily on the underlying model assumptions. Moreover, a general multivariate GARCH model (such as the VEC model of Engle and Kroner, 1995) suffers from a dimensionality problem with respect to the number of parameters to be estimated, and often fails to provide meaningful estimation results even in the trivariate system. As a result, many multivariate GARCH models currently in use are overly simplified or practically applicable only to a system with a small dimension. This suggests that univariate and multivariate GARCH models may often be too restrictive for financial data and subject to model specification error problems.

Recently, new methods of estimating volatility and covariation (or correlation) of asset returns have been proposed. These methods, called the *realized* volatility and covariation, make use of intraday observations of asset returns. In contrast with the parametric models mentioned earlier, these methods are fully non-parametric and model free, with desirable large sample properties of consistency and asymptotic normality. Andersen *et al.* (ABDL, 2003) and Barndorff-Nielsen and Shepard (BNS 2004a, 2004b) are examples of recent studies that proposed the use of realized volatility and covariation. Although the underlying theories are abstract and deep, the calculation of realized estimates is simple. With increasing availability of intraday observations in many financial markets, it is expected that the realized variability and covariation methods will play a major role in modelling and forecasting volatility and covariation of asset returns.

In this paper, the realized volatility and covariation methods are applied to three grain futures prices (corn, soybean and wheat)[2]. Recent studies that applied the realized volatility methods to futures prices (stock prices and foreign exchange) include Areal and Taylor (2002) and Thomakos and Wang (2003). This paper extends the previous analysis by applying the realized volatility methods to grain futures. The realized estimates of volatility and correlations are presented and their statistical properties are discussed. While Areal and Taylor (2002) and Thomakos and Wang (2003) mainly concerned with the descriptive and distributional nature of realized volatility estimates, this paper examines volatility spill-over effects by fitting a multivariate model to realized volatility and correlation estimates. The dynamic relationships and causations

[2] Our initial study included six grain futures including oats, soybean oil, and soybean meal in addition to corn, soybean and wheat. For simplicity of presentation, however, we decided to present only the results associated with the latter group, as those from the former group are qualitatively similar.

among the volatilities and correlations of three grain futures prices are investigated, by conducting impulse response analysis based on the vector autoregressive model.[3]

Volatility in grain futures markets (the so-called soft commodities) is an important research area. Commodity prices continue to be a major concern for both developing countries and development agencies (most notably the World Bank), especially given the importance of food and feedstock to developing countries (Morgan et al. 1994). Moreover, amplified global trade has increased interest in fluctuations in international commodity prices. This is an important issue also for developed countries that are commodity exporters. For example, wheat prices are of major interest to wheat farmers and policy makers (especially in countries such as Australia and the USA).

Most of the existing research has focussed on wheat futures and, to a lesser extent, soybeans (eg. Koekebakker and Lien 2004). Many researchers have explored the impact of regulations and market distortions on volatility of grain futures (see, for example, Crain and Lee 1996; Faruqee *et al.* 1997; Yang *et al.* 2001; and Fung *et al.* 2003). Another area of importance is the spillover of volatility. Engle *et al.* (1990) advanced the "meteor shower" hypothesis that volatility spills over from one market to the next. Volatility spillovers have been detected in many markets. For example, Booth and So (2003) found volatility spillovers across German equity index derivatives markets; Ewing *et al.* (2002) in the oil and natural gas markets; Buguk *et al.* (2003) and Apergis and Rezitis (2003) in agricultural prices; while Yang *et al.* (2003) and Roche and McQuinn (2005) investigated volatility transmissions across

[3] The conventional tests for volatility spill-over are based on parametric models such as GARCH-type models; see Cheung and Ng (1996) and Hong (2001). The volatility transmission can also be evaluated using the multivariate GARCH models. However, we prefer the realized volatility and covariance as a means of investigating the volatility transmission in this study, as we have discussed earlier.

grain producing regions. All of these existing grain studies however use daily or monthly data and none have explored realized volatility.

There are three main findings of the paper: first, the realized volatility estimates from the three grain futures are consistent with the stylized facts observed in earlier studies; second, the returns from the three grain futures are closely related with each other, yielding positive realized correlation and regression slope coefficients; and third, there exit one-way causalities from volatilities to correlations. The plan of the paper is as follows: Sections 2 and 3 present the realized volatility, correlation and regression slope estimators and their large sample properties. Section 4 presents the details of data and derived estimates of volatility, correlation, and regression slope coefficient. Section 5 presents the impulse response analysis among the realized volatility and correlation. Section 6 concludes the paper.

## 2. Alternative Realized Volatility Estimators

Let $y^*(t)$ be the log price of an asset at time $t$. Following BNS (2004a), the $j$th intra-day return for the $i$th day is defined as:

$$y_{j,i} \equiv y^* \left((i-1) + j/M\right) - y^* \left((i-1) + (j-1)/M\right),$$

where $j = 1,..., M$. With 5-minute intervals in a trading day from 9:30 am to 1:15 pm (which is the case for our data), $M = 45$. The realized variance proposed by ABDL (2003) is obtained by summing up intra-day squared returns, i.e.,

$$[y_M^*]_i^{[2]} \equiv \sum_{j=1}^{M} y_{j,i}^2 \ . \tag{1}$$

According to ABDL (2003), as $M$ increases to infinity, the realized variance given in (1) converges to the underlying integrated volatility, which is a natural volatility measure.

In addition to the realized variance, we consider an alternative realized volatility estimator based on bipower variations of intra-day returns, proposed by BNS (2004a). It is also asymptotically unbiased and model free, but differs from the realized variance in that they are robust to rare jumps in the log-price process under certain conditions. The general form of the realized intra-day bipower variation can be written as

$$\{y_M^*\}_i^{[r,s]} \equiv \{(1/M)^{1-(r+s)/2}\}\sum_{j=1}^{M-1}\left|y_{j,i}\right|^r\left|y_{j+1,i}\right|^s, \tag{2}$$

with $r$, $s \geq 0$. For this measure, we are primarily interested in $\{y_M^*\}_i^{[1,1]}$.

To present the asymptotic properties of alternative estimators under the presence of rare jumps, BNS (2004a) write the log price as a sum of two independent components:

$$y^*(t) = y^{(1)*}(t) + y^{(2)*}(t),$$

where $y^{(1)*}(t)$ is the continuous component and $y^{(2)*}(t)$ is the jump component. Note that $y^{(2)*}(t) = \sum_{i=1}^{N(t)} c_i$, where $N$ is a finite activity simple counting process so that $N(t) < \infty$ and $\{c_i\}$ is a collection of non-zero random variables. The continuous component can be written as $y^{(1)*}(t) = \alpha^* + m^*$, where $\alpha^*$ is the drift term and $m^*$ is a stochastic volatility (SV) process such that $m^*(t) = \int_0^t \sigma(u)dw(u)$. Here $w$ is the standard Brownian motion and $\sigma(t)$ is spot volatility process. The integrated variance process can be written as $\sigma^{2*}(t) = \int_0^t \sigma^2(u)du$. More detailed assumptions in relation to $y^*(t)$ can be found in Assumptions 1 and 2 of BNS (2004a, p.13). Under these assumptions, $y^*$ belongs to what BNS (2004a) referred to as the continuous SV semimartingales class.

BNS (2004a) define the quadratic variation (QV) process as the probability limit of the sum of squared log returns, i.e.

$$[y^*](t) = p\lim_{M\to\infty}\sum_{j=1}^{M}\{y^*(t_j) - y^*(t_{j-1})\}^2 .$$

They defined the rth order power variation process as:

$$\{y^*\}^{[r]}(t) = p\lim_{M\to\infty}(1/M)^{1-r/2}\sum_{j=1}^{M}| y_j(t)|^r ,$$

while the bipower variation process is defined as:

$$\{y^*\}^{[r,s]}(t) = p\lim_{M\to\infty}(1/M)^{1-(r+s)/2}\sum_{j=1}^{M}| y_j |^r | y_{j+1} |^s .$$

According to Proposition 1 of BNS (2004a), $[y^*](t) = \sigma^{2*}(t) + \sum_{i=1}^{N(t)} c_i^2$. This indicates that the QV process consists of the integrated variance and the volatility from the jump component. Further, BNS (2004a: Theorems 4 and 5) have shown that:

$$\{y^*\}^{[2]}(t) = [y^*](t) \text{ ; and } \mu^{-2}\{y^*\}^{[1,1]}(t) = \int_0^t \sigma^2(u)du ,$$

where $\mu = (2/\pi)^{0.5}$. These results indicate that, when appropriately scaled with a known constant, $\{y_M^*\}_i^{[1,1]}$ consistently estimates the integrated volatility, admitting the property of being robust to rare jumps in log price. The realized variance $\{y_M^*\}_i^{[2]} \equiv [y_M^*]_i^{[2]}$, on the other hand, is an inconsistent estimator of the integrated variance under the presence of rare jumps. More precisely, the probability limits of $[y_M^*]_i^{[2]}$ and $\mu^{-2}\{y_M^*\}_i^{[1,1]}$ are respectively $\int_{i-1}^{i}\sigma^2(s)ds+\sum_{j=N(i-1)+1}^{N(i)}c_j^2$ and $\int_{i-1}^{i}\sigma^2(s)ds$.

The asymptotic properties presented above indicate that the difference between the realized variance and the realized bipower variation consistently estimates the jump component, since the probability limit of $[y_M^*]_i^{[2]}-\mu^{-2}\{y_M^*\}_i^{[1,1]}$ is $\sum_{j=N(i-1)+1}^{N(i)}c_j^2$. Based on this, Andersen, Bollerslev and Diebold (ABD 2003) and BNS (2006) propose to separate the continuous and jump components from the realized variance estimates. One possible estimator suggested is:

$$\{J_M\}_i = \max[[y_M^*]_i^{[2]}-\{y_M^*\}_i^{[1,1]}, 0].$$

However, the jumps estimated in this way may yield too small estimates to be statistically significant. To identify statistically significant jumps, we use the adjusted ratio test suggested by BNS (2006):

$$\{Z_M\}_i=\frac{\sqrt{M}}{\sqrt{\max(1,\hat{q}_i/\{y_M^*\}_i^{[1,1]})}}\left(\frac{\mu^{-2}\{y_M^*\}_i^{[1,1]}}{[y_M^*]_i^{[2]}}-1\right),$$

which asymptotically follows the normal distribution with zero mean and variance $(\pi^2/4)+\pi-5$. Note that $\hat{q}_i$ is the realized quadpower variations that can be calculated as:

$$\hat{q}_i = M^{-1}\sum_{j=1}^{M}|y_{j,i}||y_{j+1,i}||y_{j+2,i}||y_{j+3,i}|,$$

Hence, the significant jumps can be identified by those associated with $\{Z_M\}_i$ greater than the standard normal critical value $\Phi_\alpha$. That is, the significant jump is estimated as:

$$\{J_{M,\alpha}\}_i = \mathrm{I}(\{Z_M\}_i > \Phi_\alpha)([y_M^*]_i^{[2]} - \{y_M^*\}_i^{[1,1]}), \qquad (3)$$

and the continuous component is estimated as:

$$\{C_{M,\alpha}\}_i = \mathrm{I}(\{Z_M\}_i \le \Phi_\alpha)[y_M^*]_i^{[2]} + \mathrm{I}(\{Z_M\}_i > \Phi_\alpha)\{y_M^*\}_i^{[1,1]}, \qquad (4)$$

where I() is the indicator function.

## 3. Realized Correlation and Regression Estimators

The realized covariance estimator between two asset returns can be estimated using intraday returns in a similar way. BNS (2004b) consider a bivariate semimartingale process ($y^*$, $x^*$). The quadratic covariation between $y^*$ and $x^*$ is defined as:

$$[y^*, x^*](t) = p\lim_{M\to\infty} \sum_{j=1}^{M} \{y^*(t_j) - y^*(t_{j-1})\}\{x^*(t_j) - x^*(t_{j-1})\}.$$

Under certain conditions, BNS (2004b) have shown that:

$$[y^*, x^*](t) = \int_o^t \Sigma_{y,x}(u)d(u),$$

which is called the integrated covariance where $\Sigma_{y,x}$ indicates the spot covariance. BNS (2004b) and ABDL (2003) proposed the realized covariance estimator for day $i$ day as:

$$[y_M^*, x_M^*]_i \equiv \sum_{j=1}^{M} y_{j,i} x_{j,i} \ ,$$

which is the sum of the cross products of intraday returns. BNS (2004b; Corollary 1) further have shown that the probability limit of $[y_M^*, x_M^*]_i$ is $\int_{i-1}^{i} \Sigma_{y,x}(u)du$ . The corresponding daily realized correlation coefficient can be calculated as:

$$\hat{\rho}_{(yx),i} = \frac{\sum_{j=1}^{M} y_{j,i} x_{j,i}}{\sqrt{\sum_{j=1}^{M} y_{j,i}^2 \sum_{j=1}^{M} x_{j,i}^2}}. \quad (5)$$

According to BSN(2004b; Proposition 4), as $M$ approaches infinity:

$$\frac{\hat{\rho}_{(yx),i} - \rho_{(yx),i}}{\sqrt{\left(\sum_{j=1}^{M} y_{j,i}^2 \sum_{j=1}^{M} x_{j,i}^2\right)^{-1} \hat{g}_{(yx),i}}} \rightarrow N(0,1), \quad (6)$$

where $\rho_{(yx),i} = \frac{[y^*, x^*]_i}{\sqrt{[y^*]_i [x^*]_i}}$, $\hat{g}_{(y,x)} = \sum_{j=1}^{M} m_{j.i}^2 - \sum_{j=1}^{M-1} m_{j,i} m_{j+1,i}$, and

$m_j = 0.5 y_{j,i} x_{j,i} - 0.5 \hat{\beta}_{(y,x),i} x_{j,i}^2 - 0.5 \hat{\beta}_{(x,y),i} y_{j,i}^2$, while

$$\hat{\beta}_{(y,x),i} = \sum_{j=1}^{M} x_{j,i} y_{j,i} \left(\sum_{j=1}^{M} x_{j,i}^2\right)^{-1} \quad (7)$$

is the realized daily regression slope coefficient between two asset returns. Based on (6), asymptotic confidence interval for the true correlation coefficient can be obtained. Similarly, a confidence interval for the regression slope coefficient between two assets returns can be constructed, since $\hat{\beta}_{(y,x),i}$ also follows an asymptotic normal distribution; see, for details, Proposition 2 of BNS (2004b).

## 4. Data and Derived Estimates of Daily Volatility

We have used future prices of three grains: corn (CN), soybean (SY) and wheat (WC) from 4 January 1999 to 30 November 2004. All data were purchased from www.tickdata.com.[4] The markets are open from 9:30 am to 1:15 pm, and we have taken 5-minute intervals yielding up to 45 intra-day observations per day, per grain. In the present context, we feel that this sampling frequency provides a satisfactory

[4] We are unable to make the data available to other researchers, but the data can be purchased from Tickdata. The full set of results will, however, be made available to interested researchers.

balance between the market microstructure frictions (or noise) from high frequency sampling and the accuracy of the continuous record asymptotics from low frequency sampling (see, for example, ABDL, 2000; 2003). The intra-day returns are calculated as the first difference of the logarithmic price. Following ABDL (2003), weekend days, public holidays, and other inactive trading days are excluded from the sample. This gives a total of 1,485 trading days, each with (mostly) 45 intra-day observations for a trading day.

Figure 1 plots alternative realized volatility estimates (standard deviation) for all grain prices. We present only the jump component significant at the 1% level and the continuous component, calculated as in (3) and (4), to conserve space. From Figure 1, the stylized features of the conditional volatility of financial time series, documented in the ARCH literature, are evident for all cases. The fluctuations of the continuous component of realized volatility estimates over time are consistent with the presence of positive serial correlation. They also seem to capture the property of volatility clustering effectively, showing high values for seemingly volatile periods, followed by low values otherwise. The significant jump component display similar features.

Table 1 reports the descriptive statistics of realized volatility estimates and jump components (standard deviation in natural logarithm except for the standardized return) for all grains. It appears that the (logged) realized volatility estimates are approximately normal with the values of skewness and excess kurtosis reasonably close to 0. The realized volatility estimates show strong serial correlation, as the Ljung-Box test soundly rejects the null hypothesis of zero autocorrelation. For all cases, the autocorrelation function shows the first value about 0.5 and then declines slowly from then on. The values of fractional differencing for the log realized volatilities were estimated using the Ox package (version 3.2). The estimates range from 0.32 to 0.42 and are statistically significant (see, for estimation details, Robinson, 1995) indicating the presence of long-range dependence in log volatilities. The standardized returns are found to be approximate normal and show little predictability overall. All of these features are consistent with the stylized facts of realized volatility observed in earlier studies such as ABDL (2000, 2003). The significant jump components show strong serial correlation, according to the Box-Ljung statistics reported. Although higher than expected, the proportions of significant jumps are also comparable to those reported in ABD (2003) and BNS (2006).

Figure 2 reports the 95% confidence bands for the daily correlation and regression slope coefficients given in (5) and (7) among the log returns of the three grain futures prices, for the entire sample period. The point estimates are not plotted for simplicity, because they are the mid-points of the interval. It is evident that the returns from grain futures are positively related for nearly all trading days. It also appears that the correlation and regression coefficients are statistically significantly different from zero for most trading days. The descriptive statistics for the point estimates are given in Table 2. It can be seen that the point estimates are stable around the mean over time with low variability, and they are statistically significant more than 70% of all trading days. The degree of correlation is moderate, and the pairwise regression slope coefficients among the returns are around 0.5 on average. Note that these three realized point estimates move closely over time. For example, the point estimates of realized correlations are positively correlated with correlations ranging from 0.36 to

0.55. A regression among these three correlations shows positive slope coefficients that are statistically significant, with the value of $R^2$ around 0.2.

## 5. Evaluation of volatility spill-over effects

As mentioned earlier, it is of practical policy interest to evaluate the existence and the degree of volatility transmissions across different asset markets. We use the realized volatility and correlation estimates presented in the previous section for this purpose. We conduct the impulse response analysis by fitting the vector autoregressive (VAR) model to realized volatility and correlation estimates.[5] To ensure approximate normality for the VAR model, we take the log of realized standard deviations for all assets. For the realized correlations, we take the Fisher-z transformation that transforms correlations to approximate normality.[6] With reference to the presence of long-range dependence in log realized volatilities as discussed earlier, our VAR model can be regarded an approximation to the fractionally-differenced VAR model that ABDL (2003) adopted. The use of high order VAR model makes the subsequent impulse response analysis and bootstrapping simpler, and can be justified on the basis that a time series with a long memory can be well approximated by a long AR model (see, for example, Basak *et al.*, 2001). Under this situation, the bootstrap procedure to be detailed below can be viewed as the sieve bootstrap proposed by Buhlman (1998).

We consider the *K*-dimensional VAR model of the form:

$$Y_i = \nu + B_1 Y_{i-1} + \dots + B_p Y_{i-p} + u_i, \qquad (7)$$

[5] The VAR model is popular in empirical finance as a means of investigating international transmission mechanisms; see for example, Eun and Shim (1989).
[6] The Fisher-z transform redresses the truncation of correlations (– 1 to +1).

where $Y_i$ is the $K\times1$ vector of variables at day $i$, $\nu$ is the $K\times1$ vector of intercepts, and $B$s are the $K\times K$ matrices of coefficients. Note that $u_i$ is the $K\times1$ vector of innovations with $E(u_i) = 0$ and $E(u_i u_i') = \Sigma_u$. Typical elements of $Y_i$ vector are log-transformed realized standard deviations and Fisher-z transformed realized correlations.

We conduct the generalized impulse response analysis proposed by Pesaran and Shin (1998), which does not rely on specific ordering of the variables in the VAR system. As a means of statistical inference for the generalized impulse response analysis, we use the confidence intervals based on the bootstrap method (Efron and Tibshirani, 1993). The bootstrap method has been used widely in econometrics and found to be useful in many applications (see Li and Maddala, 1996, Berkowitz and Kilian, 2000, and MacKinnon 2002). It involves generation of impulse response estimates from the pseudo-data data sets obtained through repetitive resampling of residuals. The bootstrap distribution of the impulse response estimates can be used as approximations to the true unknown sampling distributions of the impulse response estimates. One can use the bias-corrected bootstrap proposed by Kilian (1998), but we found that the effect of bias-correction is negligible in our study due mainly to our use of a large sample size.

Given $n$ realizations ($Y_1$, …, $Y_n$) of (7), the unknown coefficients are estimated using the least-squares (LS) method. The LS estimators for $B = (\nu, B_1, \ldots, B_p)$ and $\Sigma_u$ are denoted as $\hat{B} = (\hat{\nu}, \hat{B}_1, \ldots, \hat{B}_p)$ and $\hat{\Sigma}_u$, and the associated vector of residuals as $\{\hat{u}_i\}_{i=p+1}^{n}$. The generalized impulse responses are denoted as $\Theta_t$, which are obtained from the MA($\infty$) representation of (7). A typical element of $\Theta_t$ is denoted as $\theta_{kl,t}$, and it is interpreted as the response of the variable $k$ to a one-time impulse in variable $l$, $t$ periods ago. Using $\hat{B}$ and $\hat{\Sigma}_u$, the estimator for impulse response $\hat{\theta}_{kl,t}$ for $\theta_{kl,t}$, can be calculated.

The bootstrap confidence interval for $\theta_{kl,t}$ can be outlined as below:

In Stage 1, generate the pseudo-data set through the following recursion:

$$Y_i^* = \hat{v} + \hat{B}_1 Y_{i-1}^* + \ldots + \hat{B}_p Y_{i-p}^* + u_i^*, \quad (8)$$

where the first $p$ values of the original data are used as starting values and $u_i^*$ is obtained as random sampling from $\{\hat{u}_i\}_{i=p+1}^n$ with replacement.

In Stage 2, using $\{Y_i^*\}_{i=1}^n$, the VAR coefficient matrices are re-estimated and denoted as $\hat{B}^* = (\hat{v}^*, \hat{B}_1^*, \ldots, \hat{B}_p^*)$. Repeat Stages 1 and 2 sufficiently many times, say $m$, to generate bootstrap replicates of $\left\{\hat{B}^{*c}(j)\right\}_{j=1}^m$, from which $m$ bootstrap replicates $\left\{\hat{\theta}_{kl,t}^*(j)\right\}_{j=1}^m$ of impulse responses are obtained. In this paper, $m$ is set to 2,000, which is sufficiently large for bootstrap confidence intervals (see Efron and Tibshirani, 1993).

The 100(1-2$\alpha$)% bias-corrected bootstrap confidence intervals for $\theta_{kl,t}$ can be constructed as the interval [$\hat{\theta}_{kl,t}^*(\alpha)$, $\hat{\theta}_{kl,t}^*(1-\alpha)$], where $\hat{\theta}_{kl,t}^*(q)$ is the $q$th percentile from the distribution of $m$ bootstrap replicates $\left\{\hat{\theta}_{kl,t}^*(j)\right\}_{j=1}^m$, based on the percentile method of Efron and Tibshirani (1993, p.160).

First, we fit a three-dimensional VAR model to the continuous component of realized volatility estimates (those given in Figure 1) obtained by separating out the significant jumps at 1% level of significance. We have chosen a VAR order of 10 based upon Akaike's information criterion (AIC), which is also found to be adequate according to residual diagnostics. Figure 3 presents the impulse response functions with 95% confidence bands. It can be seen that all volatility estimates show long responses to own shocks. For example, the volatility of CN shows positive responses to its own shock for up to 18 days. This reflects the long-range dependence discussed earlier. As for the dynamic interactions, the volatility estimates are positively related over time for all cases, again showing significance responses for a long period. For example, the volatility of log return from CN shows positive responses to a shock in the volatility of log return of SY for up to 17 days. This finding suggests that the volatilities of log returns from grain futures are closely related over time, showing positive reactions to their own shocks, as well as shocks to the others. As expected, for all cases the initial responses (at time 0) are much larger than subsequent responses, indicating that contemporaneously volatility transmission is the highest.

The generalized impulse response was also conducted to the jump components of realized volatility estimates for CN, SY and WC. It is found that no noticeable dynamic relationship is present among the jump components. The jump component affects individual future prices independently without showing any dynamic interactions. This suggests that the shocks that generate jumps are idiosyncratic to that particular grain futures market. The detailed impulse response functions are not reported. These results indicate that the continuous component is the main driving force of volatility dynamics and spill-overs in the grain futures market, while the contribution of the jump component is negligible.

To examine the interactions between correlation and volatility, we fit a six-dimensional VAR model for the three log realized volatility and three Fisher-z transformed realized correlations. The order of this VAR model is found to be six, according to AIC, with satisfactory outcomes from residual diagnostics. The results related to the interactions among the realized volatilities are found to be similar to those reported in Figure 3 and are not repeated here. Figure 4 presents the dynamic responses of the realized correlations to a shock in realized volatility. It can be seen that the realized correlations show positive responses to a shock in realized volatility in most cases. Higher volatility of log return from a grain futures price leads to higher correlations with other log returns. Figure 5 presents dynamic responses of realized volatilities to a shock in realized correlation. In most cases, dynamic responses of volatilities appear to be statistically no different from zero over time. This indicates that, in general, the causality runs one-way from volatility to correlation. Although not reported in detail to conserve the space, it is also found that the correlations are also positively related with other correlations over time. That is, a shock to a realized correlation generates positive responses to other realized correlations over time.

Overall, we have found evidence of strong dynamic interactions among the realized volatility and correlation estimates. This suggests that there are rich spill-over effects among the grain futures markets. Volatilities of grain future returns strongly affect each other over time, and they also affect correlations among the asset returns significantly. In addition, the continuous component is found to be the dominant contributor to the volatility transmissions, while the contribution of jump component has been found to be negligible.

## 6. Conclusion

This paper calculates the realized volatility and correlations for the returns for three grain futures markets (corn, soybean and wheat) daily from January 1999 to November 2004. The properties of realized volatility estimates are found to be consistent with the stylized facts observed in earlier studies. The natural log of realized standard deviation is found to be approximately normal for all futures prices. It is also found that they exhibit long-range dependence characterized by fractionally differenced time series. The realized correlations and regression slope coefficient estimates, along with their asymptotic confidence intervals, are also calculated. It is found that the returns for the three grain futures are positively related with each other, with statistically significant realized correlation and regression slope coefficients in most days.

Using the derived realized volatility and correlation estimates, we examined whether significant volatility transmissions are present among the three grain futures returns. For this purpose, we fitted an unrestricted VAR models to realized volatility and correlations. Impulse response analyses are conducted to identify statistically significant volatility and correlation transmissions over time. We detect a rich set of dynamic interactions among the volatility and correlation among three grain future returns. The volatility of an asset responds to the others positively over time. The period of non-zero positive responses is fairly long, although the initial response is the highest as might be expected. It is also found that there is causality running one-way from volatilities to correlations.

Table 1. Descriptive Statistics for Realized Volatility Estimates

| | log(RV) | log(J(0.95)+1) | log(J(0.99)+1) | RET |
|---|---|---|---|---|
| **CN** | | | | |
| Mean | -4.596 | 0.002 | 0.001 | -0.061 |
| Std. Deviation | 0.289 | 0.003 | 0.003 | 0.868 |
| Skewness | 0.655 | 1.285 | 2.186 | -0.041 |
| Kurtosis | 1.812 | 1.404 | 4.882 | -0.477 |
| Prop | NA | 0.379 | 0.215 | NA |
| Q | 868.88* | 20.79* | 25.68* | 6.86 |
| **SY** | | | | |
| Mean | -4.573 | 0.002 | 0.001 | 0.012 |
| Std. Deviation | 0.323 | 0.003 | 0.003 | 0.944 |
| Skewness | 0.590 | 2.184 | 3.172 | -0.068 |
| Kurtosis | 0.908 | 6.039 | 11.583 | -0.383 |
| Prop | NA | 0.262 | 0.141 | NA |
| Q | 3319.0* | 22.74* | 17.17* | 26.24* |
| **WC** | | | | |
| Mean | -4.355 | 0.003 | 0.002 | -0.051 |
| Std. Deviation | 0.281 | 0.004 | 0.004 | 0.951 |
| Skewness | 0.138 | 1.364 | 2.255 | 0.082 |
| Kurtosis | 0.296 | 1.191 | 4.576 | -0.292 |
| Prop | NA | 0.335 | 0.187 | NA |
| Q | 1200.1* | 19.27* | 18.11* | 15.77 |

RET = Realized Return/RV (RV: realized standard deviation); Kurtosis indicates the excess kurtosis;
Q: Ljung Box statistic for order 10; *: 10% significance; Prop: proportion of significant jumps
CN: Corn, SY: Soybean; WC: Wheat.

Table 2. Descriptive Statistics for Realized Correlations and Betas (point estimates)

| | Realized Correlation | Realized Beta |
|---|---|---|
| **CN vs. SY** | | |
| Mean | 0.50 | 0.53 |
| Median | 0.51 | 0.50 |
| St. Dev | 0.16 | 0.23 |
| Prop | 0.88 | 0.87 |
| **CN vs. WC** | | |
| Mean | 0.39 | 0.51 |
| Median | 0.40 | 0.49 |
| St. Dev | 0.18 | 0.26 |
| Prop | 0.74 | 0.71 |
| **SY vs. WC** | | |
| Mean | 0.42 | 0.55 |
| Median | 0.44 | 0.53 |
| St. Dev | 0.18 | 0.29 |
| Prop | 0.78 | 0.75 |

Realized beta for y vs. x panel indicates the realized slope coefficients estimates from the regression of y on x (without intercept).

Prop: proportion of the realized correlation or beta statistically different from zero at 5% level of significance.

CN: Corn, SY: Soybean; WC: Wheat.

## References


Andersen, T. G., T. Bollerslev, Diebold, F. X., Labys, P. (2003). "Modeling and Forecasting Realized Volatility." Econometrica **71**(2): 579-625.

Andersen, T. G., T. Bollerslev, Diebold, F. X. (2003). "Some Like it Smooth, and Some Like it Rough: Untangling Continuous and Jump Components in Measuring, Modeling, and Forecasting Asset Return Volatility", PIER Working Paper 03-025, University of Pennsylvania.

Andersen, T. G., T. Bollerslev, Diebold, F. X., Labys, P. (2000). "Exchange rate Returns Standardized by Realized Volatility are (Nearly) Gaussian." Multinational Finance Journal **4**(3&4): 159-179.

Apergis, Nicholas and Rezitis, Anthony (2003) "Agricultural Price Volatility Spillover Effects: The Case of Greece". European Review of Agricultural Economics, **30**(3): 389-406.

Areal, N.M.P.C. and Taylor, S.J. (2002) "The Realized Volatility of FTSE-100 Future Prices", Journal of Futures Markets, 22, 7, 627-648.

Barndorff-Nielsen, O. E. and N. Shephard (2004a). "Power and Bipower Variation with Stochastic Volatility and Jumps." Journal of Financial Econometrics **2**(1): 1-37.

Barndorff-Nielsen, O. E. and N. Shephard (2004b). "Econometric Analysis of Realized Covariation: High Frequency Based Covariance, Regression, and Correlation in Financial Economics." Econometrica **72**(3): 885-925.

Barndorff-Nielsen, O. E. and N. Shephard (2006). "Econometrics of testing for jumps in financial economics using bipower variation." Journal of Financial Econometrics, forthcoming.

Basak, G. P., N. H. Chan, and W. Palma (2001) "The approximation of long-memory processes by an ARMA model." Journal of Forecasting 20, 367-389.

Berkowitz, J. and L. Kilian (2000). "Recent developments in bootstrapping time series." Econometric Reviews **19**(1): 1-48.

Bollerslev, T. (1986) "Generalized autoregressive condistional heteroscedasticity." Journal of Econometrics 31, 307-27.

Booth, G. Geoffrey and So, Raymond W. (2003) "Intraday Volatility Spillovers in the German Equity Index Derivatives Markets". Applied Financial Economics, **13**(7): 487-94.

Buguk, Cumhur, Hudson, Darren and Hanson, Terry (2003) "Price Volatility Spillover in Agricultural Markets: An Examination of U.S. Catfish Markets" Journal of Agricultural and Resource Economics, **28**(1): 86-99.

Buhlmann, P. (1998). "Sieve Bootstrap for Smoothing in Nonstationary Time Series." The Annals of Statistics **26**(1): 48-83.

Chan, Kam C., Fung, Hung-Gay and Leung, Wai K. (2004) “Daily Volatility Behavior in Chinese Futures Markets”, Journal of International Financial Markets, Institutions and Money, **14**(5): 491-505.

Cheung, Y.-W. and L. K. Ng (1996). "A causality-in-variance test and its application to financial market prices." Journal of Econometrics **72**: 33-48.

Crain, Susan J.; Lee, Jae Ha (1996) “Volatility in Wheat Spot and Futures Markets, 1950-1993: Government Farm Programs, Seasonality, and Causality”, Journal of Finance, **51**(1): 325-43.

Darbar, S. M., and P. Deb, (1997). “Co-movement in international equity markets”, Journal of Financial Research 20, 305-322.

Efron, B. and R. J. Tibshirani (1993). An Introduction to the Bootstrap. New York, Chapman & Hall.

Engle, R.F., and K.F. Kroner (1995) “Multivariate simultaneous generalized ARCH”, Econometric Theory 11, 122-50.

Engle, Robert F., Ito, Takatoshi and Lin, Wen-Ling (1990) “Meteor Showers or Heat Waves? Heteroskedastic Intra-daily Volatility in the Foreign Exchange Market.” Econometrica, **58**(3): 525-42.

Eun, C. S., and S. Shim, (1989), International transmission of stock market movements, *Journal of financial and quantitative analysis* 24, 241-256.

Ewing, Bradley T., Malik, Farooq and Ozfidan, Ozkan (2002) “Volatility Transmission in the Oil and Natural Gas Markets”, Energy Economics, **24**(6): 525-38.

Faruqee, Rashid, Coleman, Jonathan R. and Scott, Tom (1997) “Managing Price Risk in the Pakistan Wheat Market” World Bank Economic Review, **11**(2): 263-92.

Franses, P. H. and D. van Dijk (2000). Non-Linear Time Series Models in Empirical Finance. Cambridge, Cambridge University Press.

Fung, Hung-Gay, Leung, Wai K. and Xu, Xiaoqing Eleanor. (2003). “Information Flows between the U.S. and China Commodity Futures Trading”. Review of Quantitative Finance and Accounting, **21**(3): 267-85.

Hong, Y. (2001). "A test for volatility spillover with application to exchange rates." Journal of Econometrics **103**: 183–224.

Karolyi, A., (1995), “A multivariate GARCH model of international transmission of stock returns and volatility”, Journal of Business and Economic Statistics 13, 11-25.

Kearney, C., and A. J. Patton, (2000), "Multivariate GARCH modelling of exchange rate volatility transmission in the European monetary system", Financial Review 41, 29-48.

Kilian, L.(1998). "Small sample confidence intervals for impulse response functions." The Review of Economics and Statistics **80**: 218 - 230.

Kim, S. W., and J. H. Rogers, (1995). "International stock price spillovers and market liberalization: evidence from Korea, Japan, and the United States", Journal of Empirical Finance 117-133.

King, M. A., and S. Wadhwani. (1990). "Transmission of volatility between stock markets", Review of Financial Studies 62, 901-933.

Koekebakker, Steen; Lien, Gudbrand (2004) "Volatility and Price Jumps in Agricultural Futures Prices-Evidence from Wheat Options", American Journal of Agricultural Economics, **86**(4): 1018-31.

Li, H. and G. S. Maddala (1996). "Bootstraping time series models." Econometric Reviews **15**(2): 115-158.

MacKinnon, J. G. (2002). "Bootstrap inference in econometrics." Canadian Journal of Economics **35**(4): 615-645.

Morgan, C. W., Rayner, A. J. and Ennew, C. T. (1994) "Price Instability and Commodity Futures Markets." World Development, **22**(11): 1729-36

Pesaran, H. H. and Y. Shin (1998). "Generalized impulse response analysis in linear multivariate models." Economics Letters **58**: 17-29.

Robinson, P. M. (1995). "Log-Periodogram Regression of Time Series with Long-Range Dependence." Annals of Statistic, 23, 1048-1072.

Roche, M.J. and McQuinn, K. (2005). "Grain Price Volatility in a Small Open Economy", manuscript.

Thomakos, D. D. and Wang, T. (2003). "Realized Volatility in the Futures Market", Journal of Empirical Finance, 10, 321-353.

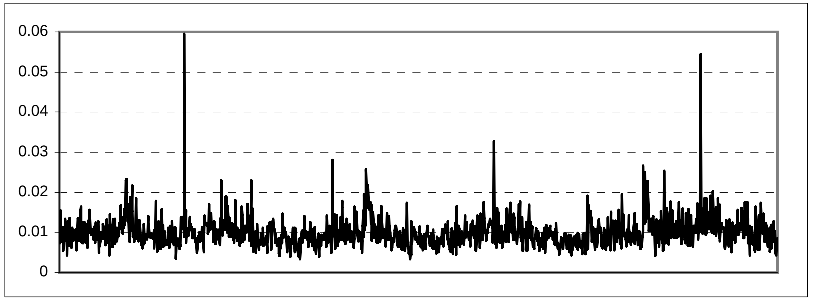
Yang, Jian; Zhang, Jin; Leatham, David J. (2003) "Price and Volatility Transmission in International Wheat Futures Markets." Annals of Economics and Finance, **4**(1): 37-50.

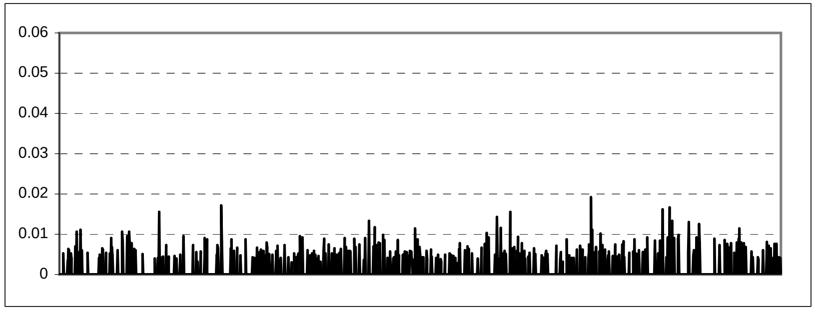
Yang, Jian; Haigh, Michael S.; Leatham, David J. (2001) "Agricultural Liberalization Policy and Commodity Price Volatility: A GARCH Application." Applied Economics Letters, **8**(9): 593-98.

Figure 1. Realised Volatility Estimates (in Standard Deviation Form)

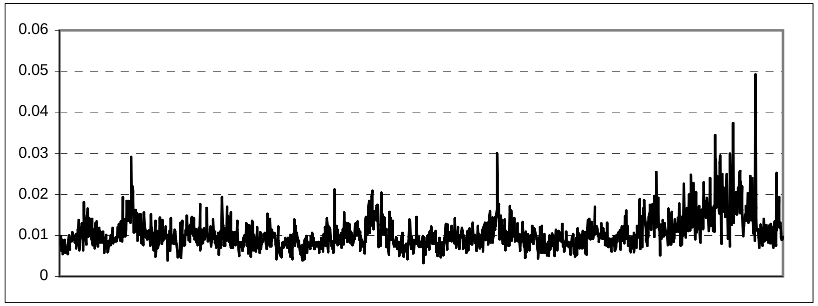
Continuous Component | Jump Component (1% significance)

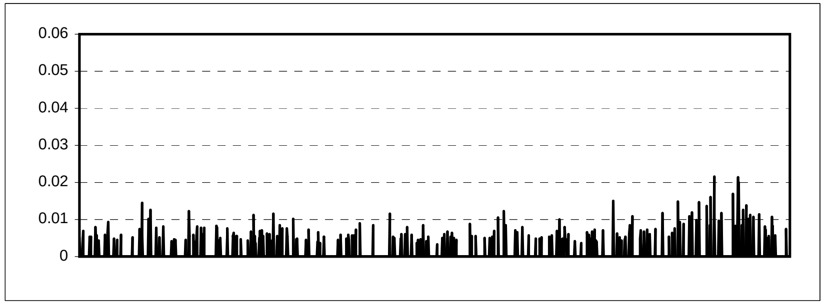
CN



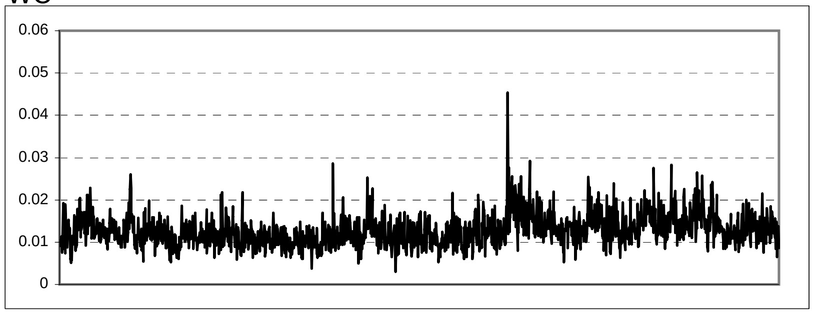



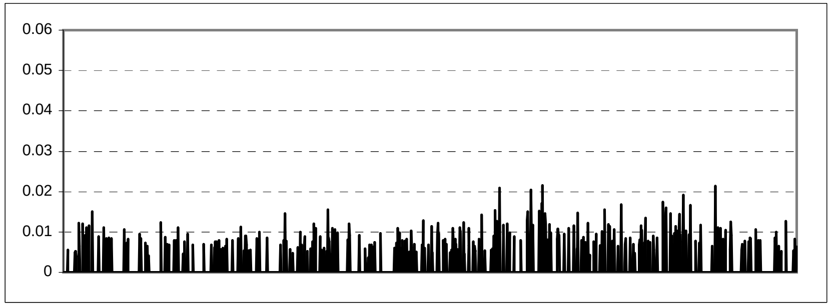

SY




WC




CN: Corn, SY: Soybean, WC: Wheat

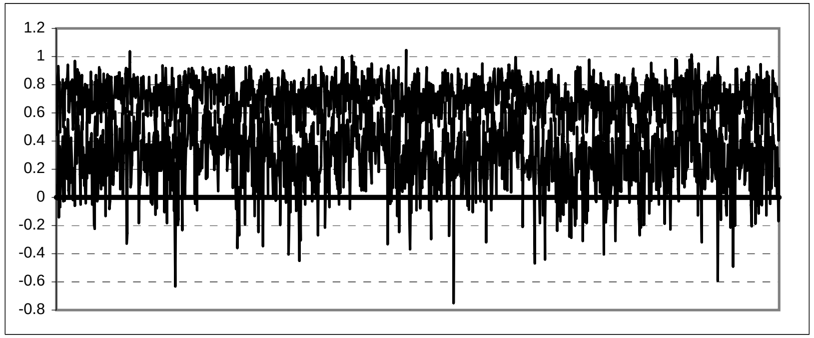
The X-axis indicates the trading days from 4 Jan 1999 to 30 Nov 2004

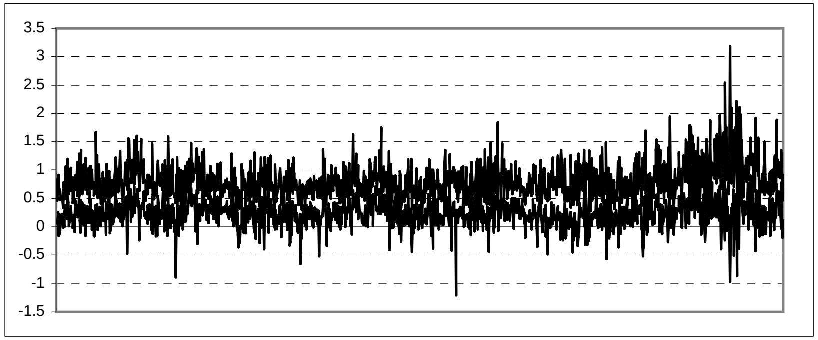
Figure 2. 95% Asymptotic Confidence Band for Realized Correlations and Betas

Correlation

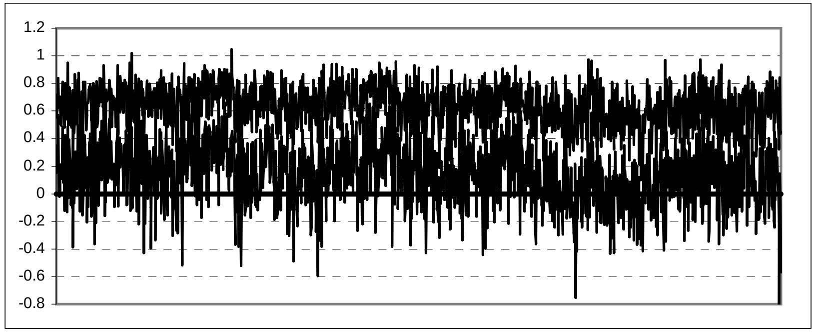
Beta

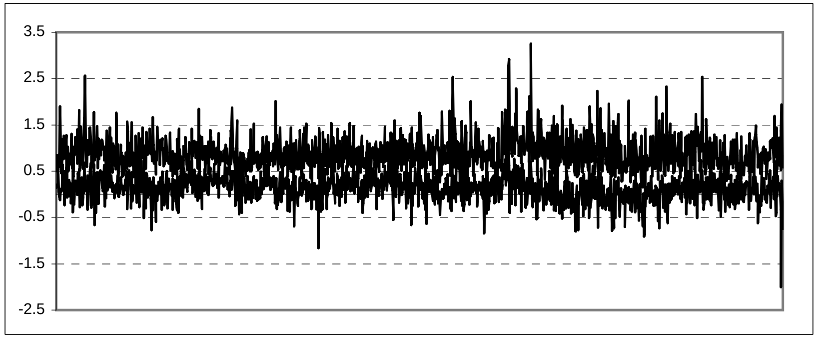
CN vs SY



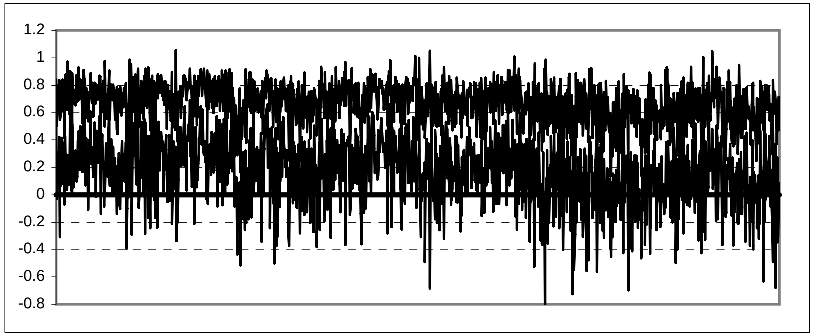



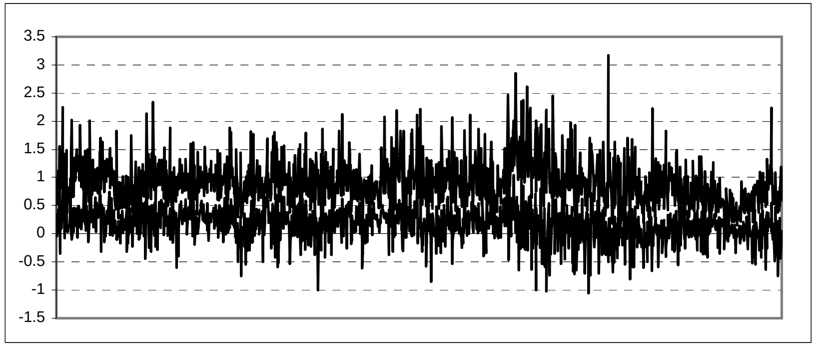

CN vs WC



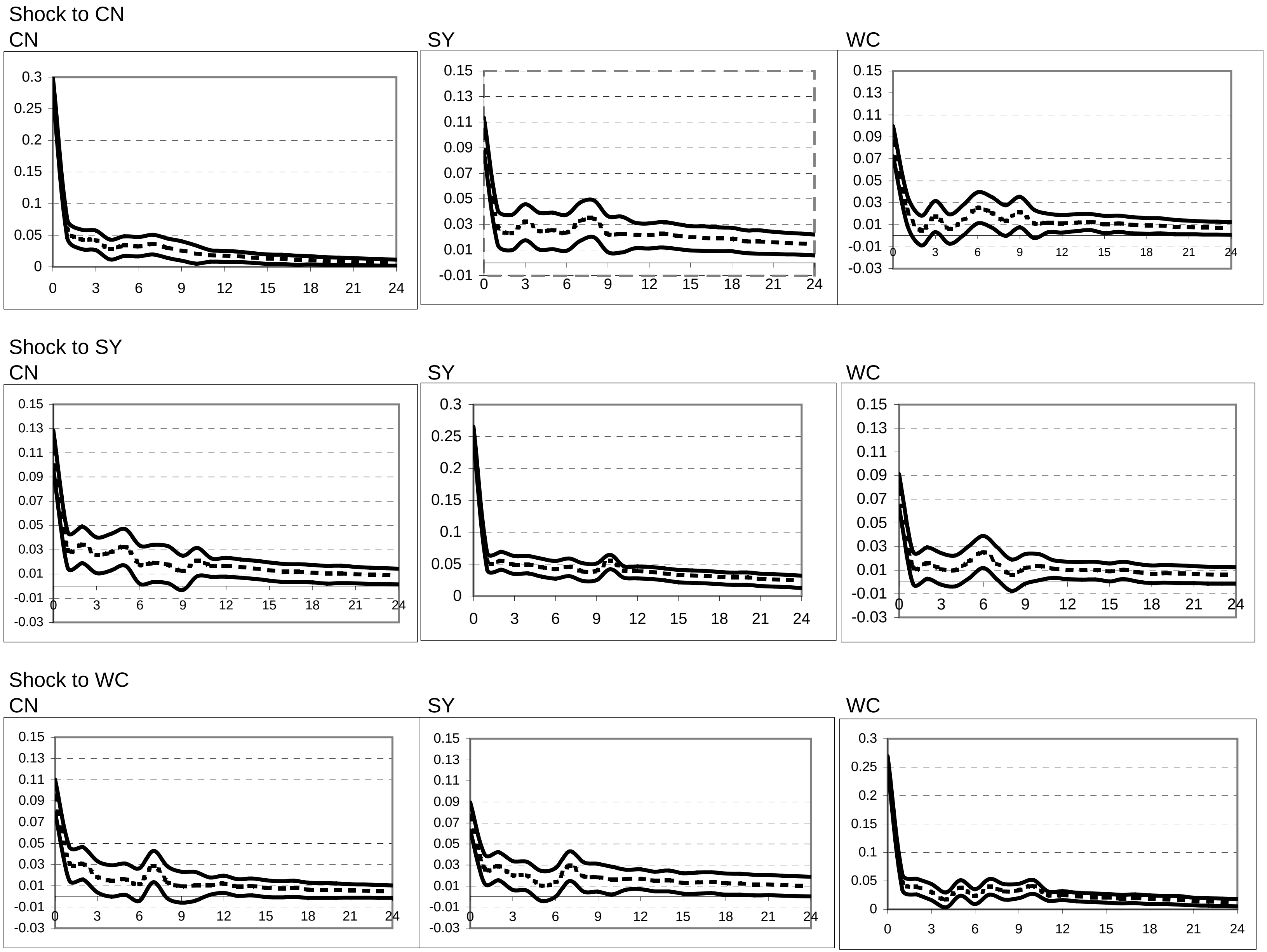

SY vs WC



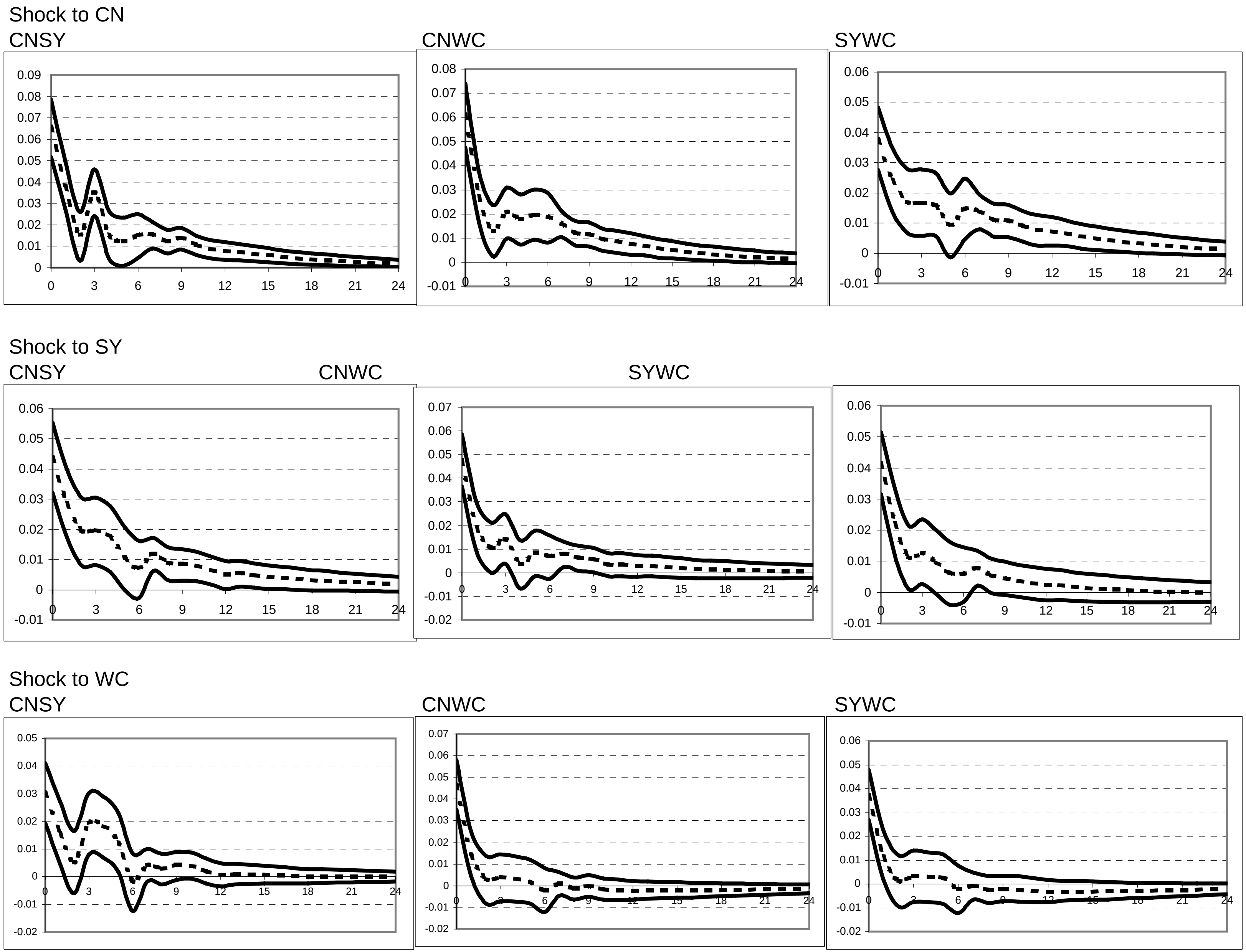

CN: Corn, SY: Soybean, WC: Wheat
The X-axis indicates the trading days from 4 Jan 1999 to 30 Nov 2004
Beta for y vs. x case is the regression slope coefficient of y on x without intercept

Figure 3. Impulse response functions and 95% confidence bands for realized volatility (continuous component)




CN: Corn, SY: Soybean, WC: Wheat
The X-axis indicates the time horizon of 0 to 24 days

Figure 4. Impulse response functions and 95% confidence bands for realized volatility and correlations




CNSY: Correation between CN and SY

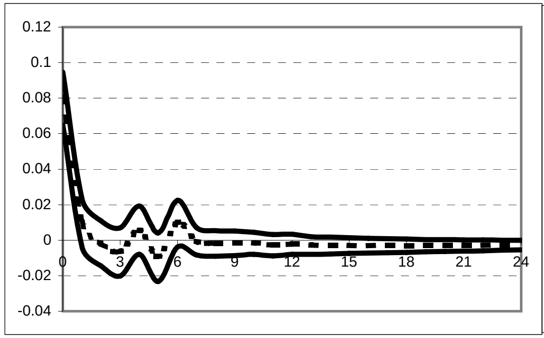
CNWC: Correation between CN and WC

SYWC: Correation between SY and WC

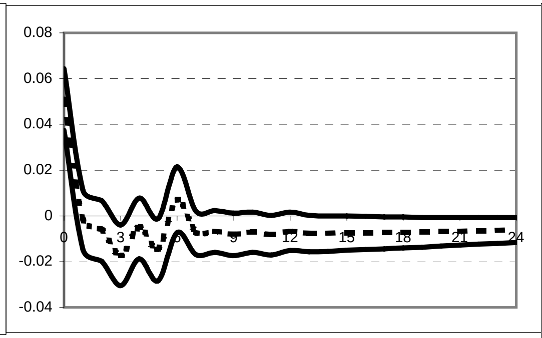
Figure 5. Impulse response functions and 95% confidence bands for realized volatility  and correlations

Shock to CNSY

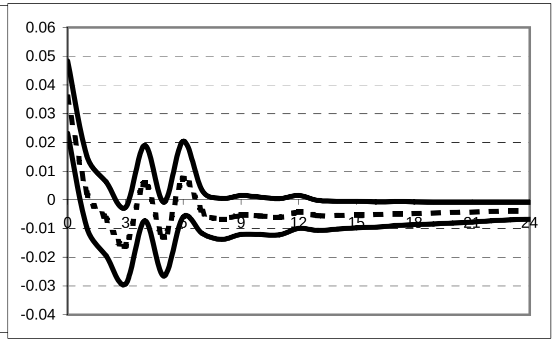
CN




SY

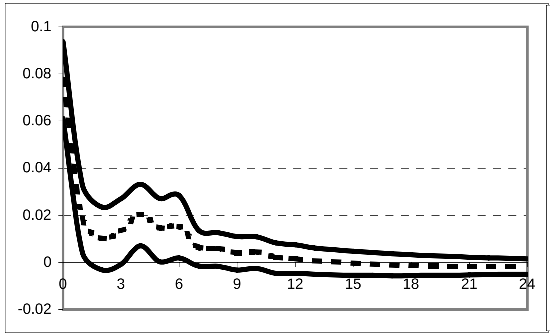



WC

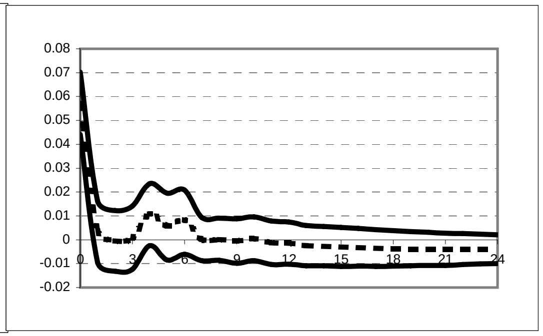



Shock to CNWC

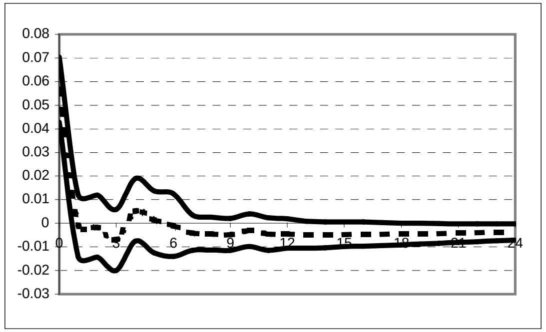
CN




SY

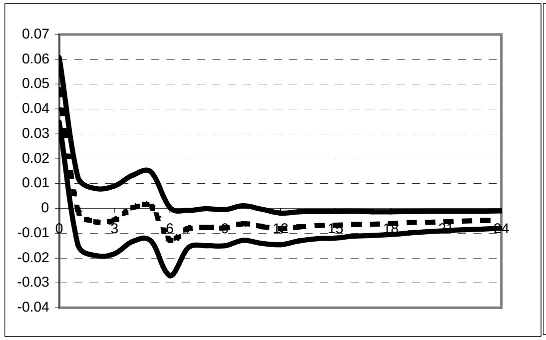



WC

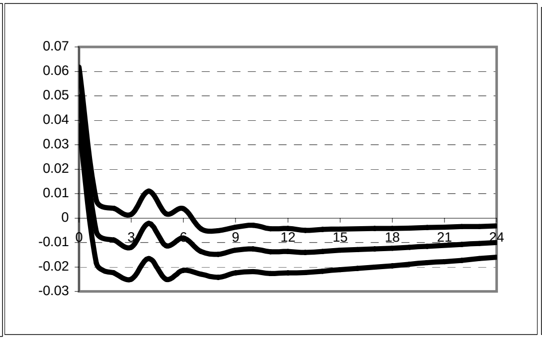



Shock to SYWC

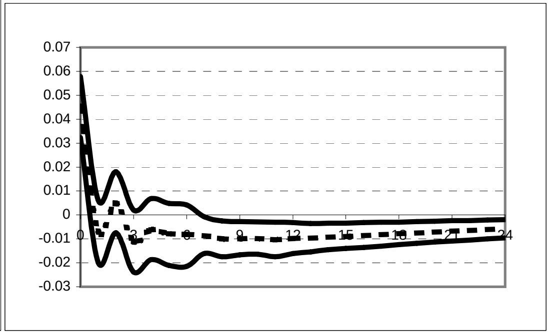
CN




SY




WC




CNSY: Correation between CN and SY

CNWC: Correation between CN and WC

SYWC: Correation between SY and WC